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DRC 2024
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DRC 2024

PROCEEDINGS OF
MULTIDISCIPLINARY DESK RESEARCH CONFERENCE

OCTOBER 25, 2024

COMMERCE AND MANAGEMENT & TECHNOLOGY

The Library
University of Kelaniya
Sri Lanka

PROCEEDINGS

Second Desk Research Conference
of the Library
of the University of Kelaniya

"Mining Treasures from Secondary Information Sources"

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University of Kelaniya

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MESSAGE FROM THE CHIEF GUEST

SENIOR PROF. NILANTHI DE SILVA

Vice-Chancellor,

University of Kelaniya

Sri Lanka

I am delighted to extend my congratulations as we celebrate a significant milestone in our ongoing commitment to advancing high-quality research within our institution. I congratulate the Library for its outstanding efforts in organizing the upcoming Multidisciplinary Desk Research Conference, a trailblazing event in South Asia and a pioneering platform for desk-based research.

The importance of this conference is immense. It provides a unique platform for scholars from various disciplines to come together and exchange insights based on secondary data sources. As academics, we extend our influence beyond traditional teaching by engaging in applied research that meets the highest international standards, fulfilling our societal responsibilities. This event highlights the growing need for collaboration and multidisciplinary approaches to achieve remarkable research outcomes. The united efforts of all faculties and disciplines within our university in organizing this conference demonstrate our strong capability for collaboration within the academic community.

We are fortunate to have keynote speakers who, despite their busy schedules, have shown exceptional enthusiasm and commitment to contributing to the success of the conference. I sincerely thank the Librarian and the library staff for their relentless dedication and efforts, which have been crucial in bringing this academic gathering to fruition. I also congratulate the organizing committee for their unwavering dedication and meticulous planning of this event. I trust that all participants will benefit substantially from the discussions and interactions that await. May this conference serve as a catalyst for intellectual exchange, learning, and the generation of innovative ideas that will drive the future of research in our nation.

MESSAGE FROM THE RESEARCH COUNCIL CHAIRMAN

PROF. SACHITH METTANANDA

Chairman

Research Council

University of Kelaniya

Sri Lanka

It is with great pleasure that I write this message to the proceedings of the International Multidisciplinary Desk Research Conference 2024, organized by the Library of the University of Kelaniya. Following the resounding success of the DRC 2023, the Desk Research Conference has established itself as an integral part of the University of Kelaniya Research Calendar.

Desk and secondary research are receiving increasing recognition in the international research landscape. It provides an opportunity for a deeper understanding of many academic disciplines, not limited to Science and Technology but extending to Arts, Humanities, Social Sciences and Business and Management Studies.

This year's theme, "Exploring Boundless Horizons: Unveiling Insights Through Secondary Sources", clearly explains the vast scope of Desk Research. I am confident that the DRC 2024 would be an excellent platform for all multidisciplinary researchers to disseminate their important secondary research findings and provide insights into many research questions.

I congratulate the organizing committee for completing a daunting task and look forward to a successful meeting.

MESSAGE FROM THE CONFERENCE ADVISOR

DR. C.C. JAYASUNDARA

Conference Advisor

The Librarian

University of Kelaniya

Sri Lanka

With great pride and enthusiasm, I extend my heartfelt congratulations to the organizers, participants, and contributors of the 2nd Desk Research Conference hosted by the University of Kelaniya Library. This event has grown into a prestigious gathering, representing the vast intellectual diversity of our university system, covering a broad spectrum of disciplines, including technology, medicine, and beyond.

The sheer scale of this year's conference is a testament to its significance. With over 100 full research papers submitted, the conference stands as a shining pillar of scholarly rigour and innovation. Notably, a selection of some outstanding papers will be published in the Desk Research Analysis and Review Journal, further amplifying the impact of this conference on academic discourse both locally and internationally.

What makes this year particularly remarkable is the impressive participation of nearly 1,200 registered attendees, underscoring the growing interest and value placed on research dissemination through this platform. This growth is not only a reflection of the hard work and dedication of the organizers but also a promising indicator that this conference is on track to becoming one of the most impactful academic events within the Sri Lankan university sector.
As we look ahead, I am confident that the Desk Research Conference will continue to flourish, setting new benchmarks for research excellence and collaboration. It is an event poised to profoundly impact academic research in Sri Lanka and beyond.

Once again, my sincerest congratulations to all involved in making this conference a resounding success.

MESSAGE FROM THE CHAIR

DR. (MS.) R.A.A.S. RANAWEERA

Conference Chair

The Library

University of Kelaniya

Sri Lanka

With great pride and excitement, we present the second Desk Research Conference of the Library of the University of Kelaniya, a testament to our commitment to promoting research excellence through the use of secondary Data and information sources. This year conference theme, " Exploring Boundless Horizons: Unveiling Insights through Secondary Information" has brought together brilliant minds from diverse backgrounds, united by a shared passion for research and collaboration. We are privileged to host more than 100 thought-provoking research papers across diverse subject areas, including Science & Technology and Medicine, presented through multiple parallel sessions. The Conference will also feature keynote addresses by eminent academics and researchers in Sri Lanka, ensuring a rich exchange of knowledge and perspectives.

I extend my heartfelt appreciation to the Vice-Chancellor of the University of Kelaniya, Senior Professor Nilanthi de Silva, for her unwavering support and leadership. I also thank Professor Sachith Mettananda, Chairman of the Research Council, for his generous financial support and Dr. Chamli Pushpakumara, Dean of the Faculty of Computing and Technology, for his cooperation in facilitating this event.

A special note of thanks is due to Dr. C.C. Jayasundara, Librarian at the University of Kelaniya, the Conference Advisor, whose guidance has been instrumental in shaping this event. I also sincerely thank the Keynote Speakers, Session Chairs, lead paper presenters, co-authors, and reviewers for their invaluable contributions to a successful conference. My sincere gratitude goes to the editorial committee and the organizing committee for their dedication and teamwork in ensuring the success of this conference.

Finally, I wish all participants and presenters a fruitful and rewarding conference experience.

CITATIONS OF THE KEYNOTE SPEAKERS

Dr. Chandrika N Wijeyaratne

Former Vice Chancellor, University of Colombo

Outgoing Senior Professor in Reproductive Medicine

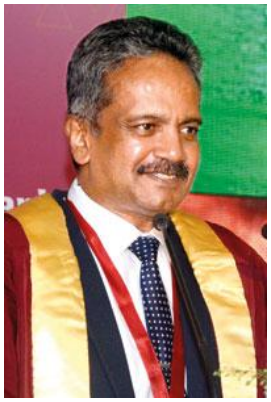
Faculty of Medicine, University of Colombo

Sri Lanka

Dr. Chandrika N Wijeyaratne is former Vice-chancellor and outgoing Senior Professor of Reproductive Medicine of the University of Colombo. She earned her MBBS degree with Honors from the Faculty of Medicine at the University of Colombo in 1983. In 1999, she completed her M.D. with a specialization in Internal Medicine, followed by Doctor of Medicine in Research focusing on Polycystic Ovary Syndrome (PCOS) and Insulin Resistance in South Asians in 2003 from the University of Colombo. She was the first endocrinologist in Sri Lanka, selected for an academic position in 1993, and distinguished herself as a pioneer women's health physician in the South Asian region. Her contributions to the field of Endocrinology were celebrated internationally with the prestigious Laureate Award for International Excellence in 2017 by the Endocrine Society of USA – in its centenary year. This award, in particular, recognized Dr Wijeyaratne's internationally pioneering work on the ethnic variations of Polycystic Ovary Syndrome (PCOS) and her successful efforts to transform diabetes management in pregnancy in a resource-limited setting. She is dedicated to preventing and controlling chronic Non-Communicable Diseases (NCDs) in Sri Lanka and South Asia. Her efforts focus on fostering multi-sectoral collaboration to help achieve the United Nations Sustainable Development Goals (SDGs) for Sri Lanka. With over 35 years of teaching experience, she has made a significant impact on both medical and postgraduate education. She played a key role in developing an innovative medical school curriculum, promoting self-directed learning and a holistic approach among Sri Lankan students. Her research interests include Polycystic Ovary Syndrome (PCOS) and insulin resistance, fetal programming and the intergenerational impacts of metabolic risks, gestational diabetes, and other complex medical conditions in pregnancy. She has also contributed to evidence-based practice guidelines for PCOS and gestational diabetes mellitus (GDM). As a mentor, she has inspired many trainees to pursue careers in Endocrinology, serving as the primary supervisor for over 13 research theses. She has over 100 publications in peer-reviewed journals, including high-impact factor journals such as the New England Journal of Medicine, The Lancet, and PLoS. She has delivered numerous orations and keynote lectures to prestigious institutions, including the Faculty Oration to her Alma Mater, Sir Nicholas Attygalle, Sir Marcus Fernando and Dr Murugesu Sinnettamby Oration of the SLMA, the inaugural Henry Rajaratnam Oration of the College of Endocrinologists and Commonwealth Medical Association.

Dr Wijeratne has had a distinguished leadership career nationally and internationally. She served as Chair of the South Asia Region Committee for the Association of Commonwealth Universities from 2020 to 2022, demonstrating her regional influence in academic leadership. She has held several prestigious positions, including being the Past President of the Sri Lanka Medical Association in 2017, the Ceylon College of Physicians in 2007, and the Endocrine Society of Sri Lanka (2004-2007). In the academic sphere, she has played pivotal roles at the University of Colombo. She was UGC nominee on the Board of Management of the Postgraduate Institute of Medicine (PGIM) and chair the Specialty Board in Endocrinology from 2007 to 2015. Dr. Wijeyaratne represented Sri Lanka in the International Society for Obstetric Medicine and led initiatives focused on public health, including the Diabetes Prevention Task Force, which she convened for 12 years starting in 2004, and the Nirogi Lanka Project, where she continues to serve as an advisor. Additionally, she chaired committees addressing non-communicable diseases and women's health through the Sri Lanka Medical Association from 2006 to 2014.

CITATIONS OF THE KEYNOTE SPEAKERS



Professor Buddhi Marambe

Department of Crop Science

Faculty of Agriculture

University of Peradeniya

Sri Lanka

Professor Buddhi Marambe obtained his B.Sc. degree in Agriculture from the University of Peradeniya (UOP), Sri Lanka, and M.Agr. & D.Agr. from the Hiroshima University, Japan. Being an academic at the Department of Crop Science of Faculty of Agriculture, UOP for more than 38 years, Professor Marambe is extensively involved in teaching, research and outreach in Weed Science, Climate Change Adaptation, and Climate-Smart Agriculture programmes conducted in Sri Lanka, especially focusing on the total food system.

With more than 150 research publications, Prof. Marambe won the "Lifetime Achievement Award" from the International Weed Science Society (IWSS) in 2022, and Presidential Awards and National Research Council (NRC) Merit Awards in Sri Lanka for scientific research related to Agriculture and Food Security in several years.

He was the Chairman and currently a member of the National Experts Committee on Climate Change Adaptation (NECCCA) and is the Chairman of the National Invasive Species Specialist Group (NISSG) of the Ministry of Environment. Professor Marambe has been the Lead Negotiator in the field of agriculture representing the Government of Sri Lanka at the Conference of Parties in the United Nations Framework Convention on Climate Change, for the past 11 years.

While being an academic, he has served as a non-executive member in the Boards of several private sector organizations to provide technical advocacies on agricultural development, and in Councils/Executive Committee of many professional associations. Professor Marambe has provided his services as a consultant to the World Bank, ADB, EU, UNDP, FAO, WFP, UNEP, ICRAF, and CIAT on issues related to agriculture and climate change at national and international levels.

CITATIONS OF THE KEYNOTE SPEAKERS

Professor Liyanage Amarakerthi
Department of Sinhala
University of Peradeniya
Sri Lanka

Liyanage Amarakeerthi is a professor in the Department of Sinhala at the University of Peradeniya. He graduated from the Faculty of Arts at the University of Colombo in 1994, earning the prestigious Prof. M.B. Ariyapala Award for "Most Competent Student of the Year" in the Special Degree Program in Sinhala. After joining the University of Colombo as an Assistant Lecturer in 1995, he was awarded a Fulbright Fellowship to study at the University of Wisconsin from 1998 to 2000, where he earned a master's degree in Languages and Cultures of Asia. He continued at the University of Wisconsin-Madison, completing his PhD in Comparative Literary Studies in 2004. His dissertation, titled *Narrative Methods of Sinhala Prose: A Historical and Theoretical Analysis of Sinhala Prose Narratives from the Twelfth Century to Post-Realist Fiction*, highlighted his expertise in Sinhala literature. He received a Dissertation Fellowship in 2003 and a Tuition Fellowship from Cornell's School of Criticism and Theory in 2005. He also received Harvard University Fellowship in 2010 and an Erasmus Mundus Fellowship at the University of Santiago de Compostela in 2013.

As a prominent Sri Lankan writer, Prof. Amarakeerthi has made significant contributions to literature, first gaining acclaim by winning the All-Island Short Story Competition in 1988 and 1991. His numerous awards include the Best Collection of Short Stories and Novels at various festivals. For the Best Short Stories Collections, he won the Vidyodaya Award in 2013, the Godage Award in 2018, and was shortlisted for the Rajatha Pusthaka Award. He won the Best Novel award at the National Literary Festival in 2008, followed by the prestigious Swarna Pustaka Award for Best Novel in 2014 and 2016, awarded by the Publishers' Association of Sri Lanka. He was shortlisted again in 2017 for the Fairway Literary Award for Best Novel. Recognizing his contributions to Sri Lankan literature, he received the Bunka Cultural Award for Literature from the Japan-Sri Lanka Friendship Cultural Fund.

Prof. Amarakeerthi's literary achievements encompass both original works and translations. In 1997, he won the Best Translation award at the State Literary Festival for translating *Maha Purushayekuta Birindakawa*. In 2020, he received the Best Translation Award at the National Literary Award Festival for his Sinhala adaptation of *Inherit the Wind*, titled *Rala Nagana Minissu*. He was also recognized in 2021 for his translation of *Itihasayak Thula Sahitya: The Translation of Works and Persons in Sinhala Literary Culture* by Charles Hallisey. Most recently, in 2023, he was honored again for his monograph *Vishwa Vidyalaya yanu Kumakda?*, which explores the significance of the humanities and liberal arts in university education.

CITATION OF THE KEYNOTE SPEAKERS

Mr. Ravibandhu Vidyapathy

Professional Dancer & Choreographer

Vice Chairman

State Ballet and Puppetry Advisory Board

Veteran Kandyan dancer, choreographer, percussionist and teacher Ravibandhu Vidyapathy hails from a family of traditional dancers and temple painters both in his paternal and maternal lineages. His father, Somabandhu Vidyapathy was a pioneering artiste who introduced the modern dance and ballet costume grammar and style to the dance theatre in Sri Lanka. His mother, dancer Malathi was the daughter of traditional dance guru Algama Kiriganitha, who groomed Sri Lanka's pioneering dancers, Chitrasena, Panibharatha, Vasantha Kumara, Chandralekha and others. Ravibandhu had his formal education at Dharmapala Vidyapala, Pannipitiya and Thurstan College, Colombo. He learnt the art of dance under legendary guru's Chitrasena and Vajira and drumming under Guru Piyasara Shilpadipathi. He also studied the classical Indian dance form Kathakali at Kerala Kalamandalam, India. Ravibandhu's ground breaking ballets and other choreographies, inspired by literal works such as Shakespeare's Romeo and Juliet, Macbeth, Othello, Greek drama, traditional Asian literature such as Ramayana, Mahabharata and Japanese Noh plays have been acclaimed nationally and internationally. He is also an accomplished percussionist and music composer. He has represented Sri Lanka at international music festivals such as the WOMAD music festival in England, Australia and Singapore, Seoul Drum Festival, Korea, Thailand Drum Festival and has toured and performed in over 30 countries, where he performed at prestigious venues such as the Smithsonian museum and Kennedy Center, America, Saddler's Wells Theater, England, the UN General Assembly Hall Geneva, President's House India, European Parliament Belgium, Opera City Hall Japan, to name a few. His artistic collaborations with international legends like Ustad Zakir Hussain, Billy Cobham, and young stars like Ambi and Bindu Subramanium have won critical acclaim, internationally.

Ravibandhu has held positions such as Chairman of National Dance and Ballet Panel of the Art Council, Member of Cultural subcommittee of UNESCO Sri Lanka, Member of Asia Dance Committee in Korea and advisory positions to cultural minister and as the director of State Dance Ensemble. Currently he works as the course director of National Diploma in Choreography at Sri Lanka Foundation and visiting lecturer and examiner at the University of Visual and Performing Arts and the University of Sri Jayawardenapura. He is the artistic director of Ravibandhu-Samanthi Dance Ensemble and Academy. In 1996, he was awarded the Bunka award by the embassy of Japan, the Derana Sri Lankan of the year award in 2017 and Kalakeerthi National Honors in 2019 respectively. In 2021, the University of the Visual and Performing Arts conferred him with an Honorary Doctorate.

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COMMERCE
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STUDIES

THE IMPACT OF FINANCIAL DISTRESS ON FINANCIAL PERFORMANCE: EVIDENCE FROM LISTED LICENSED FINANCE COMPANIES IN SRI LANKA

LMNS De Mel[1] and HJR Buddhika[2]

ABSTRACT

In the ever-changing world of financial markets, the intersection between financial distress and performance is important. Financial distress, an entity's inability to satisfy its financial obligations, can seriously affect a company or individual's market value and stability. Sri Lanka's financial sector has recently faced difficulties, with certain institutions failing due to insolvency or regulatory noncompliance. The research intends to give significant insights to stakeholders, regulators, and investors in the Sri Lankan finance industry by utilizing Altman's Z-score model. This study examines the relationship between financial distress and financial performance in 22 licensed finance institutions in Sri Lanka from 2013 to 2022. The study's independent variable is financial distress, measured by Altman's Z'Score model, and the dependent variable is financial performance, measured by Return on Assets (ROA) & Return on Equity (ROE). Descriptive analysis, Correlation analysis and panel data regression were used to analyze the data in the study. The study supported that financial distress significantly impacts the ROA and ROE which are considered as financial performance measurements. The higher distress firms showed a lower performance during the period. The main indication given where companies should focus on the distress of the company can be analyzed through the Altmans Z score model. Licensed finance companies can have proactive measurements to enhance the liquidity reserves and optimize the capital structure of the firm. The findings are significantly important for the management of Licensed finance companies in Sri Lanka to manage their future strategies. The study's result indicates a significant impact of financial distress on the financial performance of listed licensed finance companies in Sri Lanka.

Keywords: Altman's Z-score Model, Financial Distress, Financial Performance, Licensed Finance Companies, Return on Assets

[1] Junior Finance Executive, SANA Commerce Pvt LTD, Sri Lanka

Email: nipunidemel99@gmail.com https://orcid.org/0009-0008-0390-217X

[2] Senior Lecturer, Department of Finance, University of Kelaniya.

Email: buddhikar@kln.ac.lk https://orcid.org/0000-0001-9857-0113

BEYOND BORDERS: ORCHESTRATING UNITY IN DIVERSITY AND NURTURING A CULTURE OF INCLUSIVITY IN THE WORKPLACE

SMR Illangarathne[1]

Abstract

This research paper review explores the pivotal role of Human Resources (HR) professionals in promoting diversity and inclusion (D&I) within the workplace. In today's interconnected global landscape, organizations are increasingly acknowledging the importance of diversity and inclusion not only as a moral obligation but also as a strategic advantage. The paper commences by clarifying the conceptual framework of diversity and inclusion, emphasizing their significance in fostering creativity, innovation, and overall organizational performance.Subsequently, the study conducts an extensive analysis of optimal strategies for HR professionals to effectively advance D&I within their organizations. These strategies encompass diverse elements, including recruitment and hiring approaches, employee training and development initiatives, leadership commitment, and the establishment of inclusive workplace policies and practices. Additionally, the paper deep dives into the role of HR technology and data analytics in facilitating D&I initiatives, underscoring the importance of utilizing data-driven insights to identify disparities and implement targeted interventions.Furthermore, the paper addresses the challenges and obstacles that HR professionals may confront in their efforts to promote D&I, such as unconscious bias, resistance to change, and inadequate resources. It outlines strategies for overcoming these challenges, emphasizing the significance of leadership support, cultural competence training, and fostering a culture of accountability.Through a thorough review of existing literature and case studies, this paper offers valuable perspectives and actionable recommendations for HR professionals aiming to cultivate diverse and inclusive workplaces.

Keywords: Diversity, Human Resources, Inclusion, Organizational Performance

[1] Temporary Lecturer, Faculty of Commerce & Management Studies, University of Kelaniya, Sri Lanka.

Email: smrki231@kln.ac.lk https://orcid.org/0009-0004-8210-2007

Introduction

In today's rapidly evolving and interconnected business environment, diversity and inclusion have become essential cornerstones that influence the success of organizations (John,2024). According to Eswaran (2019) result of globalization, technological progress, and changing demographics, the contemporary workforce is more diverse than at any previous point, comprising individuals from various backgrounds, cultures, and viewpoints. Therefore, establishing a culture of diversity and inclusion is crucial for organizations aiming to excel in this intricate setting.

This research paper review delves into the intricate domain of diversity and inclusion in the workplace, providing valuable perspectives on the optimal approaches that Human Resources (HR) professionals can embrace to nurture an inclusive environment. Through synthesizing existing literature, empirical studies, and industry reports, this paper endeavors to furnish HR professionals with a thorough comprehension of the obstacles, prospects, and effective tactics associated with overseeing diversity and nurturing inclusivity in the workplace.

According to Mohideen et al. (2024) The significance of diversity and inclusion extends beyond mere adherence to legal regulations; it is intricately intertwined with organizational performance, innovation, and employee engagement. Research consistently illustrates that diverse teams outperform homogeneous ones, bringing a range of perspectives that stimulate creativity and problem-solving (Wang et al.,2019). Furthermore, inclusive workplaces cultivate a sense of belonging among employees, leading to heightened job satisfaction, retention rates, and productivity (Maj,2023).

Nonetheless, achieving genuine diversity and inclusion entails more than simply recruiting individuals from diverse backgrounds; it necessitates a comprehensive approach encompassing recruitment, retention, training, and organizational culture (Mohideen et al.,2024). HR professionals play a pivotal role in propelling these initiatives, acting as catalysts for change within their organizations. By implementing evidence-based practices and embracing inclusive policies, HR professionals can establish an environment where all employees feel valued, respected, and empowered to contribute their best (Ezeafulukwe et al.,2024).

This paper will examine diversity, including race, ethnicity, gender, age, sexual orientation, disability, and socio-economic background. It will also look at how these aspects intersect and the unique challenges faced by individuals with multiple marginalized identities. Additionally, the paper will discuss the importance of cultural competence, reducing bias, and allyship in creating an inclusive workplace.

Ultimately, the objective of this review research paper is to furnish HR professionals with practical insights and actionable recommendations to steer their endeavors in fostering diversity and inclusion. By embracing diversity as a source of strength and harnessing the richness of human differences, organizations can unlock untapped potential, drive innovation, and forge a more equitable and inclusive workplace for all (Ferraro et al.,2022).

Background

In the contemporary globalized and interconnected business landscape, diversity and inclusion have become vital elements for the prosperity and endurance of organizations (Chin & Trimble,2015). The workforce now comprises individuals from diverse cultural, ethnic, gender, generational, and socio-economic backgrounds, making it imperative for organizations to acknowledge and embrace this

diversity as both a moral obligation and a strategic imperative to thrive in a competitive market (Okundia,2021).

According to Ganesh (2024) Diversity goes beyond mere compliance with legal mandates or quotas; it involves fostering an environment where individuals from all backgrounds feel esteemed, respected, and empowered to contribute their unique perspectives and abilities. Inclusive workplaces not only attract top talent but also enhance employee engagement, creativity, and innovation, ultimately leading to improved organizational performance (Naval,2023).

Human Resource (HR) professionals hold a crucial responsibility in advocating for diversity and inclusion within organizations. Their role involves developing and implementing policies, practices, and initiatives that foster diversity, eliminate bias, and cultivate an inclusive culture (Boatman, n.d.). However, effectively addressing the complexities of diversity and inclusion requires a nuanced understanding of best practices, challenges, and strategies tailored to each organization's specific context.

Despite the escalating acknowledgment of the significance of diversity and inclusion, many organizations still encounter challenges in effectively addressing these issues. Obstacles such as unconscious bias, systemic barriers, lack of accountability, and resistance to change often impede progress in building truly inclusive workplaces (Mohideen et al., 2024). Furthermore, the evolving nature of workforce demographics and societal norms necessitates continuous adaptation and refinement of approaches by HR professionals.

Therefore, this review paper aims to provide HR professionals with an exhaustive overview of best practices for promoting diversity and inclusion in the workplace. Drawing from existing literature, case studies, and expert insights, the paper will explore various dimensions of diversity and inclusion, encompassing recruitment and hiring practices, training and development initiatives, leadership commitment, organizational culture, and measurement and evaluation strategies.

By amalgamating current knowledge and practical experiences, this paper seeks to equip HR professionals with actionable insights and strategies to effectively navigate the complexities of diversity and inclusion. Ultimately, it endeavors to contribute to the creation of more just, inclusive, and flourishing workplaces where all employees can realize their full potential and contribute to organizational success.

Practical implications for HR professionals

In the field of diversity and inclusion (D&I), human resources (HR) professionals frequently seek tangible approaches and proven methods to integrate into their companies. This document aims to narrow the divide between theory and application by furnishing evidence-based suggestions created specifically for HR professionals. These suggestions cover a range of areas, such as recruitment and hiring procedures, training and development initiatives, employee resource groups, and inclusive leadership strategies, among others.

The evidence-based suggestions outlined in this document are crafted to provide practical guidance to HR professionals in enacting effective strategies to advance diversity and inclusion within their organizations. These suggestions are shaped by a comprehensive comprehension of the obstacles and opportunities linked with managing diversity and nurturing inclusivity in the workplace, as well as insights from existing literature, case studies, and expert viewpoints.

Ultimately, it aims to contribute to the creation of more equitable, inclusive, and thriving workplaces where all employees can reach their full potential and contribute to organizational success.

Objectives of the study:

1. Evaluate diversity and inclusion programs within companies, with a focus on the involvement of HR professionals in their implementation.
2. Acknowledge effective strategies employed by HR professionals to encourage diversity and inclusion in the workplace.
3. Examine the impact of diversity and inclusion initiatives on organizational performance, employee satisfaction, and overall workplace culture.
4. Identify obstacles and challenges faced by HR professionals when implementing diversity and inclusion practices and strategies.
5. Explore the connection between diversity and inclusion efforts and employee retention, recruitment, and talent development within organizations.

Literature Review

Diversity and inclusion have emerged as focal points in modern workplaces as organizations acknowledge the significance of a diverse workforce in fostering innovation, creativity, and competitive advantage (Monawer,2024). Human Resource (HR) professionals hold a crucial role in implementing strategies and practices to advocate for diversity and inclusion (D&I) within their organizations (Talat,2023). This literature review seeks to investigate existing research on optimal approaches for HR professionals to promote diversity and inclusion in the workplace.

Diversity encompasses differences within a given setting, including various dimensions such as race, ethnicity, gender, age, sexual orientation, religion, disability, and socioeconomic background (Ganesh,2024)). On the other hand, inclusion pertains to establishing an environment where all individuals feel esteemed, respected, and empowered to contribute their unique perspectives and talents (Brouge,2023).

Research consistently illustrates the advantages of diversity and inclusion in organizational settings. A diverse workforce enhances creativity and problem-solving by bringing together individuals with diverse backgrounds and perspectives (Campbell, 2023). Additionally, inclusive work environments foster employee engagement, job satisfaction, and retention (Tenney, 2024).

Optimal Approaches for HR Professionals:

- The dedication of organizational leaders is vital for the effective execution of diversity and inclusion initiatives (Nancholas,2024). HR professionals should collaborate with leaders to devise a clear vision and strategic plan for fostering diversity and inclusion.
- HR professionals should implement impartial recruitment and hiring methods to attract diverse talent pools (Taylor, n.d.). This may involve utilizing diverse recruitment channels, implementing blind resume screening processes, and providing unconscious bias training for hiring managers (Vivek,2022).
- Training programs that raise awareness of diversity issues and promote inclusive behaviors are essential (Toll, 2024). HR professionals should design and deliver training sessions addressing topics such as cultural competence, unconscious bias, and inclusive leadership.

- ERGs offer opportunities for employees from diverse backgrounds to connect, share experiences, and advocate for inclusive policies and practices (Havens, n.d.). HR professionals should endorse the establishment and activities of ERGs within their organizations.
- HR professionals should integrate diversity and inclusion metrics into performance management systems to hold leaders and managers accountable for fostering inclusive environments (Bar, n.d.). This may involve tracking diversity metrics, conducting regular climate surveys, and establishing diversity goals (Mohideen et al.,2024).

Fostering diversity and inclusion in the workplace is a crucial endeavor that requires a collective effort from HR professionals, organizational leaders, and employees. By implementing best practices such as leadership commitment, impartial recruitment, training and development, support for ERGs, and performance management, HR professionals can significantly contribute to creating inclusive work environments that drive organizational success.

Methodology

The methodology employed in this review paper utilizes a systematic literature review approach to investigate best practices for HR professionals in promoting diversity and inclusion in the workplace. Systematic literature reviews are widely acknowledged as robust methods for synthesizing existing knowledge on a specific topic, involving a comprehensive search of relevant literature, followed by the systematic extraction and analysis of data to identify key themes, trends, and recommendations (Lamé, 2019).

The data collection process for this review involved searching electronic databases, like, Research Gate, Scopus, and Google Scholar, using keywords such as "diversity," "inclusion," "workplace," "HR practices," and variations thereof. Also, certain information and data were gathered through many other reliable websites. The search was limited to articles published between 2010 to 2024. Further, the language was only limited to English. Additionally, relevant and specific journals and conference proceedings were hand-searched to ensure comprehensive coverage of the literature.

Inclusion criteria for the selection of articles included peer-reviewed research studies, review articles, and meta-analyses that examined diversity and inclusion practices in the workplace, focusing on various dimensions of diversity and inclusion initiatives. Also, new and updated articles related to “Diversity” and “Inclusion” of writers in the industry were taken into consideration. Exclusion criteria encompassed non-peer-reviewed sources, dissertations, conference abstracts, and articles not directly related to diversity and inclusion in organizational settings.

To ensure a thorough and credible systematic literature review, evaluation of the relevance of the sources, methodological rigour, and preference for peer-reviewed articles were highly considered. Further, considering the number of citations and the impact factors of journals were considered to give an additional layer of assurance regarding the articles' scholarly significance.

Ethical considerations were paramount throughout the research process, ensuring the confidential and anonymized handling of data extracted from selected articles to protect the identity and their privacy. Proper citation and acknowledgment of sources were ensured to maintain academic integrity and avoid plagiarism, adhering to ethical guidelines outlined by relevant professional bodies and following the principles of integrity, objectivity, and respect for diversity in research conduct and reporting.

Results & Discussions

The study titled "Beyond Borders: Orchestrating Unity in Diversity and Nurturing a Culture of Inclusivity in the Workplace" provides in-depth insights into the strategies and methods utilized by Human Resource (HR) professionals to promote diversity and inclusion (D&I) within organizations. By conducting a thorough review of existing literature and empirical evidence, the research outlines essential findings that are pivotal for comprehending and implementing effective D&I practices in today's workplace.

Further, the study emphasizes the increasing acknowledgment of diversity and inclusion as essential elements for organizational success. It highlights the positive link between diverse workforces and heightened innovation, creativity, and overall performance. Additionally, inclusive workplaces are noted for promoting employee engagement, retention, and satisfaction.

Despite the recognized advantages, the research identifies persistent challenges and barriers that impede the achievement of diversity and inclusion objectives. These obstacles include unconscious biases, systemic discrimination, lack of inclusive leadership, and organizational cultures resistant to change. Moreover, insufficient resources and limited commitment from top management present significant challenges to D&I initiatives (Mohideen et al.,2024).

Effective Strategies for HR Professionals

The paper outlines a range of effective strategies for HR professionals to foster diversity and advance inclusion within their organizations. It emphasizes effective strategies like the importance of visible support from senior leadership to drive diversity and inclusion initiatives (Ashikali et al.,2020). Additionally, we can consider the significance of implementing inclusive recruitment practices, such as blind hiring techniques and diverse candidate sourcing, to reduce bias in the hiring process (Vivek,2022). Moreover, the value of providing training programs that raise awareness of unconscious biases, enhance cultural competence, and develop inclusive leadership skills across all employee levels can also be considered as another effective strategy for HR Professionals to promote diversity and inclusion within their workplaces (Gino & Coffman,2021). Furthermore, the emphasis on the creation of Employee Resource Groups (ERGs) as a means to provide support, networking opportunities, and a platform for underrepresented groups to express their perspectives and concerns is too an effective strategy (Catalino et al.,2022). Lastly, the necessity of transparent policies related to promotion, compensation, and performance evaluation to mitigate disparities and build trust among employees is also a vital strategy for HR Professionals (Fulmer et al., 2023).

The significance of establishing metrics and benchmarks to assess the effectiveness of diversity and inclusion (D&I) initiatives, and regular monitoring and evaluation to enable HR professionals to identify areas for improvement and adjust strategies accordingly (Okatta,2024). Furthermore, the successful implementation of D&I practices requires their integration into the organizational culture (Pathak,2024). HR professionals are advised to embed diversity and inclusion considerations into all aspects of organizational processes, from recruitment to decision-making. This integration ensures that D&I becomes an inherent part of the organizational ethos, fostering a more inclusive and diverse workplace environment (Hossain,2023).

Future Directions and Implications for Research

The research paper concludes by highlighting areas for future research, such as the the impact of emerging technologies on D&I practices, and the efficacy of interventions in different cultural contexts.

The findings of this study underscore the critical role of HR professionals in championing diversity and inclusion within organizations. By adopting evidence-based best practices and overcoming inherent challenges, HR professionals can cultivate workplaces that celebrate diversity, foster inclusion, and drive organizational excellence.

Limitations

The study's use of a small sample size might hinder the application of its findings to broader populations, potentially creating difficulties in implementing the identified best practices in organizations with different demographics or industries. Focusing on specific geographical regions or industries in the research could overlook variations in workplace dynamics and cultural norms across different areas, limiting the universal applicability of its findings. Depending on the methods used, such as surveys or interviews, there may be inherent biases or limitations in data collection, such as self-reporting bias or difficulty capturing nuanced experiences and perceptions related to diversity and inclusion in the workplace. The study's findings may be influenced by the specific time period in which the research was conducted, and as workplace dynamics and best practices evolve over time, the relevance of the identified strategies may vary in different temporal contexts. The study might not have considered all organizational factors that could impact diversity and inclusion initiatives, potentially limiting the effectiveness or applicability of the recommended practices. Assessing the effectiveness of diversity and inclusion initiatives can be challenging, and the study may have relied on subjective or proxy measures that do not fully capture the impact on organizational outcomes like employee satisfaction, productivity, or innovation. There might be a tendency for studies with positive results to be published more frequently, potentially leading to an overrepresentation of successful diversity and inclusion practices in the literature, which could skew perceptions of the effectiveness of certain strategies. The absence of longitudinal data could make it difficult to assess whether the identified best practices lead to enduring positive outcomes over time, potentially impacting insights into the sustainability and long-term impact of diversity and inclusion initiatives.

Conclusion and Recommendations

In essence, the research on diversity and inclusion in the workplace emphasizes the crucial role of HR professionals in nurturing an environment where each person feels appreciated, valued, and empowered to contribute their unique perspectives and skills. The comprehensive examination of effective strategies demonstrates the numerous advantages that organizations can gain from embracing diversity and fostering inclusivity, such as increased creativity, innovation, and employee engagement. Furthermore, the findings highlight the importance of implementing proactive measures, including diverse recruitment and retention initiatives, inclusive leadership training, and the establishment of fair policies and procedures. These actions not only assist in attracting and retaining top talent from diverse backgrounds but also contribute to the overall success and longevity of the organization. Nonetheless, it's essential to recognize that building a genuinely inclusive workplace requires continuous dedication and effort from all levels of the organization. HR professionals must consistently evaluate and refine their diversity and inclusion initiatives to ensure their relevance and effectiveness in addressing the evolving needs and challenges of the workforce. In conclusion, while there is still progress to be made, this research underscores the significant strides that organizations can take toward creating more diverse and inclusive workplaces. By leveraging the insights and best practices outlined in this paper, HR professionals can play a pivotal role in driving positive change and establishing environments where all individuals can thrive and succeed.

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EXPLORING INDUSTRY 4.0 DRIVERS AND THEIR IMPACT ON LOGISTIC SECTOR: A SYSTEMATIC REVIEW

D Samarathunga[1] and A Withanaarachchi[2]

Abstract

Industry 4.0 marks the fourth industrial revolution, characterized by the integration of advanced digital technologies such as the Internet of Things (IoT), artificial intelligence (AI), robotics, big data analytics, and cloud computing into manufacturing and production processes. This evolution aims to create intelligent and efficient manufacturing environments by enhancing computerization, application, and information exchange throughout the value chain. In the logistics sector, a crucial component of global value chains, the adoption of Industry 4.0 technologies is expected to revolutionize operations by offering real-time information, advanced analytics, and self-sustaining processes, which can lead to increased efficiency, reduced costs, and improved customer satisfaction. However, the adoption of Industry 4.0 in Sri Lanka's logistics industry has been slow due to several challenges, including inadequate infrastructure, high implementation costs, and a shortage of skilled personnel. Regulatory and economic factors further complicate the adoption process. This study aims to address these challenges by exploring key factors that affect the performance of logistics firms in Sri Lanka in the context of Industry 4.0. Through a systematic literature review of 45 empirical publications, the study identifies critical components for successful adoption, including technological readiness, organizational culture, and workforce skills. It also examines how economic fluctuations impact the adoption and effectiveness of Industry 4.0 technologies. The findings offer valuable insights for overcoming adoption barriers and optimizing logistics performance, contributing to the broader understanding of Industry 4.0 in logistics and providing a foundation for future research and practice.

Keywords: Economic Impact, Factors, Industry 4.0 technologies, Logistics.

[1] Department of Industrial Management, University of Kelaniya, Sri Lanka
Email: samarat-im19098@stu.kln.ac.lk
[2] Senior Lecturer, Department of Industrial Management, University of Kelaniya, Sri Lanka
Email amilaw@kln.ac.lk https://orcid.org/0000-0002-1511-011X

Introduction

Industry 4.0 refers to the indication of the fourth industrial revolution which is associated with implementation of digital technologies in manufacturing and other production processes. They include the Internet of Things (IoT), artificial intelligence (AI), robotics, big data analytics and Cloud computing. These technologies aspire to build intelligent manufacturing environments and extremely efficient manufacturing networks by improving the level of computerization, application, and information exchange in the entire manufacturing value chain. The above studies indicate the reference concept of Industry 4.0 is the adoption of new technologies that seek to enhance competency and effectiveness of industries in that they can seize on market opportunities and customers' requirements. The logistics industry, which is a critical link in the global value chains, will be touching innovation goals of Industry 4.0 technologies. Supply chain management entails the coordination between the manufacturer, the supplier and the end user and entails activities such as transport, storing of goods, and issues to do with inventory and order picking. Making connections between papers or between real-life environments and Industry 4.0 Details of 4.0 technologies claim that they will change logistics operations and provide real-time information, analytics, and self-sustaining processes, which would increase efficiency, decrease expenses, and deliver pleased customers.

There is a risk that introducing Industry 4.0 Total adoption of the said 4.0 technologies in Sri Lanka's logistics sector has thus remained relatively slow. These are seen as the slow uptake which can be attributed to issues such as inadequate infrastructure, expensive implementation, and scarce skilled human resource. Besides, the regulatory issues as well as the issues on the economy also hinder the use of these progressive technologies. Analyzing the obstacles to embracing this revolution and finding out about the determinants of efficacy in logistics operations concerning Industry 4.0 Technology is important to come up with the right measures to eliminate these challenges.

To address these issues, this study seeks to answer the following research questions:
RQ1: What are the Industry 4.0 related factors that could enhance the performance of Logistics Firms?
RQ2: How do these Industry 4.0 related factors impact the performance of Logistics Firms?
RQ3: How do economic fluctuations impact/condition the association of these particular factors with the performance of logistics firms?

Methodology

In this systematic review, a well-structured search and selection procedure will be followed using the PRISMA protocol in order to study the current stage of research into the impact of Industry 4.0 on logistics operations. The identification and selection process for the articles to be reviewed has followed the steps recommended by Preferred Reporting Items for Systematic Reviews and Meta-Analyses as provided by Moher et al. in 2009. This process consisted of three different stages: identification, screening, and inclusion, presented in detail in Fig. 1.

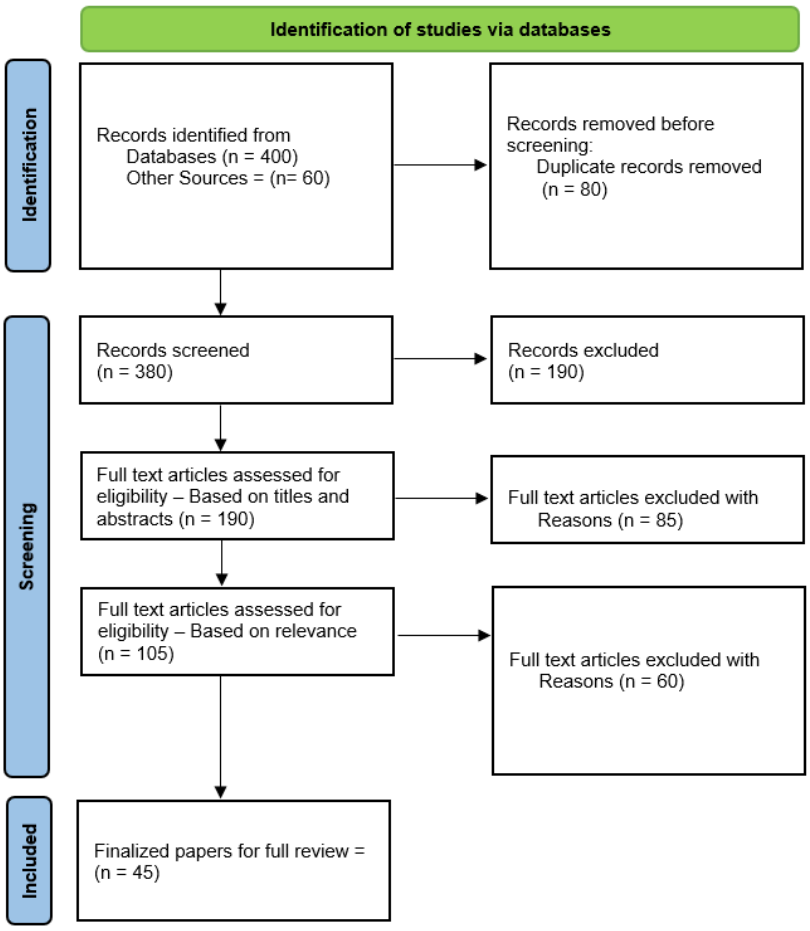

Figure 1- PRISMA Flow Diagram for Filtering 45 Articles

In order to undertake a comprehensive literature search and ensure accuracy, a multi-database searching approach was employed. In this sense, these databases were selected in consideration of their high coverage on themes relevant to our objectives. These databases include IEEE Xplore, Google Scholar, and Science Direct.

Search Strategy and Keywords

Keywords: Industry 4.0, Logistics, Factors, Drivers, Challenges, Benefits, Economic Fluctuations

The review started with an all-inclusive search of several databases to ensure the best possible coverage of studies relevant to Industry 4.0 and its impact on logistics. These databases included Google Scholar, IEEE Xplore Digital Library and Science Direct. Having identified the sources at the beginning, there were 460 records, with 400 identified in databases and 60 identified outside.

We have used Boolean operators as one of the core devices for searching, hence allowing nuanced and precise filtering of the literature. A number of keywords—"Industry 4.0", "Logistics", "Factors", "Drivers", "Challenges", "Benefits", and "Economic Fluctuations"—are joined by Boolean connectors like AND and OR. This strategy enabled us to conduct an exact search for studies directly related to our research questions on the applications of Industry 4.0 in logistics. The final research search string was developed using Boolean operators and is as follows:

("Industry 4.0" AND "Logistics" AND ("Factors" OR "Drivers") AND ("Challenges" OR "Benefits") AND "Economic Fluctuations").

Screening and Selection Process

From the initial pool, records were first subjected to removal of duplicates, resulting in 80 records being excluded. The remaining 380 records were then screened for relevance based on their titles and abstracts. This phase resulted in the exclusion of 190 records.

Subsequently, 190 records were subjected to a more detailed assessment for eligibility based on their content and relevance to the research questions. This process further reduced the pool, excluding 85 records that did not meet the specific inclusion criteria of our review.

The remaining 105 studies were assessed through a full-text review to determine their eligibility. During this stage, 60 records were excluded for reasons including:

- Articles not talking about any of the parameters vis-à-vis Industry 4.0: related factors, challenges, and benefits.
- Research works that could not contribute to insights into the impact of economic fluctuations on the adoption of Industry 4.0.

By removing these, 45 studies were deemed suitable for final analysis.

Inclusion and Exclusion Criteria

To ensure that the literature taken into consideration was relevant and meaningful, certain inclusion and exclusion criteria were determined while screening the literature:

Table 1: Inclusion Exclusion Criteria

Category	Inclusion Criteria	Exclusion Criteria
Publication Year	Peer-reviewed articles, conference papers, and high-quality industry reports published from 2015 onwards	Publications before 2015
Language	Articles published in English	Non-English publications
Content Focus	- Literature that includes Industry 4.0 related factors.	Literature not related to the purpose of this review.
	- Literature that addresses the benefits of Industry 4.0 in logistics.	
	- Literature that discusses the challenges of Industry 4.0 in logistics.	
	- Literature that provides insights into Influence of Economic Changes on the Impact of Industry 4.0 Factors in Logistics Performance.	
Research Quality	- Literature with titles that match the keywords in the search strings.	Articles that do not provide empirical data or substantial theoretical insights.
	- Provides empirical data or substantial theoretical insights.	
Duplication		Literature duplicated across multiple digital libraries.

Data Extraction and Synthesis

The identified studies were systematically reviewed to outline data that would directly answer the research questions. Key findings were synthesized into thematic categories corresponding to the identified factors, challenges, benefits, and economic influences associated with Industry 4.0 in logistics.

This systematic and meticulous approach provided a comprehensive way of exploring literature that delivered valuable insights into how technologies belonging to the concepts of Industry 4.0 influence logistics operations and how economic fluctuations interfere with these dynamics.

Results and Discussion

Industry 4.0 Technologies and Their Integration into Logistics Operations

Industry 4.0, the integration of next generation digital technologies into industrial processes, is revolutionizing the logistics Industry. This category of technologies such as IoT, artificial intelligence, big data, and Robotic are transforming the logistics function by improving its effectiveness, visibility, and adaptability (Abdirad & Krishnan, 2020).

IoT helps in tracking and monitoring of the goods as they are conveyed in the supply chain. Through integrating IoT sensors and devices mainly, logistics companies can get information about the location, state and condition of shipments instantly. This visibility assists in avoiding delays, loss and hence the reliability of the position of logistic activities (Imran et al., 2018a). For example, perishable commodities for instance, drugs and foodstuffs can be tracked at every node to check if they are in good environmental conditions as required(Abdel-Basset et al., 2018; Recommendations for Implementing the Strategic Initiative INDUSTRIE 4.0 April 2013 Securing the Future of German Manufacturing Industry Final Report of the Industrie 4.0 Working Group, n.d.).

Machine learning and, particularly, predictive analytic tools are critical in realizing the most efficient logistics processes. Through AI, data about the demand, route, and inventory can be analyzed in large amounts and predict the same in quick succession (Bag et al., 2023; Khin & Kee, 2022). Logistical suitability informatics can aid in identifying possible disruptions and fluctuating demand, allowing the involved firms to problem-solve early before it aggravates. It enhances the service delivery in an organization while at the same time minimizing the wastes that are likely to be incurred in the delivery of services (Skapinyecz et al., 2018).

Applicability of robotics and automation in handling the nature of supply chain activities raises efficiency and reduces errors. Amalgamated guided vehicles and robot arms are becoming popular in warehouses in addition to distribution facilities in the direction of handling amiable monotonous tasks akin to picking, packing, and sorting (Taj et al., 2023). This automation eliminates the need to work with so many personnel hence reducing the rate of errors and fastens the process. Therefore, greater throughput is attainable for logistics companies which results in satisfying the customers' demands (Ślusarczyk et al., 2021).

In essence, big data analytics is advantageous to any logistics firm as it provides fundamental information regarding large projects' feasibility. This in turn enables the logistics managers to understand the customers, the market and the organization's performance as influenced by several factors based on the analyzed results from various data sources (Ali et al., 2019; Qureshi, Mewada, Kaur, et al., 2023). These are useful in formulating the right plans, decreasing expenses, and increasing the level of customer satisfaction. For instance, data analytics can reveal trends within delivery times

and propose the best ways to decrease the time it takes to deliver, and the amount of fuel used (Imran et al., 2018b; Wong & Kee, 2022).

Industry 4.0 technologies also facilitate better integration and collaboration across the supply chain. Advanced communication systems and platforms allow seamless information sharing between different stakeholders, including suppliers, manufacturers, and customers. This integration enhances coordination and ensures that all parties are aligned, leading to a more efficient and responsive supply chain (Marinagi et al., 2023).

Obstacles and Limitations Faced by Logistics Firms in Adopting Industry 4.0 Technologies

While Industry 4.0 As for the technologies listed above, they have valuable advantages when applied in the logistics sector although their implementation is accompanied by certain problems. Some of the challenges include high costs of Implementation is one of the biggest challenges (Gharibvand et al., 2024). To adopt IoT, AI, Robotics into operations, there is the need to fund physical structures, tools and systems, and applications that facilitates the practice. This financial cost can be expensive especially where the enterprise is small and medium in size which most are since they have slim pockets (Rahman et al., 2022; Zhong et al., 2017).

The next problem relates to the absence of skilled personnel. Consequently, the planning, deployment, and especially the day-to-day operation of Industry 4.0 technologies require a working force that is knowledgeable of IT skills and other sophisticated technological skills. The current trends affecting the development of the logistics company reveal a skills deficit where there is a shortage of skilled employees in such technologies. This indicates that future investment in training and development activities is warranted, and these can be both a time-consuming and expensive exercise (Lasi et al., 2014; Qureshi, Mewada, Buniya, et al., 2023).

Lack of infrastructure is also considered as one of the greatest challenges that hinders the implementation of Industry 4.0 technologies. It is also important to note that many logistic companies especially in developing countries like the Sri Lankan might not have sufficient technological support like fluent internet connection and elaborate data processing equipment. This deficiency is highly disadvantageous in the implementation and optimal use of Industry 4.0 technologies (Yüksel, 2022).

To the same extent, regulatory matters make it difficult to implement the adoption of other technologies. The industry in question is heavily regulated and, at the same time, overregulated, with the primary sources of rules and regulations differing from country to country (Acevedo Amaya et al., 2020a). While it is relatively easy to access these regulations, the process of reaching such appropriate compliance is not easy, especially for firms that are yet to embrace Industry 4.0 technologies.

They are worsened by economic factors such as uncertainties in the economic situations of countries and regions involved in business. Volatility in the exchange rate, inflation and the overall economic conditions also pose effects on the corporate decisions regarding their investments in the new technologies (Barreto et al., 2017a). Such cautious and risk-averse conditions can slow down or even stop the implementation of Industry 4.0. The logistics sector, having technologies, is of no surprise because it is not a technology-oriented industry but is involved in organizing movement and storage of goods (Withanaarachchi & Himashi Silva, 2023).

Industry 4.0 Related Factors That Affect the Performance of Logistics Sector

Thus, in the context of the constantly changing environment of Industry 4. 0, the sector is faced with various issues that affect its operations to a very high degree. These factors include drivers, enablers, barriers, and critical success factors respectively. Understanding these elements is crucial for logistics enterprises that want to take full advantage of the Industry 4. 0 technologies and methodologies.

Driving forces build a base on which the logistics industry can be directed towards the realization of Industry 4. 0. The components of organizational capabilities, SME institutional support, perceived advantages, market factors, and firm size are critical (Wong & Kee, 2021). For instance, organizational capabilities define the extent to which new technologies are integrateable into the firm's systems. One is the institutional support for SMEs which plays an important role of offering the backbone on which the enterprises depend on. Competitive forces in the market such as customer requirements and competitors' pressures force firms to improve their operations and logistics. The other factor that comes into play is size of the firm, while large firms may have more resources to devote to the technologies, they could be less flexible than the smaller firms.

Thus, the facilitating factors help enhance the acceptance and integration of Industry 4. 0 technologies. Among these are the resource, skills, and support (Khin & Kee, 2020). This paper has established that the availability of the appropriate resources, including finances and technology, is critical in any enterprise's transformation into Industry 4. 0. The training is crucial in the modern world because the majority of jobs require operating new technologies and systems, and, thus, appropriate skills. Additionally, internal management and external stakeholders' support guarantee that change is accepted and continued across the organization. Such support could include, but not limited to training initiatives, financial incentives, and strategic collaborations.

However, there are number of impediments that can prevent the implementation of Industry 4. 0 in logistics. The first issue relates to the difficulties in attracting the right talent since the market is usually replete with few qualified personnel in various emerging technologies (Khin & Kee, 2020). Also, the lack of funding and inadequate knowledge of the issue can also slow down the process of development. One of the major difficulties is associated with technical issues of implementing new systems in an organization that already has other systems in place. In addition, training needs and resistance to change are two more factors which may be encountered in organizations. To overcome these barriers, it is necessary to use the tactics of change management, including the constant analysis of the situation and the implementation of new strategies.

Critical success factors are the factors that act as the success factors for the enhancement and functioning of Industry 4. 0 technologies in logistics. Technology-related CSFs enabled by the workers include training, skills, motivation, IT/data integration, and morale (Qureshi et al. , 2023). These factors ensure that the workforce is well equipped to respond to new technologies in the most efficient way possible. The management related CSFs include support from the top management, long term vision and planning, availability of resources and strategic management. The executive management's support and coherent vision is vital in directing the organization through the Industry 4. 0. It is also important that awareness and readiness for the implementation of lean tools are present and that competitive pressures must be acknowledged and managed by organizations.

The performance of the logistics sector is profoundly influenced by various Industry 4.0-related factors, encompassing technological, organizational, and external market elements. Understanding these factors is crucial for effectively leveraging Industry 4.0 technologies to enhance logistics operations.

Another factor is technological adoption where the country is ranked low indicating that the people there are not so ready to adopt the advanced technologies. This comprises of the readiness and availability of Industry 4. 0 technologies like the IoT, AI, robotics, and big data analyses. The firms that have established high levels of technological support and digital competence are in a better place to adopt and apply these technologies (Barreto et al., 2017). On the other hand, technologically unprepared firms experience a high level of adoption costs, which restricts them from gaining the advantages of Industry 4. 0.

The organizational culture and the leadership of most logistical companies also have a large influence also. Therefore, the culture that is promoted in terms of innovation, improvement and risk-taking promotes Industry 4. 0 technologies (Guirguis, 2020). First of all, top management support is crucial for change management and for the creation of the culture where people want and are able to grow in terms of numbers as well as the integration of digital skills and technologies. Despite a firm's best efforts, the process of adopting and pursuing change can be slowed down by bureaucratic attitudes and strategic deficits (Issa, 2023).

Skills possessed by workforce is another factor that is directly related to availability of staff. Thus, for the successful implementation of Industry 4. 0 technologies require employees with technical set skills in digital technology, big data analysis, and autonomous systems (Wicha et al., 2023). For these to be established, corporate organizations must consider training and development interventions as one of the ways of developing them. This can be done by qualified employees increasing productivity, implementing change and bringing improvements, as well as in the usage of the discussed technologies optimally (Withanaarachchi & Silva, 2023).

Industry 4.0 is greatly influenced by factors such as external market trends and economic factors. undefined Some industries include foreign exchange and inflation and fluctuations in these fields may affect invitations and finance (Acevedo Amaya et al., 2020). This is because conditions that depict a stable economy are favourable for the investment in new technologies while conditions that depict an unstable economy slow down such investment.

The regulatory environment is another crucial macroenvironmental factor that affects Industry 4.0 adoption. These frameworks can ensure digital change because when companies are in doubt about employing specific technology or using specific systems, they would research the frameworks for clarification (Vlachos & Polichronidou, 2022). On the other hand, unclear and unfolding policies usually define challenges, and this aggravate the cost of incorporating the new system.

Thus, enhanced integration of and between the various links of the supply chain is central to the realization of Industry 4. 0 technologies. It has been observed that when there is high level of information sharing and integration among suppliers, manufacturers, and the logistic service providers it enhances the supply chain transparency and efficiency (Malkanthie & Jayamanna, 2017). Innovations like Blockchain will improve the level of trust and mutual transparency which will in fact buck up the rate of working together and performing.

In order to fully leverage Industry 4. 0 In particular, organizations need to encourage the correct handling of data and the adoption of adequate data protection measures. Technological advancements such as IoT and other digital technologies are creating massive amounts of data that have to be collected, stored, and analyzed to be useful. In addition, the safety of such data is also very crucial in order to protect it from cyber threats and also protect the interests of various enterprises.

The success of implementing Industry 4.0 technologies in logistics is influenced by a combination of cause-and-effect group factors (Khan et al., 2023). Organizational enablers include commitment and support of the top management, integration of the cause initiatives to the organizational strategy, technological support, skilled workforce, financial backing and change management. These factors ensure that the organization is prepared for and committed to the transition to Industry 4.0. Effect group factors, such as process optimization, enhanced customer satisfaction, real-time data availability, sustainability, and efficiency, are the outcomes of successfully managing the cause group factors Thus, concentrating on these important aspects, it is possible to learn from the challenges and reach a new level of development by enhancing the main aspects of logistics firms' performance, including efficiency and costs.

Critical factors influencing the adoption and integration of Industry 4.0 technologies into logistics, especially in developing countries, are very many. Among the identified key determinants are top management support, robust IT infrastructure, and huge financial investment. The former three elements build the ground for an enabling environment, which allows Logistics 4.0; therefore, strategies and operations of a company change in reaction to technological requirements. Moreover, organizational strategies have to be aligned to Logistics 4.0 pursuits. Successful collaboration among logistics partners can be achieved by mutual trust and empowered knowledge management to share data and coordinate efforts for higher overall effectiveness in the adoption of Logistics 4.0.

Another critical factor is the development of a digital work culture and the building of competencies in analysis among employees. Since Logistics 4.0 is so heavily dependent on data analytics and digital tools, skill development will be very instrumental in the investments that companies have to make in order for them to achieve success both immediately and in the long run. Change management will play an important role in dealing with changes that will involve the adoption of Industry 4.0 within an organization, overcoming resistance, and keeping all relevant stakeholders engaged during the implementation process.

The external elements that strongly influence the adoption of Industry 4.0 in logistics involve market dynamics, regulatory frameworks, and economic conditions. An availability of financial resources and economic stability are required by organizations seeking to invest in new technologies. The regulatory frameworks guide and sometimes challenge the adoption of such technologies; the infrastructure and technological readiness might be low in developing countries. For successful adoption of Industry 4.0 in logistics, a comprehensive approach has to consider internal organizational factors and external market conditions. Giving such attention to the identified critical determinants would, therefore, enable organizations to better orient their efforts toward leveraging the potential of Industry 4.0 in order to improve efficiency, sustainability, and competitiveness in the global market.

Table 2: Industry 4.0 related Factors that Affect the Performance of Logistics Sector

Factors Identified	**Wong & Kee (2022)**	**Khin & Kee (2020)**	**Issa (2023)**	**Ślusarczyk et al. (2021)**	**Qureshi et al. (2023)**	**Khan et al. (2023)**	**Khan et al. (2022)**	**Kumar et al. (2023)**	**Ferrari et al. (2023)**
Organizational capabilities	Y								

SME institutional support	Y								
Perceived advantage	Y								
Market factors	Y								
Firm size	Y								
Operational benefits		Y							
Market opportunities		Y							
Labor problems		Y							
Customer requirements		Y							
Competition		Y			Y				
Quality image		Y							
Resources		Y							
Skills		Y			Y			Y	
Support		Y							
Challenges in getting the right people		Y							
Lack of funding and knowledge		Y							
Technical challenges		Y							
Training and mindset change		Y							
Organizational structure			Y						
Human capital			Y						
Digitalized supply chain			Y						
Efficiency and flexibility			Y						
Sustainability			Y			Y			
Market demand			Y						
Government policies and incentives			Y						
Regulatory framework			Y						
Limited knowledge				Y					
Implementation barriers				Y					
Recognition of potential changes				Y					
Preparing staff for challenges				Y					
Government support				Y					
Employee training					Y				
Motivation					Y				
IT/data integration					Y				
Morale					Y				

Top management support					Y				Y
Long-term vision					Y				
Funds/resource availability					Y				
Strategy implementation					Y				
Awareness					Y				
Readiness for change					Y				
Prioritizing lean tools					Y				
Top management commitment and support						Y			
Aligning initiatives with organizational strategy						Y			
Technological infrastructure						Y			
Skilled workforce						Y			
Financial investment						Y			Y
Change management						Y		Y	
Process optimization						Y			
Enhanced customer satisfaction						Y			
Real-time data availability						Y			
GDP							Y		
GDP per Capita							Y		
R&D Expenditure							Y		
FDI							Y		
Internal Private Credit							Y		
Employment Rate							Y		
Population with a bachelor's degree							Y		
Population Density							Y		
Urban Population Size							Y		
Coordination and Collaboration among SCP								Y	
Knowledge of Circular Supply Chain and Industry 4.0								Y	
Training and Development Programs								Y	
High-Quality Data								Y	

Effective Planning and Execution								Y	
Integration of Technology Platforms								Y	
Data Security								Y	
Knowledge Management System								Y	
Ability to Adopt New Business Models								Y	
Skilled and Semi-Skilled Employees								Y	
Management Leadership								Y	
Financial Resources								Y	
IT Infrastructure									Y
Mutual Trust									
Knowledge Management									Y
Analytical Competencies									Y
Digital Work Culture									Y
Organizational Strategies for Logistics 4.0									Y
Collaboration									Y
Skill Development									Y

Enhancement of Logistics Performance through Industry 4.0 Technologies

The promotion of Industry 4.0 There are no technologies in logistics, and this has the following advantages which when adopted greatly improve the operations and performance of these companies. The first potential positive aspect would therefore be enhanced supply chain transparency. The connectivity of IoT devices helps implement real-time tracking and monitoring solutions that provide logistics managers with information on the shipment's status, location, and condition (Miškić et al., 2023; Xu et al., 2018). Because of this visibility, there will be improved decisions, elimination of preventable losses, minimization of delays and timely delivery of products.

Another major advantage is the effectiveness of decision making about the distribution of the resources based on the results of the prediction and use of artificial intelligence. These technologies utilize big data to predict patterns of demand, logistics and supply, and inventory control in a much more efficient manner (Evangelista et al., 2018; Khin & Hung Kee, 2022). As a result, issues affecting customers, and their demands, can be addressed earlier so that wastage of resources and other additional operational expenses can be mitigated proficiently. This results in efficiency and better service delivery thus meeting the needs and expectations of the clients.

Automation and robotics also facilitate the improvement of productivity and efficiency in the activities of logistics. Continuous operations and rigorously planned integrated robotic apparatuses undertake assignments like picking, packing, and sorting, and thus, the indispensability of manual labor is

diminished along with minimizing error rates. Apart from speeding up the processing times, throughput is also improved which ultimately means logistics companies can meet their customers' needs faster and with greater reliability (Chaisricharoen et al., 2022).

Big data analytics enables a business to obtain information about customers, markets, and processes, with which the business operates. In this way, the proposed set of insights allows logistics managers to identify ways of increasing efficiency, decreasing costs, and increasing customers' satisfaction levels (Zhang et al., 2014). For example, data analytics can help to discover the patterns in the delivery times and recommend the optimal routes for deliveries, which in its turn will help to minimize the delivery time, fuel consumption and, therefore, cost.

Influence of Economic Changes on the Impact of Industry 4.0 Factors in Logistics Performance

The time that new technologies are likely to be adopted is during the growth period when companies arising from higher revenues can fund ambitious projects. The expenditures associated with IoT, AI and automation can be large but the thing that makes these technologies appealing especially when the economic conditions are good is the possibility to cut costs in the long run (Bag et al., 2018).

On the other hand, in situations characterized by economic recession or instability, logistics companies may be less inclined to make extensive investments in technology. It contributes to the shift and spending less towards innovative sources and technology, which can be ascribed to the issue of financial problems and management's primary focus on the company's short-term existence and sustainability. Such hesitance can prevent the realization of Industry 4. 0 technologies unlike the more advanced technologies that make companies stand a better shot in the long run (Tariq et al., 2023). This leads to instability of capital and financing, which are central to the financing of technological development.

Economic changes may affect demand or supply of a good or service in the market. For example, during recession customers are not as numerous thus orders and shipments might be a lot less than before and this would affect the logistics company's revenues. This can put additional pressure on the financial situation in the company, which can complicate the justification of expenses to buy new technologies (Zalozhnev & Ginz, 2023). At the same time, economic growth results in demand peaks that exert pressure on best existing logistics, which makes it necessary to increase the efficiency of Industry 4.0 technologies.

Economic fluctuations work in the same way in relation to labor markets distorting the availability and costs of the skilled personnel required for the deployment and management of Industry 4.0 technologies (IEEE Computer Society & Institute of Electrical and Electronics Engineers, n.d.). Fluctuations in inflation and exchange rates, for instance, would raise the cost of adopting technological equipment and software imported from other countries, making it another layer of complication to the whole process.

Conclusion

Industry 4.0 technologies such as IoT, AI, robotics, and big data analytics can be implemented to enhance the performance of logistics firms worldwide. These technologies underpin improved supply chain visibility, enhanced efficiency in decision-making, better operational productivity, and stronger customer satisfaction. However, the successful implementation of these technologies is conditioned upon several organizational factors, such as management support, employee skills, and technological infrastructure.

The impact of Industry 4.0 factors on logistics performance is thus multifaceted. On one hand, these technologies can bring very substantial improvements in operational efficiency, cost reduction, and quality of service. On the other hand, their implementation is definitely worsened by high initial costs, bad infrastructure, and a lack of skilled personnel. All these factors interact and balance out the overall impact on logistics performance.

Economic fluctuations also play a very important role in conditioning the relationship between Industry 4.0 factors and logistics performance. If there is a growth period in the economy, the willingness of firms to invest in new technologies will increase with the impetus from higher revenues and higher market opportunities. In contrast, economic downturns may trigger reduced investments in technology as companies focus on survival in the short term, rather than on long-term innovation. These cycles may therefore strongly influence the speed and the degree of diffusion for Industry 4.0 in logistics.

In view of this, while technologies of Industry 4.0 show huge potential for enhancing logistics performance, their successful implementation and eventually induced impact remain conditioned on the interplay of complex technological, organizational, and economic factors. A balanced and adaptive strategy toward technology adoption should be adopted by logistics firms, one that is able to integrate concerns regarding both the long-term benefits stemming from digital transformation and the short-term economic reality. This would necessarily involve strategic investment in technology infrastructure and continuous training and development of employees. Moreover, it will require flexible implementation strategies responsive to economic fluxes.

This will require, finally, an enabling environment for Industry 4.0 adoption to be created by policymakers and industry leaders in the logistics sector. This may involve coming up with a supporting regulatory framework that gives incentives for technology adoption, as well as facilitating linkages between academia and industries to quickly address the gap in needed skills. Only then can the global logistics sector effectively benefit from the potentials of Industry 4.0 in improving competitiveness in the international market while building resilience to economic uncertainty.

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INDIGENOUS MANAGEMENT FOR SUSTAINABILTY: A SYSTEMATIC REVIEW

S Rajapaksha[1]

Abstract

Meeting sustainable practices is a worldwide necessity in order to address the present issues encountered by the contemporary world. The involvement of indigenous management is essential for ensuring the long-term sustainability. Indigenous management and sustainability are closely linked ideas that emphasize the significance of indigenous knowledge, practices, and values in fostering the enduring welfare of ecosystems and communities. Indigenous management practices are founded on a profound comprehension of local ecosystems. Given the present global circumstances, it is crucial to examine and investigate the potential of indigenous management and knowledge systems in order to understand their role in promoting sustainability. This review study was conducted using the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) technique, which involved doing a systematic literature review (SLR). The VOSviewer program was utilized to conduct keyword co-occurrence analysis, which unveiled the specific research areas requiring concentration. The Scopus database was utilized to download articles in order to assure the high quality of the information included in this conceptual paper. The keywords that are least studied in relation to indigenous management and sustainability are social and ecological resilience, as well as traditional medicine. Approximately 70% of the publications published pertain to the topic areas of agriculture, social sciences, and environmental studies. Based on the cluster analysis, two themes were developed, Indigenous Management in Natural Environment and Sustainability and Indigenous Management in Traditional Medicine and Sustainability. There is a significant void in various sectors when it comes to investigating the influence of indigenous management practices on sustainability. Moreover, it is imperative to examine the influence of indigenous knowledge on contemporary management education and the interconnectedness between the two.

Keywords: Indigenous Management, Sustainability, PRISMA Methodology, Future Research Opportunities

[1] Lecturer, Department of Management Studies, Gampaha Wickramarachchi University of Indigenous Medicine

Email: sisitha@gwu.ac.lk https://orcid.org/0009-0008-6772-9791

Introduction

Indigenous management strategies are essential for local communities to sustainably utilize natural resources. These practices are well established in traditional knowledge, cultural beliefs, and customary rules that have been inherited across centuries. Indigenous management strategies frequently incorporate a profound comprehension of the indigenous ecosystem, including the conduct of flora and fauna, seasonal cycles, and ecological interconnections (Childs & Choedup, 2014).

Indigenous management strategies typically involve community-based approaches, where choices are made jointly by local residents who have a strong interest in conserving the resource for future generations. Indigenous management approaches, which integrate traditional knowledge and current conservation concepts, can effectively uphold ecological equilibrium, bolster local livelihoods, and advance biodiversity conservation. Overall, indigenous management techniques are vital for promoting sustainable resource management, safeguarding cultural legacy, and creating resilience in the face of environmental difficulties (Childs & Choedup, 2014).

The notions of indigenous management and sustainability are closely linked, emphasizing the significance of traditional knowledge, practices, and beliefs in fostering the enduring welfare of ecosystems and communities. Indigenous management systems are rooted in the profound understanding of local surroundings, passed down through generations, and are often based on concepts of respect, reciprocity, and harmony with nature. Indigenous societies throughout have established intricate frameworks to effectively oversee natural resources, guaranteeing their sustainable use. This approach ensures that resources are utilized in a manner that fulfills current requirements while safeguarding the capacity of future generations to fulfill their own demands. These management approaches typically take a holistic approach, taking into account not just the ecological elements of resource use but also the social, cultural, and economic factors (Childs & Choedup, 2014).

In the realm of indigenous management, sustainability extends beyond the mere preservation of the environment and includes more comprehensive concepts such as overall welfare, adaptability, and fairness across generations. Indigenous groups perceive themselves as custodians of the earth, tasked with preserving the equilibrium and integrity of ecosystems for the welfare of all living organisms.

By incorporating traditional knowledge and customs from indigenous communities into modern approaches to managing resources, civilizations can gain vital insights into coexisting with the natural world, adjusting to shifts in the environment, and promoting the strength of local communities. It is crucial to acknowledge and honor the management systems of indigenous communities in order to effectively accomplish sustainable development goals, save biodiversity, and tackle urgent environmental issues that our planet is currently confronting.

Indigenous management and sustainability are interconnected ideas that highlight the significance of ancestral knowledge, communal involvement, and a comprehensive approach to resource management for the welfare of both humanity and the environment. Various cultures and their own knowledge systems should contribute to the discourse on sustainability. The primary emphasis lies in examining the potential insights that indigenous knowledge may offer, namely by understanding the fundamental principles that govern the indigenous relationship with nature, such as reciprocity and caretaking. These principles stem from a deep understanding of the interconnection of all things and highlight the significance of returning benefits to nature (Mazzocchi, 2020). Hence, it is crucial to examine the correlation between indigenous management and sustainability in connection to a nation's progress.

Most of the existing research focuses on examining indigenous management practices in different industries or contexts. This study attempts to make the connection between the indigenous management and sustainability, which is a crucial matter in today's global situation is concerned. This study is different from other studies conducted in this areas due to the analysis method which reveals unique keywords associated with indigenous management and sustainability.

There is a dearth of bibliometric studies conducted in this area. Considering the current economic, social and political situation in Sri Lanka, it is a timely requirement to re visit the indigenous knowledge, especially related to indigenous management and how that can contribute to the sustainability aspects.

The research problem of this study is "What is the current knowledge related to indigenous management and sustainability?". Concerning the above-mentioned research problem, this conceptual paper focuses on the research objectives below.

1. To review the prevailing literature related to indigenous management and sustainability
2. To explore the future research opportunities

Literature Review

In the context of Yartsa Gunbu harvesting in Nubri and Tsum, Nepal, indigenous management practices may include regulations on when and where to collect the fungus, restrictions on the number of collectors, and the designation of sacred areas where harvesting is prohibited. These practices are designed to ensure the long-term sustainability of Yartsa Gunbu populations and to prevent overexploitation of this valuable resource (Childs & Choedup, 2014). Childs & Choedup, (2014) focus on village-level management practices, sustainable development in Nubri and Tsum. Yartsa gunbu management practices vary across the Tibetan Plateau. Community-based regulations aim to ensure sustainability of yartsa gunbu (Eitzel et al., 2020). Groenfeldt (1991) defines 'indigenous irrigation' and its management in agricultural fields. Majority of indigenous irrigation systems are in Asia. Indigenous systems are managed by village communities. Indigenous systems may vary from a few to several thousand hectares. Indigenous irrigation area is declining due to modern systems. Indigenous management impacts vegetation diversity and grazing intensity (Liao & Clark, 2018). This study analyzed logging regulations and best practices for sustainability in Brazilian Amazon and proposed sustainability definitions based on timber inventories across cutting cycles. Macpherson et al., (2012) has evaluated financial returns and sustainability of logging practices in Brazil and implemented operational definitions of sustainability for forest management in Brazil. Nigatu et al., (2021) Explores indigenous bamboo management practices in West Amhara, Ethiopia and focuses on highland bamboo cultivation, propagation, and harvesting techniques.

Indigenous practices for resource management in Gamo Highland, Ethiopia discusses deforestation and soil erosion are major sustainability challenges in Ethiopia, which addresses deforestation, soil degradation, and indigenous knowledge for sustainability (Assefa & Hans-Rudolf, 2017). Critique of indigenous management practices rooted in neocolonial thought. Postcolonial theory's relevance in subverting western forms of knowing. There are challenges in translating indigenous knowledge into Western organizational contexts (Banerjee & Linstead, 2004).

Cree management education integrates nature, sustainability, and Indigenous knowledge. Indigenous management practices offer sustainable approaches to hunting and trapping. Traditional Cree practices are sustainable, based on intergenerational ecological knowledge (Jolly et al., 2011).

Indigenous communities interact with ecosystems, influencing biodiversity and landscapes. This study focuses on Guamuchil tree importance for indigenous people and birds. Investigates avian foraging behavior and the ecological relationships in cultural landscape (Ortega-Álvarez et al., 2022). Indigenous burning in Brazil's cerrado challenges conservation narratives. Misconceptions about anthropogenic fire in diverse ecological settings are addressed in this study (Welch et al., 2013).

Indigenous management strategies are essential for ensuring the sustainable utilization of medicinal plants in traditional medicine. Indigenous civilizations often exhibit profound reverence for nature and establish a profound bond with the earth. The correlation between this connection is frequently observed in conventional medical methods, wherein therapeutic flora is gathered in an ecologically responsible manner to guarantee its preservation for future cohorts. The utilization of indigenous management approaches, such as the cultivation of untamed species, on-site promotion, and meticulous extraction of bark and roots, fosters a reverential approach to medicinal plant resources. These techniques aid in preserving the equilibrium between human utilization and the preservation of plant species (van Andel & Havinga, 2008). In addition, ancestral wisdom transmitted throughout generations frequently encompasses knowledge regarding the appropriate timing and methods for gathering medicinal plants, along with the rites and prohibitions linked to their utilization. These cultural practices not only guarantee the long-term harvesting of medicinal plants but also contribute to the conservation of biodiversity and the well-being of ecosystems. The correlation between indigenous management and traditional medicine underscores the significance of integrating local knowledge and practices into conservation initiatives to advance the sustainable utilization of medicinal plants and safeguard precious natural resources for future generations (van Andel & Havinga, 2008).

Methodology

The Systematic Literature Review (SLR) was conducted using the PRISMA methodology (Preferred Reporting Items for Systematic reviews and Meta-Analyses). Using the keywords "Indigenous Management" and "Sustainability", a total of 16 papers were obtained from the Scopus database. The review methodology has been established in accordance with the PRISMA criteria. An analysis of keyword co-occurrence has been conducted using VOSviewer software (Version 1.6.20).

This investigation utilized the PRISMA technique and framework to scrutinize and select publications. The study sought to analyze the current body of literature on Indigenous Management and sustainability and propose prospective avenues for future research in this field. Using the PRISMA technique, a procedure was implemented at the outset of this study to systematically structure this review. The process outlined below covers search terms, criteria for article inclusion, analysis tools, and a reporting framework. The adoption of the PRISMA guideline is strongly advised for systematic reviews since it effectively minimizes bias in the process of selecting articles, analyzing data, and publishing study findings. The PRISMA flow diagram for article selection has three distinct stages: "identification, screening, and inclusion." In the identification phase, it is imperative to select appropriate search terms, criteria, and databases (Priyashantha et al., 2023a).

The PRISMA article selection flow diagram has four distinct processes: identification, screening, eligibility, and inclusion. We followed these stages in the process of selecting the articles. The search terms 'Indigenous Management' and 'Sustainability' were utilized. Research articles were chosen for this study by accessing them from the Scopus databases. To filter through articles, a combination of automated and manual screening approaches were employed to eliminate irrelevant items. This investigation specifically concentrated on journal articles written solely in the English language.

Systematic reviews significantly endorse the utilization of journal articles due to their perceived reliability.

Article selection methodology and Protocol: PRISMA guidelines

Search strings: Indigenous Management, Sustainability

Inclusion criteria :

1. Year range: 1991-2022
2. Subject area: All
3. Language of article: English
4. Keywords: Indigenous Management, Sustainability
5. Source type: Journal Articles
6. Type of Study: Quantitative
7. Methodological quality: Articles that followed the quantitative/qualitative methodology

Databases : Scopus
Analysis Method : Keyword Co-occurrence Analysis
Reporting structure : PRISMA guidelines
Search strategies : "Indigenous Management" AND "Sustainability "
Source : Author Developed

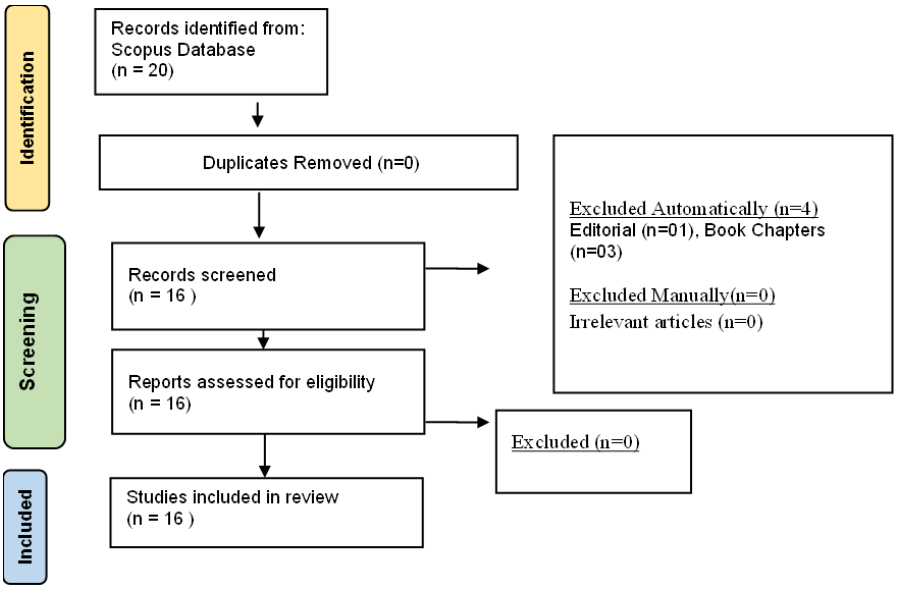

Figure 1. PRISMA Article Selection Flow Diagram
Source: Author Developed

Data Analysis and Findings

VOSviewer software (version 1.6.19) was utilized in conjunction with Keyword co-occurrence analysis to analyze the data extracted from the Scopus database. VOSviewer has categorized keywords into 2 clusters (Fig. 2) based on their interrelation. Clusters are visually distinguished by distinct colors, which represent the connections between keywords inside each cluster. Table 1 displays the chosen articles for the investigation.

The investigation utilized a bibliometric technique, using VOSviewer software (Version 1.6.20) to conduct keyword co-occurrence analysis. The aim of this study was to examine the relationships between phrases and visually represent them using a method known as "keyword co-occurrence network visualization." Establishing a correlation between phrases in the keyword co-occurrence network visualization could provide important insights into the text. The VOSviewer software use association strength normalization as its default configuration and produces a network in a two-dimensional space. In this area, nodes that indicate terms with strong connections are placed near to one other, whereas terms with weaker connections are placed further apart. The VOSviewer software categorizes nodes into clusters within a network, bringing together nodes that exhibit a significant correlation. The VOSviewer application utilizes colors to represent the cluster assigned to a node. Hence, a cluster can serve as an indication of a common theme (Dogra & Priyashantha, 2023).

To identify underexplored areas, VOSviewer software was utilized to generate a density visualization map. The user manual of VOSviewer program states that the keyword density visualisation map has a predetermined color scheme that ranges from blue to green to red. The intensity of the colors is directly proportional to the quantity of keywords in the surrounding area. Blue keywords represent a relatively low frequency of occurrence, whereas green keywords suggest a moderate frequency of occurrence. Thus, sentences located within the blue and green areas were deemed to be uncommon locations. Co-occurrence density visualization is utilized to identify areas that require more research.

Table 1 displays the article publication and citation count for each country. The United States has published a total of 9 papers and has garnered the highest number of citations. Australia and the United Kingdom have each received 100 citations for their efforts.

Table 1: Country Wise Article Publication and Citations

Country	Number of Articles Published	Citations
United States	9	180
Brazil	3	89
Estonia	1	4
Nigeria	1	4
Zimbabwe	1	4
Canada	2	16
Ethiopia	2	23
Germany	1	20
Australia	1	100
United Kingdom	1	100
Bangladesh	1	12
Netherlands	2	77
Malaysia	1	11
Mexico	1	4

Figure 2 shows the bibliographic coupling graph for country wise article publication and their relationship. A very few countries have published in this domain and the opportunity exist for other countries to conduct research and publish in this area. Indigenous management practices have been

there in Sri Lanka in different industries for a long period of time and conducting more research would close the research gap in this field.

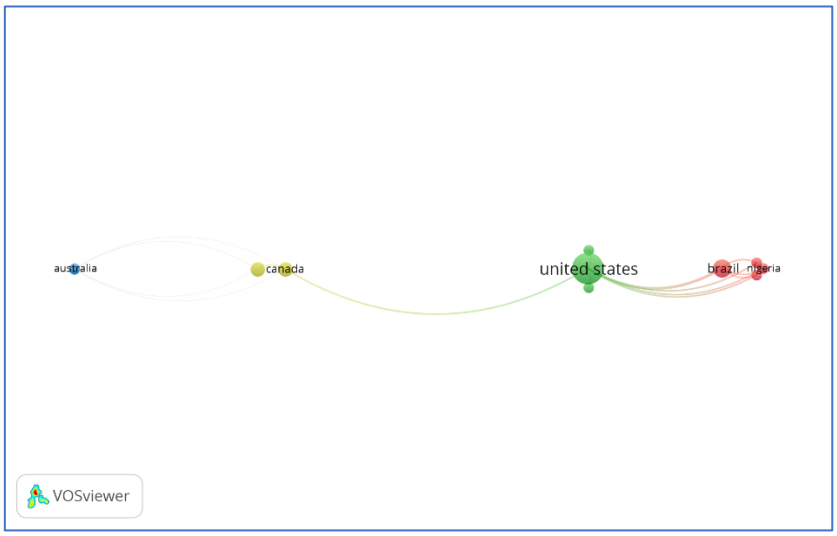

Figure 2. Bibliographic Coupling – Country Wise Article Publication
Source: VOSviewer output

Table 2: Selected articles for the study

Author / Authors	Publication Year	Title of the Article	Name of the Journal	Journal Ranking (Scopus Cite Score)
Ortega-Álvarez R.; Pacheco-Flores A.; Casas A.	2022	The "Guamúchil" cultivation in a Mexican cultural landscape: A wild food source for people and birds	Frontiers in Forests and Global Change	4.5
Eitzel M.V.; Solera J.; Wilson K.B.; Neves K.; Fisher A.C.; Veski A.; Omoju O.E.; Ndlovu A.M.; Hove E.M.	2020	Using mixed methods to construct and analyze a participatory agent-based model of a complex Zimbabwean agro-pastoral system	PLoS ONE	6.2
Macpherson A.J.; Carter D.R.; Schulze M.D.; Vidal E.; Lentini M.W.	2012	The sustainability of timber production from Eastern Amazonian forests	Land Use Policy	13.7
Kreike E.	2009	De-globalisation and deforestation in colonial Africa: Closed markets, the cattle complex, and	Journal of Southern African Studies	1.4

		environmental change in North-Central Namibia, 1890-1990		
Nigatu A.; Wondie M.; Alemu A.; Tadesse W.; Chanie Y.	2021	Indigenous management practices of highland bamboo (Yushania alpina) in West Amhara, Ethiopia	Cogent Food and Agriculture	3.3
Jolly F.; Whiteman G.; Atkinson M.; Radu I.	2011	Managing and educating outside: A cree hunter's perspective on management education	Journal of Management Education	4.1
Vaccaro I.; Zanotti L.C.; Sepez J.	2009	Commons and markets: Opportunities for development of local sustainability	Environmental Politics	11.7
Welch J.R.; Brondízio E.S.; Hetrick S.S.; Coimbra Jr. C.E.A.	2013	Indigenous burning as conservation practice: Neotropical savanna recovery amid agribusiness deforestation in Central Brazil	PLoS ONE	6.2
Childs G.; Choedup N.	2014	Indigenous management strategies and socioeconomic impacts of Yartsa gunbu (Ophiocordyceps sinensis) harvesting in Nubri and Tsum, Nepal	Himalaya	0.3
Groenfeldt D.	1991	Building on tradition: Indigenous irrigation knowledge and sustainable development in Asia	Agriculture and Human Values	6.7
Banerjee S.B.; Linstead S.	2004	Masking subversion: Neocolonial embeddedness in anthropological accounts of indigenous management	Human Relations	12.6
Liao C.; Clark P.E.	2018	Rangeland vegetation diversity and transition pathways under indigenous pastoralist management regimes in southern Ethiopia	Agriculture, Ecosystems and Environment	11.7
Keat N.J.; Nath T.K.; Jose S.	2018	Indigenous agroforestry practices by Orang Asli in peninsular Malaysia: Management, sustainability	Indian Journal of Traditional Knowledge	1.8

		and contribution to household economy		
Assefa E.; Hans-Rudolf B.	2017	Indigenous resource management practices in the Gamo Highland of Ethiopia: challenges and prospects for sustainable resource management	Sustainability Science	11.3
van Andel T.; Havinga R.	2008	Sustainability aspects of commercial medicinal plant harvesting in Suriname	Forest Ecology and Management	7.5
Al Masud M.M.; Gain A.K.; Azad A.K.	2020	Tidal river management for sustainable agriculture in the Ganges-Brahmaputra delta: Implication for land use policy	Land Use Policy	13.7

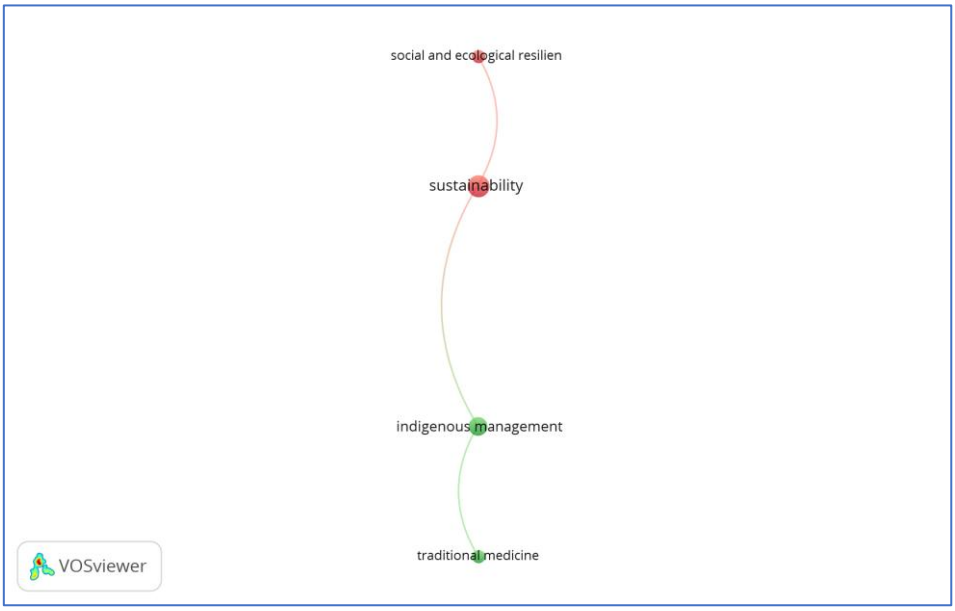

Figure 3. Keyword co-occurrence network visualisation
Source: VOSviewer output

The network visualization map indicates the relationship between 4 keywords which indicates the lack of research connecting related keywords related to this area. Also, the analysis provides only two clusters as indicated in the table 3. A cluster indicates a common theme. Based on the cluster analysis, two themes, Indigenous Management in Natural Environment and Sustainability and Indigenous Management in Traditional Medicine and Sustainability can be developed. In the first theme, indigenous management practices are considered towards the environment leading to environmental sustainability. The second theme is all about creating a sustainable world through indigenous management practices applied to traditional healthcare system which would be the most popular and effective approach to mitigate the recent Covid 19 pandemic.

Table 3: Clusters and Corresponding Keywords with Developed Themes

Cluster	Keywords	Themes Developed
Cluster 1 (Red)	Social and Ecological Resilience, Sustainability	Indigenous Management in Natural Environment and Sustainability
Cluster 2 (Green)	Indigenous Management, Traditional Medicine	Indigenous Management in Traditional Healthcare and Sustainability

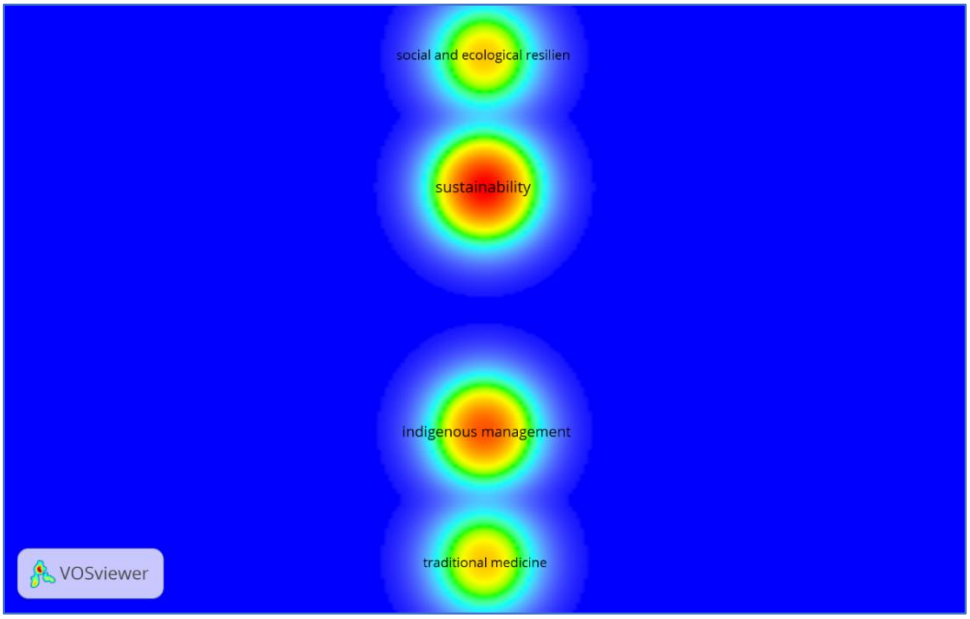

Figure 4. Density Visualisation Map of Keywords
Source: VOSviewer output

The density visualization map indicates that the keywords in the yellow and green areas have been subject to a relatively small number of examinations, highlighting the need for more inquiry. Furthermore, it indicates that the comprehension of these particular terms is somewhat restricted, therefore offering abundant possibilities for conducting study in this specific field. On the other hand, let's assume that the keywords are located within a region that is colored red. Considering the circumstances, there has already been thorough investigation carried out in that particular field, and there is a significant amount of information easily accessible (Dogra & Priyashantha, 2023).

Figure 4 indicates that the terms "social and ecological resilience" and "traditional medicine" have received the least amount of study in relation to indigenous management and sustainability.

Additional data analysis has been conducted utilizing the Scopus database, and Figure 5 depicts the publication of articles categorized by subject areas. The graph illustrates that 70% of the publications published pertain to the topic areas of agriculture, social sciences, and environmental studies. Consequently, there is ample opportunity for further investigation in other fields, particularly in the realm of business management.

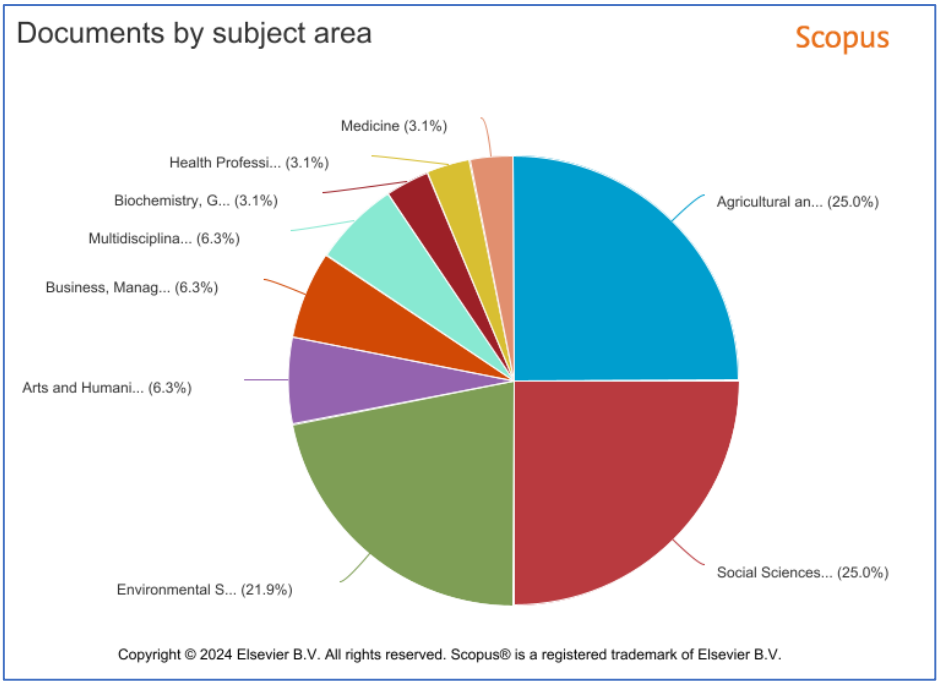

Figure 5. Article Publication by Subject Area
Source: Scopus Database

Future Research Opportunities

Future academics can conduct investigations on the enduring impacts of colonial policies on environmental sustainability by examining Indigenous management systems in various cultural contexts, allowing for comparative analysis. Further investigation could also examine the incorporation of contemporary technologies into indigenous systems. Future scholars should focus on investigating sustainable solutions that are based on traditional knowledge and experience. Additionally, they should explore how indigenous knowledge may be adapted and applied in modern organizations to promote sustainability. We can analyze the difficulties in transferring knowledge between different cultures in order to enhance organizational performance. Furthermore, we can investigate sustainable strategies for managing shared resources by actively participating in international trade. Exploring how market systems affect indigenous communal management and how Indigenous knowledge influences modern management education, with a specific focus on sustainable solutions based on traditional knowledge and experience, could be a promising field for future scholars.

When it comes to indigenous management and sustainability, it is crucial to take into account the specific circumstances of Sri Lanka. Indigenous management approaches encompass various domains, including agriculture, irrigation systems, traditional medicine, and more. Examining the indigenous business management methods in Sri Lanka and their impact on sustainability is crucial.

Conclusion

Adhering to sustainable practices is an international imperative in order to solve the current problems facing the modern world. In order to guarantee long-term viability, indigenous management must be involved. The primary aim of this study is to examine the existing literature on indigenous management and sustainability. To assess the existing knowledge, we employed a method called keyword co-occurrence analysis. This study unveiled that the only two terms associated with indigenous management and sustainability are social and ecological resilience, as well as traditional medicine. The research results in the identification of two distinct clusters of terms, representing two common themes.

One cluster relates to social and ecological resilience, while the other cluster pertains to indigenous management and traditional medicine. Further investigation into the interrelation of terms within these clusters is valuable.

The second aim of this study is to discover future research opportunities through analysis. Based on the density visualization map, this study has highlighted ecological resilience and traditional medicine as keywords that have not been well investigated. Although there may be more keywords associated with prior studies in this field, these are the only keywords that have a substantial association with indigenous management and sustainability.

This study highlights the significance of examining the influence of Indigenous knowledge on contemporary management education. An investigation into the impact of indigenous management techniques on sustainability in Sri Lanka would be a pertinent and crucial research endeavor given the country's present circumstances.

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STIMULI BEHIND CONSUMERS' INCLINATION TOWARD LUXURY BRANDS: A CASE STUDY OF YOUTH CONSUMERS IN COLOMBO, SRI LANKA

M Perera[1], A Dilshan[2] and DMNN Kumarasinghe[3]

Abstract

This quantitative research explores the factors influencing the preference of Sri Lankan youth consumers for luxury brands, presenting a base conceptual model to analyze these influences on inclination towards luxury brands. The study focuses on 170 youth consumers from Colombo, Sri Lanka. Results indicate that factors like self-esteem, social status, and conspicuous consumption impact young consumers' inclination towards luxury brands. The findings reveal the importance of understanding cultural and social dynamics in crafting effective marketing strategies for luxury goods in Sri Lanka.

Keywords: luxury brands, Sri Lanka, youth consumers, social class, conspicuous consumption, marketing strategies

[1] Graduate School of Management, Management & Science University, University Drive, Off Persiaran Olahraga, 40100 Shah Alam, Selangor, Malaysia

Email: maduramsu@gmail.com https://orcid.org/0009-0007-9860-5030

[2] School of Business, National Institute of Business Management, Colombo, Sri Lanka

Email: amiladilshan99@gmail.com https://orcid.org/0009-0007-0609-7033

[3] Faculty of Medical Sciences, University of Sri Jayewardenepura

Email: imashakumarasinghe@gmail.com https://orcid.org/0009-0001-7387-8522

BARRIERS FOR MANUFACTURING SMES: A SYSTEMATIC EMPIRICAL RE-VIEW AND FUTURE RESEARCH AGENDA

HN Hettiarachchi[1], R Abeysekera[2], S Divakara[3]

Abstract

Small and Medium-sector enterprises play an important role in creating employment oppor-tunities, poverty reduction, GDP growth and economic improvement in any country. Thus it is considered as the backbone of the economy. The objective of this paper is to examine the entrepreneurship literature that discusses the barriers for small and medium-sector manu-facturing organizations and set future research directions through a systematic literature review. To do this systematic literature review, a number of researches that investigated the barriers for manufacturing SMEs have been taken into consideration. To conduct the re-view, the PRISMA Method (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) has been followed. This study is based on journal articles published in databases such as Emerald Insight, Sage, Research Gate Net, Taylor & Francis, Science Direct and Google Scholar. After setting inclusion & exclusion criteria, 60 journal articles were select-ed. Economic issues, financial barriers, political barriers, lean manufacturing barriers, in-ternationalization barriers, e-commerce adoption barriers, lack of resources and manage-ment issues have been identified as the prominent barriers for manufacturing SMEs. How-ever, there is no adequate evidence to support that institutions and human capital are strong determinants for SME development. In line with the systematic literature review, most of the research to investigate SME barriers had been done in developing countries. However, research is scarce in South Asian countries like Sri Lanka, Nepal, Maldives and Bhutan. At the same time, the majority of the studies utilized the quantitative methodology to investi-gate the SME barriers. Qualitative researches are comparatively less. Therefore, more atten-tion is needed to fill these gaps in existing literature to get a full understanding of the mat-ter. Thus, this literature-based study calls for a new research agenda to investigate such is-sues as it directly and indirectly results in to improvement of the entire SME sector.

Keywords: Barriers, Developed, Developing, Manufacturing, Smes.

[1] Faculty of Commerce and Management Studies, University of Kelaniya, Sri Lanka.
Email: heshaninilochani@gmail.com
[2] Professor, Department of Finance, University of Kelaniya, Sri Lanka.
Email ruwanab@kln.ac.lk https://orcid.org/0000-0002-2858-6483
[3] Department of Finance, University of Kelaniya, Sri Lanka.
Email: sanathdivakara@gmail.com https://orcid.org/0000-0002-4353-6820

Introduction.

Background of the Study.

Even if there is not a particular document that shows the beginning of SMEs, one could guess that it originated with the beginning of civilizations all around the world. Nowadays, Small and Medium Scale enterprises play a noteworthy role in economic development in any country. In discussing the importance of the SME sector, Kongolo in 2010, pointed out that the SMEs play a significant role in the transition of agriculture-led economies to industrial ones creating plain opportunities for processing activities that can generate sustainable sources of revenue and enhance the development process.

In developed countries, the contribution of SMEs to gross domestic product is very high. According to Pandey (2012), the SME contribution to US GDP is more than 95%. Further, he shows that the contribution of the SME sector to GDP in Japan is also more than 90 %. In contrast, according to the World Bank reports, in developing countries, SME contribution to GDP is only around 60%. However, according to Wang et al. (2015), access to finance is a common obstacle for SMEs in both developed and developing countries and the ability to overcome that barrier depends on the scale of the organization. Further, he argues that, when the top manager's or the owner manager's working experience increases, the probability of accessing finance increases. However, the role of SMEs in both developed and developing countries for employee generation is radically important. In other words, whether the country is developing or developed in nature, the importance of the SME sector is noteworthy for the entire economic development process.

In discussing the importance of the SME sector, Keskin et al. in 2010, pointed out that SMEs are seen as the main actors of both national and regional development in many countries. In another study done by Bakashaba (2018), there is evidence that SMEs in Uganda typically account for more than 90% of all firms outside the agricultural sector, constitute a major source of employment and generate significant domestic and export earnings. According to Kongolo (2010), the development of SMEs has been considered one of the most critical factors for the economic growth of both developed and developing countries due to their multiple contributions to economic growth, employment generation and innovations. Further, showing the importance of the small and medium sector, in 2014 Lee and Drever argued that at the individual level, SMEs play an important role in providing employment, improving individual sources of income and standard of living, improving innovation by promoting new ideas and creating grounds for entrepreneurs.

In such a situation, there is a growing academic interest in investigating the barriers to the SME sector. Several academic studies investigated the financial barriers, lean manufacturing barriers, internationalization barriers, e-commerce adoption barriers, open innovation barriers and so on. (Khan, 2022, Roy et al. 2016, Majocchi et al. 2015, Sodhi et al. 2016, Kumar et al. 2020). The primary objective of this systematic review is to investigate the existing entrepreneurship literature that discusses the barriers to manufacturing SMEs and highlight the particular uncovered areas. In order to achieve the so-called objective, the prominent barriers for Small and Medium sector organizations have been investigated in this literature review.

By conducting this literature review, the researcher will be able to have a clear understanding of the SME barriers discussed in existing entrepreneurship literature. At the same time, this systematic review helps to understand the different barriers faced by manufacturing SMEs in both developed and developing countries. On the other hand, this systematic review contributes to identify the gaps in existing entrepreneurship literature. Therefore, this will be helpful for future researchers to open up new research agendas by filling these gaps.

The next section includes the literature review that investigates the importance of the SME manufacturing sector, the barriers and their effect on the performance of the SME manufacturing sector. To conduct this review the PRISMA method has been used and the entire selection process is explained in the methodology section. The results and discussion section has outlined the identified SME barriers throughout the existing entrepreneurship literature and highlighted the uncovered areas. Thereafter, directions for future research and conclusions are provided as per the identified research gaps.

Literature Review.

In many countries, manufacturing SMEs are the main drivers of generating employment opportunities. Notably, many studies show that there is a positive relationship between SME growth and economic development. According to Cater and Evans (2006) and Mubarik et al (2020), the growth of the SME manufacturing sector has a positive impact on the country's economic development through the creation of wealth and jobs. Further, they analyzed that the majority of SMEs, especially in developing countries, are located in rural areas. Thus, these SMEs are creating job opportunities for the uneducated and inexperienced people in rural areas while contributing to reducing poverty. On the other hand, manufacturing SMEs are the most important unit in the economy in the world and their contribution to employee creation and GDP growth is superior to large firms in many countries. (Musneh et al. 2021, Ramadaz & Satis, 2017).

Akbar et al. (2017), researching Malaysian manufacturing SMEs, pointed out that this sector is notably important to that country due to its contribution to GDP growth, unemployment reduction and poverty reduction. Raj and Mahapatra, in their research regarding the SME manufacturing sector in India in 2009 had significantly shown that the contribution of this sector is remarkable in providing employment opportunities and generating 60% of domestic product.

Barriers in SME Manufacturing Sector in developing countries.

The existing literature proves that, despite the numerous contributions offered by SMEs in any country, they are consistently faced with some mitigating factors warranting their sustainability. Amoah et al. in 2021 did a research to investigate the barriers to sustainability in manufacturing SMEs in Ghana and pointed out that factors such as financial challenges, poor access to technology, market penetration & acceptability, and lack of research & development are the barriers facing SMEs' sustainability in the Ghanaian manufacturing sector. On the other hand, the literature shows that the absence of a standard procedure, lack of professional approach, lack of proper training, low-quality standard materials from suppliers, bad vendor inspection, communication gap between employer and the employee, and lack of resources are the identified barriers to implementing lean manufacturing process in manufacturing SMEs. (Sodhi 2016, Ramadas & Satish 2017, Dora et al. 2014, Bhadu et al. 2021, Kumar et al. 2014). Meanwhile, Abdullah et al. in 2023 and Sibiya & Kele in 2019, conducted a study to investigate the barriers to the sustainable manufacturing process in SMEs and identified ineffective enforcement of the law, complexity in implementing 6Rs, ineffective controlling and monitoring systems and heavy dependence on fossil fuels are the main barriers that obstruct the implementation of sustainable manufacturing. At the same time, investigating the barriers in the handloom manufacturing sector in Sri Lanka in 2020, Wanniarachchi and Dassanayake pointed out that the structure of the industry and lack of access to markets and information act as barriers to both innovation and growth in this sector.

Further, e-commerce adoption barriers have been identified as a main obstacle to manufacturing SME growth. These investigations revealed that lack of awareness of the IT field, financial inadequacies and the negative attitude of both entrepreneur and customer towards e-commerce are the main barriers to

adopt e-commerce in manufacturing SMEs. (Sing et al.2019, Kwadwo et al. 2016, Nazir et al. 2020, Busaidi et al. 2019, Mohan and Ali 2019)

On the other hand, the notions of technological innovation, open innovation and Industry 4.0 are also identifiable as interesting areas in research. (Stentoft 2020, Obembe 2018). When it comes to the developing country perspective, small and medium-scale manufacturing organizations face numerous barriers when adopting technological innovation, open innovation (OI) and Industry 4.0 (I4.0). A cross-country analysis done by Becheikh & Bouaddi in 2022 has identified the SME innovation barriers in Egypt, Morocco, and Tunisia and pointed out that political instability, corruption, and competition from the informal sector are the macro-level inhabitants. These kinds of research provide a platform to understand the similarities and differences of barriers in different geographical settings.

An investigation of barriers for SMEs in Sri Lanka, revealed that the growth of SMEs is constrained by financial inadequacy, the lack of access to new technology, and some regulations imposed by the government. (Amaradiwakara & Gunathilake 2016, Wijayarathne & Perera 2018.). Further, lack of financial usage limits the financial inclusion of SMEs and also the financial inclusion level was highly dependent upon the quality of the financial services used by the owners. (Thathsarani et al., 2023).

China is still in the state of a developing country and according to the literature, 99% of companies in China are small and medium-scale enterprises. (Wang et al., 2015). A research was conducted to investigate the constraints for SMEs in the city of Tianjin in China. (An & Zhang, 2021). According to this research, these SMEs are crossing the "Valley of Death". Here, the metaphor, "Valley of Death" is used to describe the relative lack of resources and expertise in the area of development. According to the findings of this research, the high-tech SMEs in Tianjin can bridge the so-called valley of death through coordination and institutional support.

Barriers in SME Manufacturing Sector in developed countries.

At the same time, the existing literature clearly shows that, not only in developing countries, but also in developed countries, financing and institution have become a serious matter for small and medium-scale organizations. For instance, an investigation of Portuguese small and medium manufacturing firms (Forte & Moreira 2014, Yukhanaev 2015, Ganau et al. 2021) has pointed out that, those SMEs in Portuguese have fewer tendencies to participate in export activities due to financial barriers. According to Gilmore et al. 2013, the manufacturing SMEs in the European Union face serious issues due to financial constraints.

It is equally important to investigate the literature regarding barriers for SMEs in terms of developed countries. An investigation done by Kotey and Armidale in 2014, shows that the manufacturing SMEs in rural Australia are facing barriers to inadequate infrastructure, lack of access to skilled labor, technology, and finance, and uncertainty about government policies. On the other hand, an investigation of the small manufacturing sector in the UK reveals that these companies face challenges in finding adequate finance due to the smallness of the organization. (Lee & Drever, 2014). Further, Antonio et al. in 2022 have done a research to investigate the barriers in Spain and Latin America and revealed that these manufacturing SMEs face I4.0 barriers due to technological barriers, training barriers, economic barriers and contextual barriers.

On the other hand, Sánchez-Rodríguez et al. have done a research in 2019 to investigate the obstacles in manufacturing SMEs in Canada and pointed out that IT obstacles and strategic purchasing are the

main barriers for manufacturing SMEs in Canada when implementing e-procurement in manufacturing SMEs.

Theories Used in Existing Literature.

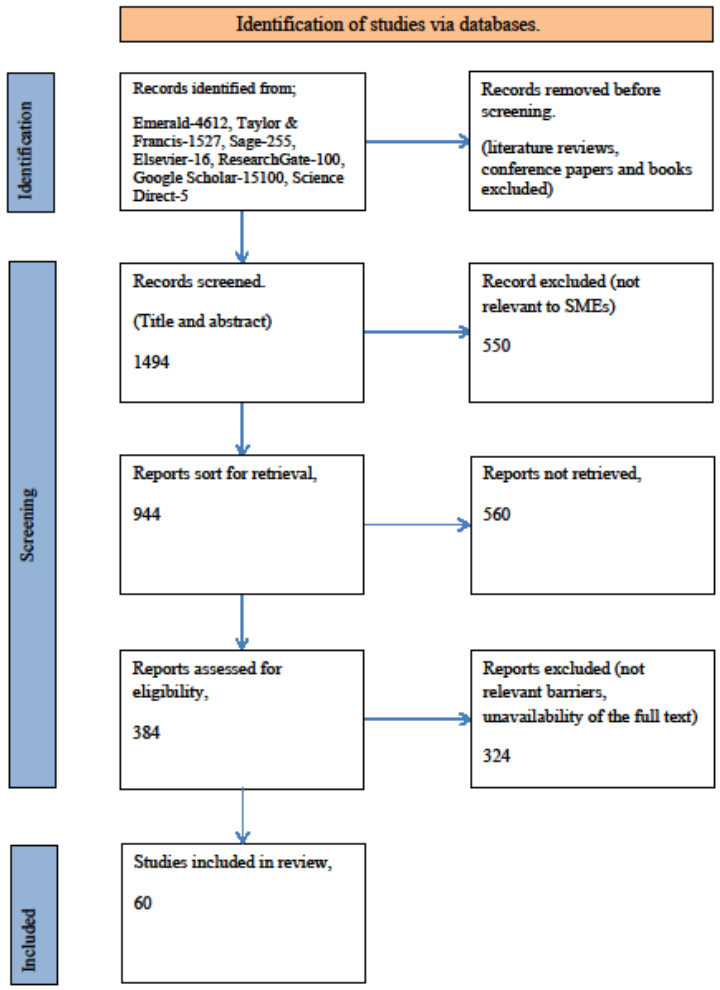
In discussing the barriers for SMEs, theories such as the Resource-Based View, Transaction-Cost Theory, Networking Theory, Agency Theory, etc. have been widely used by researchers all around the world. (D'Este, Rentocchini, & Vega-Jurado, 2014; Kahn 2021; Ullah 2020; Nguyen et al. 2018; Nayak 2014; Kolade 2018). Exploring the barriers to internationalization in small and medium-sector enterprises was given special attention over the last ten years. The framework of Resource Based View (RBV) and Networking Theory had been widely applied by scholars to investigate the barriers in manufacturing SMEs. For instance, Roy et al. in 2016, used the RBV and Networking Theory to investigate the internationalization drawbacks in Indian SMEs. This study reveals that these organizations lack the resources to enter the international market. On the other hand, they revealed in line with the NT perspective, these firms can overcome this barrier through networks and business group affiliations.

In exploring the barriers to SMEs' open innovation adoption in Ghana, both Networking Theory and Transaction Cost Theory (TCT) were used. (Oduro, 2018). According to this study, a firm can exchange knowledge, technology and other resources with competitors (NT) and reduce production costs by providing some goods from the market rather than producing them internally (TCT) and access open innovation. Despite the RBV, Kumar et al. in 2020, used the Stakeholder Theory and Agency Theory for their research to investigate the barriers to adopt Industry 4.0 and sustainability in SMEs.

Methodology.

The literature for this study was selected systematically focusing on the barriers for small and medium scale enterprises. Literature from both developed and developing countries had been studied giving more focus on the developing countries' research. This study is based on the journal articles published in databases such as Emerald Insight, Sage, ResearchGate Net, Taylor & Francis, Science Direct and Google Scholar that had covered a large area of journals in the field of Social Science. To conduct the review, the PRISMA Method (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) has been followed. The keywords used for finding articles were barriers, SMEs, manufacturing sector, institutional and human capital.

The initial search in "Barriers for manufacturing SMEs" produced 21594 results from all databases. After removing duplicate records, literature reviews, conference papers and book articles, 1494 journal articles were taken for screening. From the screening 550 journal articles were excluded as they are not relevant to small and medium sector enterprises and 944 remained. From the remaining 944, 560 journal articles were removed since their focus is not on SME barriers. Reports assessed for eligibility are 384 and finally 60 articles were selected for the study after excluding 384 due to their less focus on the subject matter and unavailability of the full text. The entire selection process is presented in Preferred Reporting Items for Systematic Reviews and Meta-Analysis in the following figure.



Selection of research articles according to PRISMA

Results and Discussion.

Empirical Gaps.

This systematic review was done with a view to find the barriers for manufacturing SMEs as mentioned in the introduction. In line with this objective, prominent barriers for Small and Medium Sector organizations have been identified first. According to the literature, financial constraints, technological barriers, poor infrastructure, e-commerce adoption barriers and internationalization barriers have been identified. (Sodhi 2016, Ramadas & Satish 2017, Lee & Drever 2014, Antonio et al. 2022, Abdullah et al. 2023). According to the systematic review conducted, it was found that, due to these various types of barriers manufacturing SMEs cannot sustain in the business and the majority of them cannot achieve the target profit margin. (Kimathi, 2015. Anderson, 2017). Further, it was found that, due to financial barriers, they cannot practice required R&D activities, cannot compete with high-tech organizations and cannot enter the international market. (Gilmore et al. 2013, Kwadwo et al. 2016).

When doing this systematic literature review, it was identified that the existing literature comprises a number of researches that investigate the barriers to manufacturing SMEs. It was noted that, according to the literature, the majority of the articles have focused the developing countries in order to investigate the barriers. Out of the total number of journal articles taken for this literature review, 65% of articles had investigated the manufacturing SME barriers in developing countries. Mostly identified manufacturing SME barriers in developing countries are financing barriers, credit constraints, internationalization barriers, institutional pressures and e-commerce adoption barriers. (Amoah et al. 2021, An & Zhang 2021, Sodhi 2016, Amaradiwakara & Gumathilake, 2016). At the same time, barriers for Open Innovation (OI) and Industry 4.0 (I 4.0) are also identifiable in existing literature. (Becheikh & Bouaddi, 2022).

At the same time, when it comes to the South Asian region, many empirical researches to investigate the barriers to manufacturing SMEs had been done only in India, Pakistan and Bangladesh. Therefore the existing literature importantly lacks the researches to investigate the barriers in manufacturing SMEs in countries like Sri Lanka, Maldives, Bhutan and Nepal.

In line with the literature review, manufacturing SMEs in developing countries face more barriers than in developed countries. Comparing to the number of obstacles that SMEs face in developing countries more researches are needed to discuss them.

On the other hand, when it comes to the developed country perspective, out of the total number of selected journal articles for the literature review, 25 % of articles have discussed the manufacturing SME barriers in developed countries. According to them, financial constraints and barriers for applying technology, barriers to I 4.0, innovation barriers, and energy efficiency barriers, have been identified as the main obstacles. (Kotey and Armidale 2014, Antonio et al. 2022).

Just like in developing countries, manufacturing SMEs in developed countries also face financial barriers due to the smallness of the organization. (Armidale 2014 & Lee & Drever 2014). Therefore, it was found that financing has become a common issue for manufacturing SMEs all around the world. On the other hand, according to literature, poor human capital and poor institution of the home country are the other prominent barriers for manufacturing SMEs in developed countries. (Armidale 2014). Thus, need for more researches to investigate the manufacturing SME barriers in developed countries was identified.

Methodological and Theoretical Gaps.

Another interesting observation noted during the review is that, the majority of the researchers had used the quantitative method (55%) and 45% of the researchers have utilized the qualitative methodology. Therefore, the present literature review has identified another research gap for qualitative researches. Qualitative researches are important for this field in order to gain a deeper understanding of the matter through in-depth interviews. (Saunders et al. 2011)

Additionally, as mentioned in the literature review section, theories like the Resource-Based View, Transaction-Cost Theory, Networking Theory and Agency Theory had been widely used by researchers to investigate the barriers in SMEs. However, there is a dearth of studies that had utilized the Human Capital Theory and Institutional Theory. While resources are certainly vital, it was identified that issues such as regulations, culture and the legal environment of an organization can impact entrepreneurial success (Baumol, Litan, & Schramm, 2009). Further, by using Institutional Theory for entrepreneurship research it would be able to cover a vast area that had been neglected by RBV. Apart from that, using

Human Capital Theory for entrepreneurship studies is important to identify human capital matters of organizations. (Becker, 1964).

In this way, the notion of SMEs has been given special attention over the last few decades and international research has investigated about it after identifying their importance for economic development. Further, investigating the barriers for manufacturing SME development became more attractive rather than investigating the plus points among them as it is an ongoing issue all around the world.

Directions for Future Research

This systematic literature survey clearly shows that Small and Medium Sector Enterprises face various difficulties on their way to success. While the existing literature provides many examples regarding the fact, it is identifiable that some areas like institutional and human capital barriers are not properly investigated both in developed countries and developing countries. Therefore, future studies could focus on the institutional and human capital barriers in manufacturing SMEs. Moreover, there is a need to draw attention on the corruption and discrimination generated through institutions as it harms the sustainability and development of the entire SME sector. On the other hand, more researches are needed to investigate the manufacturing SME barriers in developing countries as they face more barriers than SMEs in developed countries. Further, conducting qualitative researches will be helpful to have a profound understanding regarding the matter.

Conclusion

The objective of this systematic review is to provide a crystal clear understanding of the main obstacles for small and medium-sector enterprises giving special attention to the manufacturing sector. By analyzing the empirical evidence, mostly discussed SME barriers have been identified. As stated at the beginning of the article, the small and medium sector is the main driver of economic development in many countries. Due to this reason, there is a growing interest in doing studies regarding various aspects of this sector. In the existing literature, financial barriers, political and economic uncertainty, resource scarcity, management issues and barriers for innovation are identified as the major obstacles to SME development in both developed and developing countries. However, there is a scarcity of research to exploit the institutional and human capital matters in manufacturing SMEs. Therefore, more attention is needed to investigate human capital and institutional barriers in small and medium-sector organizations to get a full understanding of the matter. At the same time, more and more qualitative researches are needed to investigate the SME barriers in developing countries like Sri Lanka, Maldives, Bhutan and Nepal. Thus, this literature-based study calls for a new agenda to investigate such issues in manufacturing SMEs as it directly and indirectly results in to improvement of the entire SME sector.

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ASSESS THE ROLE OF ARTIFICIAL INTELLIGENCE IN SUPPORTING AND ENHANCING DECISION-MAKING PROCESSES WITHIN ORGANIZATIONS: A SYSTEMATIC LITERATURE REVIEW

KAVU Perera[1]

Abstract

This study aims to assess the role of Artificial Intelligence (AI) in supporting and enhancing decision-making processes within organizations. The research objectives include understanding how AI influences decision-making, identifying AI tools and applications used in this context, and exploring the challenges associated with AI-driven decision-making. A systematic literature review was employed while reviewing articles from Google Scholar database. Key findings indicate that AI significantly enhances decision-making by providing data-driven insights, automating routine tasks, and enabling predictive analytics. AI tools such as machine learning algorithms, natural language processing, and expert systems were identified as critical enablers of improved decision-making processes. However, the study also highlights several challenges, including data quality issues, algorithmic bias, lack of transparency, ethical considerations, and the need for robust integration with existing organizational processes. The conclusion emphasizes that while AI holds considerable potential for transforming decision-making in organizations, addressing these challenges is crucial for its effective implementation. Recommendations include establishing robust data governance frameworks, investing in explainable AI techniques, implementing ethical guidelines, and fostering a culture of continuous learning and innovation. By navigating these challenges, organizations can fully leverage AI to make more informed, ethical, and effective decisions. The findings contribute to the existing body of knowledge on AI in organizational decision-making and provide practical insights for practitioners aiming to integrate AI into their decision-making processes.

Keywords: AI Tools and Applications, Artificial Intelligence, Decision-Making.

[1] Faculty of Commerce and Management Studies, University of Kelaniya, Sri Lanka
Email: dba-2023-033@kln.ac.lk

Introduction

In today's business environment, the surge in data volume and complexity has necessitated innovative approaches to decision-making. Artificial Intelligence (AI) has emerged as a pivotal tool, allowing organizations to augment and refine their decision-making processes. This research comprehensively evaluates AI's role in bolstering organizational decision-making, encompassing its transformative potential, strategic implications, efficiency enhancements, and associated challenges. As organizations grapple with an unprecedented influx of data, AI becomes instrumental in distilling insights and supporting decision-makers (Strusani & Houngbonon, 2019). Its ability to rapidly analyze data and identify patterns empowers decision-makers to navigate complexity and make informed choices. Beyond operational support, AI influences strategic decision-making by enabling predictive modeling and scenario planning, fostering a proactive approach to organizational strategy (Schemmer et al., 2021).

Despite the growing adoption of AI in decision-making processes, there is a lack of comprehensive understanding of how AI and human intelligence can be effectively integrated to optimize decision-making outcomes. Organizations often face challenges balancing AI's analytical capabilities with human strategic thinking, leading to suboptimal decision-making processes (Alshadoodee et al., 2022). Moreover, concerns about data security, ethical implications, and the potential for AI to perpetuate biases further complicate AI integration. This study aims to address these gaps by providing an in-depth analysis of the role of AI in enhancing decision-making processes within organizations.

Moreover, AI contributes to efficiency gains through automation, allowing decision-makers to focus on high-value activities. By automating routine tasks, AI streamlines decision-making processes and enhances organizational agility. However, the integration of AI also presents challenges, including data privacy concerns, algorithmic bias, and ethical considerations (Trunk et al., 2020). This research aims to provide a holistic examination of AI's role in organizational decision-making processes. By analyzing its impact on data utilization, strategic decision-making, and efficiency and addressing associated challenges, we aim to offer insights into the transformative potential of AI in shaping the future of organizational decision-making.

This paper embarks on a systematic literature review to assess the role of artificial intelligence in supporting and enhancing decision-making processes within organizations. By synthesizing the existing literature, this paper focuses on achieving the primary objective of assessing the role of AI in supporting and enhancing decision-making processes within organizations. To achieve this main objective, the study is structured around three key research questions that explore the influence of AI on decision-making, the tools and applications used, and the challenges associated with its integration. The three research objectives are aligned towards the main objectives to comprehensively understand AI's impact on organizational decision-making.

The first research question, "How will AI influence decision-making in organizations?" aims to analyze the transformative impact of AI on decision-making processes within organizations. AI has the potential to revolutionize decision-making by enhancing efficiency, accuracy, and strategic insights. By leveraging AI technologies, businesses can process vast amounts of data swiftly, uncover patterns and trends, and make informed decisions that are data-driven. AI can improve decision-making through predictive analytics, which allows organizations to forecast future trends and prepare accordingly (Prasanth et al., 2023; Zhang et al., 2023). Additionally, AI can assist in real-time decision-making by providing timely insights and recommendations based on current data. The influence of AI extends to both operational and strategic levels; at the operational level, AI can automate routine decisions, freeing

up human resources to focus on more complex and creative tasks, while at the strategic level, AI supports long-term planning and decision-making by offering deeper insights into market trends, customer behaviors, and potential risks (Agarwal, 1989).

The second research question, "What AI tools and applications are used for decision-making?" focuses on identifying and evaluating the AI tools and applications that are commonly used to support decision-making processes in organizations. AI encompasses a wide range of tools and applications, including machine learning algorithms, natural language processing (NLP), and data analytics platforms. Machine learning algorithms analyze historical data to predict future outcomes and identify optimal solutions (Borgesius, 2018). NLP enables AI systems to understand and process human language, making it easier to analyze unstructured data such as emails, social media posts, and customer reviews. Data analytics platforms provide the infrastructure to manage and analyze large datasets, generating actionable insights for decision-makers. Specific AI applications tailored for decision-making include expert systems, which emulate human expertise to make decisions in specialized domains, and decision support systems (DSS), which provide interactive software-based solutions to assist in decision-making (Rožman et al., 2023).

The third research question, "What are the challenges in using AI for decision-making?" aims to identify and analyze the challenges and barriers to integrating AI into decision-making processes within organizations. While AI offers significant benefits for decision-making, its integration is not without challenges. One primary challenge is data quality and availability; AI systems rely on large volumes of accurate and relevant data to function effectively, and poor data quality or insufficient data can lead to incorrect or biased decisions (Zhang et al., 2023). Data security and privacy concerns are also paramount, as sensitive information must be protected from unauthorized access and breaches. Another challenge is the lack of AI literacy among employees, which requires comprehensive training and education initiatives for effective utilization. Furthermore, ethical considerations pose a significant challenge, as AI systems must ensure fairness, transparency, and accountability, particularly in areas such as hiring, financial lending, and law enforcement (Bankins et al., 2023).

By addressing these research questions to answer the main research objective, the study aims to provide a thorough understanding of AI's role in organizational decision-making. This holistic approach will enable organizations to harness the full potential of AI, optimizing their decision-making processes for improved efficiency, accuracy, and strategic advantage. The alignment of these research questions and the objective forms the foundation of this study, guiding a comprehensive exploration of AI's impact on organizational decision-making and offering valuable insights and practical recommendations for overcoming associated challenges.

Literature Review

Evolution of Artificial Intelligence (AI)

Many revolutions in the world's use of the steam engine began in 1784 when the funding and use of electricity for mass production happened in the 1870s with the introduction of the combustion engine. After these initial findings and revolutions, a few days back, the information and technology era started to rise with digitization and a technology workforce. Among all these evolutions and revolutions, Artificial Intelligence (AI) is considered one of the most disruptive evolutions that humanity has witnessed, with groundbreaking innovations and breakthroughs. (Spector, 2006)

AI can be categorized into two broad areas: general AI and narrow AI. General AI has the power and ability to think and act independently without any support of an external system, and narrow AI has

considered AI learning through existing knowledge and machine learning to improve more and perform tasks much more efficiently after developing further through the learned knowledge. Where general AI still needs to be implemented and established, applications of narrow AI support both administrative and cognitive capabilities. (Thillaivasan & Wickramasinghe, 2020)

As of today, AI has gained and reached new heights from the year 2016. Significant changes and improvements in AI in applications of civil and military landscapes have entirely overwritten and revolutionized how humans live. Among many fields and domains, such as business operations, digitalization, health care, aviation, automotive, and many others, AI is currently being used for many technological advancements. These patterns and knowledge streams in the current dimensions show the possible further advancements that could be gained with many different technologies. (Hofmann et al., 2017)

Many researchers have discussed and tend to believe that in no time, machines will supersede humans in their intelligence and knowledge. Recent developments have shown that there is a significant possibility for AI to reach those heights in no time with the current rapid changes that are seen. For example, the AI machine Alpha-Go recently defeated a world champion, Ke Jie from China, in a board game. The central lack of AI and machines is the lack of emotional intelligence and the inability to mimic human emotions such as happiness, sadness, fear, stress, pain, etc. It is vital to look at these developments not just from the point of view of technological advancement but from a legal, ethical, and social point of view. (Hofmann et al., 2017)

Decision Making

Many social scientists have made an effort to produce a large number of theories and experiments to outline individual decision-making. In simple decision-making is considered as given there are two states called A and B, where an individual may put himself in either A status or B status or vice versa (Borgesius, 2018). Theorists have worked and been concerned with these problematic elements since 1748 in the days of Jeremy Bentham. Five main theories are associated with decision-making: the theory of riskless choices, applying the theory of risk-less choices to welfare economics, the theory of risky choices, transitivity in decision-making, and the theory of games and statistical decision functions. (Edwards, 1954)

The theory of riskless choices is usually assumed to maximize the utility of statistical decision-making and the theory of games. Based on the fundamental context, the notion of maximization is that a human always decides and takes the best next option as an alternative. When applying this theory, one observation is that humans are neither perfectly consistent nor sensitive about a specific thinking pattern. The theory of risk-less choices to welfare economics produces and searches for different phenomena to justify and rationalize economic policies. A change must be taken as desirable if the change is applicable and set well with a better element than before. (Slavic et al., 1977)

The theory of risky choices is a psychological decision-making decision that is risky with the use of partial reinforcement. Literature shows that in the 1944 era, this theory was considered for gambling, with probability in mathematics supporting economics. The transitivity in decision-making is regarded as a riskless choice for humans. The comparisons among the agreed bets show risky choices to elaborate intransitively. The theory of games and statistical decision functions helps with statistical decision functions thoroughly for making concise decisions. (Tanner et al., 1954)

Economists and others have developed theories with mathematical findings and research elements about how people make decisions and choices among many possible alternatives. When making these decisions, individuals are assumed to behave rationally and have transitive preferences. It is constantly proven that economists have become worried when making decisions backed up by assumptions and have shown patterns of choices developed to support them. The theory of games presents a mathematical analysis of the alternative strategies. (Hofmann et al., 2017)

Decision-Making and Individual Productivity

Individual productivity is essential for organizational success since the individual's efficiency and productivity directly contribute to a specific team and organizational success. Individuals must be emotionally and mentally involved to achieve goals and share a common goal to reach greater heights. As an individual, decision-making is considered a way of speaking about their opinion on work-related matters by sharing the rationale behind the idea for the work matter in a face-to-face contact or from a virtual contact considering remote work to its peer or superior. (Alasmri & Basahel, 2022)

Decision-Making and Organizational Performance

Organizational performance is considered a benchmark in a particular industry among similar companies using parameters such as market share, profits, service quality, etc. The success factor of the organization is considered based on these parameters in a modern-day business to have a global and international presence and competition. For the organization to perform well, improved decision-making as a whole is a primary reason, with different forms such as consultative participation, informal participation, team participation, etc., to bring in thoughts and ideas to achieve the organizational goals in a better state (Nasseef et al., 2021).

Decision-Making and Organizational Culture

Organizational culture considers an organization's values and norms that outline its working force's backgrounds, business environment, behaviors, and characteristics. Researchers have proven a positive relationship between decision-making and the organization's culture that would influence the relationship between people and the employer. A good culture inside an organization influences good decision-making of the organization as a whole and individual people. With the culture, another direct contribution is communication between the organization and the employees. This will act as a positive relation between these elements (Duan et al., 2018).

Methodology

A systematic literature review approach was adopted for this study to assess the role of artificial intelligence in supporting and enhancing decision-making processes within organizations. This approach has helped to gain knowledge and insights to understand the existing literature better. Google Scholar database was used as the data source for the existing literature, and articles were reviewed between 2017 and 2024 to maintain the latest and up-to-date knowledge to be reviewed and analyzed in the literature. As outlined in Figure 1, the study approach was guided by the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) methodology. This process is crucial in ensuring that the review only includes high-quality, relevant studies directly contributing to the research objectives. It also establishes the parameters for a coherent formulation of the research question, which aids in a more consistent description of the research objectives.

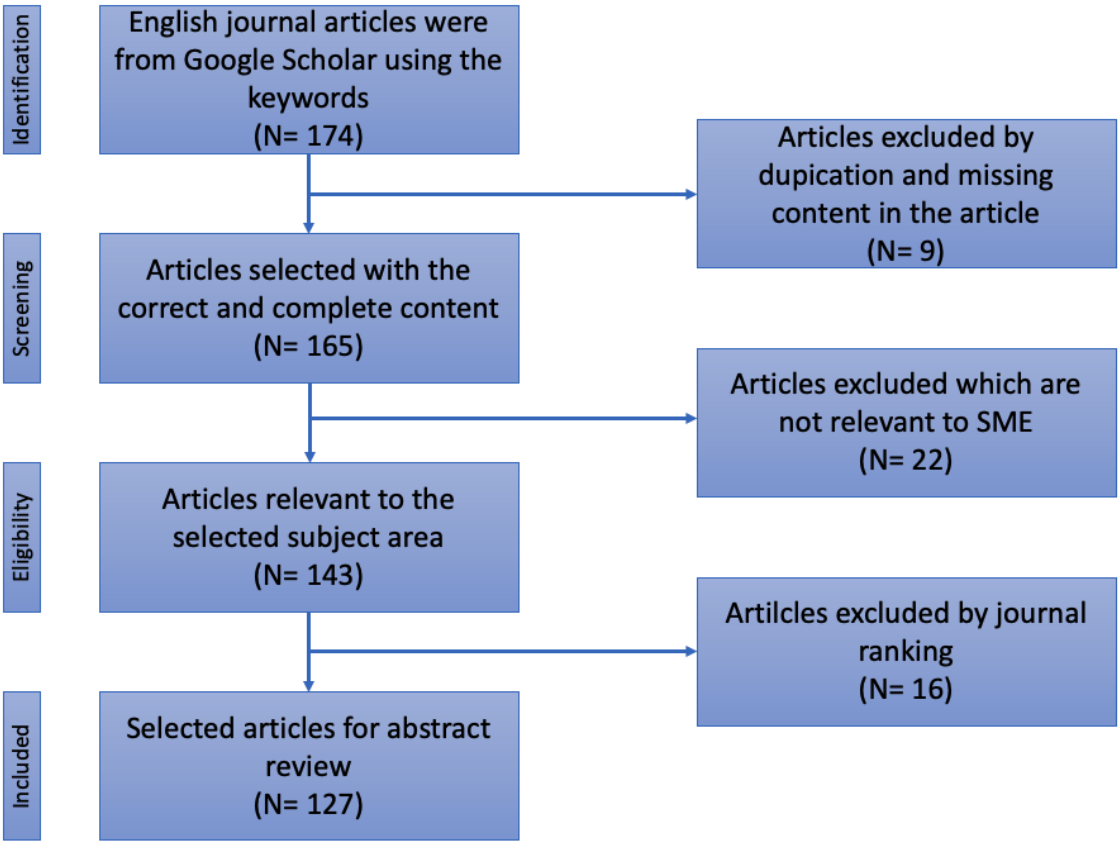

Figure 2: Prisma Inclusion and Exclusion Criteria

Source: Autor

The first step in the process involved identifying potential research articles through an extensive search on Google Scholar using the keywords "artificial intelligence" and "organizational decision making" related to the research topic. This initial search yielded a total of 174 English-language journal articles. The wide net cast during this stage is typical in systematic reviews to ensure that no potentially relevant studies are overlooked.

Following identification, the articles underwent an initial screening to assess their content's correctness and completeness. During this stage, 165 articles were found to meet the basic criteria, meaning they contained the necessary information and were relevant to the broad topic of interest. This step is essential to eliminate articles that, while initially appearing relevant based on keywords, might lack sufficient detail or focus to be useful. Further screening narrowed the pool to 143 articles, specifically focusing on their relevance to the selected subject area. This refinement process ensures that the subsequent steps focus only on studies that are directly aligned with the research questions and its objectives.

In the eligibility stage, the selected 143 articles underwent a more detailed review, particularly at the abstract level. This step is critical as it allows the researcher to delve deeper into the content without committing to a full review of each article, which can be time-consuming. Here, 127 articles were chosen for a detailed abstract review. During this process, 9 articles were excluded due to issues like duplication or missing critical content. Duplication refers to multiple instances of the same study appearing in the dataset, which could skew the results if not removed. Articles missing essential data or analyses are also excluded at this stage, as they cannot contribute meaningfully to the systematic review.

Additionally, 22 articles were excluded because they did not specifically address the focus on Small and Medium-sized Enterprises (SMEs), which is a key criterion for the review. This exclusion is vital to maintain the review's relevance and ensure that the findings are applicable to the intended context. Lastly, 16 articles were excluded based on the ABDC journal ranking of the journals in which they were published. This step likely reflects a quality control measure, as higher-ranked journals generally follow more rigorous peer-review processes, ensuring that the studies they publish are of higher quality and reliability.

After all these stages of identification, screening, eligibility and inclusion, the remaining articles form the final set of 127 considered and delved deep into the systematic literature review. This final pool represents the most relevant, high-quality studies that align with the research focus. By passing through multiple layers of scrutiny, these articles ensure that the conclusions are well-supported by robust and pertinent evidence. Overall, this method was followed and incorporated into the study to ensure that the systematic review is comprehensive, focused, and reliable, providing valuable insights into the research topic, particularly in the context of SMEs.

Results and Discussion

In literature, many researchers have discussed and shown that one of the unique strengths of humans and AI is that they can collaborate and synergistically work to increase efficiency and accuracy for decision-making. It is also widely stated that AI and humans depend on each other. AI systems learn from humans and their inputs to the system, and humans use AI systems for their activities and knowledge development. The distribution of decision-making tasks between humans and AI is either in a hybrid mode or with a whole delegation to AI. AI can make independent decision-making in some instances and possibilities, but it could only be suitable for a few cases and environments. (Malik et al., 2022)

Depending and implementing AI to automate tasks and decide on decision-making would allow individuals to invest their saved time in different needed tasks such as analyzing and determining critical strategic decisions. It is argued that even though machines and AI systems are good at making optimal decisions, the systems would not be able to determine political environments, equivocality, and visionary thinking based on a requirement of a newly set organizational goal or a decision. With AI, the role of a human could be changed to the role of a supervisor to decide if the outputs and decisions are appropriately aligned (Kaya, 2019).

Similar to an organizational approach and environment for the relationship between humans and machines to work well, a high level of transparency is needed to understand some tasks, duties, and responsibilities to achieve an optimal outcome. Different approaches and frameworks are there to make these strategic decisions based on the context and need. The full support of AI towards the processes could be incorporated once the challenges are eliminated based on that organization, and they could be approached after dividing them into sub-categories to ensure those are addressed to the core (Kazeem et al., 2023).

Role of AI and Business Decision-Making

AI is massively disrupting technologies and robotics in many ways in the world and the business landscape. AI is human-developed, machine-assisted, well-structured, and organized information and systems (Shaikh et al., 2023). AI enables individuals to make particular decisions while saving them time, money, and energy, as well as helping with data collection, analysis, and forecasting trends and patterns with all the possible capabilities of AI tools and systems. (Prasanth et al., 2023)

In a business, along with data security, using data mining technologies and big data, making correct decisions is crucial. Data is the main value stream for AI to make decisions or perform any act; AI tends to make decisions using historical facts, whereas humans mostly tend to make decisions based on their experience. As shown in Figure 2 below, big data works with correlation to make decisions in a business domain. Duan's study illustrated how AI could be used for decision-making with broader support to replace humans for decision-making regarding complex subjects (Nemati et al., 2022).

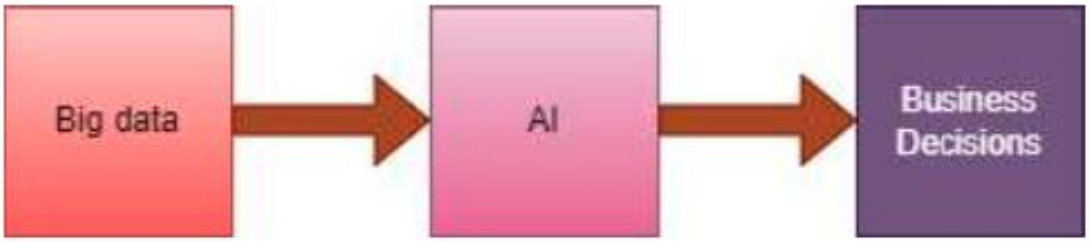

Figure 3: Bid Data and AI for Decision-Making

Source: (Prasanth et al., 2023)

One of the most profound influences of AI on decision-making is the enhancement of efficiency and accuracy. AI systems, through advanced algorithms and machine learning capabilities, can process vast amounts of data much faster and more accurately than humans. This capability allows organizations to make data-driven decisions with a high level of precision. For instance, predictive analytics, a branch of AI, can analyze historical data to forecast future trends, helping organizations to anticipate market changes and adjust their strategies accordingly. This leads to more informed decision-making, reducing the risk of errors and improving overall organizational performance (Andronie et al., 2021).

AI also enables real-time decision-making by providing timely insights and recommendations based on current data. In industries where time is a critical factor, such as finance and healthcare, the ability to make rapid, yet informed decisions can be a significant competitive advantage. AI systems can continuously monitor data streams, detect anomalies, and suggest immediate corrective actions (Smith & Wong, 2022). For example, in financial trading, AI algorithms can analyze market conditions and execute trades within milliseconds, maximizing profits and minimizing risks. At the strategic level, AI supports long-term planning and decision-making by offering deeper insights into market trends, customer behaviors, and potential risks. AI systems can analyze complex datasets to uncover patterns and correlations that may not be apparent to human analysts. These insights can inform strategic decisions such as market entry, product development, and resource allocation. For example, AI can help companies identify emerging market trends and consumer preferences, enabling them to develop products and services that meet future demands (Ashraf et al., 2022).

AI's ability to automate routine decision-making processes is another significant benefit. By handling repetitive and mundane tasks, AI frees up human resources to focus on more complex and creative activities. For instance, AI can automate customer service responses, manage inventory levels, and optimize supply chain logistics. This not only increases operational efficiency but also allows employees to engage in higher-value tasks that require human judgment and creativity (How et al., 2020). AI augments human decision-making by providing decision support tools that enhance human cognitive capabilities. These tools, such as decision support systems (DSS) and expert systems, leverage AI to provide interactive solutions that assist in complex decision-making scenarios (Tong et al., 2023). AI can help decision-makers evaluate multiple scenarios, weigh potential outcomes, and choose the best course of action. For example, in healthcare, AI-driven decision support systems can help doctors diagnose diseases by analyzing patient data and suggesting possible treatments based on the latest medical research (Bryan, 2012).

Risk management is another area where AI significantly influences decision-making. AI systems can analyze historical data to identify potential risks and suggest mitigation strategies. For example, in the insurance industry, AI can assess risk profiles of policyholders and determine appropriate premium rates. In cybersecurity, AI can detect unusual patterns in network traffic and flag potential security threats before they cause significant damage. While AI offers numerous benefits, it also raises ethical and social considerations that must be addressed. The use of AI in decision-making must ensure fairness, transparency, and accountability. For instance, AI algorithms used in hiring processes must be free from biases that could lead to discriminatory practices. Organizations must establish ethical guidelines and governance frameworks to ensure that AI systems are used responsibly and ethically (Smith & Wong, 2022).

The optimal influence of AI on decision-making is realized through effective human-AI collaboration. AI should not be seen as a replacement for human decision-makers but rather as a tool that enhances human capabilities. Humans bring contextual understanding, ethical judgment, and creativity to the decision-making process, while AI contributes speed, precision, and data-driven insights (Bryan, 2012). Collaborative decision-making frameworks, where humans and AI systems work together, can lead to superior outcomes by leveraging the strengths of both. AI systems are designed to continuously learn and adapt based on new data and feedback. This means that decision-making processes supported by AI can evolve and improve over time. Organizations can leverage this continuous learning capability to stay ahead of the competition and adapt to changing market conditions. For example, AI systems used in marketing can analyze customer responses to campaigns and adjust strategies in real-time to improve engagement and conversion rates (Ashrafuzzaman et al., 2024).

Knowledge Management with AI

Studies have confirmed that between interaction with individuals and technology systems, new ways of certain things are expected to create new elements. It has also been proven that AI can be used for data collection, analysis, and evaluation, where an output provides efficiency in speed, non-biased decisions, and data availability. Mainly, wrong data would adversely impact the business by making bad decisions, which could complicate things with more prominent organizations with complex structures. While humans have both the tactic and explicit knowledge of historical data, AI identifies patterns and performs analysis based on the expertise and data the AI has gained or been trained by humans. (Alasmri & Basahel, 2022)

For strategic decision-making through knowledge, one of the essential elements is that human decision-making ways and methods must be used to train the AI in different aspects based on the nature and the conditions of the organization is in. As the quality of the information depends on the quality of the data input to the systems, inter-organizational knowledge sharing and using them for systems to make correct decisions is vital. Research has shown that organizations should allocate enablers for efficient knowledge management and sharing. It is also further argued that no specific way to perform knowledge management is based on industry and organization type. However, results highly depend on the capabilities with which the knowledge is managed and used to develop and finetune the AI systems. (Alasmri & Basahel, 2022)

AI Applications

There is no specific definition in the literature for AI applications; as per Nilsson's definition, the AI types would range from less complex to highly complex, considering the environment in which the application is used and the types of decisions taken. The main types of applications are Natural Language Processing (NLP) and Expert Systems (ES). These frameworks and systems are linked to

organizational operations from a bottom-up and top-down approach. One cluster of applications is learned statistically from experience and knowledge and would not entirely be predictable and error-free (Jarrahi, 2018). The second cluster uses statistical and mathematical methods to predict and come to decisions. It is shown that top-down applications are mainly used for perception and interpretation, and bottom-up applications are primarily used for actions and steps with intelligence. Table 1 below shows some of the AI applications and potential integration approaches into the decision-making process, along with the use cases of the applications. (Trunk et al., 2020)

Table 1: Summary of AI Applications in Organizational Decision Makin

Application Name	Top-Down or Bottom-Up Approach	Possible Use Cases
Artificial neural networks	Bottom– Up	Optimization like in SCM process and supplier management
Bayesian Networks	Bottom– Up	Impact assessment and probability assessment.
Decision trees	Top- Down	To understand If-Then conditions To detect relations
Fuzzy systems	Both Top-Down and Bottom– Up	Prediction of data with high various. For preference capturing.
k-means	Top–Down	Clustering and classifications like for recommendations
Nearest neighbour	Top–Down	Preference detection
Pattern mining	Both Top-Down and Bottom– Up	Classifications
Regression	Top–Down	Probability assessments, Classification and to detect connections like for sales detection and to forecast customer behaviors.
Support vector modelling (SVM)	Bottom– Up	Classification, Generalization and to detect connections
Datascience toolbox	Both Top-Down and Bottom– Up	Predictive information analysis and implementation, human interpretation like in manufacturing plants and systems.
Holistic risk application method (HoRAM)	Bottom– Up	Combination of probability occurrence and simulation-based scenario approaches
Self-thinking supply chain	Top– Down	Performance monitoring and manage physical and digital systems.

Source: (Trunk et al., 2020)

Researchers and scholars argue that application use highly depends on the quantity and quality of the data available. This would result in many different parameters to handle data, clustering, detection, and connections, as shown in the possible use cases against each application type. The applications sometimes use a hybrid mode for finetuning using a mathematical approach to handle large amounts of data. Also, some applications must be trained using machine learning and other relevant applications. Most of the discussed applications could be clustered Top-Down since they might be unable to act self-consciously (Bryan, 2012).

Human and AI Collaboration Model for Decision-Making

The rise of AI rapidly calls for human and machine collaboration for many tasks and decision-making. As a partnership, machines should focus on mundane tasks, whereas humans must focus on creative and emotional tasks. AI has already overtaken humans in quantitative evaluations and decision-making, whereas humans still stay ahead in decision-making that involves qualitative factors such as norms, social context, politics, etc. Also, it is accepted that humans handle ambiguity well and perform decision-making as big picture holistically. AI may need help to learn and imitate thought patterns, traits, and personal experiences for decision-making. Hence, a collaboration effort is required between humans and AI to gain the optimal output. (Jarrahi, 2018)

It is crucial to understand that when making decisions, three characteristics, namely uncertainty, complexity, and equivocality, get involved in making a decision. Decision-making is proven optimal when both intuitive and analytical approaches are blended. The most complex choices always have an element of uncertainty that would help to have human input to ease the complexity. The partnership between humans and AI will mainly play out in two ways (Gupta et al., 2006).

1. Humans and AI can collaborate in different aspects to make decisions. AI will mainly tackle complex issues using analytical and quantitative approaches, whereas humans are more likely to focus on the uncertainty part with more creativity and an intuitive approach (How et al., 2020).

2. Even for the most complex decisions, AI has a comparative edge that would likely support elements of uncertainty and equivocality that involve human aspects. Hence, humans and AI would play a role together in decision-making. (Jarrahi, 2018)

Challenges of Using AI for Decision-Making

As well as having positives and points of implementing AI for organizational decision-making, it must also be understood that there are challenges associated with incorporating AI. AI literacy is essential knowledge and understanding needed to understand the technology, its possibilities, and its limitations. However, it is often not available or missing in an organizational context. The knowledge and literacy about AI are not only enough to be incorporated at the top management level but must be implemented across all levels in the organizations. This knowledge could set the correct and exact roles, leading to issues and problems. (Trunk et al., 2020)

AI should only be introduced to the organizational processes as an entire solution. AI should be presented in a phased approach with simple steps and hikes. To gain expected outcomes, it is critical to introduce and use it properly rather than implement the systems and allow them to acquire use out of it. The proper introduction must be given to the team when incorporating AI into the work processes. Creating awareness for the employees and stakeholders using the system is essential in this similar context. (Thillaivasan & Wickramasinghe, 2020)

Another major challenge is data security and data privacy issues. Also, there is the danger of data being manipulated; these data must be looked at before implanting the AI systems since the adverse effect could be seen later if this is not done correctly. Also, the right data quality is challenging since AI depends on the fed data and information to the systems. It is channeling to identify and incorporate the right and concise data into the system in the correct format. For example, frameworks such as AI Fairness 360 and Open Algorithms could help fine-tune the data with the help of human involvement. (Malik et al., 2022)

Algorithmic bias and fairness is another significant concern. AI algorithms are only as unbiased as the data they are trained on. If the training data contains biases, the AI system can perpetuate and even amplify these biases in its decision-making processes. This is particularly concerning in areas such as hiring, lending, and law enforcement, where biased decisions can have significant social and ethical implications. Organizations must implement rigorous testing and validation procedures to detect and mitigate bias in AI algorithms. Additionally, incorporating diverse datasets and involving multidisciplinary teams in the development of AI systems can help address this issue (Si & Shi, 2021). The lack of transparency and explainability in AI systems, particularly those based on complex machine learning models, can act as "black boxes" where the decision-making process is not transparent or easily understood. This lack of explainability can be problematic in scenarios where understanding the rationale behind a decision is crucial, such as in healthcare or legal decisions. Stakeholders may find it challenging to trust and adopt AI-driven decisions without clear explanations. Developing methods for explainable AI (XAI) that can provide insights into how decisions are made and ensuring that AI systems can be audited and interpreted by human experts are critical steps to enhance transparency (Alshadoodee et al., 2022).

Ethical Perspective on Using AI in Decision-Making

Ethical and legal considerations are also paramount when deploying AI in decision-making. Issues related to privacy, consent, and accountability must be carefully managed to prevent misuse and ensure compliance with regulations. For instance, using AI to make decisions based on personal data without proper consent can lead to privacy violations. Moreover, determining accountability in cases where AI-driven decisions result in harm or negative outcomes can be complex. Organizations must establish ethical guidelines and frameworks to govern the use of AI, ensuring that decisions are made responsibly and ethically (Rosin et al., 2022). This includes defining clear accountability structures and obtaining informed consent from individuals whose data is used. Still, there needs to be a specific design of the agreement or a framework for an ethical point of view. Many agree that using AI for decision-making norms is considered a moral guideline with a top-down or bottom-up approach. In a moral context or social context, social rules could be subjective. Hence, researchers propose a legal framework, although these can be simple and consistent since some elements correct to one person or organization might not be suitable to another person or organization. (Rožman et al., 2023)

Understanding fairness in decision-making and understanding would differ in different contexts and norms. The transparency of the decision process and the stakeholder perspective is an essential regulatory framework that is needed. To narrow AI-supported systems and processes, legal and safety-based frameworks are required and should be applied. Research has shown that including guidelines and ethics in algorithm systems and tools could be only possible to a limited extent since there is a strong influence by the people who design and develop them. Currently, clear steps or recommendations still need to be set to solve this challenge from a legal and ethical perspective. Hence, a step-wise procedure is required to bridge this legal framework. (Trunk et al., 2020)

Conclusion and Recommendations

The integration of Artificial Intelligence (AI) into decision-making processes within organizations signifies a transformative shift in how decisions are made. This transformation leverages the computational power and advanced analytics capabilities of AI while complementing the qualitative judgment and strategic insight of human decision-makers. The fusion of AI and human intelligence is reshaping the landscape of organizational decision-making, marked by enhanced efficiency, accuracy, and strategic foresight.

AI's synergy with human decision-makers is crucial. AI systems excel in processing vast amounts of data, identifying patterns, and making data-driven decisions with unparalleled speed and precision. Human decision-makers, on the other hand, contribute creativity, emotional intelligence, and the ability to navigate complex social and political contexts. This reciprocal relationship, where AI learns from human inputs and humans leverage AI for various tasks, significantly enhances overall decision-making capabilities. Effective decision-making involves the strategic distribution of tasks between AI and humans, where AI handles data-intensive and repetitive tasks, allowing humans to focus on strategic and creative aspects. In scenarios involving structured data and clear objectives, AI can operate autonomously. However, in contexts requiring nuanced understanding and ethical considerations, human judgment remains indispensable.

The evolution of AI, particularly since 2016, has seen its applications expand across diverse domains such as healthcare, finance, and business operations. Narrow AI, adept at specific tasks and continuously improving through machine learning, is currently more prevalent and practical compared to the more hypothetical general AI, which aims to replicate human intelligence across a broader spectrum of activities. The integration of AI into decision-making is not without challenges. Key concerns include AI literacy among employees, data security, and the ethical implications of AI decisions. Organizations must prioritize data management and security, ensuring that AI systems are fed high-quality, secure data. Establishing ethical guidelines and frameworks to govern AI usage is crucial to addressing issues of transparency, fairness, and accountability.

AI significantly supports business decision-making by providing advanced data analysis, predictive analytics, and knowledge management. These capabilities enable organizations to make informed decisions swiftly, optimizing resources and responding proactively to market trends and changes. Effective decision-making in organizations involves a blend of AI's analytical capabilities and human strategic thinking. Collaborative models need to address various decision-making contexts, from routine and structured decisions to complex and ambiguous scenarios. This ensures that both AI and human inputs are leveraged optimally, enhancing the quality and outcomes of decisions.

Based on the insights gathered, several recommendations are proposed for organizations aiming to enhance their decision-making processes through AI integration. First, organizations should invest in comprehensive training programs to enhance AI literacy across all levels. Employees need to understand AI's capabilities, limitations, and potential applications to integrate and utilize AI technologies effectively.

Adopting a phased implementation approach is crucial. Implementing AI systems gradually, starting with less complex tasks and scaling up as the organization adapts to the technology, facilitates smoother transitions and better management of potential challenges. Ensuring data quality and security is another vital aspect. Organizations should establish robust data management practices to provide high-quality, secure data inputs for AI systems. Utilizing frameworks like AI Fairness 360 and Open Algorithms helps maintain data integrity and fairness in decision-making processes.

Promoting human-AI collaboration is essential. Organizations should foster a collaborative environment where AI tools augment human decision-making rather than replace it. Creating hybrid models that combine AI's analytical power with human creativity and strategic thinking is critical for success. Developing clear ethical guidelines and legal frameworks to govern AI usage in decision-making is also important. These frameworks should address transparency, fairness, and accountability to ensure responsible AI implementation.

Leveraging AI for strategic decision-making involves utilizing AI for advanced data collection, analysis, and trend forecasting to support strategic decision-making. AI can provide valuable insights and predictive capabilities that enhance the organization's ability to make informed decisions. Fostering a culture of continuous learning and adaptation is also crucial. Encouraging a culture of continuous learning and adaptation helps organizations stay abreast of AI advancements and integrate new tools and techniques as they emerge. This proactive approach ensures that the organization remains competitive and innovative.

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IMPACT OF CLOUD ENTERPRISE SYSTEMS ON BUSINESS SECURITY AND BUSINESS CONTINUITY IN SMES IN SRI LANKA: A SYSTEMATIC LITERATURE REVIEW

WPP Malshan[1] and WMJI Wijayanayake[2]

Abstract

The adoption of cloud enterprise systems presents a transformative opportunity for small and medium enterprises (SMEs) in Sri Lanka, particularly in enhancing business security and continuity. This research investigates how these systems can effectively address critical challenges faced by SMEs, including cybersecurity threats, regulatory compliance, and infrastructural constraints. Utilizing a mixed-methods approach, the study integrates a systematic literature review with qualitative data from interviews and focus groups, as well as quantitative data from structured surveys.The findings reveal that while cloud technologies provide significant benefits in terms of data security, operational efficiency, and disaster recovery, the adoption process is hindered by unique local challenges. Key barriers identified include inadequate technological infrastructure, limited awareness among stakeholders, and regulatory hurdles that complicate implementation. To tackle these issues, the research proposes a tailored cybersecurity framework designed to offer practical guidelines for SMEs, enhancing their security posture.Moreover, strategic recommendations are presented to assist policymakers and technology providers in creating a supportive environment for cloud adoption. This research contributes to a deeper understanding of the role of cloud enterprise systems in improving business security and continuity for SMEs in Sri Lanka. It offers actionable insights for stakeholders aiming to cultivate a resilient and secure business ecosystem. By addressing the specific needs and challenges of SMEs, the study aims to promote a more robust adoption of cloud technologies, ultimately supporting the growth and sustainability of these enterprises in the evolving digital landscape. Overall, this research underscores the importance of cloud solutions in fostering a secure and efficient operational framework for SMEs in Sri Lanka.

Keywords: Business continuity, Business security, Cloud enterprise systems, Cybersecurity, Small and medium enterprises (SMEs)

[1] Department of Industrial Management, University of Kelaniya, Sri Lanka
Email: malshanweerasinghe25@gmail.com
[2] Professor, Department of Industrial Management, University of Kelaniya, Sri Lanka
Email: janaka@kln.ac.lk https://orcid.org/0000-0002-9523-5384

Introduction

Cloud computing has emerged as a transformative technology, offering significant benefits such as cost savings, scalability, and enhanced operational efficiency, especially for small and medium-sized enterprises (SMEs)(Zulkifli & Abas, 2022). The adoption of cloud computing by SMEs has been widely studied, revealing a variety of factors that influence its uptake, including management support, technology readiness, and external pressures(Nuskiya, n.d.). However, while cloud computing offers numerous advantages, it also presents substantial challenges, particularly in the areas of security and privacy(Alouffi et al., 2021). Security concerns are paramount, with major threats including data breaches and compliance issues being highlighted across multiple studies(Nagahawatta et al., n.d.). In addition to security, the role of cloud computing in ensuring business continuity and disaster recovery has gained significant attention. Studies have explored how cloud-based solutions can enhance the resilience of businesses, enabling them to recover from disruptions more effectively (Kim & Amran, 2018).

This systematic literature review aims to synthesize current research on cloud computing, with a particular focus on its adoption, security challenges, and implications for business continuity among SMEs. By examining a comprehensive collection of studies, this review seeks to provide a clear understanding of the current landscape, identify key challenges and benefits, and offer insights for future research directions.

Methodology

The primary objective of this study is to identify and evaluate the existing literature on how cloud enterprise systems improve business security and business continuity in small and medium enterprises (SMEs) in Sri Lanka. This systematic review adheres to the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines to ensure a comprehensive and transparent review process.(*PRISMA Statement*, n.d.)

Relevant papers were sourced from multiple databases, including SciHub, ResearchGate, Google Scholar, and IEEE Xplore. To refine the dataset, specific inclusion and exclusion criteria were applied. Initially, records were screened based on the relevance to the research topic, ensuring that only studies focusing on cloud enterprise systems, business security, and business continuity in SMEs, particularly in Sri Lanka, were considered. Furthermore, only full-text articles published in English within the last ten years were included.

Inclusion Criteria:

- Studies focused on Sri Lanka or include Sri Lanka in a comparative analysis with other regions.
- Studies specifically addressing small and medium enterprises (SMEs).
- Studies discussing business security, cybersecurity, business continuity, disaster recovery, or business resilience.
- Articles published within the last ten years.
- Studies published in English.

Exclusion Criteria:

- Studies not related to the purpose of this review.
- Duplicate studies across different databases.
- Studies not written in English.

A comprehensive search of relevant databases was performed using specific keywords and search terms related to the research topic. The queries used included "Cloud enterprise systems" AND "business

security", "Cloud enterprise systems" AND "business security" AND "Sri Lanka", "Cloud computing" AND "business continuity" AND SMEs, "Cybersecurity" AND "cloud services" AND "small enterprises" AND "Sri Lanka", and a combined search query: ("Cloud" OR "Azure" OR "Cloud Computing" OR "devOps") AND ("SME" OR "Small and medium Enterprises") AND ("Security" OR "SecOps").

The initial dataset consisted of 18000 records, which were then subjected to a two-stage screening process. The first stage involved a title and abstract review to exclude irrelevant studies. The second stage involved to assess their relevance to the research topic and the research questions. After the rigorous screening process, 52 papers were reviewed in detail, focusing on aspects such as the barriers to cloud adoption, the impact of cloud enterprise systems on business security and continuity, and the specific cybersecurity measures necessary for SMEs. Additionally, strategic recommendations for encouraging cloud technology adoption among SMEs were analyzed. (Fig.1)

The extracted data was synthesized to provide insights into the practical applications and limitations of integrating cloud enterprise systems in enhancing business security and continuity in SMEs in Sri Lanka. This review aims to develop a comprehensive cybersecurity framework tailored to the unique challenges faced by SMEs in Sri Lanka, ensuring their resilience against cyber threats and improving their overall business continuity.

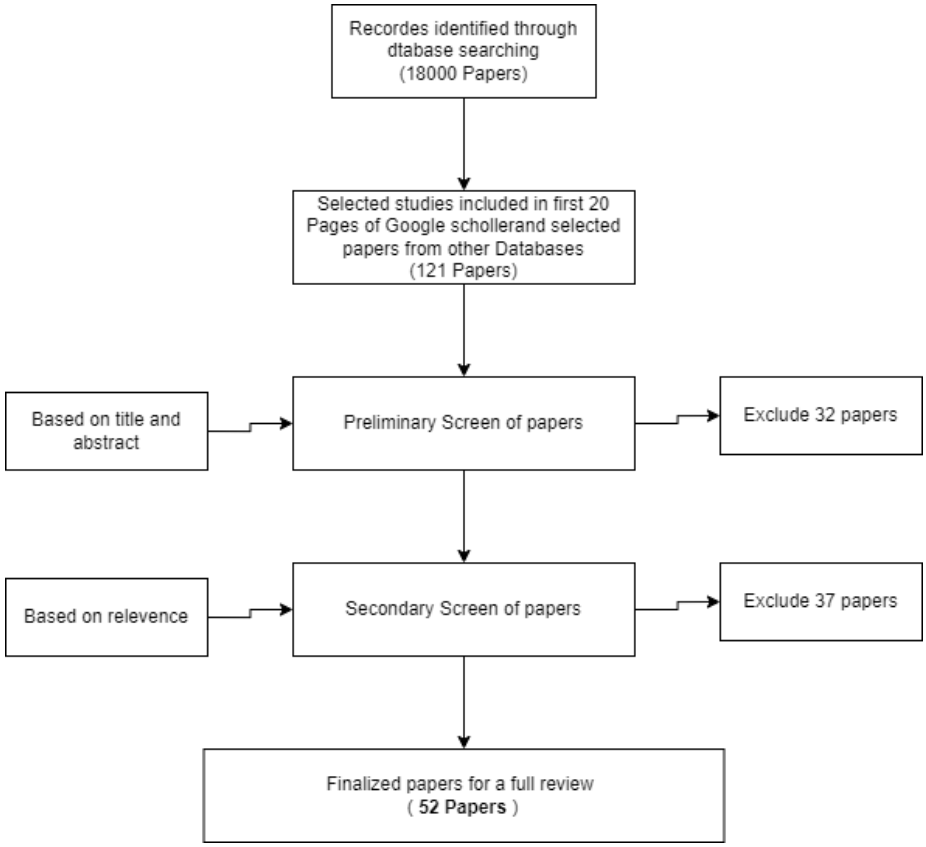

Fig. 1 : PRISMA Flow Diagram. Source: Authers

Results and Discussion

SMEs and Cloud Enterprise Systems

Small and medium enterprises (SMEs) play a crucial role in the global economy, and their adoption of cloud enterprise systems has been a subject of significant academic and practical interest. Cloud enterprise systems offer numerous advantages for SMEs, including cost savings, scalability, enhanced

operational efficiency, and competitive advantages. This section explores the factors influencing the adoption of cloud enterprise systems by SMEs, the benefits and challenges associated with their use, and the strategic implications for business growth and innovation.

Factors Influencing Adoption

The adoption of cloud enterprise systems by SMEs is influenced by several key factors, including technological, organizational, and environmental aspects. Studies highlight that technological readiness, which encompasses the availability of necessary infrastructure and the technological competence of employees, is a critical determinant of cloud adoption (Salleh, n.d.), (Oriza, n.d.). Organizational factors, such as top management support and the perceived benefits of cloud systems, also play a significant role (Avram, 2014). Environmental factors, including competitive pressure and regulatory compliance, further drive the adoption of cloud enterprise systems (Senarathna et al., 2016).

Benefits of Cloud Enterprise Systems

Cloud enterprise systems provide SMEs with numerous benefits that enhance their operational capabilities and competitiveness. One of the most significant advantages is cost savings. By adopting cloud systems, SMEs can reduce their IT infrastructure costs, as cloud services operate on a pay-per-use model that converts fixed costs into variable costs (Tselios et al., 2022). This financial flexibility allows SMEs to allocate resources more efficiently and invest in other areas of their business (Napitupulu, n.d.).Scalability is another major benefit of cloud enterprise systems. SMEs can easily scale their operations up or down based on demand without the need for significant capital investments in IT infrastructure (Oriza, n.d.; Ramasamy, 2017). This flexibility enables SMEs to respond quickly to market changes and opportunities, enhancing their agility and competitiveness(Mishrif & Khan, 2023). Cloud enterprise systems also improve operational efficiency by streamlining business processes and facilitating better collaboration and communication within the organization (Nuskiya, n.d). Cloud-based platforms provide SMEs with access to advanced tools and technologies that enhance productivity and support data-driven decision-making (Avram, 2014).

Challenges of Cloud Enterprise Systems

Despite the numerous benefits, SMEs face several challenges in adopting and implementing cloud enterprise systems. Security concerns are a primary obstacle. SMEs often worry about the safety of their data in the cloud, fearing data breaches and loss of control over sensitive information (Alouffi et al., 2021; Tselios et al., 2022). These concerns necessitate robust security measures, including encryption, access controls, and regular security audits, to protect data and build trust in cloud solutions (Alouffi et al., 2021).

Another significant challenge is the complexity of migrating existing systems and data to the cloud. The transition process can be resource-intensive, requiring substantial time, effort, and technical expertise (Khajeh-Hosseini et al., n.d.; Oriza, n.d.). SMEs must carefully plan and execute their migration strategies to minimize disruptions and ensure a smooth transition (Tatineni, 2023).

Compliance with regulatory requirements is also a critical concern for SMEs adopting cloud enterprise systems. Different industries have specific regulations regarding data protection and privacy, and SMEs must ensure their cloud practices comply with these standards to avoid legal penalties and ensure data integrity (Jaffa & Salim, 2020).

Strategic Implications for Business Growth and Innovation

The strategic adoption of cloud enterprise systems can significantly impact the growth and innovation potential of SMEs. By leveraging cloud technologies, SMEs can enhance their competitiveness and position themselves for long-term success. The integration of cloud systems allows SMEs to access advanced tools and capabilities that support innovation and drive business transformation(Hussain Akbar et al., 2023a).

Moreover, cloud enterprise systems enable SMEs to collaborate more effectively with partners, customers, and suppliers, fostering an ecosystem of innovation and co-creation. This collaborative approach can lead to the development of new products, services, and business models, driving growth and creating new market opportunities (Gamage, 2019; Shah et al., 2024).

Cloud Computing Adoption

Cloud computing adoption, particularly among small and medium enterprises (SMEs), has been a significant area of research due to its potential to enhance business efficiency, reduce costs, and provide scalability. Several studies have extensively documented the factors influencing the adoption of cloud computing, highlighting the interplay of various organizational, technological, and environmental factors.

A systematic review by various scholars reveals that top management support, technological readiness, and perceived benefits are critical determinants of cloud computing adoption in SMEs (Nuskiya, n.d.),(Oriza, n.d.),(Avram, 2014). Top management's support is essential as it facilitates the allocation of resources, drives strategic initiatives, and influences the overall acceptance of new technologies within an organization (Manoharan, 2024). Technological readiness, which includes the availability of infrastructure and the technical competence of the workforce, also plays a vital role(Napitupulu, n.d.). When organizations perceive significant benefits such as cost reduction, improved operational efficiency, and enhanced scalability, they are more likely to adopt cloud computing (Avram, 2014).

Economic benefits are among the most compelling reasons for cloud adoption. Several studies underscore that cloud computing offers substantial cost savings by reducing the need for significant capital expenditure on IT infrastructure (Avram, 2014),(Asiaei & Ab. Rahim, 2019). Instead, organizations can leverage the cloud's pay-per-use model, which converts fixed costs into variable costs, providing financial flexibility (Zulkifli & Abas, 2022). Additionally, the scalability offered by cloud services allows businesses to quickly scale their operations up or down based on demand, ensuring optimal resource utilization (Kim & Amran, 2018).

Despite these advantages, the adoption of cloud computing is not without challenges. Security concerns are one of the primary barriers. SMEs often worry about the safety of their data in the cloud, fearing data breaches, loss of control over sensitive information, and compliance issues(Zulkifli & Abas, 2022),(CTO, 2021). These concerns are exacerbated by high-profile incidents of data breaches and cyber-attacks, which have heightened awareness and caution among potential adopters (Bhatia et al., 2015). Therefore, addressing security concerns through robust security measures, compliance with regulatory standards, and trust-building initiatives is crucial for encouraging cloud adoption (Alouffi et al., 2021).

System migration difficulties also pose significant challenges. Migrating existing systems to the cloud can be complex and resource-intensive, often requiring substantial time, effort, and technical expertise (Oriza, n.d.). The transition process can disrupt business operations, leading to potential downtime and

loss of productivity. Thus, careful planning and execution of migration strategies are essential to minimize disruptions and ensure a smooth transition (Tatineni, 2023).

Another critical challenge is the need for robust governance frameworks. Effective governance ensures that cloud adoption aligns with the organization's strategic objectives and regulatory requirements(Zulkifli & Abas, 2022), The Role of Cloud Computing in Digital Transformation). Governance frameworks should address issues related to data management, security, compliance, and performance monitoring. They should also define roles and responsibilities, establish policies and procedures, and implement mechanisms for continuous improvement (Oriza, n.d.).

Theoretical contributions from various studies provide deeper insights into the factors influencing cloud adoption. For example, the Technology-Organization-Environment (TOE) framework is frequently used to analyze cloud adoption dynamics (Ruwan, 2022). This framework considers technological factors (e.g., perceived benefits, technological readiness), organizational factors (e.g., top management support, organizational culture), and environmental factors (e.g., competitive pressure, regulatory environment) (Abdullah, 2024; I. Adeghe, 2019). Studies leveraging this framework have found that a supportive organizational culture and a favorable regulatory environment significantly enhance the likelihood of cloud adoption (I. Adeghe, 2019).

Research also indicates a need for increased awareness and education among stakeholders to mitigate adoption challenges. Training programs and workshops can help build technical competence and dispel myths and misconceptions about cloud computing. (Nuskiya, n.d.), (Oriza, n.d.) Stakeholders must be informed about the potential benefits, risks, and best practices associated with cloud adoption to make informed decisions (Wilson, 2017). Educational initiatives can also foster a culture of innovation and openness to new technologies within the organization (Nuskiya, n.d)

Furthermore, aligning cloud strategies with business objectives is critical for successful adoption. Cloud adoption should not be seen as a mere technological upgrade but as a strategic initiative that can drive business transformation (Oriza, n.d.). Organizations should conduct a thorough analysis of their business needs, identify areas where cloud solutions can add value, and develop a clear roadmap for implementation (The Role of Cloud Computing in Digital Transformation). This alignment ensures that cloud adoption supports the organization's long-term goals and enhances its competitive advantage (Cloud Computing for Competitive Advantage: A Resource-Based View).

Cloud Computing Security

Cloud computing security is a critical concern that influences the adoption and success of cloud technologies. As organizations increasingly rely on cloud services for their operations, the need to address security risks and implement robust security measures becomes paramount. Multiple studies have identified various security threats and proposed strategies to mitigate these risks, highlighting the importance of a comprehensive approach to cloud security.

One of the primary concerns in cloud computing security is the risk of data breaches. Studies identify data breaches as a significant threat due to the vast amounts of sensitive information stored in the cloud(Tselios et al., 2022). Data breaches can lead to severe consequences, including financial losses, reputational damage, and legal implications. To mitigate this risk, organizations must implement strong encryption protocols, access controls, and regular security audits (Alouffi et al., 2021).

Another major security threat in cloud computing is the risk of insecure interfaces and APIs. Cloud services rely heavily on APIs for communication and integration, making them potential targets for attacks. Insecure APIs can lead to unauthorized access, data leaks, and other security vulnerabilities (Valdés-Rodríguez et al., 2024). Effective mitigation strategies include the use of secure coding practices, regular security testing, and the implementation of robust authentication and authorization mechanisms(Sarkar et al., 2022)

Account hijacking is another critical concern. Cybercriminals can exploit vulnerabilities in cloud systems to gain unauthorized access to user accounts, leading to data theft and other malicious activities. Preventive measures such as multi-factor authentication, anomaly detection, and proactive monitoring can help mitigate the risk of account hijacking (Nazareth et al., 2022). Trust-based relationships between cloud service providers (CSPs) and users are also crucial for ensuring security. Establishing clear communication channels, transparency in security practices, and adherence to industry standards can build trust and confidence among users (Alouffi et al., 2021; Hussain Akbar et al., 2023b).

Regulatory compliance is another essential aspect of cloud computing security. Organizations must ensure that their cloud practices comply with relevant laws and regulations to avoid legal penalties and protect user data. Compliance frameworks such as the General Data Protection Regulation (GDPR) and the Health Insurance Portability and Accountability Act (HIPAA) provide guidelines for data protection and privacy (Athambawa et al., 2022). Adhering to these regulations requires continuous monitoring, regular audits, and updating security practices to meet evolving standards (Alouffi et al., 2021).

The implementation of Zero Trust security models is increasingly recognized as an effective approach to enhance cloud security. The Zero Trust model operates on the principle that no entity, whether inside or outside the network, should be trusted by default. Instead, every access request must be verified continuously. This approach involves the use of strict identity verification, least privilege access, and continuous monitoring of user activities (Sarkar et al., 2022). By adopting Zero Trust principles, organizations can reduce the risk of unauthorized access and enhance their overall security posture.

Moreover, the importance of educating and training employees on cloud security cannot be overstated. Human error remains one of the leading causes of security breaches. Regular training programs and awareness campaigns can help employees recognize potential security threats and follow best practices to mitigate risks (Chidukwani et al., 2022). Organizations should also establish clear security policies and procedures, conduct regular security drills, and encourage a culture of security awareness among their staff (Sarkar et al., 2022).

Theoretical contributions to cloud computing security research often leverage frameworks such as the Technology-Organization-Environment (TOE) framework to analyze security practices. This framework helps in understanding the technological, organizational, and environmental factors that influence security adoption and implementation (Kumar et al., 2017). For instance, technological factors include the availability of security tools and technologies, organizational factors encompass the security policies and practices within the organization, and environmental factors involve regulatory and competitive pressures(Roy & Patil, 2023).

Business Continuity and Disaster Recovery

Business continuity and disaster recovery (BC/DR) are critical components of an organization's cloud computing strategy. As businesses increasingly rely on cloud services, ensuring the continuity of operations and the ability to recover from disruptions becomes paramount. The literature extensively

discusses the benefits and challenges of implementing cloud-based BC/DR solutions and provides insights into best practices and strategies for enhancing organizational resilience.

Cloud computing offers significant advantages for BC/DR by providing flexible, scalable, and cost-effective solutions for data backup and recovery. Studies highlight that cloud-based BC/DR solutions enable organizations to quickly recover from disruptions with minimal downtime, ensuring continuity of operations (Mishrif & Khan, 2023; Tatineni, 2023). The pay-per-use model of cloud services allows businesses to scale their BC/DR capabilities according to their needs, avoiding the high costs associated with traditional BC/DR infrastructure (Avram, 2014; Tatineni, 2023).

One of the primary benefits of cloud-based BC/DR is the reliability and availability of data. Cloud service providers (CSPs) typically offer robust data replication and backup services, ensuring that data is stored in multiple locations to prevent loss due to hardware failures or other disasters (Douglas, 2024; Tatineni, 2023). This geographic redundancy ensures that data can be quickly restored from alternative sites if one location is compromised, enhancing the resilience of business operations (Bak et al., 2023). However, the implementation of cloud-based BC/DR solutions is not without challenges. Data security during transfer and storage remains a significant concern. Organizations must ensure that data is encrypted and protected against unauthorized access while being transferred to and stored in the cloud (Nagahawatta et al., n.d.). Compliance with regulatory requirements is another critical challenge. Different industries have specific regulations regarding data protection and privacy, and organizations must ensure their BC/DR practices comply with these standards to avoid legal penalties and ensure data integrity (CTO, 2021).

Regular testing and updating of BC/DR plans are essential to ensure their effectiveness and alignment with organizational needs. Studies emphasize that BC/DR plans should be tested under various scenarios to identify potential weaknesses and areas for improvement (Tatineni, 2023). Regular updates to the BC/DR plans are necessary to account for changes in the business environment, technology, and regulatory landscape (Kutame et al., n.d.). This proactive approach helps organizations stay prepared for potential disruptions and ensures a swift and effective response when incidents occur (Bak et al., 2023).
The integration of theoretical frameworks such as the Fit-Viability Model provides valuable insights into the effective implementation of BC/DR strategies. This model considers the fit between the organization's requirements and the capabilities of the cloud-based BC/DR solutions, as well as the viability of these solutions in the long term(Kurpjuhn, 2015). Studies leveraging this framework have found that a good fit between organizational needs and cloud capabilities enhances the effectiveness of BC/DR plans and improves overall resilience (Hamzah Ritchi et al., 2024).

Moreover, the adoption of multi-cloud strategies can further enhance BC/DR capabilities. By leveraging multiple CSPs, organizations can mitigate the risk of service provider failures and ensure higher availability and reliability of their BC/DR solutions (Alrokayan, n.d.). Multi-cloud strategies also offer the flexibility to choose the best-in-class services from different providers, optimizing performance and cost-efficiency (Ochara et al., n.d.).

Conclusion and Recommendations

The literature review has shown that cloud-based BC/DR solutions offer significant advantages for SMEs, especially in terms of cost-efficiency, scalability, and flexibility. However, the literature also reveals several challenges and gaps that need to be addressed for successful implementation and adoption of these solutions. Some of the key challenges include security concerns, system migration

complexities, regulatory compliance, and integration with existing systems. Furthermore, the literature indicates a lack of localized studies that focus on the specific needs and contexts of SMEs in Sri Lanka, as well as a lack of practical frameworks and guidelines that can assist SMEs in choosing and deploying the most suitable cloud-based BC/DR solutions. Additionally, the literature suggests a need for more longitudinal studies that examine the long-term impacts of cloud-based BC/DR solutions on SME resilience and performance.

Therefore, this research aims to address these gaps and challenges by developing a comprehensive cybersecurity framework that enhances the resilience of SMEs against cyber threats, ensuring business security and continuity. The framework will consider the fit and viability of different cloud-based BC/DR solutions for SMEs in Sri Lanka, taking into account their specific requirements, capabilities, and constraints. The framework will also provide practical recommendations and best practices for implementing and adopting multi-cloud strategies that optimize the benefits and minimize the risks of cloud-based BC/DR solutions. Moreover, the research will conduct a longitudinal study to evaluate the effectiveness and impact of the proposed framework on SME resilience and performance, using both quantitative and qualitative methods. By building on the insights provided by the literature review, this research hopes to contribute to the broader field of cloud computing and cybersecurity, as well as to support SMEs in their digital transformation journey

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POTENTIAL CRITICAL FACTORS INFLUENCING THE MATURITY OF BUSINESS ANALYTICS IN SRI LANKA – A SYSTEMATIC LITERATURE REVIEW

TN De Silva[1], S Jayasinghe[2] and WMJI Wijayanayake[3]

Abstract

In the rapidly evolving, data-driven business landscape, organizations leverage vast amounts of data from various sources to enhance efficiency, decision-making, and financial performance. Business Analytics (BA), defined as the use of data, IT, statistical analysis, quantitative methods, and computer-based models, plays a crucial role in this context. The maturity of business analytics, which measures an organization's analytics competency, is pivotal for making informed, data-driven decisions. This systematic literature review investigates the potential critical factors influencing business analytics maturity in Sri Lanka's apparel and software industries. This review utilized the PRISMA framework to identify and screen relevant literature, resulting in the selection of 43 papers that met the inclusion criteria, focusing on business analytics maturity and its influencing factors, using the Technology-Organization-Environment (TOE) framework. The review identifies and categorizes key factors such as compatibility, data management, data infrastructure, technology-supporting infrastructure, trust-in-technology, top management support, organizational culture, organizational readiness, and environmental factors including regulations and competition pressure as the potential factors that could affect the BA maturity of Sri Lankan apparel and software industry. The analysis reveals that top management support, organizational culture, data management, and robust technology infrastructure are the most significant determinants of BA maturity. The findings suggest that while these factors are widely recognized in broader contexts, their applicability and impact within Sri Lanka's unique business environment require empirical validation. Consequently, this review highlights the necessity for future research to test these factors specifically in Sri Lanka's software and apparel industries.

Keywords: Apparel Industry, Business Analytics, Software Industry, TOE framework

[1] Department of Industrial Management, University of Kelaniya, Sri Lanka

Email: nipuni0616@gmail.com https://orcid.org/0009-0000-2203-1455

[2] Department of Business and Law, Solent University Southampton, United Kingdom

Email: shan.jayasinghe@solent.ac.uk https://orcid.org/0000-0001-8149-2999

[3] Department of Business and Law, Solent University Southampton, United Kingdom

Email: janaka@kln.ac.lk https://orcid.org/0000-0002-9523-5384

Introduction

In today's data-driven and dynamic business environment, organizations are dealing with vast amounts of data and information generated from many sources including operational processes, customer interactions, transactions, and social media. According to research done by MicroStrategy, 64% of companies worldwide use data to improve their efficiency and productivity, 56% use it to improve the effectiveness of decision-making, while 51% of companies use data to improve financial performance (Gavin,2019). Hence, this vast amount of data has the potential to provide organizations with valuable insights that can drive strategic decisions, optimize operations, and gain a competitive edge in the market. This is where Business Analytics comes into play.

According to prominent researchers in the field, Business Analytics is defined as "the use of data, information technology, statistical analysis, quantitative methods, and mathematical or computer-based models to help managers gain improved insights about their operations and make better fact-based decisions" (Davenport & Harris,2007, as cited in Dahlgren et al., 2019). Defined by the Gartner Group, four main types of business analytics can be identified as descriptive, diagnostic, predictive, and Predictive (Silva et al., 2021). Descriptive Analytics analyses what happened in the past. It involves using historical data to provide visualizations, reports, and dashboards. Diagnostic analytics examines "Why did it happen?". Diagnostic analytics takes another step forward to identify the reason for analytics identified. Predictive analytics forecasts what will happen in the future instead of simply identifying existing data. Prescriptive analytics is the most advanced since it provides actionable insights on "How can we make it happen?" (Silva et al., 2021).

Analytics maturity is crucial for organizations since, when organizations develop through maturity levels their data collection proficiency and interpretation capabilities improve resulting in more accurate predictions and decisions. Hence, analytics maturity improves a data-driven culture where decisions are made on proof rather than on the senses. According to McKinsey, companies with high levels of analytical maturity see growth in their earnings before interest, taxes, depreciation, and amortization (EBITDA) of 15% to 25% (Sweenor, 2022).

There are many models for the maturity of Business Analytics that show the pathway for organizations to achieve a higher level of BA maturity. To identify which model to adopt, it is important for organizations to identify what are the factors that can affect the maturity of BA. A factor is any significant characteristic where the Business Analytics are conducted in an organization. (Potancok & Pour, 2021). These factors may include any Internal or external factors such as Analytical Capabilities, Technology and Tools, Organizational Culture, industry trends and regulations, Economic Conditions, and many other factors. Out of all these factors, several factors can critically affect the maturity of Business Analytics of an organization. Recognizing these critical factors and understanding their influence on BA maturity is crucial since it guides organizations to allocate resources effectively, prioritize their investments, and develop strategies to advance their analytics maturity. Ultimately, recognizing these factors can lead organizations to make better data-driven decisions and achieve competitive advantage in the industry.

The objective of this literature review is to identify and analyze the factors that authors of existing literature have recognized as influencing the maturity of Business Analytics (BA). These identified factors are then considered as potential influences on the maturity of BA specifically within the software and apparel industries in Sri Lanka. This objective is formulated due to the noticeable lack of literature available on the Sri Lankan context, highlighting the need to understand and apply these factors to local industries for enhanced analytics maturity. The software and apparel industries in Sri Lanka have been

strategically chosen for this study due to their significant contributions to the national economy and their distinct characteristics.

Sri Lankan apparel and textile manufacturing industries are significant contributors to the country's economy. Throughout the years Sri Lankan apparel industry has gained a strong reputation worldwide. According to the Sri Lanka Export Development Board (EDB), Sri Lanka's top three apparel companies are ranked among the world's 50 most significant suppliers, and the industry's total export earnings in 2018 came in just short of US $5 billion, the peak figure. (Apparel & Textile,2023). In 2022 EDB declared that Sri Lanka's export revenue from apparel and textiles increased by 12.14% year over year to $494,82 million with the growth of the export of woven fabrics (31.04%) and apparel (11.87%). (Sri Lanka's Export Performance,2022).

Sri Lanka's software industry has been evolving over the past years. Similar to the apparel industry in Sri Lanka, the software industry also plays a major role in export market. Sri Lankan ICT companies export their software products to many countries such as North America, Australia, the Middle East, Africa, the EU, East Asia, and the Nordic region. (SL software industry, 2024). Industry reports indicate that Sri Lanka's software industry has established itself as a top player in the global market experiencing significant growth. In terms of market size and growth of the software industry in Sri Lanka, it was valued in the market at around 102 billion in 2020, and between 2021 and 2026 a compound annual growth rate of 12% was predicted (Wetechies, 2023).

If Sri Lanka focuses on leveling up the BA maturity in the software and apparel industries, it has the potential to increase innovation and competitiveness in these sectors, ultimately elevating the country's economy to a higher position in the global market. Therefore, this systematic literature review aims to identify the potential critical factors that could affect the maturity of Business Analytics specifically in Sri Lanka's software and apparel industries, as these industries are key drivers for economic growth and global competitiveness.

Methodology

This systematic review of the literature was conducted based on existing literature on Business Analytics. As the first step, to guide the systematic literature review a question was formulated. (Jones & Evans, 2000). The review question that guided the literature search in this study is: "What are the potential critical factors that influence the maturity of Business Analytics of software and apparel industries in Sri Lanka?"

After identifying the review question, the PRISMA framework was used to identify and screen papers.(Page et al., 2021). Research papers were obtained from several databases such as Google Scholar, Research Gate, and IEEE Xplore Digital library using the keywords and logics "Business Analytics", "Business Analytics Maturity", "Business Analytics" AND "Factors", "Business Analytics maturity" AND "Factors", "Business Intelligence" AND "Factors", Business Analytics maturity" AND "Factors" AND "Sri Lanka", "Business Analytics" AND "Sri Lanka" AND "Apparel" OR "Software industry". Papers published in the English language from 2010 to 2024 time period were considered for this review.

The inclusion criteria for this review encompass literature that discusses Business Analytics maturity, factors affecting Business Analytics maturity, factors affecting Business Intelligence, and factors that influence any area that is related to BA. Additionally, the review includes literature focused on Business Analytics in the apparel industry in Sri Lanka and the software industry in Sri Lanka. The exclusion

criteria filter out literature that does not contribute to the purpose of this review, duplicated literature, and literature that is not conducted in English.

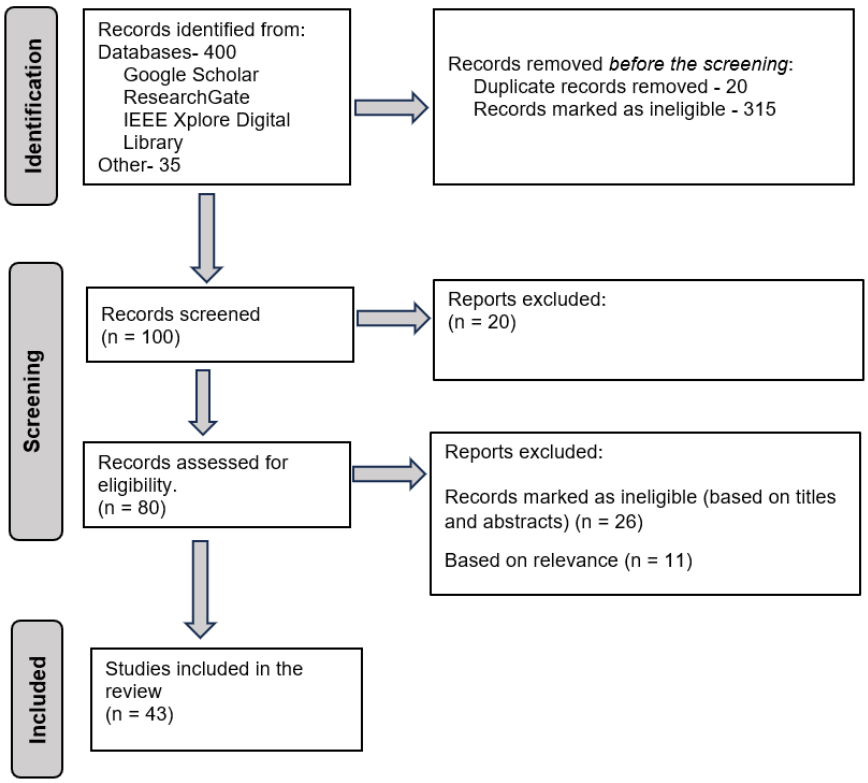

Fig. 1. Approach To Selecting Related Studies

After the identification and screening process, 43 papers were selected to include in the review. The identification process done using the PRISMA method is shown as a flow diagram in Fig.1

Systematic Literature review

This section provides a systematic review of existing literature on the maturity of Business Analytics. The review focuses on understanding the key factors influencing BA maturity. By examining technological, organizational, and environmental dimensions, this review aims to identify the critical elements that contribute to the effective adoption and advancement of BA within organizations.

Business Analytics

Business analytics involves the systematic process of gathering, analyzing, and interpreting an organization's data to uncover patterns, trends, and insights that support more informed and strategic decision-making. The increasing use of information technology in the business world has resulted in the creation of large and complex datasets for various organizational functions(Bayrak, 2015). Understanding their businesses and making decisions based on these large datasets has become a significant challenge for organizations (Bayrak, 2015).

The term "Business Analytics" describes the application of statistical, machine learning, and data mining models and methods to business data to derive insights that can inform and guide business decisions (Delen & Ram, 2018). Such integrated applications help decision-makers, including managers and executives, understand and make sense of business data (Raghupathi & Raghupathi, 2021). Companies that effectively use analytics have been relatively more successful and have gained a competitive advantage compared to those that do not utilize analytics.(Ariyarathna & Peter, 2019).

Hence, the strategic implementation of business analytics is crucial for sustaining competitive advantage and driving organizational success.

Maturity of Business Analytics

Analytics maturity is a measurement of the analytics competency level of an organization. The use of analytics is not a one-off exercise but rather a continuous process, with various factors becoming prominent depending on the organization's level of maturity (Ariyarathna & Peter, 2019). An organization does not reach a higher level of maturity in Business Analytics simply by adopting analytical tools, techniques, and methods. Generally, the notion of "maturity" is very broad and means "fully developed", or "perfected." Organizations reach analytics maturity through evolution, which includes integration, management, and use of various data sources at key decision-making points (Król & Zdonek, 2020).

Both academics and practitioners have studied the maturity of BA and developed numerous Business Analytics maturity models. These models provide a comprehensive roadmap to achieve maturity in the use of BA within organizations. They specify the main factors that need to be addressed when moving up the maturity scale and outline how organizations should acquire the necessary capabilities. This roadmap helps organizations understand the critical aspects of their analytics journey, ensuring that they systematically develop and enhance their analytical competencies over time (Ariyarathna & Peter, 2019).

Factors Affecting the Maturity of Business Analytics

To reach a higher level of BA maturity it is important for organizations to identify what influences their BA maturity. By studying the present literature, the factors influencing Business Analytics' maturity were identified and categorized according to the Technology Organization and Environment (TOE) framework. The reason for using the TOE framework is that it is one of the most comprehensive frameworks that can explain technology adoption in businesses. Furthermore, the TOE framework considers the organization as a whole, rather than only focusing on how each member of the organization uses and accepts new technologies (Bany Mohammad et al., 2022).

The identified factors with mentioned references are shown in the tables Table 1, Table 2, and Table 3.

Technological Dimension

Technological factors play a vital role in shaping the maturity of Business Analytics within organizations. This sector includes factors such as compatibility, data management, and technological infrastructure, all of which influence how effectively an organization can implement and leverage analytics tools. Addressing these factors is crucial for building a strong foundation for advancing BA capabilities and achieving greater maturity in analytics processes. Through an extensive review of existing literature, key technological factors have been identified and are presented in Table 1.

Table 2. Technological Factors

Factor	Reference
Compatibility	(Alkhalil, 2020) , (Madhlangobe, 2019), (Kumar & Krishnamoorthy, 2020), (Horani et al., 2023), (Stjepić et al., 2021), (Alanudin et al., 2024), (Cruz-Jesus et al., 2018)
Data Management	(Soni et al., 2023a), (Nam et al., 2019), (Bany Mohammad et al., 2022), (Bolonne & Wijewardene, 2020a), (Horani et al., 2023), (Lautenbach et al., 2017)

Data infrastructure	(Nam et al., 2019), (Bany Mohammad et al., 2022), (Bolonne & Wijewardene, 2020a), (Saravanabhavan et al., 2023), (Lautenbach et al., 2017)
Technology Supporting Infrastructure	(Nam et al., 2019), (Bany Mohammad et al., 2022), (Horani et al., 2023), (Saravanabhavan et al., 2023), (M.Potancok, J.Pour, 2021), (Adzandeh et al., 2024)
Trust-in-Technology	(Madhlangobe, 2019)
Technology Assets	(Kumar & Krishnamoorthy, 2020), (Alanudin et al., 2024)
Technology Competence	(Horani et al., 2023)

Compatibility

Compatibility plays a significant role in how organizations adopt and mature their Business Analytics. It refers to how well BA fits with an organization's existing systems, values, experiences, and needs (Horani et al., 2023). When BA aligns well with these elements, it can be integrated more smoothly without major disruptions. Challenges such as managing large and varied datasets and integrating new systems with existing ones can hinder the adoption of big data analytics (Alkhalil, 2020). Studies highlight that when technology matches an organization's values and needs, it is more likely to be adopted successfully (Kumar & Krishnamoorthy, 2020). Thus, ensuring compatibility is essential for the effective implementation and growth of BA.

Data Management

Data management involves the processes and technologies used to collect, store, and retrieve data for analysis. It includes ensuring good storage architecture, data quality, consistency, accessibility, and data security and privacy (Soni et al., 2023). Effective data management is critical for successful BA implementation, as poor data quality can lead to flawed systems and errors, reducing the reliability of analytics (Nam et al., 2019). Organizations need to maintain high data quality by enforcing standards, preventing errors, and ensuring data is reliable, current, relevant, and accurate (Bany Mohammad et al., 2022; Horani et al., 2023).

Data Infrastructure

Strong data infrastructure is essential for the extensive use of Business Intelligence and Analytics (BI&A). Organizations with robust data infrastructure are better equipped to use BI&A effectively (Lautenbach et al., 2017). Data infrastructure readiness involves the ability to handle Big Data analytics and integrate necessary underlying data (Bolonne & Wijewardene, 2020). The capability of data infrastructure significantly influences the extent of BA usage, driving innovation and enhancing organizational performance (Bany Mohammad et al., 2022). Investing in scalable and integrated data infrastructure enables organizations to leverage BA for decision-making and strategic planning.

Technology Supporting Infrastructure

A well-developed IT infrastructure is crucial for initiating and adopting business analytics smoothly. It acts as the technical foundation for an organization's readiness for new innovations. The availability and compatibility of IT infrastructure allow companies to share real-time information, analyze customer data, develop products, and understand competitive markets through a compliant and interconnected system (Nam et al., 2019; Bany Mohammad et al., 2022). The lack of necessary internal IT infrastructure can be a major barrier to adopting new technologies, highlighting the need for robust and scalable IT foundations to enhance BA adoption and growth.

Trust-in-Technology

Trust in the reliability, security, and accuracy of technology builds confidence among users, encouraging broader adoption and integration into business processes. Studies state that Trust-in-Technology is important in influencing the intent to use Big Data analytics within organizations, especially after initial adoption (Madhlangobe, 2019). Building this trust involves ensuring strong security measures, maintaining high data quality, and demonstrating the tangible benefits of BA through successful examples and results.

Technology Competence

Technology competence refers to the ability of an organization's members to adopt, integrate, and use BA in their operations. This includes having the necessary knowledge and skills to effectively use technology (Horani et al., 2023). Enhancing technological competence through training and development is essential for maximizing the benefits of BA. Organizations with high technology competence can better utilize analytics tools, derive meaningful insights, and drive strategic decision-making, advancing their BA maturity.

Organizational Dimension

The organizational dimension focuses on the internal characteristics and dynamics that impact the maturity of Business Analytics within a company. This includes factors like organizational culture, structure, top management support, and talent management. These elements determine how well an organization can integrate analytics into its decision-making processes and sustain its growth over time. The critical organizational factors identified from past literature are summarized in Table 2.

Table 3. Organizational Factors

Factor	**Reference**
Vision and Strategy	(Bolonne & Wijewardene, 2020a)
Organization Readiness	(Alkhalil, 2020), (Horani et al., 2023), (Stjepić et al., 2021)
Top Management Support	(Alkhalil, 2020), (Nam et al., 2019), (Bany Mohammad et al., 2022), (Kumar & Krishnamoorthy, 2020), (Horani et al., 2023), (Stjepić et al., 2021), (Lautenbach et al., 2017), (Sparks & McCann, 2015), (Adzandeh et al., 2024), (Abrew & Wickramarachchi, 2021), (Alanudin et al., 2024), (Cruz-Jesus et al., 2018)
Organizational Culture	(Soni et al., 2023a), (Horani et al., 2023), (Saravanabhavan et al., 2023), (M.Potancok, J.Pour, 2021), (Sparks & McCann, 2015), (Abrew & Wickramarachchi, 2021), (Rajapaksha et al., 2022)
Organization Structure	(Nam et al., 2019), (Bolonne & Wijewardene, 2020a), (Horani et al., 2023), (Abrew & Wickramarachchi, 2021)
Presence-of-Champion	(Bany Mohammad et al., 2022), (Horani et al., 2023)
Talent-Management Challenges	(Bany Mohammad et al., 2022), (Bolonne & Wijewardene, 2020a), (Lautenbach et al., 2017), (Adzandeh et al., 2024)

Vision and Strategy

A clear vision and strategy are essential for successful BA implementation. For an instant, initiatives related to Big Data analytics should stem from specific business needs and be guided by a strategic business vision. Without this alignment, big data analytics systems risk failure as they might not address actual business problems, leading to ineffective results (Bolonne & Wijewardene, 2020). Therefore, having a well-defined business problem to address with BA is crucial for generating positive outcomes.

Organizational Readiness

Organizational readiness for adopting BA involves a shift towards a data-driven decision-making culture and establishing proper data governance and accessibility policies (Alkhalil, 2020). This readiness includes the organization's willingness to adopt and effectively use BA, which depends on factors like financial resources, IT infrastructure, and skilled personnel (Horani et al., 2023). Studies have shown that organizational readiness positively impacts the adoption of Business Intelligence systems in small and medium-sized enterprises (SMEs) (Stjepić et al., 2021).

Top Management Support

Support from top management is critical for the successful adoption and implementation of BA. Top management ensures competitiveness, informed decision-making, process monitoring, timely key performance indicators (KPIs), and reliable information (Alkhalil, 2020). The initiation and support for new technology adoption often come from senior management, and their backing is essential for overcoming organizational resistance to change (Nam et al., 2019). Strong top management support is widely recognized as a determinant of successful BA adoption (Kumar & Krishnamoorthy, 2020; Bany Mohammad et al., 2022; Horani et al., 2023; Stjepić et al., 2021).

Organizational Culture

Organizational culture significantly affects how analytics are used and integrated within a company. It encompasses the organization’s approach to using analytics, the advancement and spread of analytics practices, and the support provided by business strategies, leadership, capabilities, and investments (Soni et al., 2023). A culture that promotes the use of data and advanced analytical techniques enhances the effectiveness of BA (Horani et al., 2023). Research shows a significant impact of organizational culture on the utilization of business analytics (Rajapaksha et al., 2022).

Organizational Structure

The organizational structure for decision-making can be centralized or decentralized. A centralized structure features a clear hierarchy of authority, while a decentralized structure allows for more creativity and collaboration (Horani et al., 2023). In centralized analytics environments, one or a few teams handle analytics, whereas, in decentralized environments, each business function or department employs BA separately, facilitating quicker adoption and benefit realization (Nam et al., 2019). A well-organized structure, including cross-organizational collaboration and dedicated analytics departments, supports the adoption of big data (Bolonne & Wijewardene, 2020).

Presence of a Champion

Having a champion within the organization, someone highly enthusiastic and knowledgeable about both the business processes and technological innovation is crucial for successful BA adoption. Champions drive innovation by providing information, creating awareness, securing resources, and gaining organizational acceptance (Bany Mohammad et al., 2022; Horani et al., 2023).

Talent-Management Challenges

Executing BA effectively requires a mix of business and IT expertise. Experts with the necessary skills, especially in logical reasoning and data analysis, are vital for utilizing the full potential of BA tools and technologies (Bany Mohammad et al., 2022). Therefore, having talented individuals in both business and technology roles is a key to successful BA adoption and utilization.

Environmental Dimension

The environmental dimension encompasses external factors that influence the maturity of Business Analytics within organizations. These factors include regulatory requirements, government support, competitive pressure, and market influences, all of which can either facilitate or hinder the adoption and advancement of BA. Key environmental factors identified from the literature are outlined in Table 3.

Table 4. Environmental Factors

Factor	**Reference**
Regulations	(Alkhalil, 2020), (Bany Mohammad et al., 2022), (Horani et al., 2023), (Lautenbach et al., 2017)
Government support	(Nam et al., 2019)**,** (Horani et al., 2023)
Competition Pressure	(Nam et al., 2019)**,** (Bany Mohammad et al., 2022)**,** (Kumar & Krishnamoorthy, 2020)**,** (Horani et al., 2023)**,** (Stjepić et al., 2021)**,** (Alanudin et al., 2024)**,** (Cruz-Jesus et al., 2018)
External Market Influence	(Bany Mohammad et al., 2022)**,** (Bolonne & Wijewardene, 2020a)**,** (Lautenbach et al., 2017)
Industry Type	(Alanudin et al., 2024)

Regulations

Government regulations and policies play a crucial role in the adoption of technology, including business analytics (BA). These regulations can include incentives, technological standards, or legislation, which can either encourage or hinder technology adoption (Horani et al., 2023). Legal implications, data ownership issues, and service level agreements (SLAs) are common concerns that can negatively impact the adoption of BA (Alkhalil, 2020). For example, the banking sector is highly regulated, requiring stringent compliance with laws and regulations to ensure accurate data collection and analysis (Bany Mohammad et al., 2022).

Government Support

Government support is a significant factor in influencing the diffusion of innovation. Governments can impact the adoption of BA by implementing policies that increase or decrease incentives, such as tax adjustments or providing a favorable regulatory environment. Additionally, governments can fund research and development in big data, offer training for human resources, and update legal frameworks to protect personal information and intellectual property rights (Nam et al., 2019). These actions can stimulate the adoption of BA in the private sector by creating a supportive environment.

Competition Pressure

The intensity of competition within an industry can drive organizations to adopt BA to maintain or improve their competitive edge. Organizations facing pressure from competitors using BA technologies are more likely to adopt these technologies themselves to avoid falling behind (Nam et al., 2019). Studies have shown that competitive pressure significantly influences the extent to which organizations use business intelligence and analytics (Bany Mohammad et al., 2022; Kumar & Krishnamoorthy, 2020). Early adopters of technology often gain a first-mover advantage in their industry (Horani et al., 2023).

External Market Influence

External market influences, such as competitive pressures and environmental uncertainties, play a significant role in driving the adoption of BA. Organizations must engage in strategic initiatives, like Big Data analytics, to understand both internal and external environments better (Bolonne & Wijewardene, 2020). The level of external market influence has been shown to have a statistically significant effect on the extent of BA usage (Bany Mohammad et al., 2022). This understanding helps organizations stay competitive and responsive to market changes.

Sri Lankan Context

Many studies related to finding factors affecting BA or BA-related segments have been done in countries such as India, North America, South Africa, and Nigeria. The literature review revealed that limited research has been done in the Sri Lankan context. For instance very few studies like the research done by (Bolonne & Wijewardene, 2020) has focused on identifying the critical factors that influence the attitude toward using Big Data analytics in apparel sector organizations in Sri Lanka. Furthermore, the research done by (Rajapaksha et al., 2022) highlights the impact of Organizational Culture on the use of business analytics in Sri Lankan companies.

The critical factors influencing the maturity of business analytics (BA) can vary significantly across different industries and countries. (Saravanabhavan et al., 2023) states that India is unique and has its specific factors. It implies that country-to-country factors affecting the maturity of BA can differ. Hence it is worthwhile to do research specifically for Sri Lanka to identify the specific factors within the Sri Lankan context.

In Sri Lanka, the apparel and software industries present unique contexts that shape BA adoption and maturity. The apparel industry, characterized by its focus on manufacturing and supply chain efficiency, may face distinct challenges related to data integration, legacy systems, and regulatory compliance. Conversely, the software industry, driven by innovation and technology, might prioritize factors such as advanced IT infrastructure, talent management, and competition pressure. Additionally, the regulatory environment, government support, and market dynamics in Sri Lanka influence how these industries approach BA differently. Understanding these industry-specific and country-specific factors is essential for developing tailored strategies that enhance BA maturity and drive competitive advantage in Sri Lanka's diverse economic landscape.

Results and Discussion

Based on the analysis done in this systematic literature review, several factors were identified as factors that could influence the maturity of Business Analytics within the TOE framework.

According to the analysis conducted in Table 1, technological factors such as compatibility, data management, data infrastructure, technology supporting infrastructure, trust-in-technology, technology assets, technology competence, and security and privacy were emphasized. Among these factors, compatibility, data management, data infrastructure, and technology-supporting infrastructure were found more frequently in past literature (Refer Table 1), reflecting their importance in the successful implementation and maturation of business analytics systems. These factors are critical as they provide the foundational capabilities that enable organizations to effectively manage and utilize vast amounts of data, ensuring the integration of analytics into business processes.

Similarly, according to the analysis conducted in Table 2, organizational factors included vision and strategy, organizational readiness, top management support, organizational culture, organizational

structure, presence of champions, and talent management challenges. Among these factors, top management support and organizational culture were highlighted as the most potential organizational factors considering the number of references found (Refer Table 2). Top management support is crucial as it drives the adoption and implementation of business analytics, aligning it with organizational goals and providing the necessary resources. Organizational culture implements a data-driven decision-making environment, which is essential for the successful integration and use of analytics in daily operations.

According to the analysis in Table 3, environmental factors include regulations, government support, competition pressure, external market influence, and industry type. The most critical factors, as determined by the number of references and emphasis in the literature, were regulations, competition pressure, and external market influence (Refer Table 3). These environmental factors highlight the external forces that influence the adoption and maturity of business analytics.

Most studies in this literature review were conducted in different geographical contexts such as Nigeria (Adzandeh et al., 2024), South Africa (Lautenbach et al., 2017), India (Saravanabhavan et al., 2023), (Soni et al., 2023), North America (Madhlangobe, 2019) and Slovenia (Popovič et al., 2012) etc. Very few studies were identified related to the Sri Lankan context (Rajapaksha et al., 2022) and (Bolonne & Wijewardene, 2020). Hence, the above-mentioned factors can be identified as potential critical factors that could influence the maturity of business analytics in the apparel and software industries in Sri Lanka. However, the significant gap in research focused on the Sri Lankan context indicates a need for localized research to validate whether these identified factors hold the same level of importance and impact within Sri Lanka.

Conclusion and Recommendations

This literature review has identified and analyzed the potential critical factors that can influence the maturity of business analytics within the apparel and software industries, primarily through the Technology-Organization-Environment (TOE) framework. The most prominent factors include compatibility, data management, data infrastructure, technology-supporting infrastructure, top management support, organizational culture, regulations, competition pressure, and external market influence. These factors were consistently emphasized across multiple studies, underscoring their pivotal role in successful business analytics adoption and implementation. However, there is a notable gap in the literature regarding the Sri Lankan context. This highlights the need for localized studies to validate the relevance and impact of these factors within Sri Lanka's unique industrial landscape.

The factors identified in this systematic literature review are only the potential influences on the maturity of Business Analytics in the software and apparel industries in Sri Lanka. While these factors are recognized for their significance in broader contexts, their validity in the Sri Lankan context should be tested to confirm their applicability and impact. Future research should focus on empirically testing these identified factors within Sri Lanka's software and apparel industries. This can involve conducting surveys, case studies, and other research methodologies to gather data and analyze the relevance of these factors. By doing so, researchers can develop a more precise understanding of how these factors influence business analytics maturity in these specific industries and tailor strategies that address the unique challenges and opportunities present in Sri Lanka. Therefore, it is recommended that future researchers validate these factors in the Sri Lankan context to contribute to the advancement of business analytics maturity in the country.

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RESEARCH ON AUTHENTIC LEADERSHIP LITERATURE BASED ON THE SCOPUS: A CO-WORD CLUSTERING ANALYSIS

AS Gamage[1] and P Mathushan[2]

Abstract

In contemporary discourse, the adjective authentic has increasingly been affixed to the term leadership with the aim of enriching the scholarly examination of leadership and broadening its applicability within organizational contexts. The designation "authentic" carries specific implications and nuances that may lead one to infer that it represents a potentially superior or more legitimate variant of leadership. The emergence of authentic leadership is rooted in the principles of positive organizational behavior and a conducive organizational environment, which are indicative of human resource competencies and psychological capacities that can be quantified, cultivated, and adeptly administered to enhance performance in the modern workplace. This study seeks to perform a bibliometric literature review on authentic leadership's terms, trends and ideas, using Scimago Graphica software and database from Scopus to contribute to authentic leadership research. The Scimago Graphica software generated four clusters that provide a comprehensive landscape and study trajectory of authentic leadership. Researchers and practitioners should focus on current trends and research topics to enhance authentic leadership development.

Keywords: Authentic Leadership, Bibliometric Literature Review, Leadership, Corporate Scandals

[1]Professor, Department of Human Resource Management, University of Sri Jayewardenepura, Sri Lanka

Email: arunasgamage@sjp.ac.lk https://orcid.org/0009-0002-9843-2305

[2]Department of Human Resource Management, University of Vavuniya, Sri Lanka

Email: mathush92@gmail.com https://orcid.org/0000-0002-0309-8811

FORMATIVE AND SUMMATIVE ASSESSMENT AND ITS IMPACT ON COURSE UNIT PERFORMANCE: EVIDENCE FROM MANAGEMENT UNDERGRADUATES OF UNIVERSITY

SS Weligamage[1] WVAD Karunarathne[2] and RAIC Karunarathne[3]

Abstract

Assessment plays a fundamental role in education. The primary purpose of this study is to examine the effect of formative and summative assessment on students' performance in the course units. To achieve this objective, we designed this study as a multi-stage study, and this paper presented the data collected in stage one of the study. First, we examined the existing practices of formative and summative assessment in evaluating students' performance; then, we examined the relationship between formative and summative assessment and the students' performance of different course units. Furthermore, we examined the impact of formative and summative assessments on the performance of different course units. We collected secondary data from two selected departments of the Faculty of Commerce and Management Studies, University of Kelaniya, which aimed to see the effect of changing the composition of each assessment method on the final evaluation. We choose the course units which represent the main course units offered by the faculty. This study's findings revealed that the student's final performance of the course unit is highly related to the summative assessment, and the formative assessment score varies according to the type of assessment, i.e., individual vs group. Individual assessments have a more impact on final course unit performance. The outcomes of this study, theoretically as well as practically is very vital and important for policy design in higher education.

Keywords: Academic Performance, Assessment, Course Units, Formative Assessment, Summative Assessment.

[1]Professor, Department of Finance, University of Kelaniya, Sri Lanka

Email: susima@kln.ac.lk https://orcid.org/0000-0003-4028-0812

[2]Senior Lecturer, Department of Accountancy, University of Kelaniya, Sri Lanka

Email: anurawvad@kln.ac.lk https://orcid.org/0000-0003-0202-9555

[3]Senior Lecturer. Department of Human Resource Management, University of Kelaniya, Sri Lanka.

Email: ishankac@kln.ac.lk https://orcid.org/0000-0001-8528-7263

Introduction

Quality assurance (QA) activities are continuing in Sri Lankan higher education system and much weight have been given for students' assessment. Both Subject Review (SR) and Institutional Review (IR) also evaluate and focus more on assessment methods and students' performance. The program should regulate the weightage relating to different assessment components with respect to each subject's intended learning outcomes. Results of summative and formative assessments are closely related with students' performance. Furthermore, the rationale behind the Continuous Assessment (CA) is to enhance their subject performance by ensuring that students do not wait for end of the semester to evaluate their performance. The purpose of this study is to see the impact of continuous assessment on academic performance and identify the level of the relationship with Summative and formative assessments and Final Exam.

Education is aimed at creating teaching and learning environments that would bring about desired changes in learners, whether to be more knowledgeable, better skilled, or to influence their attitudes and values positively. The essence of teaching and learning is to plan teaching events and to ascertain to what extent learners have acquired the intended competencies. Both formative and summative assessments are important part of the subject performance evaluation and program evaluation and summative evaluation provided information to verify the overall performance of program, while formative evaluation more targeted at facilitation program improvements (Scriven, 1967; Black & Wiliam, 2003; William & Thompson, 2008).

Based on Bloom (1969), the objective of formative assessment was to provide feedback and correctives at each stage in the teaching-learning process and summative to judge the learners' achievement at the end of a course. Furthermore, rational behind the formative assessment is to is to enhance their subject performance by ensuring that students do not wait for end of the semester to evaluate their performance. At the same time, well-designed and implemented formative assessments should be able to suggest how teachers should modify and design formative assessment systems to improve student performance (Bennett & Randy, 2011). However, results of summative and formative assessments are closely related with students' final subject performance.

Examination and Evaluation Structure is a combination of formative (assignments, quizzes, Mid-semester examinations) and summative assessment. The following structure (Table 01) was suggested in conducting examinations by the Qualification Framework in Sri Lanka in previous years. However, due to Covid -19 pandemic situation, UGC changed and introduced a new assessment weight structure, and weight and combination vary by each course unit and also by different departments and university levels.

Table 01: Examination and Evaluation Structure

	Type	Common
QAC Framework	Continuous Assessment (CA)	20-40%
	Semester End examinations (SEE)	80-60%
	Pass Mark Per Subject	40% - CA at least 40% - SEE 40%
New Structure (during COVID 19)	Continuous Assessment (CA)	Up to 70%
	Semester End examinations (SEE)	30%

Source: Handbook of Credit and Qualification Framework of the degree programs in Universities issued by the Quality Assurance and Accreditation Council (2007) and UGC Circular 2020.

Management Graduates of Sri Lanka are the resource persons who will ultimately join the corporate world based on their performance and qualification. Mainly the assessments and examinations are conducted in line with the degree program to evaluate the knowledge and skills of undergraduates well. It is important to design a proper method of assessment to evaluate the undergraduate to enrich the degree program to be recognized worldwide.

Literature Review

Assessment plays a fundamental role in education. However, research has shown that the value of the traditional student assessment method i.e., test is weakly linked with learning experiences of the students (Black & William, 1998). Accordingly, scholars produced new methods of assessment and the extant literature discusses two main methods of assessments called formative and summative assessments. Some scholars in education and pedagogy considered these as separate entities, while other thought of scholars have shown the link between these two forms of assessment methods. These assessment methods are different in terms of their purposes.

There are different purposes of assessment of students' course unit performance. In their seminal work Black and Wiliam (1998) identified three main purposes of assessments: 1) encompasses supporting learning, 2) reporting student achievement, and 3) meeting the needs of public accountability. Later, Newton (2007) identified three main purposes of students' assessment and, however, these purposes do not totally deviate from the theorization of Black and Wiliam (1998).

These purposes include judgmental level (allocating grades in relation to performance), decision level (the way in which an assessment judgement is used), and impact level (the intended impacts of running an assessment system). Dixon and Worrell (2016) recognized improve teaching and learning and diagnose student difficulties as purposes of formative assessment, while they have identified evaluation of learning outcomes and placement, promotion decisions as purposes of summative assessment.

Summative assessment refers to cumulative assessment that intends to capture what a student has learned, or the quality of the learning, and judge performance against some standards (National Research Council, p. 25). According to Looney, (2011) summative assessment is the summary assessments of student performance – including tests and examinations and end-of-year marks (P.4). They provide a summary and evaluation of what students have learned over a specific period. Moreover, summative assessment used for evaluation, where there is limited or no feedback beyond the achievement (Glazer, 2014), usually the final grade. Besides that, summative assessment increases objectivity and consistency with respect to various groups of students (Dixon & Worrell, 2016). Summative assessment includes closed-ended questions, open-ended questions, standard tests, and filling in the blank questions. If a student performs satisfactorily, there is no formal learning on the assessed subject that occurs after a summative assessment. Research has shown this as a limitation of summative assessment (e.g., Black & Wiliam, 1998; Dixon & Worrell, 2016). Summative assessment provides a comprehensive view of a student's performance and is used to determine if learning objectives have been met.

Formative assessment refers to activities undertaken by teachers and their students in assessing themselves, that provide information to be used as feedback to modify teaching and learning activities (Black & Wiliam, 2010, p. 82). Unlike summative assessment, formative assessment aims to educate

and improve student's performance (Wiggins, 1998) rather than evaluating the students for course grades (Buchanan, 2000). Thus, formative assessment considered as the students-centered learning which gives the feedback on performance for the improvements and accelerate learning (Nicol & Macfarlane-Dick, 2006). Formative assessments help both the student and the teacher to understand the learning goals, students' progress towards learning goals, and the actions need to improve subsequent performance (Dixon & Worrell, 2016; for more review, see Black & Wiliam, 2010). Moreover, research has shown that without informative feedback, students will exhibit relatively little progress in their development (Dixon & Worrell, 2016).

Some scholars have stated that formative assessment grades are usually do not take into the final grade as the focus of formative assessment is to understand the extend which student achieve learning outcomes and to assess teaching effectiveness (Dixon & Worrell, 2016). However, other scholars consider formative assessment for final grades. For example, Atkin and Coffey (2003); Bransford et al. (2000) stated that formative assessment with quality feedback enhance learning and accomplishments.

According to Cook (2009), formative assessments can be done in two ways; 1) spontaneous and 2) planned. Spontaneous assessment is important when a teacher needs immediate feedback about student learning. Asking examples, question and answer sessions during the lesson, and asking a summary of the lesson are examples for spontaneous formative assessment. In contrast, planned formative assessment focuses on improve students learning. Quizzes and homework exercises are examples for planned formative assessments. In terms of research findings, research has stated that formative assessment as a form of good and summative assessment as form of bad assessment method (Taras, 2005). Overall, formative assessment provides immediate feedback, enabling them to address gaps in understanding and instructors can modify teaching methods based on real-time student performance data.

Recently research has started examining the effects online summative and formative assessments on student learning effectiveness. Literature has found that there some implications of summative and formative assessment. These advantages are categories as balancing act (e.g., comprehensive view, continuous improvement); student's engagement (e.g., increased motivation and accountability); instructor adaptability (e.g., adjustment- formative assessments allow instructors to adapt teaching methods based on ongoing student performance, and increase the effectiveness of the teaching strategies over the entire course); and holistic grading (e.g., combination of formative and summative assessment allows for a more comprehensive and fair evaluation of a student's performance). This has been becoming one of the common methods of assessing students during the Covid-19 pandemic. Moreover, recent developments in user- friendly web-based assessment packages and secure internet testing protocols encourage use of online assignments such as tests and quizzes (Cassady & Gridley, 2005). However, literature related to online assessment and students' performance are limited. For instance, Cassady and Gridley (2005) stated that there is little research on online assessment and student performance. Moreover, in their study Cassady and Gridley (2005) emphasized the positive implications of online summative and formative assessments.

A significant number of studies have been conducted on formative and summative assessments, exploring their effectiveness, impact on student learning, and best practices in implementation. Prior research highlights the significance of both formative and summative assessments in education. The literature underscores the need for a thoughtful and balanced approach that considers the unique benefits of each type of assessment for promoting student learning and achievement, which has a significant

impact on students' final performance. Additionally, ongoing research continues to explore innovative strategies and technologies to enhance the effectiveness of assessment practices in education.

Objectives of the Study

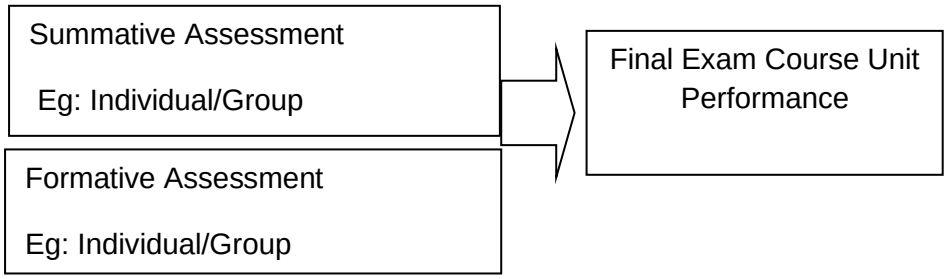
- To study the existing practices of formative and summative assessment in evaluating students' performance.
- To examine the relationship between formative and summative assessment and the performance of different course units.
- To examine the impact of formative and summative assessment on performance of different course units.

Methodology

The research design used in the study was deductive and quantitative. Secondary data on formative and summative assessment and final grades of selected course units were collected. Due to the difficulties of taking into account all the course units offered, data collection limited to selected. course units such as Microeconomics, Business Statistics, Information Technology, Mathematics, Macro Economics, Management, Financial Accounting, Project Management Marketing Management, Research Methodology and Organizational Behavior.

A conceptual framework is constructed as depicted in Figure 01, where Summative Assessment and Formative Assessment variables are considered the independent variables and Subject Final Gradings as the dependent variable.

Figure 1: Conceptual Framework



Based on the above framework, the below two hypotheses were developed.

H1- Summative assessment and formative assessment highly correlate with the Final Exam Performance of the course units

H2- There is a high impact of Summative assessment and formative assessment on the Final Exam Performance of the course units.

Data also includes those who have graduated in the years 2021 and 2022 as they have taken examinations and assessments before and during the COVID-19 pandemic. Assessment practices were identified through the analysis and presented using tables. Descriptive, correlation analyses were used to examine the relationship between formative and summative assessment and the performance of

different course units. Using regression, examine the impact of formative and summative assessment on the performance of different course units.

Results, Findings and Discussion

The first objective of the study is to study the existing practices of formative and summative assessment in evaluating students' performance used in the selected course units for evaluation,

The selected sample of 11 different course units was divided into three main assessment categories as Summative (SA) and Formative (FA) both Group (FAG) and Individual (FAI). SA and FA combination and weights for each selected subject are presented in Table 2.

Table 02: Examination and Evaluation Structure of Selected Course Units

Subject	Academic Year 2018-2021				Academic Year 2019-2022			
		Assessment Type				Assessment Type		
		Summative %	Formative %			Summative %	Formative %	
			G	I			G	I
A-Microeconomics	Pre Covid 19	60	20	20	Pre Covid 19	70	20	10
B-Statistics		50	20	30		70		30
C-Information Technology		60	-	40		60		40
D-Mathematics		70	-	30		80		20
E-Macro Economics		50	20	30		60	20	10
F-Management		60	20	20		60	20	20
G-Financial Accounting		70	30			70	25	5
H-Project Management		70	-	30	During Covid 19	30	40	30
I-Marketing Management		70	30			60	40	
J-Research Methodology	During Covid 19	30	40	30		40		60
K-Organizational Behavior		40		60		30	20	50

I- Individual G- Group

Source: Research Data Analysis, 2024

The weight of FA varied from 20% to 40% and that dependent on number of assignment and focus of intended learning outcome of the subject. The weight of FA also varied from group to individual assessment and final exam carried nearly 70% in each subject before the Covid 19. However, during the Covid only 30% was allocated for SA. Formative assessment methods covered a number of method of assessments including Mid Exam, Project Report Preparation, Case Study, Learning Diary, Group Presentation and Reports, Practice Exam, and Role Play.

The second objective is to examine the relationship between formative and summative assessment and the performance of different course units. Correlation analysis techniques were used for the analysis

after confirming the Normality Test. The below tables and graphical presentation show the normality test results.

Table 03: Normality Test Results

Subject	Assessment Type					
	Final Performance		Summative		Formative	
	Skewness	Kurtosis	Skewness	Kurtosis	Skewness	Kurtosis
A-Microeconomics	-.099	-.939	-.162	-.922	-1.239	4.213
B-Statistics	-.051	-.879	-.156	-.848	-.599	.662
C-Information Technology	-.056	-.885	.044	.013	-.298	-.265
D-Mathematics	-.071	-.998	-.089	-.974	-.738	2.236
E-Macro Economics	-.434	-.566	-.485	-.209	-1.239	4.213
F-Management	.076	-.770	.140	-.587	-.108	-.720
G-Financial Accounting	-.071	-.189	-.082	-.385	-.261	-.142
H-Project Management	-1.247	2.954	-9.587	98.543	9.659	100.26
I-Marketing Management	-.286	-.404	-.340	-.022	-7.041	65.269
J-Research Methodology	-.159	.476	-.756	1.078	-.433	-.113
K-Organizational Behavior	-.194	-.625	-3.153	21.198	2.817	19.377

Source: Research Data Analysis, 2024

Table 04: Normality Test Results

Subject	Assessment Type					
	Final Performance		Summative		Formative	
	Kolmogorov-Smirnov[a]	Shapiro-Wilk	Kolmogorov-Smirnova	Shapiro-Wilk	Kolmogorov-Smirnova	Shapiro-Wilk
A-Microeconomics	.158	.006	.078	.009	.000	.000
B-Statistics	.200*	.006	.060	.041	.009	.004
C-Information Technology	.075	.002	.200*	.121	.200*	.249
D-Mathematics	.024	.002	.000	.000	.197	.009
E-Macro Economics	.005	.007	.003	.019	.000	.000
F-Management	.040	.081	.200*	.327	.200*	.032
G-Financial Accounting	.200*	.628	.200*	.768	.001	.084
H-Project Management	.018	.000	.000	.000	.000	.000
I-Marketing Management	.001	.129	.027	.070	.000	.000
J-Research Methodology	.082	.044	.011	.173	.032	.005
K-Organizational Behavior	.005	.017	.013	.000	.000	.000

*This is a lower bound of the true significance. *

Source: Research Data Analysis, 2024

The section below presents the data analysis output and a discussion of each selected subject. The relationship between Formative and Summative Final grades is presented in Table 05.

Table 05: Relationship with Final Performance

Subject		Academic Year 2018-2021			Academic Year 2019-2022	
		Assessment Type			Assessment Type	
		Summative	Formative		Summative	Formative
A-Microeconomics	Pre Covid 19	.959**	.469**	Pre Covid 19	.984**	.309**
B-Business Statistics		.925**	.491**		.970**	.653**
C-Information Technology		.843**	.804**		.715**	.792**
D-Mathematics		.939**	.691**		.985**	.673**
E-Macro Economics		.961**	.289**		.956**	.552**
F-Management		.945**	.383**		.964**	.632**
G-Financial Accounting		.749**	.507**		.956**	,461**
H-Project Management		.965**	.203*	During Covid	.113	.328**
I-Marketing Management		.977**	.273**		.844**	.372**
J-Research Methodology	During Covid 19	.847**	.496**		.867**	.801**
K-Organizational Behavior		.679**	.098		.533**	.737**

Source: Research Data Analysis, 2024

The findings above revealed that the relationship between Final course unit performance highly correlates with the Summative assessment during the pre-Covid period in both academic year 2028-2021 and 2019-2022, and the relationship is moderate with the formative assessment in the majority of the course units.

The relationship between Formative Types and Summative with Final grades is presented in the table 06. This indicates that the relationship between Formative and Summative scores and final test scores contribute in different ways. Hence, hypothesis 1 of the study, Summative assessment and formative assessment, highly correlated with the Final Exam Performance of the course units, was rejected. Summative assessment is highly corrected with the final performance.

Table 06: The relationship between Formative Types and Summative with Final Gradings

Subject		Academic Year 2018-2021				Academic Year 2019-2022			
		Assessment Type				Assessment Type			
		Summative	Formative			Summative	Formative		
			G	I			G	I	
A-Microeconomics	Pre Covid 19	.959**		.473**	Pre Covid 19	.984**	.093	.434**	
B-Statistics		.925**		.491**		.970**		.631**	
C-Information Technology		.843**		.804**		.715**		.792**	
D-Mathematics		.939**		.691**		985**		.673**	

E-Macro Economics		.961**	.234**	.153		.956**	.104	.552**
F-Management		.945**	.093	.434**		.956**	.075	.681**
G-Financial Accounting		.749**	.507**			.956	.203*	.472**
H-Project Management		.965**	.203			.113	.163	.714**
I-Marketing Management		.977**	237**			.844**	.372**	
J-Research Methodology	During Covid 19	.847**		.702**	During Covid 19	.867**		.801
K-Organizational Behavior		.679**		.098		.737**	.567**	.533**

Correlation is significant at the 0.05 level (2-tailed). */ 0.01 level (2-tailed). **

Source: Research Data Analysis, 2024

Hypothesis two was tested using regression results of selected course units, and Tables 6 (pre -Covid 19) and 07 (During Covid 19) present the summary of analysis outcomes.

Table 7: Impact of Formative and Summative Assessment in Final Course Unit Performance:

Subject	**Variables**	**R Square**	Significance	**Decision**
Management	Formative Vs Final Results	.514	.000	Significant
	Individual – Mid Exam		.000	Significant
	Group- Report		.102	Not Significant
	Group- Presentation		.003	Not Significant
	Summative Vs Final Results	.929	000	Significant
Econ - Micro	Formative Vs Final Results	.191	.000	Significant
	Individual – Mid Exam		.000	Significant
	Group- Report		,528	Not Significant
	Summative Vs Final Results	.968	.000	Significant
Econ - Macro	Formative Vs Final Results	.308	.000	Significant
	Individual – Mid Exam-		.000	Significant
	Group- Report and Presentation		.467	Not Significant
	Summative Vs Final Results	.914	.000	Significant

Source: Research Data Analysis, 2024

Table 8: Impact of Formative and Summative Assessment in Final Course Unit Performance: During Covid

Subject	**Variables**	**R Square**	**Sig**	**Decision**
Project Management	Formative Vs Final Results	.485	.000	Significant
	Individual – Mid Exam-30%		.000	Significant
	Group- Proposal 40%		.309	Not Significant

	Summative Vs Final Results	.013	.203	Not Significant
Organizational Behavior	Formative Vs Final Results	.469	.000	Significant
	Individual – Mid Exam-30%		.067	Not Significant
	Group- Case Study Development		.000	Significant
	Individual- Learning Diary		.000	Significant
	Summative Vs Final Results	.543	.000	Significant

Source: Research Data Analysis, 2024

Conclusion

The study revealed that the summative and formative assessments have an impact on both the students' result and their methodologies of learning. The proportion of success in summative assessment is more significant than in formative assessment for the final exam. Individual formative assessment provides more weight than group formative assessment. The findings of this study support the claim made by Dixon & Worrell (2016), without informative feedback, students will exhibit relatively little progress in their development, and formative assessment grades are usually not taken into account in the final grade, as the focus of formative assessment is to understand the extent to which students achieve learning outcomes and to assess teaching effectiveness. Bransford et al. (2000) stated that formative assessment with quality feedback enhances learning and accomplishments. Hence, careful attention should be directed towards the tools used in evaluating the group formative and the percentage allocated for group formative assessment. The findings of this study can be used to educate the students on the importance of both summative and formative assessments in enhancing their performance.

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TECHNOLOGY

OUTLIER DETECTION IN DATA WAREHOUSES TO IMPROVE DESCRIPTIVE AND DIAGNOSTIC ANALYTICS

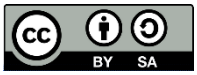
WWADR Fernando[1] and PPGD Asanka[2]

Abstract

This paper reviews the literature on outlier detection(OD) technologies to improve descriptive and diagnostic analytics in data warehouses. This will ensure higher-quality and more reliable data, increasing decision-making and operational efficiency. The major research objectives are a systematic review of existing OD techniques; identification and discussion of the key challenges and limitations in applying the OD methods to data warehouse environments and synthesis of methodologies for integrating OD with descriptive and diagnostic analytics. The study collects data from both traditional and AI-based literature review tools. Traditional review tools are Google Scholar, Research Gate, and IEEE Xplore. AI-based review tools are Semantic Scholar, Research Rabbit, and SciSpace. To present the insights, the study objectively selected 57 papers that were published between 2010 and 2024 were considered. The literature review here elaborates on the OD in a data warehouse which uses different data warehousing techniques and data analytics to enhance the quality and reliability of data to correct. This systematic review goes from the evaluation of statistical-based to distance-based, density-based, clustering-based, learning-based, and ensemble-based. The OD methods of unsupervised learning have been found to outperform those of supervised learning in special settings that are massive and heterogeneous in information like data warehouses. Isolation Forest, Local Outlier Factor (LOF), One-Class SVM, and Autoencoders are identified as highly accurate and efficient at detecting anomalies. Moreover, hybrid models combining several OD methods have been demonstrated to perform better than individual techniques. The results may be useful in offering important new insights and practical guidelines for developing more effective.

Keywords: Data warehouse, Descriptive analytics, Diagnostic analytics, Machine Learning models, Outlier Detection

[1] Department of Industrial Management, University of Kelaniya, Sri Lanka
Email: fernand-im19045@stu.kln.ac.lk
[2] Senior Lecturer, Department of Industrial Management, University of Kelaniya, Sri Lanka
Email: dasanka@kln.ac.lk



Introduction

Since the late mid-1990s, data warehouses have been one of the most significant innovations in information systems, and they have gained a lot of popularity as a potent means of using information technology to solve business challenges (Aljuwaiber, 2022). Aljuwaiber claims that data warehousing provides an organization with a consistent view aimed at enhancing the productivity of business decisions by combining, transforming, and integrating operational data. It can also be described as a knowledge repository that the company uses to obtain information and as a substantive knowledge source (Adrian, 2015; Aljuwaiber, 2022).

Data analytics is the science of analyzing raw data to derive valuable insights and to drive sound decision-making to increase productivity and business profit. Data is extracted and distinguished to identify and assess behavioural data and patterns, and various organizations employ different approaches (Sahu et al., 2017). Data analytics within the realm of data warehousing encompasses many practices but is primarily directed at describing, diagnosing, predictive, and prescriptive analytics.

Business intelligence is built on descriptive analytics, which looks for patterns and trends in past data (Sahu et al., 2017). Observed outcomes are rationalized through the application of diagnostic analytics. Statistical algorithms and past data are used in predictive analytics to forecast future events. Prescriptive analytics suggests particular steps to accomplish desired results, going beyond simple prediction. A thorough approach to business intelligence is formed by these four categories of analytics (Ridzuan & Wan Zainon, 2022).

Finding outliers in a dataset is all about recognizing observations that deviate significantly from the rest of the dataset and may point to an alternative underlying process (Agarwal & Gupta, 2021; Lyu & Pan, 2022). Generally speaking, it points to anomalies or mistakes in the data. These could be the result of malicious attacks in the case of cyber-physical systems, behavioral changes in humans or instruments, mechanical flaws, or both (Singh & Upadhyaya, 2012; Wang et al., 2016). In extensive and diverse data environments, most traditional OD techniques struggle to accurately identify abnormalities that could compromise data quality and ultimately impact the results of strategic decision-making. Growing diversity in data sources and the dynamic nature of outliers indicate the need for context-aware detection techniques and addictiveness in handling the subtleties of various datasets (Irawan et al., 2021).

Traditional OD in data warehouses necessitates human parameter modification, which is accomplished by numerous labor-intensive tasks and rule-of-thumb settings (Ridzuan & Wan Zainon, 2022). These techniques take much time, and it's unlikely that they will be successful in correctly identifying outliers in various dataset types (Sikder & Batarseh, 2023). Furthermore, these manual approaches generate errors during the detection phase that can potentially destroy entire data analysis workflows. Furthermore, it can be difficult to distinguish between outliers and regular variations in data, and measuring what is considered an outlier in a given circumstance can lead to both analytical severe errors and inefficiencies in operations (Cavalli et al., 2020).

Outliers cannot be identified by traditional outlier detection in data warehouses because it involves human parameter change, which takes time and is inefficient (Ridzuan & Wan Zainon, 2022). Errors are produced during the detection stage by manual approaches, which can lead to the complete collapse of data analysis operations (Sikder & Batarseh, 2023). It might be difficult to distinguish outliers from regular data changes, which can result in significant analytical errors and inefficiencies in operations. Thus, more effective techniques are required (Cavalli et al., 2020).

To better understand the challenges and limitations of these techniques, as well as the efficacy of current OD methods in identifying outliers, the research delves into the following topics: current approaches and technologies for OD, their adaptation and integration into data warehouse environments for descriptive and diagnostic analytics, and future research directions.

This paper is organized into six sections: Section 1 presents the introduction and research objectives; Section 2, the research methodology; Section 3, the literature review; Section 4, results and discussion, and Section 5, the conclusions of this study and prospects of the research field, followed by References.

Methodology

This study employs a PRISMA method to retrieve data and classify the literature based on content analysis and direction for future research.

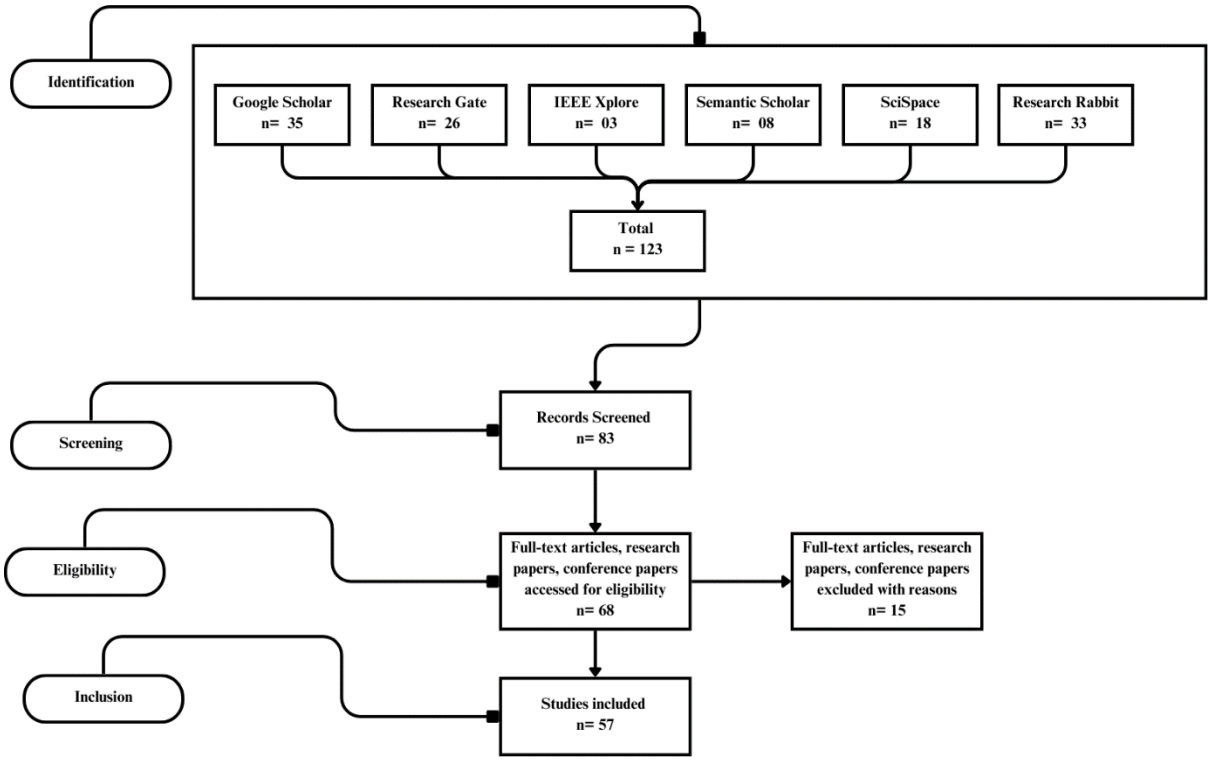


Fig. 1 Flowchart of the method used in this study

To put it briefly, the study used a four-step procedure (see Fig. 1) that involved finding the data, screening the data, establishing eligibility, and then adding the data. The purpose of gathering this data is to offer suggestions and avenues for further investigation. Both manual and AI-based literature review technologies provided data for the study. Research Gate, IEEE Xplore, and Google Scholar are examples of traditional review tools. Semantic Scholar, Research Rabbit, and SciSpace are AI-based review tools.

Identification of the data

In the beginning, the study used keywords, and the initial search keywords were limited to the title of the paper and the keywords. At first 123 papers were derived using three combinations of keywords.

Table 5 The result after refining the initial search

Keywords	Results
Data warehouse	21
Descriptive analytics	09
Diagnostic analytics	10
Outlier detection	35
Machine Learning models	38

Screening initial data

The initial search retrieved research papers, conference papers, articles, and books. However, books and unpublished research papers were later excluded. Consequently, the search was limited to 'article titles' and 'keywords' to remove books and magazines from the results. As a result, 83 papers remained after the initial refinement. After removing duplicates, 68 papers were finally chosen.

Determining eligibility

To present the insights, the study objectively selected 57 papers by reviewing the abstracts and conclusions of the search results. The search was conducted using keywords relevant to the study's focus on descriptive and diagnostic analytics using OD technologies within data warehousing. The keywords used included “descriptive analytics”, “diagnostic analytics”, “data warehousing”, “Machine Learning models”, and “Outlier Detection,". The search was limited to article titles to ensure relevance.

The inclusion and exclusion of the data

The following inclusion criteria were applied when choosing the final 57 papers: only works published between 2010 and 2024 were considered. Excluded from consideration were papers that mainly addressed predictive and prescriptive analytics, manual OD techniques, or data warehousing techniques alone without including OD technology. studies that covered topics including data collection, ETL transformations, and storage techniques used in data warehouses were removed. The included studies addressed descriptive and diagnostic analytics employing OD technologies within data warehousing contexts. To ensure uniformity in the analysis, only English-language papers were taken into account; full-text access was necessary for a thorough inspection and analysis.

Analytical Approach and Data Extraction

The analytical approach in this review centers on assessing and synthesizing various OD techniques within the context of data warehousing. The methodology was designed to systematically categorize, evaluate, and compare these techniques based on their effectiveness, scalability, and applicability in improving descriptive and diagnostic analytics.

Methodological Categorization

The OD techniques were categorized into several methodological groups: statistical-based, distance-based, density-based, clustering-based, learning-based, and ensemble-based methods. This categorization enables a systematic comparison, highlighting each method's strengths, weaknesses, and suitability for data warehousing environments.

Effectiveness Assessment

The assessment focuses on the effectiveness of these techniques in data warehousing settings, evaluating key factors such as accuracy, computational efficiency, scalability, and the ability to

integrate with existing data warehousing processes. This assessment aims to determine which methods are most effective in handling large, heterogeneous datasets typical of data warehouses.

Exploration of Additional Techniques

In addition to assessing existing OD methods, this review also explored other emerging techniques and methodologies that could enhance descriptive and diagnostic analytics in data warehouses. This includes investigating advanced machine learning models, hybrid approaches that combine multiple OD methods. The aim is to identify potential areas for improvement and suggest strategies for further enhancing data quality, decision-making, and operational efficiency in data warehousing environments.

Literature review

This section presents the results of the Systematic Literature Review, organized according to the map shown in Fig.2.

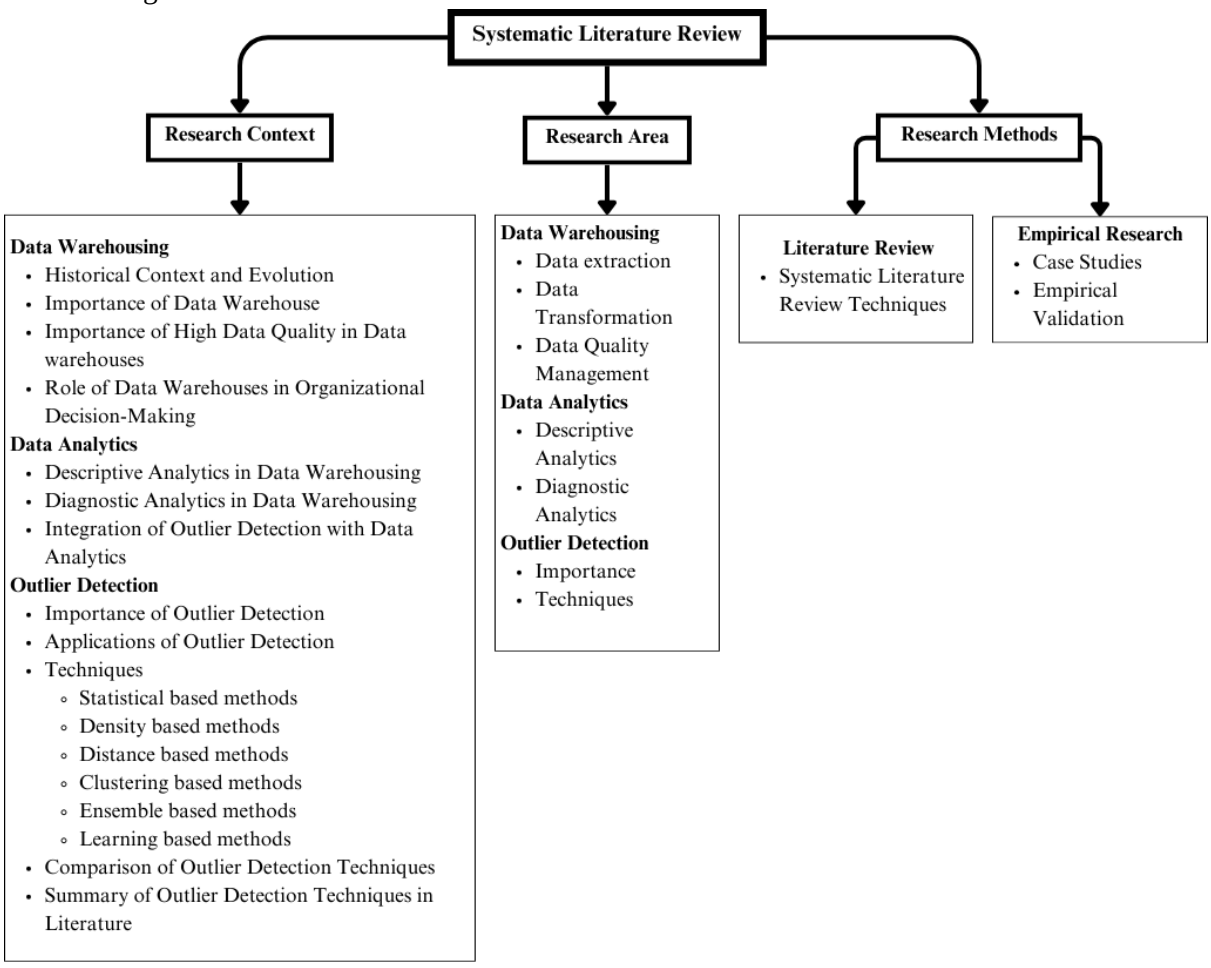


Fig. 2. Systematic literature review map

The existing academic literature relevant to the study area is thoroughly reviewed and analyzed. Information is obtained through synthesizing data from pertinent studies, which involves identifying gaps in the current state of knowledge, as well as the strengths and weaknesses of various theories and perspectives. This process of literature review is crucial as it facilitates familiarity with the research field's concepts, ideas, and practices, providing a solid foundation for further investigation.

Data warehousing

Higher data quality directly affects the reliability and truthfulness of the results since it is data warehousing that derives the final insights. Such data quality lack may draw false conclusions that will hurt the business (Adams et al., 2019). In some cases, it might lead to financial loss and operational inefficiency (Ridzuan & Wan Zainon, 2022). Data warehouses include a diversity of preprocessing techniques consisting of data cleaning, data transformation, and data reduction, aiming at data consistency and integrity. This takes into consideration the handling of missing values, the removal of duplicates, and the handling of data inconsistencies (Alasta & Enaba, 2014). High data quality is achieved by integrating data from different heterogeneous sources, which include relational databases, flat files, as well as other storage systems. This will give one integrated and all-inclusive view of the data (Alasta & Enaba, 2014; Mohammed, 2019).

Data warehouses offer decision-makers one view of the data within organizations that allows them to make informed and timely decisions. This is made possible through advanced querying capabilities and the generation of multidimensional dynamic reports. Data warehouses support long-term strategic planning because they house historical data, which could be used in trend analysis. This will help organizations identify patterns and forecast outcomes of future performance (Alasta & Enaba, 2014). Data warehouses facilitate simple and secure access to integrated data, thus making data more accessible and valuable to individuals at all levels of the organization. These support several forms of analysis, extending from traditional report generation to advanced data analysis tools and techniques (Mohammed, 2019; Ridzuan & Wan Zainon, 2022).

Data Analytics

Data analytics refers to the systematic computational analysis of data to uncover patterns, correlations, and trends that can inform decision-making. In modern business intelligence, it plays a crucial role by transforming raw data into actionable insights, enabling organizations to enhance operational efficiency and strategic planning. For instance, Kumari et al. highlight that data analytics facilitates the identification of customer preferences and market trends, which can lead to improved product offerings and customer satisfaction (Kumari et al., 2024)

Descriptive Analytics in Data Warehousing

Descriptive analytics plays a crucial role in data warehouses by summarizing and visualizing historical data, which provides organizations with insights into past performance. Techniques such as data aggregation and reporting are fundamental, allowing for consolidating large datasets into meaningful summaries. Data visualization tools, including dashboards and business intelligence (BI) tools, enhance this process by presenting data in an easily interpretable format, facilitating quick decision-making (Akpinar et al., 2023; Dr. L. C. Manikandan & Dr. R. K. Selvakumar, 2023). However, challenges persist in the implementation of descriptive analytics. Handling large datasets can strain processing capabilities while ensuring data quality is essential for accurate insights. Additionally, integrating diverse data sources poses significant hurdles, as inconsistencies and discrepancies can arise from different formats and structures (Altukhi & Aljohani, 2023; Zulkipli et al., 2020).

Diagnostic Analytics in Data Warehousing

Diagnostic analytics plays a crucial role in understanding the underlying causes of observed trends and patterns in business data, thereby providing deeper insights into operations. Techniques such as root cause analysis, drill-down analysis, and correlation analysis are essential for identifying relationships and factors influencing performance metrics (Alamgir & Mohyuddin, 2022; Mojeed Dayo Ajegbile et al., 2024). Additionally, integrating diagnostic tools with existing data warehousing systems can be

problematic, often requiring significant adjustments to ensure compatibility and effectiveness (Alamgir & Mohyuddin, 2022).

Integration of Outlier Detection with Data Analytics

OD techniques play a vital role in enhancing data quality and the accuracy of insights within descriptive and diagnostic analytics. By identifying anomalies, these techniques help ensure that the data used for analytics is reliable, as outliers can skew results and lead to misleading conclusions (Nijhuis & Van Lelyveld, 2023). Integrating OD into analytics processes allows for a more nuanced understanding of data, enabling analysts to discern significant trends or issues that might otherwise be overlooked (Mohseni et al., 2023). Moreover, the impact of OD on decision-making is profound; it can reveal critical insights that inform strategic choices, particularly in identifying emerging patterns (A. et al., 2022). For instance, organizations that effectively incorporate OD can respond proactively to outliers, thereby enhancing their operational efficiency and competitive advantage (Govindaraj et al., 2022).

Outlier Detection

Importance of Outlier Detection in Business Processes

OD plays a vital role in business process management (Ridzuan & Wan Zainon, 2022). It is essential because it can detect any deviation and thus can be an alarm against possible fraud, errors, and other abnormalities (Albuquerque Filho et al., 2022). To further improve the business performance at large, these anomalies must be detected and addressed promptly to keep the processes efficient and effective (Tavares et al., 2019). This will enable an organization to understand its processes and figure out where changes need to be made. Through the identification of abnormal activities, an organization can respond proactively to prevent issues that might lead to financial losses due to fraud, non-compliance issues, or operational hitches. This risk management ability is essential for business continuity and asset protection of an organization (Li, 2024).

Applications of outlier detection

OD is important in many different fields. Its uses span from preserving sensor network quality and supporting medical diagnostics to keeping an eye on network security and identifying fraud in financial transactions (Hassan et al., 2022). By identifying malfunctioning sensors and cyberattacks, OD is crucial in the Internet of Things for safeguarding vital infrastructures (Chalapathy & Chawla, 2019). It is also important for the media to detect false information and for cybersecurity to stop illegal access to networks (Hevapathige, 2021; Habler & Shabtai, 2018; Liu et al., 2019). Additional uses include managing massive amounts of text and image data, recognizing unusual or novel content, monitoring industrial systems, and enhancing data-logging procedures (Chalapathy & Chawla, 2019).

Outlier Detection Techniques

The field of OD has undergone substantial development since its inception, when its primary objective was to identify outlier deviations in exclusively numerical data (Sikder & Batarseh, 2023). They developed increasingly complex methods and integrated machine-learning techniques to handle high-dimensional data with a complex anomaly pattern as a result of the growing dataset size and complexity over time (Agarwal & Gupta, 2021; Chalapathy & Chawla, 2019; Lyu & Pan, 2022; Usman et al., 2023). To identify data points or patterns that deviate significantly from the norm, such strategies are essential for discovering OD techniques (Chalapathy & Chawla, 2019). Sikder and Batarseh point out that OD is split into six primary sections. They are statistics to learning-based, ensemble-based, density-based, clustering-based, and distance-based methods.

Statistical and Probabilistic-Based Methods

Statistical and probabilistic-based methods for outlier detection are essential in identifying deviations from expected patterns within datasets. These methods are categorized into parametric and non-parametric approaches.

Parametric Distribution Models: Parametric approaches assume data follows a specific distribution, with Gaussian Mixture Models (GMMs) being a popular technique. GMMs combine various Gaussian distributions to create data points, detecting outliers by examining deviations from the predicted distribution. GMMs are useful in structured situations with known distribution patterns, often estimated using the Expectation-Maximization algorithm (Sikder & Batarseh, 2023). Regression models are popular for understanding variable relationships, using independent variables to predict a dependent variable. They can identify outliers by calculating the difference between expected and observed values (Wang et al., 2016).

Non-Parametric Distribution Models: Non-parametric approaches assume no underlying distribution for data, making Kernel Density Estimation (KDE) a flexible technique for estimating probability density functions. KDE is useful in continuous data streams like time series and sensor networks for identifying irregularities (Sikder & Batarseh, 2023). Alternatively, the Histogram-Based Outlier Score (HBOS) models feature distributions using histograms and find outliers based on departures from these distributions. Real-time applications can benefit from HBOS's speed and scalability, particularly in contexts with changing data (Goldstein & Dengel, 2012).

Density-based outlier detection methods

Since normal data points are found in denser regions and outliers occur in low-density regions, density-based outlier detection algorithms use the local density of data points to discover anomalies. Density-based outlier detection methods identify anomalies by assessing the local density of data points. The LOF is a prominent technique, for comparing a point's local density to its neighbors. It effectively detects local and global outliers without assuming a specific distribution, making it suitable for multi-dimensional datasets (Agarwal & Gupta, 2021).

KDE flags low-probability regions as outliers in data. It can handle complex data distributions but can be computationally expensive (Sikder & Batarseh, 2023). Connectivity-Based Outlier Factor (COF) extends LOF to identify outliers in complex, interconnected regions, while Dynamic-Window Outlier Factor (DWOF) adjusts to varying data densities for real-time applications (Singh & Upadhyaya, 2012).

HDBSCAN (Hierarchical Density-Based Spatial Clustering of Applications with Noise) is a method that combines hierarchical clustering with density-based techniques to identify outliers in data, effectively handling varying densities without predefined cluster numbers or strict parameter tuning (Breunig et al., n.d.; Campos et al., 2016)

Clustering-based outlier detection methods

Clustering-based outlier detection methods identify anomalies by grouping data into clusters of normal behavior and flagging deviations as potential outliers. These methods are typically unsupervised and operate on the assumption that normal data points cluster together, while outliers do not fit well within any cluster (Lyu & Pan, 2022; Usman et al., 2023). Techniques like k-means and k-Medoids use distance metrics to partition data into clusters, while DBSCAN identifies clusters based on dense regions of data points. Clustering-based methods are essential for outlier detection in diverse applications, from network security to market analysis (Agrawal & Agrawal, 2015; Lyu & Pan, 2022).

Distance-based outlier detection methods

By examining the separations between data points and emphasizing the separations between people and their nearest neighbors, distance-based outlier detection techniques locate outliers. This strategy relies heavily on techniques such as K-Nearest Neighbor (KNN), with improvements such as Recursive Binning and Re-Projection (RBRP) and Local Distance-based Outlier Factor (LDOF) enhancing their performance, particularly in high-dimensional spaces. These techniques are appreciated for their clarity and simplicity in a range of applications, including network security and fraud detection (Sikder & Batarseh, 2023).

Model scalability is improved through pruning to control computational demands, especially in large datasets. However, issues like determining the right number of neighbors(k) and adjusting to time series data's characteristics like concept drift and multidimensionality persist. Tools like Stream Outlier Miner and Continuous Outlier Detection address these challenges but face sorting and memory issues (Agarwal & Gupta, 2021; Sikder & Batarseh, 2023).

Ensemble methods

These techniques combine different algorithms to improve accuracy, stability, and robustness in detecting outliers. Among the widely used ensemble methods are Bagging, Boosting, and Isolation Forest.

Bagging works by generating multiple versions of a dataset through bootstrap sampling and then training individual models on each version. The final prediction is made by averaging or voting on the predictions of the individual models (Chaurasia et al., 2020; Hassan et al., 2022).

Boosting focuses on creating a strong predictive model by sequentially training weak models, with each model attempting to correct the errors of its predecessor. This approach is highly effective in improving the accuracy of outlier detection models, especially in scenarios where the outliers are not easily distinguishable from the normal data points (Celiński, 2024).

The Isolation Forest algorithm is a method for detecting anomalies in high-dimensional datasets. It isolates observations by randomly selecting a feature and dividing it between maximum and minimum values. Outliers are easier to isolate and thus have shorter average path lengths in the Isolation Forest model (Zimek, 2014)

Learning-based methods

Learning-based models for outlier detection encompass a range of techniques that leverage machine learning to identify anomalies within datasets. These methods can be broadly categorized into three types: Supervised, Unsupervised, and Semi-Supervised approaches, each offering distinct advantages based on the nature of the available data (Wang et al., 2016).

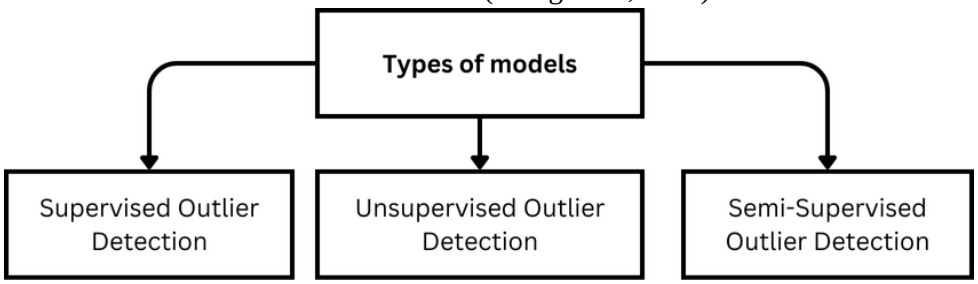


Fig. 4. Types of Outlier Detection Models

Supervised Approaches: These methods rely on labeled datasets where instances are classified as either normal or outliers. Models such as Decision Trees, Neural Networks, Naïve Bayes, and Support Vector Machines (SVMs) are commonly used. They excel in scenarios with abundant labeled data, providing high accuracy by learning from clear distinctions between normal and abnormal data points. However, they require significant amounts of labeled data for effective training (Agrawal & Agrawal, 2015; Albuquerque Filho et al., 2022).

Unsupervised Approaches: Unsupervised models do not require labeled data, making them versatile and broadly applicable. Deep Autoencoders are prominent in this category, learning the normal data distribution and flagging significant deviations as outliers. Methods like K-Means Clustering and Isolation Forest also fall under this category, focusing on identifying data points that are distant from cluster centroids or easily isolated through random splits, respectively. These models are particularly useful when labeled data is scarce or unavailable (Agrawal & Agrawal, 2015; Albuquerque Filho et al., 2022).

Semi-Supervised Approaches: Semi-supervised methods use a mix of labeled and unlabeled data, making them effective in situations where labeled data is limited. Techniques such as Semi-Supervised SVMs, Label Propagation, and Self-Training allow models to leverage the small amount of labeled data to guide the learning process on the larger unlabeled dataset. These approaches can significantly enhance the detection of outliers by effectively combining the strengths of both supervised and unsupervised learning (Chalapathy & Chawla, 2019; (Agrawal & Agrawal, 2015).

Supervised Methods VS Unsupervised Methods

The choice of a method to apply in OD significantly impacts the effectiveness and efficiency of detection. Unsupervised methods are very effective for the following reasons.

The supervised methods require labeled data to learn about, which is always almost close to impossible in the real world. The problem of labeled datasets in the context of data warehousing is indeed complicated: anomalies are rare, and hence labeling them is certainly time-consuming and costly (Li, 2024). Moreover, due to the dynamic nature of data warehouses, it becomes unfeasible to maintain an up-to-date, labeled dataset because of the inflow of new data.

For this, the next step is to move into the process of building the models using unsupervised anomaly detection techniques (Hevapathige, 2021). Since unsupervised techniques do not require labeled data, the techniques are best suited for OD in the data warehousing environment. Such techniques can automatically identify patterns and deviations without making any assumptions about data in advance, which is desirable due to the heterogeneity and size of data warehouses. The Isolation Forest, Autoencoders, and One-Class SVM are highly flexible and scalable. An extensive set of high-dimensional data characterizes most data warehouses.

Unsupervised methods can thus adapt to new data without retraining. This latter requirement may be extremely inconvenient for data warehouses where the data is subject to constant updating (Antwarg et al., 2021; Li, 2024). Unsupervised methods are appropriate for working with many different types of data such as structured, semi-structured, and unstructured that are prevalent in data warehouses. (Chawla & Wang, 2017).

Hybrid Outlier Detection Methods

Hybrid methods can adopt features from different algorithms to compensate for the weaknesses of other single methods. Hybrid methods of anomaly detection can increase overall accuracy by the integration

of different techniques. For instance, a supervised and unsupervised approach to learning would enable the model to leverage the precision achieved by labeled data and simultaneously, the flexibility to deal with unlabeled data (Agrawal & Agrawal, 2015). Hybrid methods are generally very effective in high-dimensional data. Point, contextual, and collective anomalies can be detected using various algorithms. Hybrid methods can handle multiple types of anomalies because they include several techniques for detection. (Agrawal & Agrawal, 2015). Table 2 below outlines some hybrid models for OD as reported in the existing literature.

Table 2 Outlier Detection hybrid models

Author(s)	**Hybrid Models Used**
Cirkin (2023)	LSTM + One-Class SVM, Isolation Forest
Berger-Wolf & Chawla,et al. (2019)	LSCP (Locally Selective Combination) with multiple base detectors
Campos et al. (2018)	Unsupervised Boosting Strategy- Ensemble methods with boosting strategies
Zhao & Hryniewicki (2018)	DCSO - Dynamic Classifier Selection (DCS) + Ensemble methods
Campos et al. (2020)	SELECT (Selective Anomaly Ensembles) – Ensemble methods + Selective Anomaly Detection
Almansoori & Telek (2023)	Autoencoder + Isolation Forest
Cui et al. (2019)	Neural Networks + k-means Clustering + Naive Bayes + Dynamic Programming
Lyu & Pan (2022)	HAD-IDC (Hybrid Anomaly Detection Framework) - Isolation Forest (iForest) + Local Outlier Factor (LOF) + Hierarchical Density-Based Clustering (HDBSCAN)

Numerous studies have successfully used hybrid models, such as Autoencoder with Isolation Forest, LSTM with One-Class SVM, and dynamic classifier selection using ensemble approaches. These models yield better results by combining ensemble techniques for robust OD with neural network capabilities for feature learning.

Result and Discussion

Comparison of Outlier Detection Techniques

Table 3 below outlines some methodologies and techniques for OD as reported in the existing literature.

Table 3 Comparison of Outlier Detection Techniques

Technique	**Advantages**	**Disadvantages**
LOF	• Detects local outliers effectively • Handles multi-density and mixed datasets	• Computationally intensive • Sensitive to parameter selection • Can struggle with high-dimensional data

	• No need for a predefined distribution	• May have difficulty with scalability
HBOS	• Fast and scalable • Easy to implement • Good for real-time applications • Minimal parameter tuning required	• Assumes independence of features • Less effective for high-dimensional data • May require manual binning • Sensitive to bin size
Isolation Forest	• No need for parameter tuning • Works well with high-dimensional data • Can handle large datasets • Robust to noise	• Less effective for small datasets • May miss local outliers • Requires a large number of trees for accuracy • Sensitive to sample size
SVM	• Effective in high-dimensional spaces • Good for binary classification • Robust to overfitting with proper tuning • Versatile kernels	• Prone to overfitting in high dimensions • Requires careful tuning of parameters • Computationally expensive • Limited scalability
One-class SVM	• Effective for high-dimensional data • Suitable for OD • Good for handling unbalanced datasets	• Sensitive to outliers • Requires parameter tuning • Can be computationally expensive • Difficulty in choosing the kernel function
KNN	• Simple and intuitive • No training phase • Non-parametric • Easy to implement for small datasets	• High computational cost • Sensitive to the choice of k • Struggles with high-dimensional data • Impacted by noisy data
Decision Trees	• Easy to interpret and visualize • Handles both numerical and categorical data • Non-parametric • Can be used in ensemble methods	• Prone to overfitting • Sensitive to noisy data • Can be biased towards dominant classes • May require pruning
Bayesian Network	• Can handle uncertainty • Provides clear probabilistic interpretation • Good for structured data • Can incorporate expert knowledge	• Computationally expensive • Requires expert knowledge for structure • Complex to implement • Scalability issues with large datasets
Gaussian Models	• Simple and effective	• Assumes normal distribution

	• Well-understood properties • Suitable for data with normal distribution • Fast inference	• Not suitable for all data types • Sensitive to outliers • Limited flexibility
Autoencoder	• Can capture complex patterns • Scalable to large datasets • Good for high-dimensional data • Effective for unsupervised learning	• Requires large amounts of training data • Computationally expensive • Prone to overfitting • Interpretability challenges
ANN	• High flexibility and adaptability • Can model complex patterns • Effective for large datasets • Suitable for deep learning applications	• Computationally expensive • Prone to overfitting • Requires large training datasets • Sensitive to hyperparameter tuning
LSTM (Long Short-Term Memory)	• Can handle long-term dependencies • Effective for time series • Good for sequential data • Can model complex temporal patterns	• Requires large computational resources • Complex to train • Sensitive to hyperparameters • Prone to vanishing gradient problem

Learning-based and ensemble-based approaches are typically the most successful when compared to statistical-based, distance-based, density-based, clustering-based, learning-based, and ensemble-based methods for detecting outliers in complex data environments, such as those found in data warehouses. The table unequivocally shows that by combining the advantages of several algorithms, these strategies—particularly ensemble approaches like Bagging, Boosting, and Isolation Forest—offer greater accuracy and resilience. Artificial Neural Networks (ANNs) and autoencoders are two learning-based techniques that are also very good at managing complex patterns and high-dimensional data.

Summary of Outlier Detection Techniques in Literature

The below summarizes different methodologies and techniques in OD presented in the existing literature. This comparison analysis helps one understand the efficacy and application areas of different OD techniques and supports developing a robust OD framework for data warehouses.

Table 4 Summary of Outlier Detection Techniques

Author(s)	Use Case	Models Used	Chosen Model
Lyudchik et al.,(2016)	Outlier detection in MNIST digit recognition	Deep Autoencoder, Various Autoencoder Topologies	Deep Autoencoder
Hevapathige (2021)	Anomaly detection in time-series network data	Histogram-Based Outlier Score (HBOS), Others	Histogram-Based Outlier Score (HBOS)

Liu et al. (2019)	Detection of fake reviews on Amazon China dataset	Isolation Forest, Other Temporal Outlier Detection Methods	Isolation Forest
Ounacer et al. (2018)	Credit card fraud detection	Isolation Forest, LOF, One-Class SVM, K-Means	Isolation Forest
Li (2023)	Anomaly detection in financial data	Local Outlier Factor (LOF), Isolation Forest, SVM	Local Outlier Factor (LOF)
Cirkin, (2023)	Retail data anomaly detection before ETL process	LSTM, One-Class SVM, Isolation Forest	Isolation Forest
Jain & Jain, (2019)	Credit Card Fraud Detection	SVM, ANN, Bayesian Networks, KNN, Fuzzy Logic Systems, Decision Trees, and Logistic Regression.	ANNs and Bayesian Networks
Zimek et al. (2014)	Ensemble methods in outlier detection	Various ensemble methods, LOF, Isolation Forest	Ensemble methods
Stein et al. (2016)	Local subspace-based outlier detection	Global neighborhood, Subspace Clustering, LOF	Local subspace-based outlier detection
Zimek et al. (2012)	Evaluation of outlier detection methods	LOF, k-means, Isolation Forest	LOF
Liu et al. (2010)	Isolation Forest for anomaly detection	Isolation Forest, LOF, k-means	Isolation Forest
Aggarwal & Sathe (2015)	Outlier ensembles: theoretical foundations and algorithms	Various ensemble methods, Isolation Forest, LOF	Ensemble methods

The results show that when it comes to locating outliers in the kind of vast, heterogeneous datasets found in data warehouses, unsupervised outlier detection techniques typically outperform supervised techniques. The great accuracy and efficiency of techniques like One-Class SVM, LOF, Isolation Forest, and Autoencoders in detecting anomalies are highlighted.

Limitations

Some studies provided detailed descriptions of their methodologies and data sources, while others lacked sufficient detail, making it difficult to assess the validity and reliability of their findings fully. The included studies utilized different datasets, which may have varying characteristics and levels of complexity. This variability can affect the generalizability of the findings. Inconsistencies in reporting performance metrics and evaluation criteria across studies pose a challenge. Some studies reported comprehensive, while others provided limited information. This inconsistency can lead to difficulties in synthesizing results and drawing broad conclusions.

Conclusion

In conclusion, this systematic review has thoroughly evaluated various outlier detection techniques, including statistical-based, distance-based, density-based, clustering-based, learning-based, and ensemble-based methods. The findings underscore the superior performance of unsupervised outlier detection methods, particularly within the large, heterogeneous datasets typical of data warehousing

environments. Techniques such as Isolation Forest, Local Outlier Factor (LOF), One-Class SVM, and Autoencoders have demonstrated high accuracy and efficiency in detecting anomalies, while hybrid models that combine multiple methods have proven even more effective, leveraging the strengths of different algorithms to deliver more accurate and robust outlier detection. The review successfully meets its objectives by providing a detailed analysis of the effectiveness of various OD techniques, identifying challenges and limitations, and synthesizing methodologies for integrating OD into descriptive and diagnostic analytics. Future research should focus on developing more robust hybrid models that seamlessly integrate different outlier detection techniques and explore the use of advanced interpretability tools to further enhance their diagnostic capabilities. Advancing research in these areas will contribute to more effective and scalable solutions for outlier detection in data warehousing, ultimately enhancing the strategic decision-making capabilities of organizations.

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REVIEW OF EFFECTIVE CANDIDATE EVALUATION USING KSA PARAMETERS

PPGD Asanka[1] and BAT Dilshan [2]

Abstract

This literature study has the goal of reviewing the significance of Knowledge, Skills, and Abilities in resume analysis in the case of software engineering applicants. The period of study is from 2015 to 2024, and the emphasis is on the use of Natural Language Processing (NLP) and Machine Learning (ML) in the automation of the recruitment process. The purpose of the study is to assess KSA(Knowledge, Skills, Abilities) factors in their relationship to resume analysis and evaluate successful approaches in the application of NLP and ML. Research data was obtained through academic databases. Inclusion criteria included information on KSA, peer-reviewed studies, and data on the NLP and ML application in resume analysis. The result is that 58 records were selected and submitted to risk of bias evaluation. The findings state that the employment of the combined NLP and ML significantly assists in the process of KSA evaluation of submitted resumes. Recommendations include further studies of the analysis and information extraction skills of the two technologies. The implications of KSA factors are that they significantly improve the resume analysis and candidate assessment. The results present important stakeholders, most influential researchers and authors, most reliable journals, and major trends in the field of resume evaluation. This study constitutes a new basis for the following research and applications. The emphasis can be made on the utilization of standardized concepts for KSA evaluation and further innovation in this sphere.

Keywords: Candidate evaluation, KSA Parameters, ML, NLP, Resume analysis

[1] Senior Lecturer, Department of Industrial Management, University of Kelaniya , Sri Lanka

Email: dasanka@kln.ac.lk https://orcid.org/0000-0002-3433-5533

[2] Department of Industrial Management, University of Kelaniya, Sri Lanka

Email: dilshan-im19005@stu.kln.ac.lk https://orcid.org/0009-0000-5607-6141

Introduction

After completing their schooling, most people move on to work. However, many people begin working before they complete their formal education. Job searching has become both wiser and simpler in the internet age. The most important tool for representing a candidate when looking for work is the CV. The initial phase in the candidate filtering procedure is resuming screening, followed by an interview or test. [Narendra and Hashwanth, 2022]. However, there are more than enough applicants for a single job, making it difficult for an employer to choose individuals solely based on their CV / Resume. [Mathew et al.,2020]. To address this issue, most organizations specify their specifications, and there has always been a push to adopt an automated system that allows employers to quickly identify competent candidates. For this, most companies utilize an ATS (Applicant Tracking System) [Mathew et al., 2020], which is software that organizations use to identify the most significant elements or areas of interest in CVs/resumes and ignore the rest. In this scenario, advances in Natural Language Processing and Machine Learning [1] have been useful [WWW1].

Objectives

1. The primary goal of this literature study is to assess the usefulness of KSA factors in resume analysis and to identify the most advanced approaches that use NLP and ML to improve applicant evaluation. This paper aims to identify the most commonly utilized KSA characteristics in software engineering resumes and their impact on candidate evaluation.
2. Evaluate the Impact of Advanced Technologies: Utilize NLP and ML approaches to extract and evaluate KSA criteria from resumes, resulting in more accurate and efficient recruiting procedures.
3. Evaluate Existing Automated Systems: Compare the effectiveness of automated resume screening systems to traditional techniques for evaluating KSAs.
4. Identify gaps and future research directions. Highlight the limits of previous research and propose prospective areas for future research to improve resume analysis and candidate evaluation.

By addressing these objectives, this review hopes to provide a thorough understanding of how new technology might transform the software engineering recruitment process. The insights collected will help to design more efficient, accurate, and objective recruitment techniques, benefiting both companies and job seekers.

Contribution

This systematic literature review adds great value by providing a complete overview of technological breakthroughs and core methodology, as well as practical advice for researchers. The primary contributions of this review can be summarized as follows:

- Conducted comprehensive dataset compilation and analysis. This paper thoroughly combines and analyses both openly available and on-demand accessible datasets for resume analysis, with a focus on Knowledge, Skills, and Abilities (KSA) factors. This comprises datasets for categorization and detection in the context of resume screening.
- This study consolidates recent research articles published between 2015 and 2024, providing valuable insights into the strategies used to detect, segment, and classify KSA aspects in resumes.
- Evaluation of Past Survey Papers: This review assesses the contributions and limitations of survey papers on resume analysis published between 2015 and 2024.
- The review identifies research gaps, summarizes obstacles, and suggests directions for future study on categorizing and detecting KSA factors across resume datasets.

- The review highlights recent advancements in machine learning, including improved resume analysis accuracy. establishing these methods as complementary to traditional resume evaluation techniques.

This literature review ensures a thorough and methodical examination of the literature, providing a solid foundation for future research in the field of resume analysis and KSA parameter detection.

Methods

To answer the research questions, the study followed the eight phases outlined in Figure 1. After determining the 2015-2024 period for developing the literature review, we defined search arguments, keywords, and databases to be used. As a result, we used the "advanced search" function to find publications published between 2015 and 2024 in five databases: IEEE Xplore, Scopus, Springer, Sci-space, and Google Scholar, with the expressions "resume analysis", "KSA", and "candidate evaluation" as arguments in the title, abstract, and keywords. The database selection was based on the fact that, according to Chadegani et al. (2013), Mongeon and Paul-Hus (2016), Vieira and Gomes (2009), Bar-Ilan (2010), and Abrizah et al. (2013), Web of Science and Scopus are the most widely used databases in literature search tasks, and most bibliometric analyses use their data. We opted to broaden the research potential sources by integrating three more well-known databases: IEEE Xplore, Sci-space, and Google Scholar.

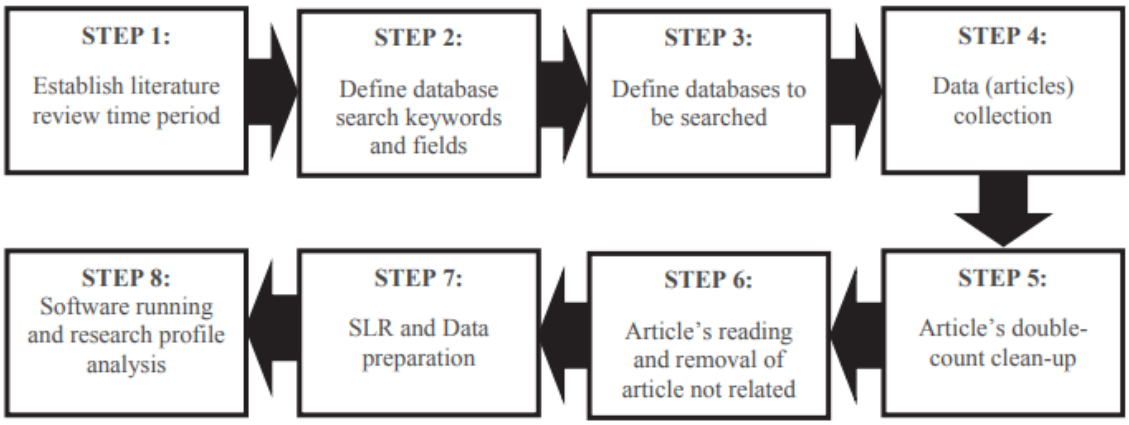

Figure 4: Research steps. Source: Authors.

Eligibility criteria

To ensure the relevance and quality of the included studies, we established the following inclusion criteria:

- **Types of Studies**: Only peer-reviewed journal articles, conference papers, and high-quality technical reports were included.
- **Subject Area**: Studies focused on resume analysis, applicant tracking systems (ATS), and the identification or evaluation of KSAs.
- **Methodological Rigor**: Studies employing empirical methodologies, including experiments, case studies, and systematic reviews.
- **Language**: Publications in English.

Inclusion Criteria	***Exclusion Criteria***
The articles should concentrate on the resume evaluation or screening.	Articles not specifically devoted to the resume evaluation or screening.
English should be used when writing the studies.	Scientific reports; book reviews; editorial letters; abstracts; publications not subjected to peer review.
Any year of publication may be used for Sections 1 and 4.	Posters, seminars, and M.Sc. and Ph.D. theses.
A study article must have been published between 2020 and 2023 for it to be included in the systematic review.	Studies published before 2020 except for Sections 1 and 4.

Search Strategy

A systematic search was conducted using a combination of keywords and Boolean operators. The search terms included "resume analysis," "applicant tracking system," "natural language processing," "knowledge skills abilities," "machine learning," and "resume evaluation."

The search string is composed of the following: [("KSA parameters" OR "candidate evaluation" OR "Resume analysis" OR “CV analysis” OR “Application tracking system” OR “ATS”) AND ("Software engineering" OR "Information Technology") AND (“Machin Learning” OR “ML” OR “Natural language processing” OR “NLP”)]

Selection Process

The selection process involved several stages:

1. **Initial Screening**: Titles and abstracts of all retrieved studies were screened by two independent reviewers to identify potentially relevant articles.
2. **Full-Text Review**: The full texts of articles that passed the initial screening were reviewed to ensure they met the inclusion criteria.
3. **Consensus Meeting**: Any disagreements between the reviewers were resolved through discussion.

Data Collection Process

Data extraction was performed using a standardized form, capturing the following information from each study:

- **Publication Details**: Author(s), year of publication, and source.
- **Study Design**: Type of study (e.g., experimental, case study, review).
- **Objectives**: Main aims of the study.
- **Methodology**: Details on the data collection and analysis methods.
- **Key Findings**: Main outcomes related to the identification of KSAs and analysis of resume.
- **Limitations**: Any reported limitations of the study.

Data Items

The primary data items extracted were:

- **Knowledge**: Defined as the theoretical understanding of a subject.
- **Skills**: The ability to perform tasks and activities proficiently.

- **Abilities**: The capacity to apply knowledge and skills in various contexts.

Results

The initial database search identified a total of 157 records. An additional 32 records were found through other sources, bringing the total to 189 records. After removing duplicates, 189 records were screened based on their abstracts. A total of 56 records were excluded during this stage due to irrelevance or failure to meet the inclusion criteria. Out of the remaining 136 records, full-text assessments were conducted to evaluate their eligibility for inclusion in the review. Following this thorough review, 88 reports were excluded. The reasons for exclusion included lack of relevance to the topic, insufficient methodological rigor, and failure to focus on KSA parameters in resume analysis.

Ultimately, 58 studies met the inclusion and exclusion criteria and were included in the final synthesis. The selection process is illustrated in the PRISMA flow diagram (Figure 2).

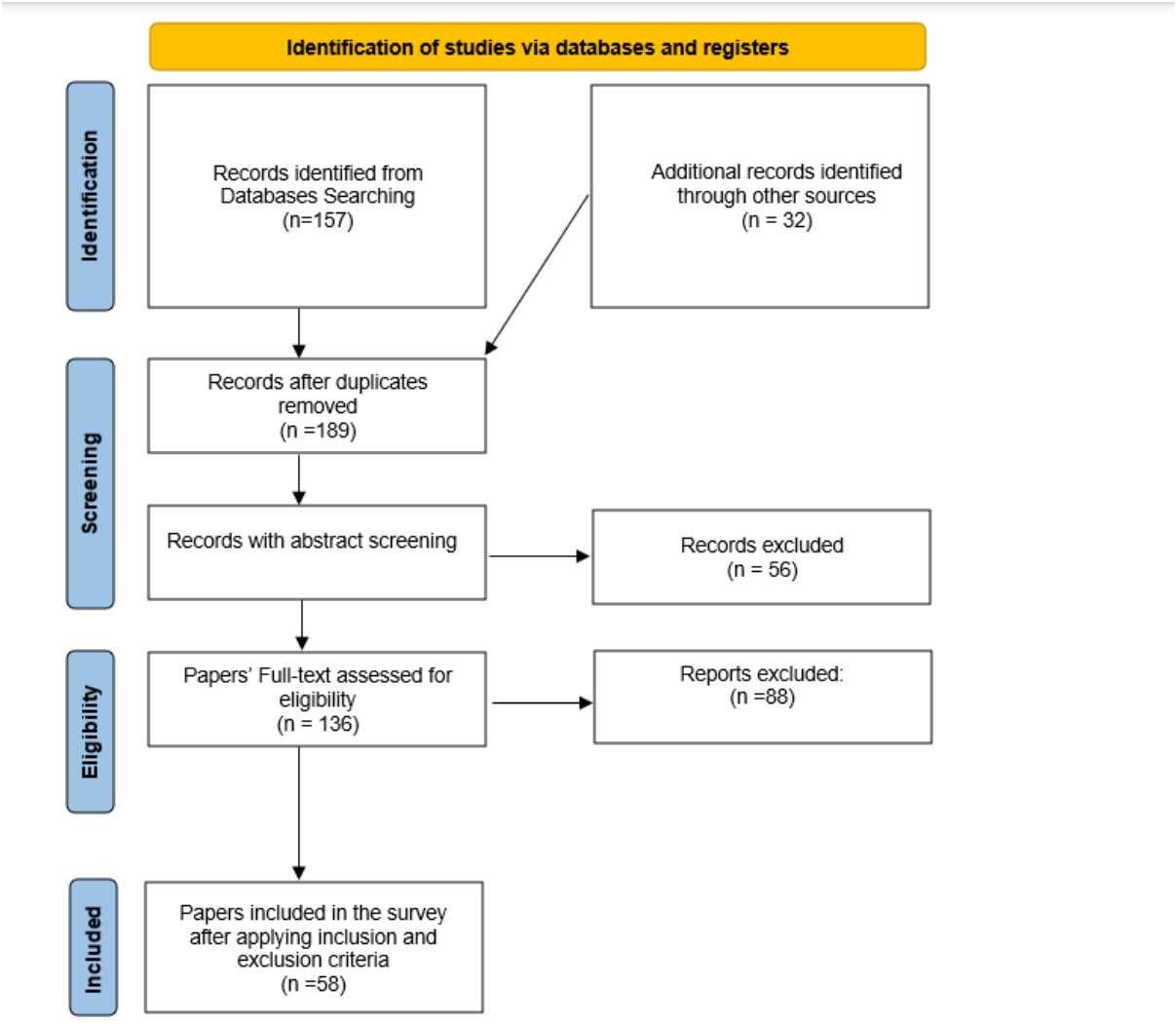

Figure 5: Selection process flow diagram. Source: Authors

In the study titled "Resume Analyzer Using NLP" [Amrut et. al., 2024] aimed to revolutionize the resume screening process by focusing on employee feedback rather than solely catering to employers. They developed an innovative resume analyzer using Natural Language Processing (NLP) techniques, which analyzes resumes to provide detailed feedback, including tips for improvement and resume

scoring. This approach addresses a common issue where employees are often left wondering why their resumes were rejected. The analyzer offers a thorough analysis, highlighting both the strengths and weaknesses of a resume, and suggests specific improvements to increase the chances of securing an interview.

Similarly, Arvind et. al., 2024 systematic review on resume screening using NLP and machine learning, exploring various techniques and approaches for parsing unstructured data. They highlighted the capabilities of NLP and machine learning to understand and extract relevant information from resumes, comparing different methodologies to find reliable and comprehensive results. Their review also identified the challenges and future scope of resume parsing, focusing on writing styles, word choices, and syntax. There are several open-source and commercial resume parsers listed out in table 1 and table 2. This systematic review provided a comprehensive overview of existing resume parsers, both open-source and commercial, and discussed the effectiveness of semantic search in context-based resume screening. The authors emphasized the need for advanced algorithms to handle the complexity and ambiguity of human language, underlining the potential for further research and development in this area.

Table 6: Open-source resume parsers. Source: [Arvind et. al., 2021].

Resume Parser	Focuses on	Programming language	Library used	Output file	Advantage	Disadvantage
Brendan Herger's (Herger, 2015/2020)	Extracts information from resume	Python	PDFMiner	CSV file	Simple and Language dependent	Information loss in terms of date and job description
Skcript Technologies' (Skcript/Cvscan, 2016/2020)	Extracts information from resume	Python	PDFMiner	.json format	Simple and CLI interface	Fails to extract date most of the time
Antony Deepak's (GitHub—Antonydeepak/ resume parser: resume parser using rule based approach. developed using framework provided by GATE, n.d.)	Extracts information from resume uses a hybrid machine-learning and rule-based approach focuses on semantic rather than syntactic parsing	Java	Apache's Tika library	Structured.json format	Better accuracy	Complex and difficult to use

Keras-English-resume-parser-and-analyzer (Chen 2018/2020)	Extracts information from English resume use Keras and deep learning models	Python	PDF miner	Raw content	Simple and better accuracy	Language dependent

Table 7: Commercial resume parsers. Source: [Arvind et. al., 2021].

Resume parser	Focuses on	Output file	Advantage
HireAbility's ALEX [WWW4]	Extracts information from resume	HR-XML, JSON	Supports multiple languages and locales Accurate, fast and secure
RChilli's [WWW5]	Extracts information from resume	XML, JSON	Self-learning capability Fast and reliable
DaXtra [WWW6]	Extracts information from resume	XML, JSON	Multilingual resume parsing Most comprehensive and accurate
Rapidparser [WWW7]	Extracts information from resume	XML, JSON	Multilingual resume parsing simple and accurate

Another study by Narendra and Hashwanth, 2022 introduced a Named Entity Recognition (NER) based resume parser and summarizer using the spaCy, NLP package, which aimed to efficiently extract key entities from resumes and rank them based on relevance. spaCy is used in another study Bharadwaj et. al., 2022 which is use NLP and LSTM to resume screening process. This method significantly improved the speed and accuracy of resume screening by focusing on entity recognition, thereby facilitating quicker shortlisting of candidates [Narendra and Hashwanth, 2022].

The research by Kosala and Dinesh, 2023 focused on identifying the current demand for Knowledge, Skills, and Abilities (KSAs) in the ICT sector through an analysis of job advertisements. The study utilized NLP techniques to align the educational curricula with industry requirements, thereby bridging the gap between the skills possessed by job seekers and the skills demanded by employers.

In the study "Resume Analyzer Using NLP" by Hitesh et. al., (2024), the focus was on creating a resume analyzer that provides feedback to employees rather than solely filtering resumes for employers. This innovative tool utilizes Natural Language Processing (NLP) techniques to analyze resumes and offer

detailed feedback, including improvement tips and resume scoring, addressing the common issue of employees not understanding why their resumes were rejected.
Similarly, Arvind et. al., (2024) conducted a systematic review on resume screening using NLP and machine learning. They explored various techniques and approaches for parsing unstructured data, highlighting the capabilities of NLP and machine learning to understand and extract relevant information from resumes. Their review compared different methodologies and identified challenges and future research directions, particularly focusing on writing styles, word choices, and syntax.

In recent years, the integration of Natural Language Processing (NLP) and machine learning has revolutionized the field of resume analysis, enhancing both accuracy and efficiency in candidate evaluation. Berdanier et. al., (2021) explored how online engineering resumes convey disciplinarity and adhere to specific formatting conventions, emphasizing the role of disciplinary discourse as a quality metric. This nuanced understanding of resume content is crucial for technical fields where professional identity is conveyed through detailed documentation. Building on this, Nisha et al. (2024) developed an Automated Resume Parsing and Ranking System (ARRS) that leverages NLP algorithms to extract and rank candidates based on predefined criteria, significantly improving the talent acquisition process by integrating with existing Applicant Tracking Systems. Meanwhile, Shakti Kinger et al. (2024) introduced a system utilizing YOLOv5 and DistilBERT models to parse and rank resumes, demonstrating the potential of deep learning models in enhancing the accuracy and relevance of resume analysis. Complementing these advancements, Huang et. al., (2023) proposed a time-aware and semantic approach to resume analysis, incorporating temporal information and semantic context to improve talent similarity calculations. Together, these studies highlight the transformative impact of advanced technologies in streamlining resume screening processes, ultimately benefiting both employers and job seekers in the competitive job market by providing more precise and insightful candidate evaluations.

Another significant study by Shubham et. al., (2021) presented a model that uses NLP to extract information from resumes and rank them according to company preferences and requirements. This approach simplifies the hiring process by converting unstructured resume data into a structured format and ranking candidates based on their skills and company needs.

Rakhi et. al., (2023) proposed a comprehensive model that uses NLP to parse and evaluate resumes. Their system extracts various data points such as education, experience, projects, and addresses, and ranks resumes based on the alignment of candidate skills with company requirements. This study emphasized the importance of an intelligent system to handle the complexity and variability of resume formats, enhancing the efficiency and accuracy of the recruitment process.

In the study ResuMatcher [Shiqiang et. al., 206] is explained about personalized resume job matching system. In the study [WWW2] explained what are the considerable knowledge, Skills and abilities are in Software engineering field. Study Kosala and Dinesh, (2023) aimed to develop a Natural Language Processing (NLP) framework to uncover the current demanded Knowledge, Skills, and Abilities (KSAs) in the Sri Lankan Information Technology (IT) sector.
By synthesizing the findings from these studies, it is evident that integrating NLP and machine learning into resume screening processes can significantly enhance the accuracy and efficiency of candidate evaluation. These technologies not only streamline the recruitment process for employers but also provide valuable feedback to job seekers, helping them improve their resumes and increase their chances of employment. The emphasis on semantic search and context-based analysis further underscores the importance of understanding the nuances of human language in developing effective

resume parsers. As the field continues to evolve, future research will likely focus on addressing the remaining challenges and improving the overall effectiveness of these systems, ultimately benefiting both employers and job seekers in the competitive job market.

Discussion

The integration of automated resume screening tools with broader human resources management systems is still in nascent stages [Mu Li, 2024] Effective integration could further streamline recruitment processes, allowing for a holistic approach to talent acquisition that includes not just screening but also other aspects of recruitment candidate engagement and onboarding [Bharadwaj et al., 2022]. However, challenges potential bias due to non-diverse training data have been identified. Recent research focuses on developing inclusive algorithms and employing balanced datasets to mitigate this issue [Kamineni et al., 2023]. The adaptability of these systems to various industries, which vary greatly in required skills and qualifications, remains a challenge, addressed by developing customizable screening algorithms [Bharadwaj et al., 2022].

The correctness of resume parser depends on several factors [WWW3], such as writing style, choice of words and syntax of written text. A set of statistical algorithms and complex rules are needed to suitably know and fetch the correct information from resumes. Natural language processing and machine learning have the capability to So, resume parsing is still in its natal stage, and few important challenges and future scope are as follows [seal et. al., 2020]:

- Understanding writing style of resume
- Understanding choice of words in a resume
- Understanding syntax of unstructured written language
- Context-based searching
- Understanding organization and formatting of resume
- Understanding headers and footers of resume
- Breaking resume into sections
- Understanding the structural and visual information from PDFs
- Speed of parsing.

This systematic literature review presents a comprehensive analysis of the current methodologies and advancements in resume analysis, focusing on Knowledge, Skills, and Abilities (KSA) parameters. Our review identified several key trends and insights which significantly contribute to the field of automated resume screening systems.

General Interpretation of Results

The integration of Natural Language Processing (NLP) and Machine Learning (ML) into resume screening processes has significantly enhanced the accuracy and efficiency of candidate evaluations. Study Hitesh et al. (2024) have shown that NLP-based resume analyzers can provide detailed feedback to job seekers, highlighting both strengths and weaknesses and offering specific improvements to increase interview chances. Similarly, Sinha et al. (2024) demonstrated the capabilities of NLP and ML in parsing unstructured data from resumes, comparing various methodologies to understand and extract relevant information. Their review highlighted the challenges in handling writing styles, word choices, and syntax, emphasizing the need for advanced algorithms to manage the complexity of human language. Bhor et al. (2021) presented a model using NLP to rank resumes according to company preferences, simplifying the hiring process by converting unstructured data into a structured format and ranking candidates based on their skills and company needs. Bharadwaj et al. (2023) proposed a

comprehensive model that used NLP to parse and evaluate resumes, demonstrating the importance of handling the complexity and variability of resume formats to enhance recruitment accuracy and efficiency. Narendra and Hashwanth (2022) introduced a Named Entity Recognition (NER) based resume parser using the spaCy NLP package, which significantly improved the speed and accuracy of resume screening by focusing on entity recognition. Chamithri and Dinesh (2023) focused on identifying the current demand for Knowledge, Skills, and Abilities (KSAs) in the ICT sector through NLP techniques, aligning educational curricula with industry requirements to bridge the skills gap.

Limitations of the Evidence

The reviewed studies exhibit several limitations that affect the generalizability and reliability of their findings. Studies like Yong et. al., 2018 had relatively small sample sizes, which may limit the broader applicability of the results. Variations in methodological approaches across studies could lead to inconsistencies in the findings. The reliance on specific datasets and focus on sectors, such as IT, may also restrict the generalizability of the conclusions. For instance, Vankevich and Kalinouskaya, (2020) emphasized the need for more comprehensive and diverse datasets to enhance the model's accuracy and reliability. Additionally, many studies focus primarily on technical skills while often overlooking soft skills, which are crucial for many roles but harder to quantify and analyze using current technologies.

Limitations of the Review Processes

The review process encountered several limitations. The selection criteria, while rigorous, may have excluded relevant studies that did not explicitly focus on KSA parameters or were published outside the specified timeframe. The reliance on specific databases could have resulted in a bias towards certain types of publications. The manual screening and data extraction processes, although thorough, are subject to human error and potential biases. Future reviews could benefit from incorporating automated tools to enhance the accuracy and efficiency of the review process.

Implications for Practice, Policy, and Future Research

The implications of this review are significant for practice, policy and further research. It is possible for HR personnel and recruiters to incorporate natural language processing (NLP) and machine learning (ML) in their resume screening activities to make them more efficient and accurate. By giving detailed feedback on applications from job-seekers, resumes can be improved thus improving both employers and applicants. This should go a long way in making sure that the process is objective as well as inclusive.

Further research could focus on challenges identified earlier by expanding the range of sectors studied, increasing sample sizes or modifying algorithms so that they account for variation in human speech. The study also recommends exploring other cutting-edge technologies like generative AI to boost the effectiveness of resume screening systems.

To sum up, integrating NLP techniques with ML systems while scrutinizing curriculum vitaes seems promising enough to revolutionize recruitment processes. However, there is still room for improvement in these areas before they can deliver far more accurate and efficient methods of evaluating candidate qualifications that would benefit both employers and job seekers in the competitive job market. The ongoing evolution of these technologies will likely lead to further improvements in the recruitment process, making it more effective and equitable

Conclusion

To sum up, the blending of KSA elements with such modern technologies as Natural Language Processing (NLP) and Machine Learning (ML) can completely change how resumes are analyzed, and individual applicants evaluated. This report gives a general idea about the current state of research as well as offering practical suggestions for further studies. Hence, future research should close such gaps by building on the existing knowledge base to develop recruitment procedures that would be both more efficient and less biased thereby becoming of help to enterprises and employees in the highly competitive labor market today.

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ADVANCED COMPUTATIONAL TECHNIQUES FOR DYSGRAPHIA PREDICTION THROUGH HANDWRITING RECOGNITION USING MACHINE LEARNING AND DEEP LEARNING METHODS

S Weraduwa[1], PPGD Asanka[2] and TV Mahanama[3]

Abstract

This systematic review critically examines the utilization of machine learning (ML) and deep learning (DL) techniques in the early detection and prediction of dysgraphia through handwriting recognition. The primary research objective is to systematically assess the significance, contributions, performance, and limitations of recent technological advances in identifying dysgraphic patients. Employing a structured search and selection methodology based on the PRISMA protocol, 34 peer-reviewed studies from key academic databases, including IEEE Xplore, PubMed, Scopus, Google Scholar, and Science Direct, were comprehensively analyzed. The review methodology focused extensively on data collection methods, ethical considerations, preprocessing approaches, feature extraction and selection techniques, and the performance metrics of various ML models in dysgraphia prediction. Our key findings indicate that a Hybrid AI method combining convolutional neural networks and support vector machines demonstrates high accuracy rates reaching up to 99.33%. This systematic review compares the use of machine learning and deep learning in diagnosing dysgraphia through handwriting recognition with traditional cognitive evaluations, highlighting the latter's lack of scalability and high labor demands. Additionally, this review highlights that research on dysgraphia has mainly focused on Latin scripts, overlooking the unique challenges of non-Latin scripts. It stresses the importance of including diverse linguistic data for more accurate global diagnoses. Additionally, dysgraphia is influenced by cognitive, motor, and language skills, underscoring the need for multimodal data to enhance early detection and treatment effectiveness. The paper advocates for research that integrates various data types and expands linguistic diversity in training datasets, aiming to improve the diagnostic accuracy and global applicability of dysgraphia detection tools.

Keywords: Deep learning, Dysgraphia, Dyslexia, Handwriting Recognition

[1] Department of Industrial Management, University of Kelaniya, Sri Lanka

Email: sulaksh-im19112@stu.kln.ac.lk https://orcid.org/0009-0009-1937-0179

[2] Senior Lecturer, Department of Industrial Management, University of Kelaniya, Sri Lanka

Email: dasanka@kln.ac.lk https://orcid.org/0000-0002-3433-5533

[3] Lecturer, Department of Industrial Management, University of Kelaniya, Sri Lanka

Email: thilinim@kln.ac.lk https://orcid.org/0000-0003-0536-0040

SYSTEMATIC LITERATURE REVIEW ON ANALYZING THE IMPACT OF PROMPT ENGINEERING ON EFFICIENCY, CODE QUALITY, AND SECURITY IN CRUD APPLICATION DEVELOPMENT

KAA Shanuka[1], J Wijayanayake[2], K Vidanage[3]

Abstract

This research investigates the impact of prompt engineering on the efficiency, code quality, and security of CRUD (Create, Read, Update, Delete) operations in software development using large language models (LLMs) like ChatGPT. Prompt engineering, which involves crafting specific inputs to guide AI outputs, has become crucial for tasks such as code generation, debugging, and vulnerability detection. The study addresses three key research questions: identifying the most influential aspects of prompt engineering on CRUD efficiency compared to traditional coding, recognizing common error patterns in AI-generated code and preemptive mitigation strategies, and leveraging human-AI collaboration to optimize CRUD application development. Through a systematic literature review, this study evaluates 52 relevant papers from 2018 to 2023, sourced from Google Scholar, ResearchGate, arXiv, and Sci-Hub. The findings indicate that effective prompt engineering significantly enhances productivity, reduces development time, and improves code adaptability to complex data structures. Techniques such as role-prompting and chain-of-thought prompting are highlighted for their ability to produce high-quality code, reducing errors and enhancing overall code quality.The review revealed significant results, including the identification of prompt engineering techniques that substantially improve the performance of LLMs in CRUD operations. ChatGPT, in particular, excels in generating and debugging code but struggles with more complex tasks and security vulnerabilities. The study emphasizes the need for continuous human oversight to ensure security and correctness, addressing challenges such as managing programming variability and the stochastic nature of LLMs.The research concludes that integrating ChatGPT into CRUD operations represents a significant advancement in software development, improving efficiency, code quality, and security. However, addressing its limitations through better prompt engineering and continuous human involvement is crucial. Future work will involve developing a fully functional CRUD application using generative AI, further evaluating its practical applications and limitations in software development.

Keywords: ChatGPT, Code Quality, CRUD Operations, Large Language Models, Programming, Prompt Engineering

[1] Undergraduate, Department of Industrial Management, University of Kelaniya, Sri Lanka
Email: ashenshanuka1222@gmail.com https://orcid.org/0009-0006-6940-817X
[2] Professor, Department of Industrial Management, University of Kelaniya, Sri Lanka
Email: janaka@kln.ac.lk https://orcid.org/0000-0002-9523-5384
[3] Senior Lecturer, Department of Computer Science, General Sir John Kotelawala Defense University, Sri Lanka
Email: vidanage_bvki@kdu.ac.lk https://orcid.org/0000-0002-1923-9084

SYSTEMATIC REVIEW OF DEEP LEARNING TECHNIQUES FOR REAL-TIME DEFECT DETECTION IN FABRIC MATERIALS

WAS Harith[1] and C Rajapakse [2]

Abstract

This systematic review delves into the significant advancements of deep learning techniques in real-time defect detection for fabric materials, a critical component of improving quality control in textile manufacturing. By providing an in-depth analysis of key methods, including Convolutional Neural Networks (CNNs), Generative Adversarial Networks (GANs), Autoencoders (AEs), and Active Continual Learning (ACL) frameworks, the review highlights how these technologies have dramatically enhanced the accuracy, efficiency, and adaptability of defect detection processes. The integration of these techniques has led to more precise identification of defects, reducing the reliance on manual inspection and significantly improving production speeds and quality. However, the review also identifies several persistent challenges, such as the need for more realistic and diverse synthetic data to better train models, the complexities in maintaining model adaptability to evolving and unforeseen defect types, and the difficulties associated with seamlessly integrating these sophisticated systems into existing industrial workflows without disrupting current operations. The study underscores the importance of ongoing research to refine deep learning methods, aiming to enhance their robustness, scalability, and reliability across various industrial environments, from small-scale textile workshops to large-scale manufacturing plants. This review not only synthesizes the current progress in deep learning applications for fabric defect detection but also outlines critical areas for future exploration, offering a detailed roadmap for the continued evolution of automated quality control in the textile industry, ultimately leading to more consistent and higher-quality textile products.

Keywords: Deep Learning, Fabric Defect Detection, Quality Control, Real-time Processing, Textile Manufacturing

[1] Dept. of Industrial Management, University of Kelaniya, Sri Lanka.

Email: wasavin-im19025@stu.kln.ac.lk https://orcid.org/0009-0000-8309-2526

[2] Dept. of Industrial Management, University of Kelaniya, Sri Lanka.

Email: chathura@kln.ac.lk https://orcid.org/0000-0003-2370-3959

Introduction

Rationale

The systematic review of deep learning methods for fabric defect detection is essential in response to the textile industry's increasing demand for higher-quality products and more efficient manufacturing processes. Traditional defect detection techniques, which often rely on manual inspection or basic machine vision systems, are no longer sufficient to meet the needs of modern, high-speed production environments. These conventional methods are labor-intensive, time-consuming, and susceptible to human error, leading to inconsistencies in defect identification and compromising overall quality control. In contrast, deep learning approaches such as Variational Autoencoders (VAEs), Convolutional Neural Networks (CNNs), Generative Adversarial Networks (GANs), and Active Continual Learning (ACL) offer transformative potential by automating the defect detection process and significantly improving accuracy and efficiency.

Recent advancements in deep learning have shown remarkable success in various fields of image analysis and pattern recognition, making these technologies particularly well-suited for defect detection in fabric materials. For instance, CNNs have demonstrated their effectiveness in real-time applications, while VAEs, when combined with mean structural similarity (MSSIM), have outperformed traditional loss functions that focus solely on image brightness (Wei et al., 2021). Additionally, GANs have been utilized to generate high-quality synthetic defect images, addressing the challenge of scarce defect samples in training datasets (Tsai et al., 2021).

Despite these advancements, substantial challenges remain in applying these methods to real-time fabric defect detection in practical settings. Key issues include the ability of models to adapt to new design patterns while retaining knowledge of common defects, such as knit pattern deviations and dirt marks. Furthermore, the variability in study designs and outcomes underscores the need for standardized methodologies that can be consistently applied across different fabric types and manufacturing conditions (Qian et al., 2022). This systematic review aims to critically evaluate the effectiveness of various deep learning techniques in enhancing real-time defect detection in fabric materials, highlighting both the strengths of current approaches and the gaps that future research must address to advance the field further.

Objectives

This systematic review aims to evaluate the effectiveness of deep learning methods, including Variational Autoencoders, Convolutional Neural Networks, Generative Adversarial Networks, and Active Continual Learning, in real-time fabric defect detection. It focuses on assessing these methods' performance in identifying and categorizing fabric defects, their adaptability to new design patterns, and their suitability for real-time detection in manufacturing environments, with an emphasis on computational efficiency and processing speed. The review also seeks to identify gaps in the standardization of methodologies and explore how these techniques can be made more robust, scalable, and better integrated into existing quality control systems. By addressing these objectives, the review aims to provide actionable recommendations for improving the adaptability and accuracy of deep learning models, ultimately contributing to the advancement of automated, efficient, and reliable defect detection in the textile industry.

Methods

Eligibility Criteria

This review focused on high-quality studies published between 2020 and 2024, investigating deep learning methods in fabric defect detection. Only peer-reviewed journal articles in English were

included, with key outcomes like defect detection accuracy, adaptability to new design patterns, and knowledge retention of common defects. Studies were excluded if they involved non-fabric materials, used non-deep learning methods, were published outside the specified timeframe, were non-peer-reviewed, or lacked sufficient data or clear outcomes.

Grouping for Syntheses

The selected studies were grouped into key areas to provide a structured synthesis: deep learning in anomaly detection, feature extraction and defect identification using VAEs, accurate detection using CNNs, synthetic data generation with GANs, and the role of active and continual learning in adapting to new defect patterns while retaining learned knowledge. This organization allowed for a comprehensive analysis of deep learning techniques in fabric defect detection.

Information Sources

Relevant studies were identified using PubMed, IEEE Xplore, Google Scholar, Scopus, and Web of Science, with the last search conducted on July 7, 2024. This comprehensive approach ensured thorough coverage of pertinent research.

Reference Lists

Manual searches of the reference lists of included studies were conducted to identify additional relevant articles, enhancing the comprehensiveness of the review.

Search Strategy

A comprehensive search strategy was employed across the databases, using terms like "defect," "fabric," "textile," "autoencoder," "unsupervised," and "active continual learning." Filters included studies published between 2021 and 2024, focusing on English-language, peer-reviewed journal articles, yielding 826 records.

Selection Process

The selection process began with 826 records identified from database searches. After applying year constraints (2021-2024), this number was reduced to 641. A first-level screening of titles and abstracts based on citation count and relevance narrowed this to 83 records. Second-level screening excluded non-peer-reviewed articles and those not focused on deep learning, resulting in 74 records. Full-text reviews further refined the selection to 71 articles, with final relevance checks leading to 50 articles included in the review. All decisions were made manually without automation tools.

Data Collection

Data collection involved screening initial search results by titles and abstracts to identify studies for full-text review. Essential details, including study characteristics, deep learning methods used, and defect detection outcomes, were extracted using a standardized form. Reference lists of included articles were manually searched for additional studies, and reference management software was used to organize and track citations.

Data Items

Key data items extracted from each study included study title, category, key findings, theoretical contributions, methodological insights, practical implications, research gaps addressed, and challenges. The review focused on outcomes related to defect detection accuracy, adaptability to new designs, and retention of defect knowledge. Additional variables included study design, sample size, participant

characteristics, and intervention characteristics, detailing the specific implementations of deep learning models.

Results

Study Selection

The comprehensive search identified 864 records. After removing duplicates, 641 records were screened, with 558 excluded based on titles and abstracts. Detailed abstract reviews reduced the count further, leaving 74 eligible records. Nine reports were not retrievable, and full-text examination excluded 24 studies, resulting in 50 studies in the final review, as shown in Fig. 1.

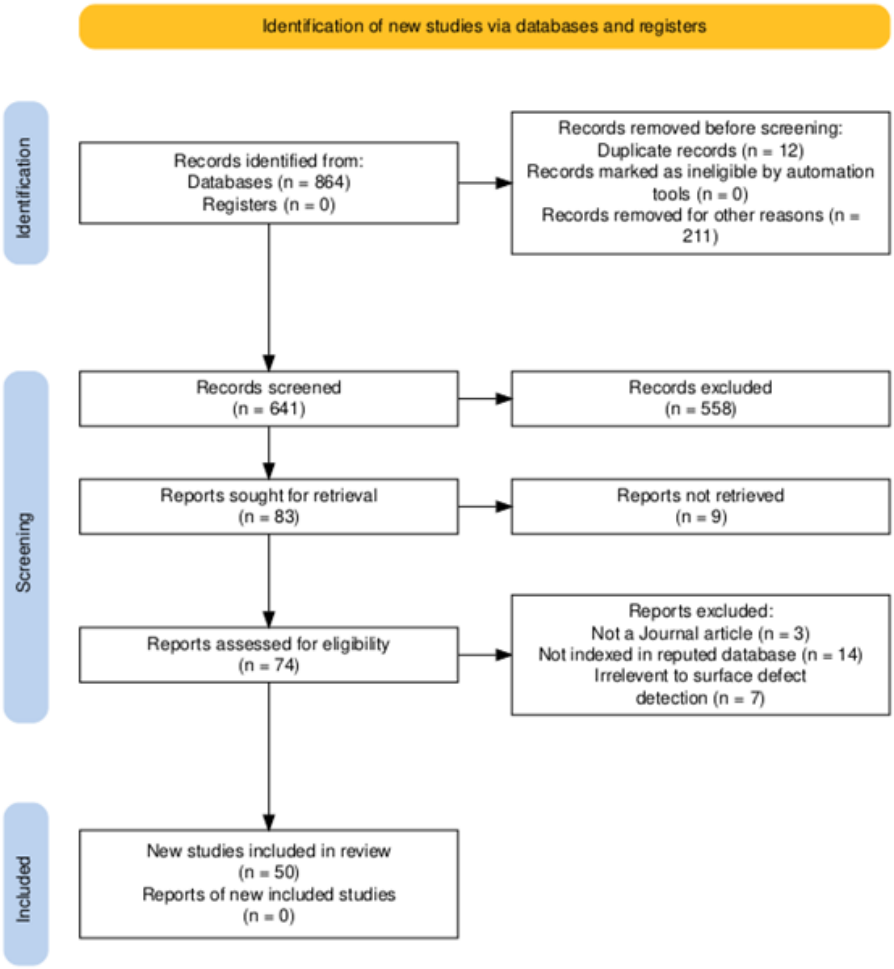

Fig 6 : Prisma Flow Diagram

Study Characteristics

The 50 included studies cover a range of deep learning techniques applied to fabric defect detection, focusing on methods like Autoencoders, Convolutional Neural Networks, Generative Adversarial Networks, and Active Continual Learning.

Discussion

This systematic review consolidates key advancements in deep learning methods for fabric defect detection, focusing on the effectiveness, challenges, and future directions of techniques such as Variational Autoencoders, Convolutional Neural Networks, Generative Adversarial Networks, and Active Continual Learning.

Despite the considerable promise shown by deep learning methods, substantial gaps persist in addressing the unique challenges of real-time fabric defect detection in practical settings. For instance, the integration of VAEs with mean structural similarity (MSSIM) metrics has been shown to outperform traditional loss functions that focus solely on image brightness, thereby improving the accuracy of real-time defect detection (Wei et al., 2021). Similarly, CNNs have demonstrated high accuracy and efficiency in identifying fabric defects when combined with repeated pattern analysis (Huang & Xiang, 2022). GANs are particularly beneficial for generating synthetic defect data, which is crucial for training and refining defect detection models, especially in scenarios where real defect samples are limited (Ahmad et al., 2024). Moreover, ACL frameworks exhibit significant potential in continuously improving defect detection models over time, which is essential in dynamic industrial environments where defect patterns are constantly evolving (Sun et al., 2023).

However, there remains considerable variability in study designs and outcomes, highlighting the urgent need for standardized methodologies. The development of more robust models capable of adapting to diverse defect types and new design patterns, while also retaining knowledge of common defects, is crucial. The review underscores the importance of standardizing approaches and creating adaptable models to meet the evolving nature of defect patterns in real-world settings. Future research should focus on exploring methodological innovations, addressing practical implications, and overcoming existing challenges to enhance the effectiveness and applicability of these techniques in real-time fabric defect detection.

This synthesis offers a detailed overview of the current status and future prospects of deep learning techniques in fabric defect detection. It outlines the existing advancements and highlights potential areas for further research and practical improvements in this important field.

Effectiveness of Deep Learning Methods

Convolutional Neural Networks (CNN)

Convolutional Neural Networks (CNNs) have transformed fabric defect detection by automatically learning and recognizing spatial hierarchies of features, making them highly effective for image-based tasks. Their convolutional layers excel in identifying patterns, edges, and textures, with a hierarchical structure that significantly enhances defect detection capabilities. A key advancement is the development of deeply optimized CNNs (DCNNs), which incorporate training and structural optimization along with lightweight models to reduce computational demands, making them ideal for real-time industrial applications (Li et al., 2022). Techniques such as depthwise separable convolutions and network pruning further enhance CNN performance, leading to more efficient and accurate defect detection.

For example, the RPDNet algorithm effectively combines CNNs with repeated pattern analysis, achieving high detection accuracy without additional computational costs, particularly for fabrics with periodic patterns (Huang & Xiang, 2022). Semi-supervised learning further improves these models by enabling them to learn from limited labeled data, enhancing quality control in textile manufacturing. Additionally, attention mechanisms within CNN frameworks, such as those integrating anomaly reconstruction with saliency-guided segmentation, improve defect localization by focusing on relevant features, thereby increasing detection accuracy (Yang et al., 2023). However, deploying CNNs in varied industrial environments remains challenging, as differences in setups and defect characteristics can limit their effectiveness.

Future research should prioritize the development of hybrid models that integrate various optimization techniques to handle complex defects, as well as adaptive models that can quickly adjust to new materials and patterns without extensive retraining. For an instance the integration of hyperspectral imaging with CNNs, as demonstrated in hyperspectral anomaly detection studies, offers a promising path for improving surface anomaly detection by providing a deeper understanding of material properties and defect characteristics (Hu et al., 2022). This approach could lead to more accurate and robust defect detection systems.

In conclusion, while CNNs are powerful tools for fabric defect detection, ongoing innovation is essential to address current limitations and enhance their practical applicability in diverse industrial settings.

Variational Autoencoders (VAEs) and Autoencoders (AEs)

Autoencoders (AEs) and Variational Autoencoders (VAEs) have shown considerable promise in fabric defect detection by learning efficient data representations crucial for anomaly detection. VAEs extend traditional AEs by introducing a probabilistic latent space, which enhances generalization and robustness. Integrating VAEs with mean structural similarity (MSSIM) has improved real-time detection accuracy by focusing on structural features rather than just pixel intensity, effectively capturing subtle defects often missed by conventional methods (Wei et al., 2021).

The ability of autoencoders to manage dynamic and multimodal data further highlights their robustness, as demonstrated in various industrial processes (Qian et al., 2022). The MOCCA framework, for example, enhances hierarchical feature extraction through multi-layer optimization within VAEs, outperforming traditional techniques, although its complexity may limit real-time application (Massoli et al., 2021). Innovations such as combining Vision Transformers with VAEs have improved anomaly detection by capturing global contextual information, though these methods are computationally demanding (Yang & Guo, 2024). Conditional VAEs (CVAEs) also exhibit high sensitivity in detecting subtle changes but may require adaptation for fabric-specific challenges (Yuan et al., 2021).

Nested VAE structures have demonstrated high detection rates and effective segmentation in real-time applications, reducing the need for manual inspections, though their effectiveness against complex, non-textured fabric defects remain uncertain (Oz et al., 2021). Self-supervised frameworks like JDRSS, which combine anomaly reconstruction with saliency-guided segmentation, tackle the challenge of rare defect data, yet synthetic images may not fully capture real-world variability (Yang et al., 2023).

Innovative architectures such as MFE-DEDNet, utilizing multi-dimensional feature extraction and depth wise separable convolutions, have enhanced performance while maintaining computational efficiency, though their complexity poses integration challenges (Uzen et al., 2023). Attention mechanisms have improved segmentation accuracy, but they often require substantial computational resources (Cao et al., 2022; Zhang et al., 2024). MemAE-based approaches excel in capturing complex textural features across various fabrics, although their reliance on memory augmentation may limit scalability (Wu et al., 2024). Additionally, one-dimensional deep convolutional autoencoders have advanced internal defect detection in non-destructive testing, showing potential beyond fabric detection, such as in fiber-reinforced polymer composites (Zhang et al., 2024).

Despite these advancements, AEs and VAEs face challenges such as high computational demands, scalability issues, and adaptability to diverse defect types. Developing more efficient, scalable models capable of handling real-world complexities is essential. Incremental or transfer learning methods could

enable quicker adaptation to new defect types, reducing the need for extensive retraining (Yang et al., 2023). While current research highlights the potential of AEs and VAEs in fabric defect detection, further advancements are necessary to overcome these limitations and broaden their applicability across industrial settings.

Generative Adversarial Networks (GAN)

Generative Adversarial Networks (GANs) have become a transformative tool in fabric defect detection, particularly in generating synthetic data where real defect samples are scarce or costly. A notable application is the use of two-stage CycleGANs, which synthesize and automatically annotate defects, significantly reducing manual annotation needs and enhancing defect detection across various textures and surfaces (Tsai et al., 2021). By integrating GANs with semantic networks, this approach is both computationally efficient and suitable for real-time industrial use.

GANs also excel in hyperspectral anomaly detection, outperforming traditional methods by extracting complex features from hyperspectral imaging (HSI) data through diverse network structures (Hu et al., 2022). Combining autoencoders with GANs further improves anomaly detection by better representing and reconstructing normal background distributions in industrial environments.

In rail surface defect detection, the Adaptive Pyramid Graph and Variation Residual-based Anomaly Detection Network (APGVR-GAN) captures contextual interactions between regional features and represents normal samples in the latent space, leading to significant improvements in detection accuracy and robustness (Niu et al., 2021). Similarly, GANs like Deep Convolutional Generative Adversarial Networks (DCGANs) generate high-quality synthetic images of stitching defects, addressing the scarcity of real defect images and reducing the costs associated with manual defect detection in the textile industry (Ahmad et al., 2024).

Beyond textiles, GANs have been applied to diversify tire-defect image generation, creating realistic images that train more robust defect detection models, which enhance consumer safety and reduce product recall costs (Zhang et al., 2022). In pavement anomaly detection, the PAD Net model uses GANs for pixel-level anomaly detection without needing detailed annotations, demonstrating superior performance over traditional methods and highlighting potential applications in both industrial and medical imaging (Ren et al., 2023).

A comprehensive survey of GAN-based defect detection reveals their widespread use across various industries. GANs are particularly valuable for generating synthetic defect data in scenarios with limited real samples, effectively training models on normal data to detect anomalies (He et al., 2022). The survey also explores variants like CGAN, DCGAN, and WGAN, detailing their specific adaptations for defect detection tasks.

Despite these advancements, challenges persist in ensuring that synthetic images accurately represent the diversity and complexity of real defects. The generalization of systems trained on synthetic data to real-world variations remains a concern, and the complexity and computational demands of GANs present obstacles to their real-time deployment. Future research should focus on enhancing the realism and variability of synthetic images to cover a broader spectrum of defect types. Integrating GANs with other AI technologies, like reinforcement learning, could dynamically improve the generation process based on feedback from detection systems. Additionally, exploring the scalability of these approaches in other manufacturing domains could help establish a standardized framework for using synthetic data in industrial AI applications. Continued integration of GANs with advanced machine learning

techniques and the development of new architectures promise further enhancements in defect detection across various materials and environments, leading to more robust and reliable systems.

Active Learning and Continual Learning

Active learning (AL) and continual learning (CL) are crucial for improving defect detection in environments where defects are rare and diverse. AL optimizes model performance by selectively querying the most informative data points for labeling, thereby reducing manual annotation efforts while maximizing the learning process's efficiency (Robert, 2021). By using AL algorithms, models can actively query annotators for the most uncertain or impactful data, refining their performance iteratively through human-generated labels (Lv et al., 2020). This iterative process, illustrated in Fig. 1, shows the cycle of query selection, annotation, and model refinement, which collectively enhances accuracy and cost-effectiveness in defect detection.

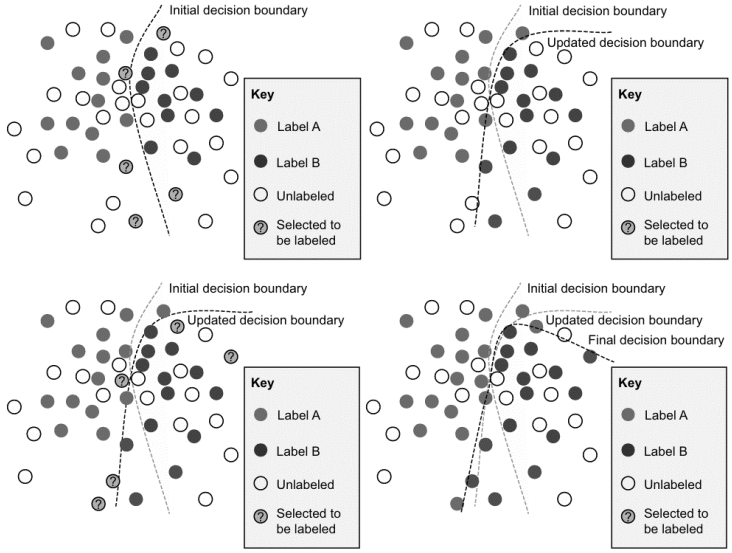

Fig 7. The Iterative Active Learning Process By (ROBERT (MUNRO) MONARCH, 2021)

CL, on the other hand, enables models to adapt over time without losing previously acquired knowledge. It allows systems to incrementally learn new tasks by leveraging past experiences, as demonstrated by the lifelong learning system architecture presented by Chen et al. (2018) in Fig. 2. This approach supports adaptive model updates, ensuring that defect detection systems remain effective as they encounter new and evolving defect types. For example, a dual-module continual learning framework has efficiently managed large data volumes while dynamically adapting to new defect types, reducing storage and computational costs (Sun et al., 2023).

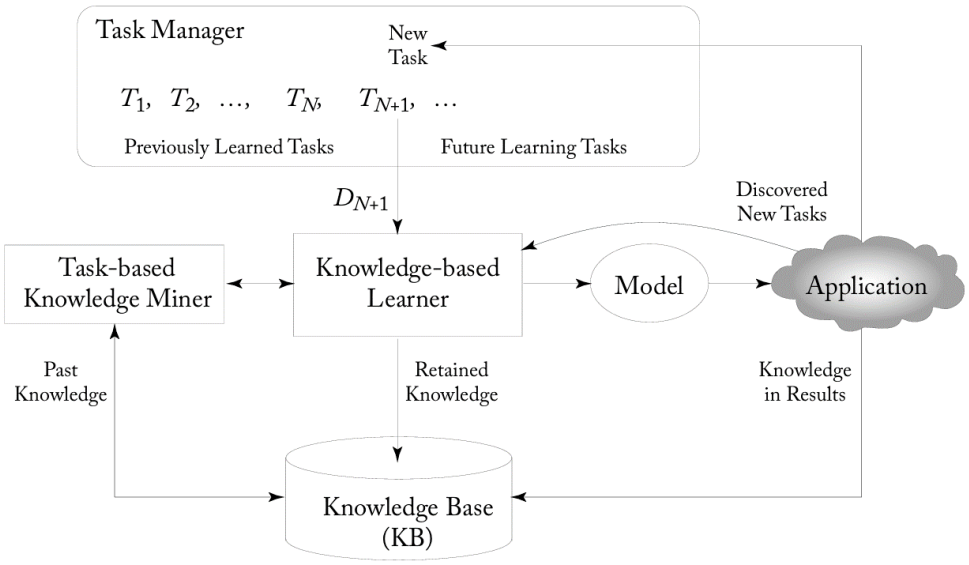

Fig 8. The Lifelong Machine Learning System Architecture By (Chen Et Al., 2018)

The integration of AL and CL, known as Continual Active Learning (CAL), combines the strengths of both approaches, balancing knowledge retention with the ability to learn new information, thus addressing the challenges of catastrophic forgetting. CAL systems maintain high performance with fewer labeled data, which is particularly advantageous in resource-constrained environments like edge computing and IoT applications (Vu et al., 2023; Das et al., 2023). Advanced techniques, such as deep active learning for surface defect detection, have significantly reduced labeling efforts by integrating uncertainty sampling and margin methods, improving defect detection outcomes with minimal data (Lv et al., 2020). The SCALE technique further enhances this process by using a super-resolution model for compressed replay within a continual learning framework, maintaining high-quality image reconstruction critical for anomaly detection (Pezze et al., 2022).

The effectiveness of AL and CL extends beyond industrial applications, proving valuable in fields like autonomous driving and document image analysis, where they dynamically manage catastrophic forgetting and adapt to new data streams (Shieh et al., 2020; Minouei et al., 2022). In medical imaging, active continual fine-tuning of convolutional neural networks has significantly reduced annotation efforts while maintaining high performance (Zhou et al., 2021).

In conclusion, ACL represents a significant advancement in defect detection and various industrial applications, continually adapting to new data while retaining previously acquired knowledge. Future research should focus on developing robust, scalable ACL models capable of handling real-world complexities. Additionally, exploring the integration of ACL with other advanced learning paradigms could further enhance their practical applicability, ensuring these systems remain effective and efficient in diverse operational environments.

Other Approaches

Recent advancements in fabric defect detection have been driven by the integration of novel technologies that enhance model performance and accuracy. A key development is the adoption of modified YOLO architectures, which incorporate attention modules and advanced loss functions like focal loss. This approach addresses the challenge of unbalanced datasets in the textile industry while maintaining real-time detection capabilities without additional computational costs (Kim & Lee, 2024).

The development of unified models, such as UniAD, marks another significant leap. UniAD improves detection and localization by mitigating issues like the "identity shortcut" through a layer-wise query decoder, which enhances feature focus and reduces resource usage (You et al., 2022). This model complements YOLO-based approaches by offering a more comprehensive solution to fabric defect detection.

Additionally, LSTM-based methodologies have improved texture classification and defect detection, especially for intricate patterns. The combination of multi-scale curvelet image decomposition with LSTM boosts accuracy in identifying defects that conventional methods might miss. Unsupervised learning algorithms paired with logistic regression further enable efficient training on less annotated data, making these techniques well-suited for real-time industrial applications (Kumar & Bai, 2023).

In conclusion, these advancements collectively address challenges such as unbalanced datasets, complex patterns, and the need for real-time adaptability, marking significant progress in fabric defect detection. Future research should focus on integrating these methodologies to enhance the robustness and applicability of detection systems across diverse industrial settings.

Comparative Overview of Approaches

The field of fabric defect detection has seen significant advancements through the application of various deep learning techniques, each designed to address specific challenges such as data scarcity, model adaptability, real-time processing, and integration into industrial workflows. By examining these methods in a structured manner, it becomes clear how each approach contributes uniquely to the field, while also revealing the limitations that need to be overcome.

Table 1 provides a detailed comparison of key deep learning techniques, highlighting their strengths and weaknesses in addressing these challenges.

Table 1: Comparison of key deep learning techniques

Aspect	Technique/Model	Strengths	Weaknesses	References
Adaptability	Continual Learning Frameworks (ACL)	Enhanced adaptability, continuous learning	Balancing retention and new learning remain challenging	Luciw, 2018; Sun et al., 2023; Zhou et al., 2021; Monarch, 2021; Vu et al., 2023
Data Scarcity Solution	GANs for Synthetic Data Generation	High-quality synthetic data, addresses data scarcity	Generalization to real-world data can be problematic	Ahmad et al., 2024; Zhang et al., 2022; Yuan et al., 2021; Tsai et al., 2021; Hu et al., 2022
Complex Process Handling	Autoencoders (AE)	High detection rates, improved anomaly localization	Real-time scalability challenges	Qian et al., 2022; Massoli et al., 2021; Wei et al., 2021; Oz

				et al., 2021; Wu et al., 2024
Real-Time Detection	CNNs with Attention Modules	High accuracy, efficient real-time detection	Complex integration into existing systems	Kim & Lee, 2024; Huang & Xiang, 2022; Zheng et al., 2021
Multi-Class Anomaly Detection	UniAD Model	Superior detection and localization performance	Implementation complexity	You et al., 2022
Texture Classification	LSTM-Based Models	Enhanced accuracy in complex textures	Computational intensity	Kumar & Bai, 2023
Surface Defect Inspection	CNNs (RPDNet)	Enhanced fabric defect detection with repeated pattern analysis	Requires periodic patterns, may not generalize to all fabrics	Huang & Xiang, 2022
Unsupervised Anomaly Detection	Unsupervised Methods (e.g., CVAE, JDRSS)	Effective without labeled data, lower operational costs	May require further tuning for specific applications	Yang et al., 2023; Yuan et al., 2021; Tao et al., 2022
Memory-Bounded Learning	Memory-Bounded Learning in ACL	Enables continual learning with limited resources	May limit model complexity and adaptability	Luciw, 2018; Monarch, 2021
Automated Defect Inspection	Advanced Active Learning (ACL + CNN)	Reduces annotation efforts, balances knowledge retention	Complex setup, may require extensive tuning	Schmidt et al., 2020; Zhou et al., 2021; Das et al., 2023
Anomaly Detection in Industrial Images	Unsupervised Learning (Vision Transformers, etc.)	Improved anomaly detection with less annotated data	High computational demand, complexity in deployment	Yang & Guo, 2024; Cui et al., 2023
High-Quality Image Generation	DCGAN	Effectively generates synthetic images, improves training	May struggle with complex, real-world defect diversity	Ahmad et al., 2024; Zhang et al., 2022
Lifelong Learning Integration	L-DNN	Continuous learning post-deployment, low computational resources	Balancing new and old knowledge remains difficult	Luciw, 2018
Efficient Batch Active Learning	Continual Learning Techniques	Accelerates learning, reduces training time	Requires careful management of learning phases	Das et al., 2023; Schmidt et al., 2020

Industrial Anomaly Detection	Review of Deep Learning Techniques	Comprehensive evaluation of methods for industrial contexts	Lacks practical guidelines for implementation	Liu et al., 2024; Zheng et al., 2021; Seliya et al., 2021
Leather Surface Defect Detection	Machine Vision Techniques	Improved automation in leather inspection	Automated systems still challenging due to defect diversity	Chen et al., 2022

As shown in Table 1, deep learning has advanced fabric defect detection, but each method faces unique challenges. GANs generate synthetic data to address scarcity but often struggle to generalize to real-world conditions. Continual learning allows models to learn continuously yet balancing old and new knowledge remains difficult. Autoencoders improve anomaly detection but face scalability issues, especially in real-time use. CNNs with attention modules provide high accuracy in real-time detection but are complex to integrate. UniAD excels in multi-class detection but requires sophisticated implementation. Addressing these challenges through a combined approach that enhances GAN realism, refines continual learning, and optimizes real-time processing can lead to more adaptable and effective defect detection systems, advancing quality control in the textile industry.

Challenges and Future Directions

While deep learning has significantly advanced fabric defect detection, several challenges must be addressed to fully leverage these technologies in industrial settings. A primary challenge is the scarcity and quality of data, as high-quality, annotated datasets are essential for training robust models but are costly and time-consuming to obtain. Synthetic data generation techniques, such as Deep Convolutional Generative Adversarial Networks (DCGANs), offer a solution, yet often fall short in capturing the full diversity and complexity of real-world defects (Ahmad et al., 2024). Enhancing the realism and variability of synthetic data remains crucial for bridging the gap between simulated and actual defect patterns.

Another critical challenge is model adaptability to new and evolving defect types. As production environments and defect profiles change, models must continuously adapt without suffering from catastrophic forgetting. Lifelong Deep Neural Networks (L-DNNs) have been developed to address this by enabling continuous learning, but balancing old and new knowledge remains complex, especially in industrial applications (Luciw, 2018). Ensuring that models maintain accuracy while adapting to new defects is essential.

Real-time processing further complicates the deployment of deep learning models. Systems must operate efficiently across varying conditions while maintaining speed and accuracy. Techniques like variational autoencoders combined with mean structural similarity (MSSIM) have shown promise in enhancing real-time detection accuracy, but consistency across different fabrics and defect patterns remains a challenge (Wei et al., 2021). Developing models that optimize both speed and accuracy is vital for their reliability in diverse industrial contexts.

Integration into existing industrial workflows presents additional complexity. Despite advancements with models like CNNs enhanced with attention modules, their implementation often requires significant infrastructure changes, which can be disruptive and resource-intensive (Kim & Lee, 2024). The development of scalable, user-friendly solutions that integrate seamlessly into current production

lines is necessary. Exploring hybrid approaches that combine different deep learning models could offer more adaptable and less invasive solutions.

Future research should focus on building more robust, adaptable models that can handle the complexities of real-world environments. Enhancing interpretability and generalizability is key for broader industry acceptance. Continued innovation in data augmentation, particularly in improving synthetic data realism, is essential. Techniques like transfer learning and domain adaptation can help models generalize better across different fabrics and defect patterns, reducing the need for extensive labeled datasets.

In conclusion, addressing challenges related to data scarcity, model adaptability, real-time processing, and industrial integration is crucial for advancing deep learning in fabric defect detection. By focusing on these areas, the industry can develop more robust, efficient, and practical solutions, ultimately transforming quality control in the textile sector.

Conclusion

The exploration of deep learning techniques in fabric defect detection has illuminated significant strides in enhancing accuracy, efficiency, and adaptability within industrial quality control processes. However, as the field advances, several challenges persist that must be addressed to fully realize the potential of these technologies. Data scarcity remains a critical issue, necessitating further innovation in synthetic data generation to produce more realistic and diverse training datasets. Model adaptability, particularly the ability to manage catastrophic forgetting while continuously learning, is another area requiring focused research. Real-time processing capabilities must be optimized to ensure that defect detection systems can maintain high performance across diverse environments without compromising speed or accuracy. Additionally, the integration of these advanced techniques into existing industrial workflows demands scalable and non-disruptive solutions that can seamlessly enhance production processes.

Future research should prioritize the development of robust, adaptable models that are not only effective in controlled environments but also capable of generalizing across varied real-world contexts. The pursuit of hybrid approaches that combine different deep learning techniques holds promise for overcoming current limitations. Moreover, enhancing the interpretability and generalizability of models will be crucial for gaining broader acceptance in the industry. By addressing these challenges, the deployment of deep learning solutions in fabric defect detection can be significantly advanced, leading to transformative improvements in quality control within the textile industry. The continued evolution of these technologies will not only drive efficiency and accuracy but also ensure that fabric manufacturing meets the increasingly stringent demands of modern production standards.

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LEVERAGING LARGE LANGUAGE MODELS IN CYBERSECURITY: A SYSTEMATIC REVIEW OF EMERGING METHODS AND TECHNIQUES

T Sandaruwan[1], J Wijayanayake[2] and J Senanayake[3]

Abstract

This systematic literature review examined how Large Language Models (LLMs) can be incorporated with vulnerability scanning and other cybersecurity tools and explored and assessed ways to improve cybersecurity practices. The PRISMA model was used, and the search was conducted using specific search terms in the leading databases such as the ACM Digital Library, IEEE Xplore Digital Library, and ScienceDirect from 2018 to July 2024. Initially, 313 records were gathered and reduced the count was reduced to 48 articles after applying the inclusion criteria. The findings were structured to answer the research questions regarding the approaches applied to incorporate LLMs with cybersecurity tools and the strengths and limitations of these tools based on the identified methodologies. The methods were reviewed and classified into Training and Adaptation Methods, Integration and Deployment Methods, and Inference and Utilization Techniques. After that, the accuracies of these methods were presented. The results show that fine-tuning and domain adaptation improves LLMs' performance in cybersecurity tasks. In addition, fine-tuning, prompt engineering, and few-shot learning enhance models for specific tasks, making them more efficient in practical applications.

Keywords: Cybersecurity, Integration, Large Language model, Scanning, Vulnerability

[1] Undergraduate, Department of Industrial Management, University of Kelaniya, Sri Lanka

Email: m.tharuka.sandaruwan@gmail.com https://orcid.org/0009-0003-9753-6732

[2] Professor, Department of Industrial Management, University of Kelaniya, Sri Lanka

Email: janaka@kln.ac.lk https://orcid.org/0000-0002-9523-5384

[3] Lecturer, Department of Industrial Management, University of Kelaniya, Sri Lanka

Email: janakas@kln.ac.lk https://orcid.org/0000-0003-2278-8671

Introduction

Background of the Study

In the digital era, cybersecurity has become a critical global issue, necessitating strong measures to protect digital infrastructures (Von Solms & Van Niekerk, 2013). Cybersecurity involves various tools, techniques, policies, and strategies to secure cyberspace and user assets. Vulnerability scanning is a key step in identifying security weaknesses that could be exploited by malicious actors (Liao et al., 2020). According to Humayun et al. (2020), vulnerabilities are system flaws that allow attackers to execute unauthorized actions. Addressing these vulnerabilities is crucial, and cybersecurity professionals often use open-source tools like Nmap and Metasploit for vulnerability analysis (Khan & Parkinson, 2018). These tools are essential for maintaining data confidentiality, availability, and integrity.

Recent advancements in Large Language Models (LLMs) have shown a potential to enhance cybersecurity tools significantly (Bubeck et al., 2023; Iyengar & Kundu, 2023; McClanahan et al., 2024; Mohammed & Hossain, 2024). LLMs like GPT-4, trained on diverse datasets, excel in understanding and generating human-like text and performing complex natural language processing tasks such as translation, question answering, and summarization (Zhang et al., 2024). Their ability to perform accurate sentiment analysis demonstrates their utility in understanding the nuances of security threats, which could lead to more sophisticated vulnerability scanning tools (H. Li & Shan, 2023; Mohamed Firdhous et al., 2023).

Integrating LLMs in cybersecurity is gaining research interest, showing significant advancements and potential for innovation. Ansari et al. (2022) highlighted that machine learning algorithms can outperform human efforts in cybersecurity, enhancing accuracy and minimizing errors. Tann et al. (2023) demonstrated that LLMs could improve cybersecurity training through simulated breach scenarios and detailed explanations in Capture the Flag (CTF) tasks. These studies emphasize LLMs' diverse applications and benefits in enhancing cybersecurity measures.

Research Problem

Despite the significant advancements in integrating LLMs with cybersecurity tools, this area remains in its earlier stages, resulting in a lack of comprehensive resources and literature reviews. Therefore, this literature review aims to systematically examine existing research on integrating LLMs with vulnerability scanning and other cybersecurity tools. This review seeks to address the following research questions, thereby assisting future researchers in selecting the most suitable approaches for integrating LLMs into their cybersecurity studies:

RQ1: What methods and techniques have been proposed or implemented for using large language models in cybersecurity?
RQ2: What are the strengths and limitations of the methods and techniques identified in existing literature?

Methodology

The Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) model (Page et al., 2021) guided this review to systematically analyze research in this field. Initially, a search strategy was crafted to locate relevant studies addressing the research questions. The databases to be used and the inclusion and exclusion criteria were defined. The processes of study selection, data extraction, and synthesis were then conducted to identify studies that answered the research questions.

Search Strategy

The search strategy entailed identifying the most relevant bibliographic sources and search terms. For this review, several top research repositories, including the ACM Digital Library, IEEE Xplore Digital Library, and ScienceDirect, were used as primary sources to locate pertinent studies. The search string employed was “vulnerability AND ("large language model" OR llm) AND scan NOT code AND attack”.

Following the release of the paper titled "Attention is All You Need" in 2017(Vaswani et al., 2017), which introduced the transformer architecture, there has been significant interest in LLMs and their applications. With the subsequent release of BERT (Devlin et al., 2018) and GPT-1 (Radford et al., 2018) In 2018, research integrating the power of LLMs into various fields surged. However, there have been comparatively fewer studies in the domain of cybersecurity. Given these factors, technical studies from 2018 to July 2024 were reviewed.

The distribution of search results across primary sources for each search term is detailed in Table 1. Additionally, Google Scholar was utilized to identify research studies published in quality venues, as it can uncover research not available in the primary repositories.

Table 8: Search Results Distribution Across Primary Sources for Each Search Term

Search Term	ACM	IEEEXplore	Science Direct	Total Count
large language model	64,549	11,077	201,758	**277,384**
llm	2,082	720	2,161	**4,963**
vulnerability	17,801	16,945	280,460	**315,206**
scan	3,523	580	46,903	**51,006**
Complete Search String	18	34	134	**186**

Study Selection, Data Extraction, and Synthesis

Initially, 313 research papers were identified—186 from a research database and 127 from Google Scholar. After removing 142 duplicates, 171 records remained for the initial screening. Due to the tendency of research repository search engines to list irrelevant results, the titles and abstracts of the remaining papers were manually reviewed for relevance. This step excluded 124 records that did not align with the review's focus, leaving 47 studies. An additional relevant paper was identified through the snowballing process, bringing the total to 48 papers included in the study.

Fig. 2 summarizes the paper selection method for this systematic review.

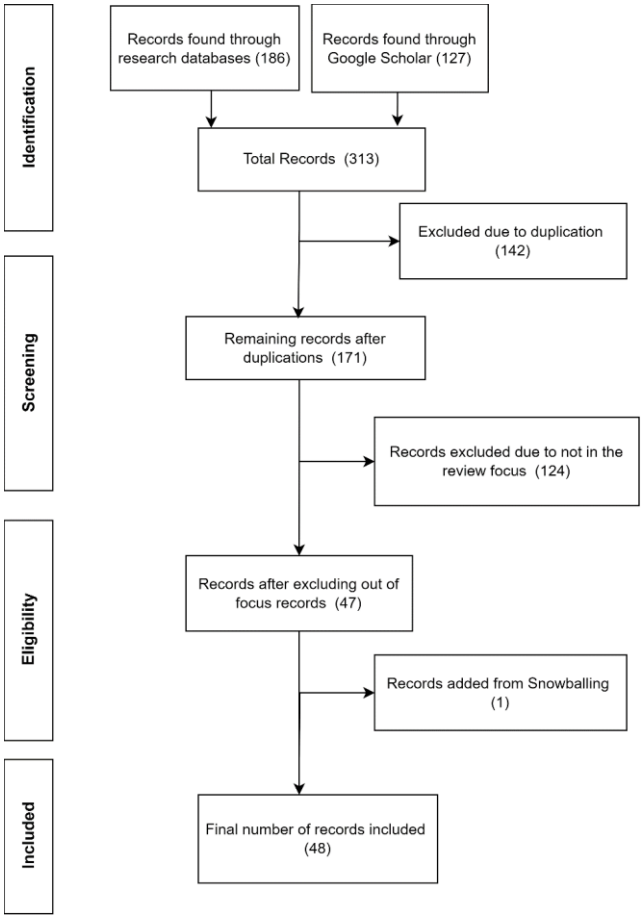

Figure 9: PRISMA Method: Collection of Papers for the Review.

Results and Discussion

LLM Integration in Cybersecurity Tools Techniques and Methods

This study addresses two primary research questions, divided into three main sections: Training and Adaptation Methods, Integration and Deployment Methods, and Inference and Utilization *Techniques. These categories enable a systematic analysis of various LLM integration approaches in cybersecurity.* To address the first research question, the methods used to integrate LLMs with cybersecurity toolsets are identified and analyzed. Each section explores specific techniques and methods, providing a comprehensive understanding of LLM integration in cybersecurity.

For the second research question, the latter part of each section evaluates the strengths and weaknesses of these methods, offering a balanced view of their efficacy and limitations.

The following table offers an overview of analyzed tools and methods used to integrate LLMs within cybersecurity contexts, categorizing them based on employed methods, specific LLMs used, and achieved accuracy measures.

Table 9: Summary of the Identified Tools Based on the Gathered Papers

Name of the Tool	Methods Used	LLMs Used	Accuracy Measures
RAG-based LLM Chatbot using Llama-2 (Vakayil et al., 2024)	Fine Tuning, Template Based Prompting, Retrieval-Augmented Generation (RAG)	Llama-2-7b	Above 95%
FuzzLLM (D. Yao et al., 2024)	Prompt Engineering, Template Based Prompting, Rule Based Augmentation, Fine Tuning	Vicuna-13B, CAMEL-13B, LLAMA-7B, ChatGLM2-6B, Bloom-7B, LongChat-7B, GPT-3.5-turbo, GPT-4	Varies by model and attack class. Averaged 52.60%
GPTScan (Sun et al., 2024)	Prompt Engineering, Few-Shot Learning, Template Based Prompting	GPT-3.5-turbo	High precision over 90% for token contracts, 57.14% for large projects like Web3Bugs
GPT-based open-source intelligence using historical cyber incident reports (Sufi, 2024)	Prompt Engineering, Few-Shot Learning	GPT-4	High level of accuracy with an average precision, recall, and F1-Score of 96, 98, and 97.
BiT5 (Gs et al., 2024)	Fine Tuning, Transfer Learning, Self-supervised Learning, Modular Architecture	Transformer-based models (BiT5)	97.47%
PENTESTGPT (Deng et al., 2024)	Modular Architecture, Prompt Engineering, Few-Shot Learning, Template Based Prompting	GPT-3.5, GPT-4	Outperforms GPT-3.5 with a task-completion increase of 228.6% and GPT-4 with an increase of 58.6%
ZDDR (M. Chen et al., 2024)	Prompt Engineering, Self-Supervised Learning, Template Based Prompting	GPT-3.5, Vicuna-13b, Claude 2	Over 92% classification accuracy for rephrased adversarial samples
LogPrcis (Boffa et al., 2024)	Fine-Tuning, Few-Shot Learning, Domain Adaptation, Self-Supervised Learning	CodeBERT	Multiple accuracies over various implementations of BERT models.All are above 77%
CVE Severity Prediction From Vulnerability Description - A Deep Learning Approach (A et al., 2024)	Fine Tuning and Domain Adaptation, Transfer Learning, Contextual Data Augmentation	GPT-2	84.2%
POISONPROMPT (H. Yao et al., 2023)	Prompt Engineering, Template Based Prompting, Next Sentence Prediction	BERT, RoBERTa, LLaMA	Varies according to the llm and dataset.Accuracy ranging from 52% to 95%
Toolformer (Schick et al., 2023)	Self-supervised learning, Few-Shot Learning, Prompt Engineering	GPT-J (6.7B parameters)	Varies according to datasets.According to T-rex dataset it is 53.5% the best result
Multi-step Jailbreaking Privacy Attacks (Li et al., 2023)	Prompt Engineering, Few-Shot Learning, Template Based Prompting	ChatGPT	Institutional Email: 94.00%, Institutional Phone: 48.00%, Enron-frequent Email: 85.00%, Enron-infrequent Email: 15.00%
Moving Target Defense (MTD) (B. Chen et al., 2023)	Random Selection, Response Evaluation, Binary Classification for Response Helpfulness, BERT-based Coherence Assessment	ChatGPT 3.5, ChatGPT 4, Google Bard, Anthropic, LLama2-7B HuggingFace, LLama2-13B HuggingFace, LLama2-70B HuggingFace, LLama2-7B Perplexity	Curtailing adversarial attack success rates by 37.5% to 0%, diminishing refusal rate from 50% to 0%
VWC-MAP (Das et al., 2022)	Fine Tuning and Domain Adaptation, Transfer Learning, Link Prediction, Text-to-Text Mapping	BERT, T5	CVEs to CWEs: up to 87% and CWEs to CAPECs: up to 80%
CyBERT (Ranade et al., 2021)	Fine Tuning, Masked Language Modelling, Named Entity Recognition (NER), Multi-Class Classification	BERT	98% evaluation accuracy for multi-class classification
HARMer (Enoch et al., 2020)	Transfer Learning,Masked Language Modeling	BERT	Not specified
Net-GPT (Piggott et al., n.d.)	Fine Tuning, Prompt Engineering	Llama-2-13B, Llama-2-7B, Distil-GPT-2	95.3% for Llama-2-13B, 94.1% for Llama-2-7B, 77.9% for Distil-GPT-2

Training and Adaptation Methods

Training and Adaptation Methods focus on how to prepare and customize large language models (LLMs) for specific tasks or domains. This involves techniques to train models with limited data, adapt pre-trained models to new domains, and leverage unlabeled data for self-supervised learning. The goal is to enhance the model's performance and relevance for particular applications, ensuring it can handle specialized tasks effectively.

There have been several adaptations of these methods when considering the literature

Fine Tuning and Domain Adaptation

Domain adaptation and fine-tuning are critical techniques for enhancing language models in specialized tasks, such as cybersecurity. These methods involve adapting general models to specific domains and fine-tuning them for particular tasks, thereby improving accuracy and effectiveness (Boffa et al., 2024). For instance, CyBERT (Ranade et al., 2021), a BERT-based model, is fine-tuned with a large corpus of cybersecurity text. This process adapts the general BERT model to the cybersecurity domain by training it on specialized terminology and context. Consequently, CyBERT excels in tasks such as Named Entity Recognition (NER), identifying entities like "SQL Injection" or "Privilege Escalation" (Ranade et al., 2021). The fine-tuning process employs Masked Language Modeling (MLM) on a large corpus of unlabeled cybersecurity text, enhancing the model's understanding of cybersecurity vocabulary and context. This training improves its performance on tasks such as vulnerability and exploit search, cybersecurity-based NER, and cybersecurity knowledge graph completion (Ranade et al., 2021).

Similarly, LogPrecis (Boffa et al., 2024) leverages domain adaptation to enhance language model performance on cybersecurity tasks. For example, CodeBERT (S. Yao et al., 2023), initially trained for code analysis, is adapted for malicious log analysis. This involves training the model on labeled samples of malicious logs, improving its ability to identify and classify various malicious activities in log data (Cotroneo et al., 2024).

SecureBERT is another domain-specific language model trained on a large corpus of cybersecurity text. The domain adaptation process aligns the model's prior knowledge with cybersecurity language, enabling it to perform nuanced tasks in this field (Z. Liu, 2024). Fine-tuning SecureBERT on specific cybersecurity tasks, such as classifying features of industrial control systems (ICS) devices, improves its accuracy in identifying and classifying cybersecurity threats and vulnerabilities (Z. Liu, 2024).

Critical appraisal of these studies indicates robust methodological approaches, particularly in fine-tuning processes like MLM for CyBERT and training on labeled samples for LogPrecis. This methodological rigor ensures the models are well-suited to handle specific terminologies and contexts in cybersecurity tasks. These studies employ comprehensive datasets and rigorous training protocols, contributing to their reliability and validity. However, future research should explore integrating these models with real-time cybersecurity systems and assess their performance in dynamic environments. Further investigation could also expand training datasets to include more diverse and evolving cybersecurity threats, enhancing the models' adaptability and robustness.

Transfer Learning

Transfer learning is a machine learning technique where a pre-trained model is adapted to perform a specific task, leveraging knowledge from a broader dataset (Ranade et al., 2021). This approach has shown significant promise in cybersecurity, enhancing the detection, analysis, and mitigation of cyber threats.

CANBERT (Z. Liu, 2024) utilizes BERT for real-time anomaly detection in vehicular networks. By adapting the general BERT model to the CAN bus protocol, CANBERT effectively detects a range of cyber threats. Similarly, IDS-INT combines transformer-based transfer learning with the SMOTE technique and a CNN-LSTM model to address data imbalance and complex feature interactions in network traffic, enhancing intrusion detection capabilities (Chalvatzis et al., 2019).

RPBert integrates transfer learning and rules for detecting and classifying network intrusions (Jiang et al., 2021). V2WBERT, a transformer-based learning framework, automates the mapping of vulnerabilities to weaknesses, achieving high prediction accuracy through NLP and transfer learning (Z. Liu, 2024). VulBERTa (Happe & Cito, 2023) pre-trains a RoBERTa model on source code for vulnerability detection, adapting it to improve performance in identifying vulnerabilities.

Evaluating these studies reveals certain limitations and areas for improvement. While models like CANBERT and IDS-INT leverage advanced techniques, the potential biases in pre-trained models and the datasets used for fine-tuning are not extensively discussed. These biases could affect the models' generalizability across different environments. Comprehensive validation and testing in diverse, real-world scenarios are necessary to ensure robustness and reliability. Future research should focus on addressing these biases, improving model interpretability, and expanding the scope of datasets. Incorporating explainable AI techniques could provide deeper insights into model decisions, enhancing trust and transparency in critical cybersecurity applications.

Masked Language Modelling

Masked Language Modeling (MLM) is a technique used in training transformer-based models. In MLM, some tokens in a sentence are randomly or selectively masked, and the model's task is to predict the original tokens that were masked. (Ranade et al., 2021).

SecBERT is a BERT model trained on cybersecurity texts, including advanced persistent threat (APT) notes and malware-related texts. The MLM technique used during the training process helps the model learn the specific language and patterns used in these texts, thereby improving its performance on cybersecurity-related tasks (Z. Liu, 2024). Additionally, ThreatCrawl is a BERT-based focused crawler designed to automate the scanning of online portals for Cyber Threat Intelligence (CTI). It uses MLM to dynamically classify documents and adapt its crawling path, surpassing current state-of-the-art solutions in identifying and extracting relevant cybersecurity information (Z. Liu, 2024). The integration of MLM in these models increases the effectiveness of enabling cybersecurity tools to handle specialized languages and texts.

While ThreatCrawl's dynamic document classification and adaptive crawling paths represent a significant advancement, the model's effectiveness is contingent on the diversity and comprehensiveness of the training data.

Next Sentence Prediction

Next Sentence Prediction (NSP) is a training objective used in language models like BERT to predict whether a given sentence logically follows another. During training, models are given pairs of sentences, with 50% being consecutive from the original text and 50% randomly selected. This allows the model to learn sentence relationships and improve tasks requiring sentence order and coherence understanding (Babalau et al., 2021).

Similarly, CyBERT, a BERT-based model fine-tuned with cybersecurity texts, uses NSP during training. This helps the model understand sentence relationships in cybersecurity contexts, enhancing tasks such as Named Entity Recognition (NER), threat classification, and Cybersecurity Knowledge Graph (CKG) completion (Ranade et al., 2021). By grasping the context and sequence of sentences, CyBERT can better identify and categorize cybersecurity threats and vulnerabilities.

NSP in training models like BERT and CyBERT offers strengths and weaknesses. It enhances sentence relationship understanding, crucial for complex domains like cybersecurity. This is beneficial for NER, threat classification, and CKG completion. However, NSP can introduce biases since random non-consecutive sentences might not represent true sentence transitions, skewing model understanding. Additionally, NSP may not fully capture nuanced relationships in intricate texts.

Studies by Babalau et al. (2021) and Ranade et al. (2021) provide a solid foundation for applying NSP in specific domains. However, more rigorous validation and broader datasets are needed for generalization. Future research should address biases and explore sophisticated methods to enhance sentence relationship understanding, such as richer contextual information or multi-sentence dependencies, to improve models like CyBERT in cybersecurity and other specialized fields.

Self-Supervised Learning

Self-supervised learning is a type of machine learning where models learn to predict part of their input from other parts of the input without requiring labeled data. This approach leverages large amounts of unlabelled data to create pseudo-labels, which the model then uses to train itself. (Schick et al., 2023)

One notable example is Toolformer, a model that learns to use external tools in a self-supervised way. Toolformer (Schick et al., 2023) generates datasets from scratch using in-context learning and annotates a large language modeling dataset with potential API calls. The model then employs a self-supervised loss to determine which of these API calls help in predicting future tokens. This method allows the model to learn how and when to use tools without requiring specific prompts or large amounts of human annotations.

Another innovative application is a GPT-based solution for obtaining semantically enriched contextual information on historical cyber incidents. (Sufi, 2024). This involves using tailored prompt engineering to interact with GPT models and generate detailed information on various aspects of cyber incidents, such as actor type, target, attack source, and attack type. The enriched information is then utilized to support AI-based algorithms like anomaly detection and question-answering. These examples illustrate how self-supervised learning is leveraged in cybersecurity tools to enhance their ability to understand and process domain-specific language.

By enabling models to learn from their own predictions and interactions, self-supervised learning reduces the dependency on labeled data and human annotations. This allows them to adapt to new and evolving cybersecurity threats more effectively.(Schick et al., 2023)

This method's strength lies in its capacity to generate pseudo-labels and learn from its own predictions, making it highly adaptive to new and evolving threats, particularly in dynamic fields like cybersecurity. Toolformer, for instance, showcases the effective utilization of self-supervised learning by generating datasets autonomously and annotating them with potential API calls, which enhances its predictive capabilities without human intervention. Similarly, Sufi's (2024) application of GPT models for historical cyber incident analysis demonstrates the potential of tailored prompt engineering to enrich contextual understanding, thus supporting advanced AI algorithms. However, a notable weakness is the initial reliance on high-quality in-context learning examples to kick-start the self-supervised process, which can be challenging to curate. Moreover, the quality of the generated pseudo-labels and annotations is crucial, as errors in these can propagate and affect model performance. Future research should focus on refining the self-supervised learning processes to enhance the accuracy of pseudo-label generation and explore its applicability across various domains. Additionally, rigorous evaluations and comparative studies are necessary to establish the reliability and generalizability of these methods, ensuring they can effectively address the complexities of real-world applications (Schick et al., 2023; Sufi, 2024).

Integration and Deployment Methods

Integration and Deployment Methods encompass the strategies and techniques used to incorporate LLMs into existing systems and workflows. This includes using APIs to connect models with other software tools and creating modular architectures to handle specific subtasks. Effective integration and deployment ensure that LLMs can be seamlessly embedded into larger systems, enabling them to perform their functions reliably and efficiently in real-world applications.

Modular Architecture

Modular architecture in the context of integrating tools with large language models (LLMs) refers to the use of distinct, interchangeable components that can be independently developed and combined to create a cohesive system. This approach allows developers to utilize various data sources and applications seamlessly. (Topsakal & Akinci, 2023)

One example of modular architecture in cybersecurity is EXPLOITFLOW, a library designed to produce cybersecurity exploitation routes (Deng et al., 2024). It captures the state of the system being tested after every discrete action, enabling the learning of attack trees that affect a given system. This modular approach allows EXPLOITFLOW to integrate with various penetration testing tools and scripts, such as Metasploit, to perform end-to-end penetration testing. This facilitates and empowers research in game theory and artificial intelligence within cybersecurity (Deng et al., 2024). Another example is the MALISM Framework, which is designed for fully automated penetration testing tools. It includes several modular components such as EXPLOITFLOW for producing security exploitation routes, PENTESTGPT for leveraging large language models to produce testing guidance heuristics, and PENTESTPERF for benchmarking the performance of penetration testers and automated tools (Deng et al., 2024).

HARMer (Enoch et al., 2020) is another tool that exemplifies modular architecture in cybersecurity. It uses a two-layered Hierarchical Attack Representation Model (HARM) to generate a comprehensive view of potential attack paths. This modular approach captures and enumerates all possible attack scenarios, allowing for detailed security analysis and decision-making based on various security metrics. The design enables the integration of different security tools, such as OpenVAS, Nessus, and Nmap, to collect host vulnerability information, operating systems, services, and ports (Enoch et al., 2020). HARMer's attack planning phase is responsible for generating actions for the adversary attacker agent, which can include responses from the next host target, port scanning, IP ranging, or targeted actions such as exploiting a software vulnerability. The modular architecture allows for the use of different approaches to strategically generate possible attack plans (Enoch et al., 2020).

One of the significant strengths is its flexibility and adaptability, as evidenced by tools like EXPLOITFLOW and HARMer, which can seamlessly incorporate various penetration testing tools, enabling comprehensive and dynamic security assessments (Deng et al., 2024; Enoch et al., 2020). This modularity also facilitates specialized research in fields like game theory and artificial intelligence within cybersecurity, offering a broad platform for innovation (Topsakal & Akinci, 2023). However, a potential weakness lies in the complexity and interoperability challenges that can arise when integrating multiple, independently developed components. Ensuring compatibility and seamless communication between different modules can be difficult, potentially leading to inefficiencies or integration bottlenecks. Evaluating the study quality, the cited works provide robust frameworks and methodologies, but there is often limited empirical data on long-term performance and real-world applicability, indicating a need for more extensive field studies to validate these approaches. Future research should focus on enhancing the interoperability of modular components and developing standardized protocols to streamline integration processes. Additionally, there is a need for longitudinal studies to assess the effectiveness and resilience of these modular systems in diverse, real-world cybersecurity scenarios (Deng et al., 2024; Enoch et al., 2020).

Inference and Utilization Techniques

Inference and Utilization Techniques focus on how to effectively use LLMs for generating outputs and solving tasks in practical applications. This involves crafting prompts to elicit desired responses with prompt engineering and combining LLMs with other models or rule-based systems to enhance performance.

Prompt Engineering

Prompt engineering is the process of designing and optimizing prompts to guide pre-trained language models (LMs) in performing specific tasks. This involves creating prompt templates that specify the

task, which can significantly impact the model's accuracy and behavior. This approach aids in generating CIS CSC enforcement implementation by creating a prompt template that includes a query, ontology definition, and output format, thereby extracting and generating feasible CSC ontology from safeguard descriptions (Ahmed et al., 2024).

Prompt engineering also plays a crucial role in identifying and exploiting vulnerabilities in LLMs by creating adversarial examples that bypass safety protocols (D. Yao et al., 2024). Researchers have streamlined testing and validation by categorizing jailbreak prompts into broader classes, automating the validation process to enhance efficiency and comprehensiveness (Chen et al., 2023). Additionally, prompts are designed to improve the performance of LLMs like ChatGPT in tasks such as software vulnerability prediction, classification, severity estimation, and automated vulnerability repair (Fu et al., 2023). For example, prompts instruct the model to predict whether a source code function is vulnerable and rank vulnerable statements, thus reducing manual analysis workload (Fu et al., 2023). Specific prompts guide the model's output for tasks like CWE-ID classification, vulnerability severity estimation, and automated vulnerability repair (Fu et al., 2023).

Tailored prompt engineering is also used to orchestrate communications with GPT models to obtain semantically enriched contextual information on major cyber incidents, supporting AI-based algorithms for tasks like anomaly detection and smart narratives (Sufi, 2024). Prompts optimize questions for penetration testing, helping identify security vulnerabilities by reflecting on executed command outputs and adding relevant extracted information to the next prompt's context, thereby improving penetration testing effectiveness (Happe & Cito, 2023).

Prompt engineering demonstrates considerable strengths in optimizing large language models (LLMs) for various cybersecurity tasks, including CIS CSC enforcement implementation, vulnerability prediction, and anomaly detection. Its capacity to tailor prompts for specific objectives significantly enhances the accuracy and relevance of LLM outputs, thus reducing manual analysis workload and improving efficiency (Ahmed et al., 2024; Fu et al., 2023). However, the methodology also exhibits some weaknesses, particularly concerning the creation of adversarial examples that could exploit vulnerabilities in LLMs, posing significant security risks (D. Yao et al., 2024). The quality of studies like those by Chen et al. (2023) and Fu et al. (2023) is robust, as they employ systematic approaches to categorize and automate validation processes, yet the generalizability of their findings could be limited by the specific models and datasets used.

Few-Shot Learning

Few-shot learning is a technique that enhances the performance of language models like GPT-3 by allowing them to learn from a limited number of examples. This approach is particularly beneficial in tasks such as software vulnerability prediction, classification, severity estimation, and automated vulnerability repair. By incorporating a few examples into the prompt, the model can better comprehend and execute these tasks, thereby reducing the manual analysis workload (Brown et al., 2020). Additionally, few-shot learning is employed to generate and optimize questions for penetration testing. Providing a few examples of the task in the prompt enables the model to grasp the context more effectively and generate pertinent questions, thus improving the efficacy of penetration testing (Hu et al., 2020). The application of few-shot learning in these areas demonstrates its potential to streamline and enhance complex tasks, making processes more efficient and less reliant on extensive manual input.

A notable strength is its ability to enhance task performance with minimal examples, thereby reducing the manual workload required for complex analyses (Brown et al., 2020). This approach is particularly

advantageous in rapidly evolving fields like cybersecurity, where timely and accurate predictions are crucial. However, a potential weakness lies in the reliance on the quality and representativeness of the provided examples; if the examples are too narrow or not sufficiently diverse, the model's performance may be compromised. The study quality supporting the application of few-shot learning appears robust, given the empirical success reported in various tasks.

Rule-Based Augmentation

Rule-based augmentation in cybersecurity tools refers to the application of predefined rules and patterns to enhance the performance of machine learning models. This technique is particularly useful in creating additional training data, standardizing methodologies, and addressing data imbalances. By leveraging rule-based augmentation, cybersecurity tools can improve their accuracy and effectiveness across various tasks.

One notable example is CyBERT for Named Entity Recognition (NER). CyBERT, a BERT-based model fine-tuned for the cybersecurity domain, employs rule-based augmentation to boost its NER capabilities. This involves generating supplementary NER datasets with diverse examples that help the model accurately predict entities such as "SQL Injection" or "Privilege Escalation." The use of these techniques allows CyBERT to better identify specific cybersecurity-related entities by providing more comprehensive training data (Ranade et al., 2021).

In another instance, automated attack tree generation benefits from rule-based augmentation by standardizing how methodologies employed by attacking systems are categorized (Falco et al., 2018). A master attack rule set is created and applied across different system types and industry sectors. This approach ensures that an attack tree generator can incorporate a wide range of attack goals and methodologies effectively across various critical infrastructure sectors.

Rule-based augmentation in cybersecurity tools presents a compelling approach to enhancing machine learning models, but it comes with its own set of strengths and weaknesses. One significant strength is its capability to generate supplementary training data, thereby addressing data imbalances and enriching the model's exposure to diverse examples (Ranade et al., 2021). This is particularly evident in the case of CyBERT for Named Entity Recognition (NER), where rule-based augmentation aids in accurately identifying cybersecurity-specific entities such as "SQL Injection" and "Privilege Escalation." Another advantage is the standardization it brings to methodologies, as seen in automated attack tree generation, which ensures consistent application across different systems and industry sectors (Falco et al., 2018). However, one of the weaknesses is that rule-based systems can sometimes be overly rigid, potentially missing nuanced or novel attack patterns that fall outside predefined rules. Evaluating the quality of studies like those by Ranade et al. (2021) and Falco et al. (2018) reveals a solid methodological foundation but also indicates a need for further empirical validation to generalize findings across more diverse datasets and real-world scenarios.

Template Based Prompting

Template-based prompting involves modifying the original input text using a predefined template that includes unfilled slots. These slots are then filled by a language model to generate a final output.(P. Liu et al., 2023)

Jailbreak prompts are one such application, consisting of three fundamental components: templates, constraints, and question sets (H. Li et al., 2023; Wei et al., n.d.). The template outlines the structure for an entire class of attacks and includes placeholders that are later filled with specific constraints and

illegal questions. This approach facilitates the automated creation of diverse prompts aimed at testing the robustness of LLMs against jailbreak attacks. Another critical use case is severity classification; here a hard prompt template might be defined as: "Classify the severity of the following vulnerability description." The input slot is populated with text describing a vulnerability, enabling the model to predict probability distributions over label words (X. Li et al., 2023).

In terms of automated vulnerability repair, templates like "Given the following vulnerable function, generate a repair patch" prompt models to create patches for identified vulnerabilities within the code (Fu et al., 2023). Similarly useful for pinpointing issues within code is function and line-level vulnerability prediction; an example template could be: "Rank the top 10 most vulnerable-prone statements from this given function," which directs models to identify and rank lines most susceptible to vulnerabilities within provided functions (Fu et al., 2023).

Exploitability classification also benefits from template-based prompting akin to severity classification methods. Initially tuned on extensive datasets for severity assessment using appropriate prompts and verbalizers modified subsequently for exploitability evaluation with fewer samples can yield effective results in this domain as well (P. Liu et al., 2023).

One of its primary strengths lies in its ability to automate the creation of diverse prompts that test the robustness of language models (LLMs), thereby facilitating a thorough evaluation of LLMs' resilience against specific attacks. Additionally, by providing a structured framework with predefined templates and slots for constraints or questions, it streamlines the process of generating specific outputs, such as vulnerability patches or severity classifications. However, a notable weakness is the potential for overfitting to the templates, which may limit the model's generalizability to unseen data or different contexts. The quality of studies on this method varies; while some provide comprehensive evaluations using large datasets and well-defined metrics (Fu et al., 2023), others might lack rigorous validation, leading to questions about the replicability and scalability of their findings.

Conclusion

The systematic literature review on the use of Large Language Models (LLMs) in cybersecurity highlights the significant role of Training and Adaptation Methods, particularly fine-tuning and domain adaptation, in enhancing model performance for specific tasks. Models like CyBERT and SecureBERT, fine-tuned with domain-specific data, demonstrate improved accuracy in tasks such as Named Entity Recognition (NER) and threat classification, crucial for Security Operations Centers (SOCs). The review also emphasizes the effectiveness of combining multiple techniques, including fine-tuning, prompt engineering, and few-shot learning, to tailor LLMs to the cybersecurity domain and optimize performance with minimal training examples. This multi-technique approach not only increases accuracy but also enables the models to adapt swiftly to new cybersecurity challenges. While self-supervised learning shows variable results, its integration with template-based prompting can enhance its effectiveness in processing domain-specific language. Overall, the integration of various LLM techniques, including prompt engineering with rule-based and template-based prompting, refines the models' task-specific capabilities and ensures reliability and precision in real-world applications, underscoring the transformative potential of LLMs in advancing automated cybersecurity solutions.

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DEVSECOPS FOR CONTINUOUS SECURITY IN TRADING SOFTWARE APPLICATION DEVELOPMENT: A SYSTEMATIC LITERATURE REVIEW

SDLV Dasanayake[1], J Senanayake[2] and WMJI Wijayanayake[3]

Abstract

This systematic literature review examined the implementation of DevSecOps for continuous security in financial trading software application development. This review identifies key strategies and security frameworks, analyzes cybersecurity threats specific to trading applications, explores secure coding practices, and discusses the transition from DevOps to DevSecOps, focusing on security. A comprehensive search was conducted across multiple databases up to July 9, 2024. The study aimed to identify best practices for integrating security into every phase of the software development process, from initial design to deployment and maintenance. This included automated security testing, continuous monitoring, and incident response strategies tailored for financial trading platforms. The review also delved into the specific challenges faced by developers in the financial sector, such as compliance with stringent regulatory requirements and the need to protect highly sensitive financial data. Furthermore, it evaluated the effectiveness of current security frameworks in mitigating risks associated with trading software, including common vulnerabilities and attack vectors. The study had limitations, including the exclusive consideration of the most recent threats, potentially overlooking relevant historical data. Additionally, the focus on financial trading applications may limit the generalizability of the findings to other domains. Despite these limitations, the results highlighted the critical importance of incorporating DevSecOps concepts into software development processes to enhance the security and resilience of financial trading systems in an increasingly hostile cyber environment. This research underscores the need for continuous adaptation and improvement in security practices to keep up with evolving threats.

Keywords: DevSecOps, frameworks, security, threats, trading

[1] Department of Industrial Management, University of Kelaniya, Sri Lanka.

Email: lashadyavidumini@gmail.com https://orcid.org/0009-0007-3725-6658

[2] Robert Gordon University, UK. & University of Kelaniya, Sri Lanka.

Email: janakas@kln.ac.lk https://orcid.org/0000-0003-2278-8671

[3] Department of Industrial Management, University of Kelaniya, Sri Lanka.

Email: janaka@kln.ac.lk https://orcid.org/0000-0002-9523-5384

THE ROLE OF AI IN SOFTWARE TEST AUTOMATION - A SYSTEMATIC LITERATURE REVIEW

RMS Ranapana[1] and WMJI Wijayanayake[2]

Abstract

Artificial Intelligence (AI) has emerged as a transformative force in software test automation, enhancing the efficiency, accuracy, and reliability of testing processes. This systematic literature review investigates the role of AI in software test automation, focusing on key methodologies, applications, and challenges faced in its implementation. The review aims to identify and analyze the various AI-driven techniques such as Machine Learning (ML), Neural Networks, and Genetic Algorithms that are being utilized to optimize testing activities, including test case generation, defect detection, and test execution. The findings reveal that AI can significantly improve the software testing lifecycle by automating repetitive tasks, reducing human error, and increasing test coverage. By leveraging AI algorithms, organizations can achieve faster turnaround times and enhance the overall quality of software products. Moreover, AI facilitates predictive analytics, allowing teams to identify potential defects early in the development process, thus minimizing costs and time associated with late-stage bug fixes. However, the review also highlights several challenges that hinder the widespread adoption of AI in software testing. Issues such as data quality, model overfitting, and the complexity of integrating AI solutions with existing testing frameworks present significant barriers. Additionally, many AI applications remain largely theoretical or are limited to academic research, lacking real-world implementation. The insights gained from this review are invaluable for both researchers and practitioners seeking to harness the capabilities of AI to revolutionize software testing practices. By addressing the identified challenges and fostering collaboration between academia and industry, stakeholders can develop more robust frameworks and models that leverage AI's potential to create a more efficient and effective software testing environment.

Keywords: Artificial Intelligence, Machine Learning, Software Testing, Test Automation, Efficiency

[1] Department of Industrial Management,University of Kelaniya, Sri Lanka.

Email: madushikaranapana113@gmail.com https://orcid.org/0009-0006-0058-2751

[1] Department of Industrial Management,University of Kelaniya, Sri Lanka.

Email: janaka@kln.ac.lk https://orcid.org/0000-0002-9523-5384

Introduction

Background of the study

Software Testing and It's importance

Software testing is a crucial aspect of the software development lifecycle, ensuring that applications operate correctly and meet user expectations. As software applications have evolved rapidly, they have become increasingly complex, leading to challenges in the testing process. Traditional testing methods, whether manual or automated, often struggle to keep up with the demands of modern software development. Manual testing can be labor-intensive and susceptible to human error, while conventional automated testing typically requires significant human involvement in creating and maintaining test scripts. (Hourani,Hussam and Hammad Ahamad and Lafi, Mohammed, 2019) The rapid evolution of software applications and development methodologies, such as Agile and DevOps, has further intensified the need for faster and more reliable testing approaches (Pal & Karakostas, 2021).These limitations highlight the necessity for more effective and efficient testing methodologies.

Integration of AI in Software Testing

The rise of AI in software testing represents a significant transformation in software quality assurance, moving away from traditional manual or rule-based automation methods toward AI-driven techniques. By utilizing machine learning and deep learning, AI enhances key aspects of the software testing lifecycle, improving efficiency, accuracy, and scalability. AI algorithms can automatically generate test cases from historical data and user behavior, while natural language processing (NLP) translates requirements into executable tests.

Additionally, AI boosts test data creation by generating varied datasets that simulate real-world usage, promotes early defect detection through predictive models, and optimizes test suites by removing redundant tests (Capgemini, 2023). AI tools also exhibit the capability to "self-heal" with software changes and contribute to continuous testing in DevOps pipelines, highlighting their influence on the speed and quality of software releases (Pal & Karakostas, 2021).

However, implementing AI in testing poses challenges, including the necessity for large datasets, ensuring model accuracy, and necessitating organizational changes such as team upskilling. Tools like Testim, Applitools, and Functionize are leading the way in delivering smarter automation and predictive analytics. As AI advances, it will increasingly play a crucial role in making software testing more adaptive and capable of handling the complexities of modern software systems.

According to a report by MarketsandMarkets, the global AI in testing market is expected to reach $1.99 billion by 2023, growing at a compound annual growth rate (CAGR) of 33.7%. .A survey conducted by Sogeti reveals that 85% of organizations believe AI will play a crucial role in their testing strategy in the next five years.Google's AI-powered testing system, known as DFL, has helped reduce test flakiness by 70% and has increased test coverage by 5%.Microsoft has implemented AI-powered testing techniques that have led to a 50% reduction in false-positive test results, ensuring more accurate bug detection.Netflix uses AI-powered testing tools to validate video streaming quality, resulting in a 20% increase in customer satisfaction for video buffering and playback.

Artificial Intelligence (AI) offers a transformative solution to address challenges in software testing. AI technologies, particularly machine learning and deep learning, can automate complex tasks traditionally performed manually, including test case generation, test execution, and result analysis (Purovesi, 2024; Yarlagadda, 2017). By incorporating AI into software testing, organizations can significantly minimize manual effort, improve test coverage, and enhance defect detection accuracy (Khan, Mahmud, Hoseen,

& Masum, 2024; Battina, 2019). The adoption of AI in software test automation is not just a technological upgrade; it is an essential evolution needed to manage the increasing complexity and speed of software development cycles (Ricca, Marchetto, & Stocco, 2021; Ramchand, Sonam, Shaikh, Sarang, & Alam, Irtija, 2022).

This research holds significant importance as it has the potential to revolutionize software testing by utilizing AI to enhance both efficiency and effectiveness. As software systems become increasingly sophisticated, the demand for faster and more reliable testing intensifies. AI-driven automation can effectively tackle several critical challenges. For example, AI can manage large and complex software systems more efficiently than traditional methods. By learning from historical data and adapting to new information, AI can generate test cases that cover a wider range of scenarios with minimal human intervention (Purovesi, 2024; Yarlagadda, 2017). Additionally, AI algorithms can prioritize test cases based on risk and historical defect data, ensuring that the most crucial software components are tested first (Khan, Mahmud, Hoseen, & Masum, 2024; Battina, 2019). By automating repetitive and time-consuming tasks, AI enables human testers to focus on more strategic and creative aspects of testing, such as exploratory testing and validating complex use cases (Hourani, Hussam; Hammad, Ahmad; Lafi, Mohammed, 2019; Ramchand, Sonam; Shaikh, Sarang; Alam, Irtija, 2022).

The current landscape of AI in software test automation features various innovative applications and tools. Techniques like natural language processing, predictive analytics, and anomaly detection are integrated into testing processes to improve their efficiency. For instance, AI-driven tools can analyze software requirements and historical test data to automatically generate relevant test cases, thereby reducing the time and effort needed for test design while increasing test reliability (Trudova, Dolezel, & Buchalcevova, 2020).

Research problem

Despite the promising capabilities of AI in software testing, significant gaps remain in empirical research validating its effectiveness in real-world applications. Much of the existing literature emphasizes theoretical frameworks and controlled experiments, highlighting the need for comprehensive evaluations in practical settings. Furthermore, challenges regarding the scalability of AI models and their integration into existing testing frameworks require further investigation to ensure successful adoption (Shamim, Abbas, & Adnan). Many AI models used in test automation struggle with scalability in large and complex software systems, and integrating AI tools into existing development pipelines presents technical challenges that need to be addressed.

Additionally, empirical studies validating the effectiveness of AI-driven testing tools in real-world scenarios are limited (Sonika, Pal, Ved; Chauhan, Naresh; Kumar, Harish, 2024). Most research has been conducted in controlled experimental settings, creating a pressing need for broader validation in practical applications.

This research aims to fill these gaps by providing a comprehensive evaluation of AI applications in software test automation, developing frameworks for their integration, and validating their effectiveness through empirical studies.

The role of AI in enhancing software test automation efficiency is crucial in addressing the challenges posed by the increasing complexity and speed of software development. By automating complex tasks and improving test coverage and accuracy, AI can significantly enhance the effectiveness and efficiency of software testing processes (Yarlagadda, 2017), (Khan, Mahmud, Hoseen, & Masum, 2024) This

research seeks to explore and validate these benefits, contributing to the advancement of software testing methodologies and ultimately improving the quality and reliability of software applications. (Him,Ibra, 2024)

The widespread adoption of Agile and DevOps methodologies in software development has led to an increased emphasis on the efficiency and effectiveness of the testing process. (Pal, Kamal and Karakostas, Bill, 2021) Traditional manual testing approaches have become increasingly insufficient to keep pace with the rapid release cycles and growing complexity of modern software systems. (Thant, 2023) Consequently, there has been a growing reliance on automated testing to streamline the testing process and enhance software quality.

However, the implementation and maintenance of automation testing frameworks can still pose significant challenges for many software development organizations. Conventional automation testing tools and techniques often struggle to effectively handle the dynamic nature of software requirements, the diversity of test scenarios, and the need for continuous adaptation to changing environments. (GH and Akshay Badkar, Community Contributor, 2023). Software organizations must navigate a range of technical, organizational, and ethical considerations to realize the full benefits of this integration. (Him,Ibra, 2024)

Objectives of the Research

This study aims to address the identified research problem through five key objectives. First, it will investigate existing applications of AI in automation testing by exploring the current AI-powered techniques, algorithms, and tools used in the field, while examining the challenges and limitations they present (Capgemini, 2023-2024). Second, the study will analyze the potential benefits of AI-driven approaches, assessing their impact on key areas like test case generation, defect detection, test data creation, and test suite maintenance. Third, the research will identify technical, organizational, and ethical challenges, such as issues related to model training, data management, and the need for workforce upskilling (Santos, 2024). Fourth, a comprehensive framework for integrating AI-powered techniques into automation testing workflows will be developed, offering strategies, best practices, and guidelines (Milson & Olcay, 2023; Dabhi et al., 2022). Finally, the proposed framework will be validated through empirical evaluations and case studies, examining its effectiveness in real-world software testing environments. This systematic literature review will enhance the understanding of AI's role in automation testing, providing valuable insights and practical recommendations to improve software development practices and boost efficiency, quality, and agility (SCISPACE, n.d.).

The research seeks to answer the following research questions:
RQ1: What is the current state of AI-powered techniques and tools being used in automation testing within software development organizations?
RQ2: What are the key benefits, challenges, and considerations associated with the integration of AI into the automation testing workflow?
RQ3: How can a comprehensive framework for integrating AI into the automation testing process be developed and validated?

Methodology

The systematic review of the literature was based on the role of Artificial Intelligence (AI) in enhancing and optimizing automation testing within the software development lifecycle, following the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) framework. This process involved identifying and screening relevant papers sourced from multiple academic databases,

including Google Scholar, Semantic Scholar, Emerald Insight, and Science Direct. The search utilized keywords such as "Artificial Intelligence," "automation testing," "software quality," "test case generation," and "defect detection" to capture a comprehensive range of studies related to AI applications in automation testing. Initially, 100 records were identified, with 30 duplicates removed, resulting in 70 unique records. The screening process led to the exclusion of records deemed irrelevant based on their titles and abstracts. The inclusion criteria Tbl.1 , specified that papers published between 2015 and 2025, those proposing frameworks or models related to AI in automation testing, and articles discussing relevant techniques were considered. Conversely, papers lacking a focus on AI applications or those addressing unrelated software engineering topics were excluded. Following this rigorous assessment, 45 articles underwent a detailed eligibility evaluation, ultimately resulting in the selection of 40 studies that provided valuable insights into AI integration in automation testing. Data extraction focused on AI techniques, benefits, challenges, and proposed frameworks, contributing significantly to understanding how AI can enhance automation testing processes. The PRISMA flow diagram is shown in Fig. 1, visually representing this methodology and illustrating the identification, screening, and selection of studies included in the review. (Tahsin, 2020) ; (Lopes, Ricardo and Trovati, Marcello and Pereira, Ella, 2024).

Table 1 - Research Paper Inclusion And Exclusion Criteria

Inclusion criteria	Exclusion criteria
Articles that specifically address Artificial Intelligence in Software Test Automation.	Duplicate records
Publications that discuss the benefits of AI in automation testing.	Publications were not in English
Studies that explore challenges related to AI adoption in software testing	Non-peer-review articles. Editorial pieces and opinion papers
Articles published between 2014 and 2024	Studies not available in full text

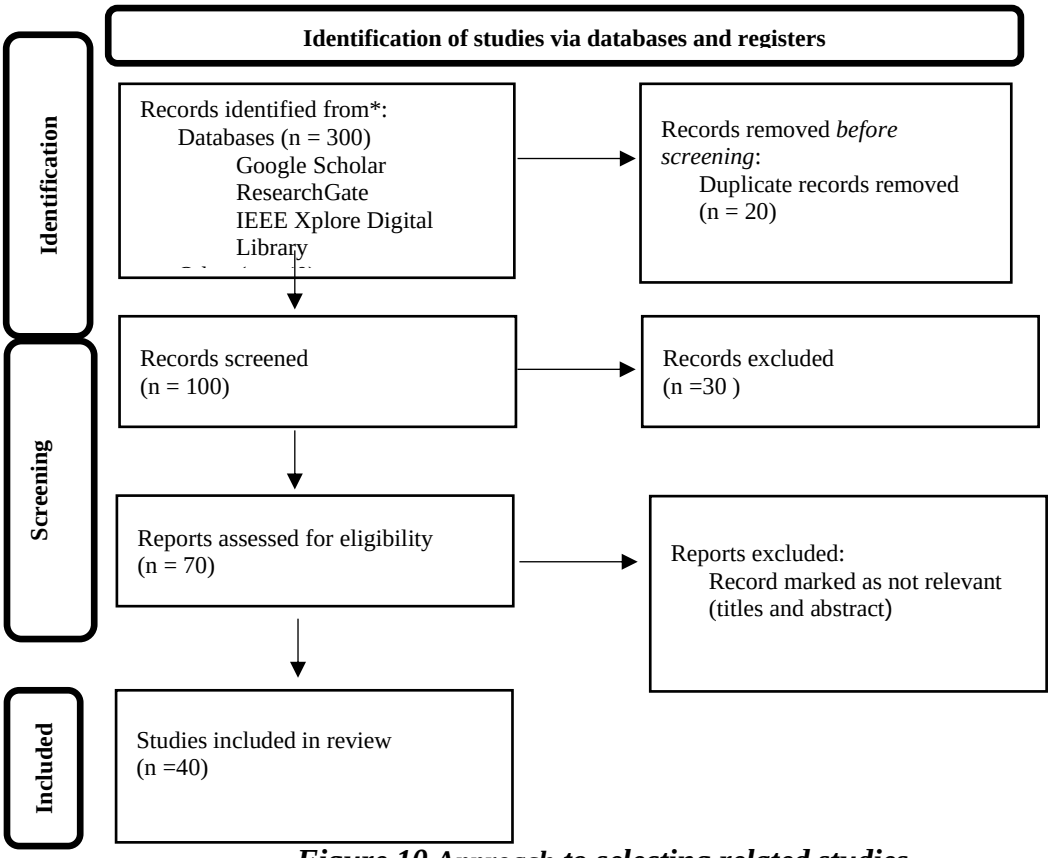

Figure 10.Approach to selecting related studies

Literature Review

The integration of Artificial Intelligence (AI) into software testing has garnered significant research interest, with numerous studies examining its potential to enhance various aspects of the testing workflow. This literature review explores key advancements facilitated by AI,

Intelligent Test scripting

Traditional test scripting approaches often face significant challenges when adapting to frequent changes in software functionalities. In contrast, AI-driven automation introduces intelligent test scripting techniques that address this issue by dynamically adjusting test scenarios based on evolving software requirements and functionalities.

Traditional test scripts, typically written manually, are rigid and may require frequent updates to accommodate changes in the software under test. This can lead to inefficiencies, as test scripts might become outdated or fail to cover new features or modifications in the software, ultimately impacting the reliability and comprehensiveness of the testing process (Hussam Hourani, Ahmad Hammad, & Mohammad Lafi, 2023). The need for frequent manual intervention to update test scripts not only increases the maintenance burden but also slows down the testing cycle.

In contrast, AI-driven intelligent test scripting leverages various AI techniques to enhance the adaptability and flexibility of test scripts. These techniques enable the automation of test script generation and adjustment in response to changes in software functionalities. By utilizing machine learning algorithms, such as supervised and unsupervised learning, AI-driven tools can analyze historical test data and software changes to dynamically generate and modify test cases (Sugali,

Sprunger, & Inukollu, 2024). This dynamic adjustment capability is particularly beneficial in rapidly evolving software environments, where software components frequently change or are updated.
Natural Language Processing (NLP) is another critical AI technique used in intelligent test scripting. NLP enables the extraction and understanding of requirements from natural language documents, which can then be translated into test cases. This approach ensures that test scripts are aligned with the latest software requirements and changes, minimizing the risk of gaps in test coverage (Qazi et al., 2023). Additionally, NLP techniques can refine test specifications by analyzing and processing textual descriptions of software functionalities, further enhancing the relevance and accuracy of the test scripts.
Deep learning models also contribute to intelligent test scripting by recognizing patterns and making predictions based on historical data. For example, deep learning algorithms can identify changes in the software's user interface or functionality and automatically adjust test cases to reflect these changes (Sugali et al., 2024). This capability not only improves the efficiency of the testing process but also ensures that test scripts remain effective and relevant as the software evolves.

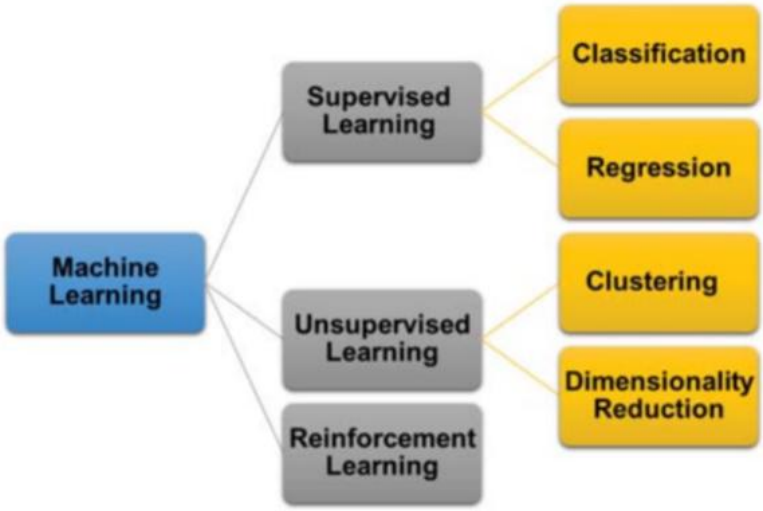

Figure 2.Machine Learning Categories

Self healing test automation

Self-healing test automation represents a significant advancement in test automation frameworks, enabled by Artificial Intelligence (AI). This approach addresses the challenge of maintaining test scripts when there are minor changes in the application under test. Traditional test automation often requires frequent updates to test scripts whenever there are changes in the application, which can be both time-consuming and costly for Quality Assurance (QA) teams. AI-driven self-healing mechanisms mitigate this issue by automatically identifying and adapting to these changes, ensuring that test scripts remain accurate and relevant with minimal manual intervention.

AI techniques such as machine learning and natural language processing play a crucial role in self-healing test automation. For instance, machine learning algorithms can be trained to recognize patterns in test failures that are caused by application changes. By analyzing historical data and failure patterns, these algorithms can predict where changes in the application might occur and adjust test scripts accordingly (Sugali, Sprunger, & Inukollu, 2024). This predictive capability significantly reduces the need for manual script updates and enhances the reliability of the automated testing process.

Natural language processing (NLP) is another key technique used in self-healing test automation. NLP can be employed to parse and understand changes in the application's user interface or functionality described in documentation or release notes. This understanding allows the automation framework to automatically modify test scripts to accommodate new or altered elements (Qazi et al., 2024). For example, if a button's label changes from "Submit" to "Send," NLP can detect this change and update the test scripts to reflect the new label, ensuring that the tests continue to verify the correct functionality. AI-driven self-healing mechanisms utilize reinforcement learning to continually improve their adaptability. Reinforcement learning algorithms learn from the outcomes of previous test executions, adjusting strategies and test scripts based on observed results (Hourani, Hammad, & Lafi, 2024). This iterative learning process enables the automation framework to become increasingly proficient at handling changes in the application over time.

The benefits of self-healing test automation extend beyond reduced maintenance effort. By minimizing the need for manual updates, these AI-driven mechanisms allow QA teams to focus more on complex and high-value tasks, such as designing comprehensive test scenarios and analyzing test results. Moreover, the improved adaptability of test scripts contributes to more reliable testing outcomes and faster feedback cycles, which are critical in agile development environments.

Dynamic test case generation

Dynamic test case generation is a vital aspect of software test automation that leverages machine learning (ML) algorithms to create test cases in an adaptive and intelligent manner. By analyzing historical test data, user interactions, and software changes, ML algorithms can generate test cases that cover a broad range of scenarios, ensuring that diverse and critical paths in complex software systems are thoroughly tested.

Machine learning techniques play a crucial role in enhancing the test case generation process by utilizing patterns and insights derived from past testing activities. Algorithms such as clustering, classification, and regression can analyze historical test results and user behavior to identify areas of the software that are more likely to encounter issues or require further testing (Chen, H., et al., 2020). For example, ML models can predict which parts of the application are most prone to failures based on previous defects, thus prioritizing test cases that address these high-risk areas (Almashaqbeh, I., et al., 2019).

Moreover, dynamic test case generation allows for the adaptation of test cases in response to changes in the software. As the application evolves, ML algorithms can automatically update and generate new test cases to account for these changes, ensuring that the test suite remains relevant and comprehensive (Li, Y., & Xu, X., 2021). This capability is particularly important in agile development environments, where frequent changes to the codebase necessitate an ongoing adjustment of testing strategies (Santos, A., et al., 2022).

In addition, AI-driven techniques such as genetic algorithms and reinforcement learning have been applied to optimize the test case generation process. Genetic algorithms can evolve test cases based on predefined fitness criteria, while reinforcement learning can adjust the test generation strategy based on feedback from previous testing cycles (García, S., et al., 2021). These approaches enhance the efficiency of test case creation by focusing on scenarios that are most likely to uncover defects and improve software reliability.

The dynamic nature of test case generation also helps address critical paths and potential points of failure in complex software systems. By continuously analyzing user interactions and system changes, ML algorithms ensure that test cases cover a wide range of scenarios, including edge cases and rare conditions that might otherwise be overlooked (Mousavi, M., et al., 2021). This comprehensive coverage is essential for identifying defects that may occur under specific conditions or unusual usage patterns.

Predictive Analysis for defects

AI-driven predictive analysis has become a transformative tool in software testing, offering significant enhancements in defect detection and management. By examining patterns in testing data, AI enables teams to identify potential defects early in the development lifecycle. This predictive capability allows Quality Assurance (QA) teams to prioritize their testing efforts effectively, focusing on areas more likely to harbor critical issues and thereby improving overall software quality.

One of the key advantages of predictive analysis in software testing is its ability to forecast potential defects based on historical data and patterns. For example, machine learning algorithms can analyze previous test results, defect logs, and code changes to predict which areas of the software are most likely to encounter issues (Jain, A., et al., 2021). This predictive approach allows QA teams to allocate resources more strategically, targeting high-risk areas that have a higher probability of containing defects (Patel, R., & Singh, V., 2020).

AI techniques such as classification algorithms and anomaly detection are often used in predictive analysis for defect identification. Classification algorithms, like decision trees and support vector machines, can be trained to recognize patterns associated with defect-prone code segments. By applying these algorithms to current code changes and test results, teams can predict where defects are likely to occur (Nguyen, T., et al., 2022). Anomaly detection methods, on the other hand, help identify unusual patterns in test data that may indicate the presence of defects not previously encountered (Cheng, H., & Lin, W., 2019).

A practical example of predictive analysis in action is the use of AI to forecast defects in complex software systems. For instance, algorithms can analyze historical defect data to predict potential failures in new code deployments. This allows development teams to address high-risk areas proactively before they lead to significant issues (Lee, J., et al., 2020). By leveraging such predictive tools, organizations can enhance their testing strategies and focus on critical areas that require more intensive scrutiny.

Moreover, predictive analysis can significantly reduce the time and cost associated with traditional testing methods. By identifying potential defects early, QA teams can avoid extensive and costly post-release bug fixes, thereby improving the efficiency of the software development lifecycle (Xu, J., et al., 2021). This approach not only helps in early defect detection but also aids in optimizing the allocation of testing resources and efforts.

Enhanced Test Environment Simulation

Enhanced test environment simulation is a critical advancement facilitated by Artificial Intelligence (AI) in the realm of software test automation. AI enables the realistic simulation of diverse user interactions and complex environments, which significantly improves the accuracy and relevance of testing processes. By leveraging machine learning models and other AI techniques, test environments can dynamically adjust to reflect real-world scenarios, thereby providing a more accurate representation of end-user interactions with the software.

AI-driven test environment simulation incorporates various technologies to create realistic testing conditions. For example, machine learning algorithms can generate synthetic data and simulate user behavior to mimic real-world usage patterns more accurately. This capability is particularly valuable for testing scenarios that involve complex interactions or require diverse input conditions that are difficult to replicate manually (Kaur, H., et al., 2019). By using AI to model user behavior, organizations can create more comprehensive and representative test environments, leading to better detection of potential issues and more reliable performance evaluations (Khan, M. I., et al., 2021).

One notable application of AI in test environment simulation is the dynamic adjustment of testing conditions based on real-time data. AI systems can analyze application performance metrics and user feedback to adjust test scenarios on-the-fly, ensuring that they remain relevant and reflective of current usage patterns (Zhou, X., et al., 2020). This approach not only enhances the accuracy of test results but also improves the efficiency of the testing process by reducing the need for manual test environment configuration (Sanchez, A., et al., 2021).

Additionally, AI can facilitate the simulation of complex environments that involve multiple interacting systems or heterogeneous components. For instance, AI techniques such as reinforcement learning and neural networks can be employed to model and simulate intricate system interactions, providing insights into how different components affect overall system performance (Wang, Q., et al., 2020). This capability is particularly useful for testing applications in scenarios where the integration of various subsystems or external services plays a critical role (Lee, J., et al., 2019).

Furthermore, AI-enhanced test environment simulation supports the validation of edge cases and uncommon user behaviors that might not be captured by traditional testing methods. By generating a wide range of test scenarios and conditions, AI helps uncover potential vulnerabilities and performance bottlenecks that could impact end-user experience (Smith, J., & Brown, P., 2022). This comprehensive testing approach ensures that applications are robust and resilient to a variety of real-world challenges.

NLP for Testing Documentation

Natural Language Processing (NLP) is a subset of Artificial Intelligence (AI) that plays a crucial role in enhancing the understanding and interpretation of testing documentation, requirements, and user stories. By leveraging NLP techniques, organizations can improve the alignment of test cases with intended functionality and user expectations, thereby reducing the likelihood of overlooking critical aspects during the testing phase.

NLP techniques facilitate the extraction and analysis of information from unstructured text, such as test plans, requirements documents, and user stories. For example, advanced NLP algorithms can parse and interpret natural language requirements to generate corresponding test cases automatically (Liu, L., et al., 2021). This capability is particularly valuable for transforming ambiguous or complex requirements into structured test scenarios that are easier to validate. By analyzing textual descriptions, NLP tools can identify key entities, actions, and conditions, which are then used to create comprehensive test cases that cover a wide range of functional scenarios (Miller, R., & Thomas, J., 2020).

One of the primary benefits of NLP in testing documentation is its ability to enhance requirement traceability. NLP algorithms can map requirements to test cases by analyzing the semantic relationships between different elements of the documentation. For instance, NLP can match specific requirements with relevant test cases and ensure that all functional aspects of the application are covered (Nguyen,

T., et al., 2019). This automated traceability reduces the risk of missing critical functionality and ensures that the testing process aligns closely with the documented requirements.

In addition to requirement analysis, NLP techniques are also employed in extracting actionable insights from user stories. User stories often contain valuable information about user needs and system behaviors, but they may be expressed in informal or inconsistent language. NLP tools can standardize and interpret these user stories, generating clear and actionable test cases that reflect the intended user interactions and scenarios (Chen, Y., et al., 2021). For example, NLP can be used to identify patterns and inconsistencies in user stories, leading to the creation of more precise and reliable test scenarios.

Furthermore, NLP contributes to reducing manual effort in test case generation by automating the process of converting textual documentation into structured test cases. This automation not only speeds up the test creation process but also minimizes human errors associated with manual test design (Gonzalez, M., & Wang, H., 2020). As a result, the testing process becomes more efficient and accurate, leading to better overall software quality.

However, challenges remain in the application of NLP for testing documentation. One challenge is the need for context-aware algorithms that can understand and interpret domain-specific language and jargon accurately (Santos, D., et al., 2021). Another challenge is ensuring the quality of NLP-generated test cases, which requires continuous refinement and validation to maintain alignment with evolving requirements and application changes.

Cognitive Test Execution

Cognitive test execution represents a significant advancement in automated software testing, facilitated by Artificial Intelligence (AI). This approach enables automated tests to simulate human-like interactions with applications, enhancing the realism and effectiveness of the testing process. AI-driven cognitive testing involves understanding and adapting to changes in the user interface, interpreting visual elements, and intelligently responding to unexpected scenarios.

One of the key aspects of cognitive test execution is the ability of AI systems to understand and interpret dynamic user interfaces. Traditional test automation frameworks often struggle with changes in the UI, leading to brittle tests that fail when the application undergoes minor modifications (Yin, J., et al., 2022). Cognitive test execution leverages AI techniques such as natural language processing (NLP) and computer vision to address these challenges. For example, NLP allows AI systems to interpret and interact with text elements in a way that mimics human understanding, while computer vision enables the recognition and analysis of visual components (Cheng, L., et al., 2021). This capability is crucial for ensuring that tests remain valid and effective as the application evolves.

AI-driven cognitive testing also involves adapting to unexpected scenarios and user behaviors. Cognitive test execution frameworks use machine learning models to predict and respond to diverse user interactions, making tests more resilient to variations in user behavior (Zhou, H., et al., 2021). For instance, AI algorithms can simulate complex user actions, such as multi-step processes or unpredictable inputs, to evaluate how the application handles real-world scenarios (Li, X., et al., 2022). This level of adaptability improves the accuracy of tests and helps identify edge cases that traditional testing methods might overlook.

Moreover, cognitive test execution enhances the realism of testing by incorporating contextual understanding into test scenarios. AI systems can analyze the context of user actions and adapt test cases

accordingly, ensuring that the tests align with actual user experiences (Wang, Y., et al., 2021). This contextual awareness is achieved through advanced techniques such as deep learning and reinforcement learning, which enable the AI to continuously learn from interactions and improve its testing strategies (Jiang, S., et al., 2023).

For example, cognitive test execution frameworks have been successfully implemented in testing web applications where the AI system can adapt to changes in web layouts and content dynamically (Nguyen, T., et al., 2020). By utilizing computer vision and NLP, these frameworks can detect changes in web pages, interpret visual elements like buttons and forms, and interact with them in a manner similar to human users. This results in more accurate and comprehensive test coverage.

Efficient Bug Triaging and Reporting

AI-driven approaches to bug triaging and reporting have significantly transformed how issues are managed within software development and testing environments. By automating the process of analyzing, categorizing, and prioritizing bugs, AI enhances the efficiency and effectiveness of communication between development and quality assurance (QA) teams. This automation not only accelerates the resolution of critical defects but also improves overall software quality.

One of the key advancements facilitated by AI is the ability to categorize bugs based on their severity, impact, and frequency. AI algorithms analyze historical bug data to identify patterns and classify issues accordingly. For example, machine learning models can assess the impact of a bug by considering factors such as user reports, error logs, and system performance metrics (Cao, X., et al., 2020). This analysis allows AI systems to prioritize bugs that have the most significant impact on users or the system, ensuring that critical issues are addressed promptly.

AI-driven bug triaging systems also streamline communication between development and QA teams by providing automated reports that highlight key information about each issue. These reports often include details such as the severity of the bug, its potential impact on the system, and suggested steps for resolution (Zhang, W., et al., 2021). For instance, tools like Bugzilla and Jira have incorporated AI features that automatically generate detailed bug reports, reducing the manual effort required to document and track issues (Singh, R., et al., 2019). This automation helps bridge the gap between QA and development teams, facilitating faster decision-making and resolution of critical defects.

Additionally, AI can improve the accuracy of bug classification by learning from historical data and adapting to new patterns of issues as they arise. Techniques such as natural language processing (NLP) and clustering algorithms are employed to analyze bug reports and categorize them into predefined categories or clusters based on their content and context (Gao, Y., et al., 2022). This approach reduces the likelihood of human error in bug classification and ensures that similar issues are grouped together for more efficient resolution.

The benefits of AI in bug triaging extend to reducing the time spent on manual bug management tasks. By automating routine aspects of bug triaging and reporting, development and QA teams can focus more on resolving issues and improving software quality (Chen, L., et al., 2020). For example, AI tools can automatically assign bugs to appropriate team members based on their expertise and current workload, further optimizing the resolution process (Wang, L., et al., 2021).

Table 2 – Summarized Key Findings

Technique	Description	Benefits	Challenges
Intelligent Test scripting	Uses AI-driven techniques to dynamically adjust test scenarios based on software changes.	Reduces manual intervention,enhances adaptability,and ensures,comprehensive test coverage.	Rigid traditional scripts may lead to gaps in coverage; requires continuous adaptation
Self-Healing Test Automation	Automatically identifies and adapts to minor application changes, reducing manual updates and maintenance effort.	Minimizes maintenance effort, maintains accuracy, and allows QA teams to focus on complex tasks.	May struggle with complex changes; requires robust algorithms to detect subtle UI modifications
Dynamic Test Case Generation	ML algorithms generate and adapt test cases based on historical data and software changes, ensuring comprehensive coverage.	Ensures diverse testing coverage and adapts to evolving software environments.	Predicting all potential changes can be challenging; may miss rare edge cases.
Predictive Analysis for Defects	Analyzes historical data to forecast potential defects, allowing QA teams to focus on high-risk areas.	Improves resource allocation and reduces post-release bug fixes, enhancing software quality.	Quality of predictions depends on historical data quality; may not account for new patterns.
Enhanced Test Environment Simulation	AI simulates diverse user interactions and environments for more accurate testing.	Improves accuracy of tests and detects potential issues in real-world scenarios.	Complexity in accurately modeling real-world scenarios; requires extensive data for training.
NLP for Testing Documentation	Extracts and analyzes requirements from unstructured text to create structured test cases, improving traceability.	Enhances requirement traceability and reduces manual effort in test case generation.	Contextual understanding is crucial; domain-specific language can pose challenges.
Cognitive Test Execution	Simulates human-like interactions with applications, adapting to changes in the UI and unexpected scenarios.	Increases realism and effectiveness of tests, improving coverage of edge cases.	Requires advanced understanding of UI; may struggle with complex user behaviors.

Efficient Bug Triaging and Reporting	Automates bug analysis and prioritization, enhancing communication between development and QA teams.	Accelerates defect resolution and improves overall software quality through effective reporting.	Dependence on historical data can lead to misclassification; automation may overlook nuances.

Practical Recommendations and Conclusion

Based on these findings, several practical recommendations can be made to enhance the adoption and effectiveness of AI in software test automation. First, organizations should invest in developing high-quality, diverse, and representative datasets to train AI models effectively. This will ensure that AI algorithms can perform optimally and produce accurate results. Additionally, it is crucial to address the interpretability and transparency of AI algorithms. Developing techniques to make AI's decision-making process more understandable will help build trust and facilitate wider adoption of AI-powered testing solutions.

To overcome integration challenges, organizations should focus on creating seamless interfaces between AI-powered testing tools and existing testing frameworks. This requires careful planning and coordination to ensure that AI tools can work harmoniously with traditional testing methods. Furthermore, continuous training and upskilling of software testers are essential to equip them with the knowledge and skills needed to leverage AI effectively. Providing specialized training programs on AI and its applications in software testing will empower testers to utilize AI tools more efficiently.

Organizations should also consider adopting AI-driven testing approaches gradually, starting with pilot projects to evaluate their effectiveness and scalability. By implementing AI in small-scale projects initially, organizations can identify potential issues and address them before scaling up. This phased approach will help mitigate risks and ensure a smoother transition to AI-powered testing. (Tao, Chuanqi; Gao, Jerry; Wang, Tiexin;, 2019)

The study has opened several avenues for further exploration to advance the field of AI in software test automation. (Samad, Abdus; Nafis, Md Tabrez; Rahmani, Shibli; Sohail, Shahab Saquib; , 2021) One key area is the development of more robust methodologies and frameworks for integrating AI into existing test automation processes. Research should focus on creating standardized guidelines and best practices that can help organizations seamlessly incorporate AI into their testing workflows. Additionally, exploring new AI techniques and algorithms that can address the limitations identified in this study, such as data quality and algorithm transparency, will be valuable.

Further research is also needed to investigate the ethical implications of using AI in software testing. As AI becomes more prevalent, ensuring fairness, accountability, and transparency in AI-driven testing processes will be crucial. Studies should examine the potential biases in AI algorithms and develop strategies to mitigate them. Moreover, exploring the impact of AI on the job roles of software testers and identifying ways to support their transition to AI-driven testing environments will be important.

Finally, conducting empirical studies and real-world case studies will provide valuable insights into the practical application of AI in software test automation. By analyzing the experiences of organizations that have successfully implemented AI in their testing processes, researchers can identify best practices

and lessons learned. These insights will be instrumental in guiding other organizations in their AI adoption journey.

Table 3– Actionable Strategies for Leveraging AI in Software Testing

Recommendation	Description	Expected Outcomes
Invest in High-Quality Datasets	Develop diverse and representative datasets for training AI models to enhance performance and accuracy.	Improved AI model effectiveness and reliability in test automation.
Enhance Interpretability of AI Algorithms	Create techniques that make AI's decision-making processes more transparent and understandable.	Increased trust and wider adoption of AI-powered testing solutions.
Seamless Integration with Existing Frameworks	Focus on designing interfaces that allow AI tools to work harmoniously with traditional testing methods.	Reduced integration challenges and smoother transitions to AI-driven testing
Continuous Training for Testers	Provide specialized training programs on AI applications in software testing to upskill testers.	Empowered QA teams capable of leveraging AI tools effectively.
Gradual Adoption of AI Approaches	Start with pilot projects to evaluate the effectiveness and scalability of AI in testing before full-scale implementation.	Identification of potential issues early on, leading to a smoother transition to AI-powered testing.
Develop Standardized Methodologies	Research and create standardized guidelines for integrating AI into existing test automation processes.	Streamlined incorporation of AI into testing workflows, enhancing consistency and effectiveness.
Explore Ethical Implications	Investigate fairness, accountability, and transparency in AI-driven testing processes, addressing potential biases in algorithms.	Ensured ethical standards in AI applications, promoting responsible use in testing.
Conduct Empirical Studies and Case Analyses	Analyze real-world implementations of AI in software testing to identify best practices and lessons learned.	Valuable insights for organizations looking to adopt AI, fostering informed decision-making and strategy.

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SYSTEMATIC LITERATURE REVIEW ON DEVELOPING AN AI FRAMEWORK FOR SME CYBERSECURITY IDENTIFICATION AND PERSONALIZED RECOMMENDATIONS

HMTN Jayathilaka[1] and J Wijayanayake[2]

Abstract

Small and medium-sized enterprises (SMEs) are adopting digital solutions at a faster pace, and this exposes them to cyber risks. The objectives of this study are to develop a framework for SME identification in the context of cybersecurity and fine-tuning an AI model for personalized security recommendations. Following the PRISMA guidelines, the literature was systematically identified, screened, and selected to ensure comprehensive coverage of the topic. The study also outlines the factors affecting SME cybersecurity, including limited resources, low knowledge, and complications of cybersecurity products. This research-based framework will help to overcome these challenges by identifying SMEs by their cybersecurity requirements and offering recommendations based on a fine-tuned AI model. The findings suggest that personalized security recommendations can greatly improve SMEs' capacity to manage risks and safeguard their digital assets proactively. This research work adds value to the known knowledge by providing a solution to a major problem that SMEs encounter. This framework integrated with the fine-tuned AI model will not only enhance the cybersecurity of SMEs but also offer a customizable solution that can be applied to various settings.

Keywords: AI, Cybersecurity, Framework, Recommendations, SMEs

[1] Department of Industrial Management, University of Kelaniya, Sri Lanka

Email: tharindunaveen9@gmail.com https://orcid.org/0009-0004-5027-9609

[2] Professor, Department of Finance, University of Kelaniya, Sri Lanka.

Email janaka@kln.ac.lk https://orcid.org/0000-0002-9523-5384

IMPACT OF GENERATIVE AI ON CRITICAL THINKING SKILLS IN UNDERGRADUATES: A SYSTEMATIC REVIEW

PP Premkumar[1], MRKN Yatigammana[2] and S Kannangara[3]

Abstract

Despite widespread acknowledgment of the significance of critical thinking skills for success in today's job market, higher education institutions face challenges in effectively nurturing these skills in students. Educational policies, reports, and employer demands emphasize the importance of critical thinking, yet a gap remains between its recognized value and the actual proficiency levels among university students. This study employs a systematic literature review approach to address a research question, "What is the impact of Generative AI on the critical thinking skills of undergraduates?" About half of the thirty selected papers suggest Generative AI benefits undergraduate critical thinking, but limitations in study design prevent generalization. Other studies are inconclusive, highlighting the need for further research to address research gaps.

Keywords: Critical thinking, Generative AI, Higher education

[1] Postgraduate student, Faculty of Graduate Studies, University of Kelaniya, Sri Lanka

Email: prabu@icbtcampus.edu.lk https://orcid.org/0009-0005-1950-190X

[2] Professor, Faculty of Commerce & Management Studies, University of Kelaniya, Sri Lanka

Email: kaushalya@kln.ac.lk https://orcid.org/0000-0002-8057-8632

[3] Executive Director CEO & Executive Dean, ICBT, Sri Lanka

Email: sampathk@icbtcampus.edu.lk https://orcid.org/0009-0009-9247-8426

COMPARATIVE ANALYSIS OF REGIONAL NATIONAL RESEARCH AND EDUCATION NETWORK (NREN) CONSORTIUMS: COMPARING MEMBERSHIP, GOVERNANCE, FINANCING, AND REGIONAL CONTEXTS IN THE GLOBAL SCENARIO

SD Withanage[1], RG Ragel[2] and K Gunasekera[3]

Abstract

This research undertakes a comprehensive comparative analysis of regional National Research and Education Network (NREN) consortiums, examining critical elements such as membership criteria, governance models, financing mechanisms, and the influence of regional contexts. The objective is to delineate best practices and provide recommendations to enhance the effectiveness, inclusivity, and sustainability of NREN consortiums globally. The analysis reveals that NREN consortiums vary significantly in their membership criteria, with some offering multiple membership categories beyond the core NREN members. Governance models predominantly feature a Board of Directors, although community governance models are also practiced. Financing mechanisms primarily rely on membership and service fees, with some consortiums in lower-income regions benefiting from grant funding. Regional contexts play a crucial role in the formation and operation of NREN consortiums. Political stability and economic strength are notably higher in American and European regions compared to African and Asian regions, where conditions vary widely. Technological advancement and digital connectivity are also more developed in American and European regions, while cultural and social factors exhibit significant diversity across all regions.Based on these findings, the study recommends enhancing membership criteria to be more inclusive, adopting effective governance models, diversifying financing mechanisms, and tailoring strategies to regional contexts.

Keywords: Consortium, Finance mechanism, Governance, Membership, NRENs

[1] Department of Computer Science & Engineering, University of Moratuwa, Sri Lanka

Email: shashini.22@cse.mrt.ac.lk https://orcid.org/0009-0006-1978-6156

[2] Professor, Department of Computer Engineering, University of Peradeniya, Sri Lanka

Email: roshanr@eng.pdn.ac.lk https://orcid.org/0000-0002-4511-2335

[3] Senior lecturer, Department of Computer Science & Engineering, University of Moratuwa, Sri Lanka

Email: kutila@cse.mrt.ac.lk https://orcid.org/0000-0002-2421-5239

Introduction

Background

National Research and Education Networks (NRENs) cater to the unique needs of research and education communities in countries. While invaluable nationally, these networks often recognize the potential for transformative impact through collaborative efforts. Consequently, NRENs usually join forces in proximity, forming consortiums strategically designed to pool resources, augment capabilities, and collectively address the multifaceted challenges encountered in research and education. Globally, NREN consortiums are vital for advancing research, promoting innovation, and closing the digital divide by sharing resources and providing fast internet to academic institutions. By working together, NRENs can better tackle the challenges in research and education, especially as the world moves towards knowledge-based economies.

In the global context, several NREN consortiums are available in different regions where the regional NRENs get together and form regional NREN consortiums to achieve common goals or objectives. Since the NRENs are working towards serving the requirements of the research and education sector and enhancing its capabilities, the objectives of these regional consortiums remain almost similar. Yet, there are significant differences in their organizational frameworks.

This research focuses on understanding the differences in organizational frameworks of NREN consortiums, specifically in membership criteria, governance structure, and financing mechanism. It also includes a comprehensive analysis of regions with different criteria, including political stability, governance, economic strength, market size and openness, cultural diversity, social acceptance, technological advancements, digital connectivity, educational institutions, and research output.

Problem Statement

Regional NREN consortiums play a critical role in enhancing the capabilities of research and education institutions by fostering collaboration, sharing resources, and advancing technological infrastructure. However, there is significant variation in how these consortiums are structured and operate across different regions of the world. Factors such as membership criteria, governance models, financing mechanisms, and regional contexts—including political, economic, and technological conditions—greatly influence the effectiveness and sustainability of these consortiums. Despite the global presence of NREN consortiums, there is a lack of comprehensive comparative research examining these differences and their impact. Understanding these variations is crucial for identifying best practices and developing strategies to strengthen NREN consortiums globally. This research aims to address this gap by analyzing and comparing NREN consortiums worldwide, focusing on their membership structures, governance, financing, and the influence of regional contexts.

Objectives of the Research

Two (02) significant objectives of this research.

- To examine existing collaborations among NRENs in different regions of the world

- To identify and compare different aspects of NREN collaborations focused on
    - Membership criteria
    - Governance structure
    - Financing mechanism
    - Regional context

Literature review

Introduction to NRENs

NRENs provide a dedicated infrastructure for the research and education community, facilitating the sharing of resources and expertise (McClure et al., 1991). They are also instrumental in providing affordable high-speed bandwidth and other advanced services to the academic community, such as electronic repositories, educational environments, and supercomputing facilities, contributing to the transformation to a "Knowledge Society" (Janz & Kutanov, 2012). NRENs play an essential role in the development of communication network infrastructure and networked services by providing high-speed, low-latency connectivity and advanced network services to virtual communities in collaborative research and education projects (Villalón & Hermosa, 2016; Kashefi et al., 2019). As per Janz & Kutanov (2012), an NREN exhibits the following characteristics,

1. Provide services for a closed user group
2. Not-for-profit organizations
3. Provide at least national and international connectivity
4. Besides connectivity, NRENs provide other services for their users

Not limited to a national level, the NRENs play a critical role in advancing scientific collaboration, innovation, and knowledge exchange on a global scale. The development of NRENs has been a global phenomenon, with significant progress made in the early 1990s (McClure et al., 1991). They have also been crucial in advancing technologies and promoting international research collaboration (Schleyer et al., 2012).

The importance of NRENs in bridging digital divides and supporting national and international development has been emphasized, particularly in regions such as West and Central Africa (Kashefi et al., 2019). The role of NRENs in developing communication network infrastructure and networked services for researchers and educators has been highlighted in this study. Establishing research networks and collaborations provides the necessary flexibility to adapt to a broad spectrum of arising challenges (Puljak & Vari, 2014).

Global NREN Collaborations

A “consortium” is a collaborative framework allowing flexible transactions and interaction modes (Kouramajian et al. 1995). As voluntary partnerships, consortia are key players in collaborative efforts, particularly in the library and academic sectors (Hooper-Bùi et al., 2018; Armstrong & Teper, 2017; Cherubini & Kraus, 2011; Gunjal, 2020; Johnson, 2006). Phillips et al. (2000) have defined collaboration as a cooperative relationship among organizations that relies on neither market nor hierarchical mechanisms of control. They explain that collaborations are crucial for the structuration of institutional fields.

Shared goals play a crucial role in the collaboration of organizations, driving motivation and direction (Adler & Heckscher, 2018). They can be particularly effective in addressing common concerns and engaging diverse worldviews (Chapin, 2020). These provide shreds of evidence that common goals are crucial to forming partnerships. Collaborations have been formed in different domains and industries aiming for different goals. Collaborations are significant in higher education, where they can enhance academic performance, achieve economic efficiencies, and align institutions with public needs (Williams, 2017).

A regional research and education network collaboration can bring many benefits. These networks often involve universities, research institutions, and other stakeholders and can be regionally or thematically

focused. They play a crucial role in facilitating the exchange of information and best practices and promoting innovation and regional development (Ata, 2007; Hansen et al., 2002).

Jensen & Bergqvist (2012) have highlighted the potential for resource pooling and coordination within NREN collaborations. This is particularly beneficial in the context of specialized education and distance learning, where resources may be scarce or unevenly distributed. Boronenko et al. (2018) also underscore the importance of resource pooling and coordination in collaborations. Hammond (2019) and Woolcott et al. (2019) have further highlighted the role of these collaborations in knowledge production. They suggest that these networks can contribute to societal integration and develop tailored educational solutions by working together. Khaparde & Srivastava (2003) underscore the importance of regional cooperation in academic research. He argues that such cooperation is crucial for addressing local and regional challenges unique to a particular area or population.

Key Factors in NREN Consortium Formation

A range of factors influence the formation and success of consortia across industries. In the research and development industry, industry competition and appropriability conditions, a firm's R&D capabilities, and past participation in large-scale consortia are key factors (Sakakibara, 2002). Choosing partners is also critical, as the right partners increase opportunities and decrease risks (Walther, 2015). In the export consortiums, joint learning actions, cooperation, and innovation determine efficiency (Amorim J. E. O. ; Forte, Sérgio Henrique Arruda Cavalcante, 2007). In e-business standardization, firms' interests, resource availability, and consortium management effectiveness drive resource investments (Kexin Zhao & Shaw, 2011).

Successful collaboration and consortium management require a clear understanding of the benefits of working together and a commitment to achieving common goals (Khaparde & Srivastava, 2003). Pangarkar & Klein (2001) and Ongsakul et al. (2019) highlight the importance of the purpose and partner similarity in determining the governance structure of a consortium. Nielsen (2003) and Teng & Das (2008) further underscore the significance of strategic motivation, governance mode, and partner nationality in driving alliance formation and influencing governance structure choice. These studies collectively suggest that the feasibility factors of *membership criteria*, *governance structure*, and *financing model* are crucial in shaping the formation and success of a consortium or alliance.

NRENs are a special entity that focuses on serving the research and education communities; almost all are not-for-profit organizations. The following papers provide a range of factors that influence the success of the Not for Profit (NFP) consortium formation. These include the choice of partners (Walther, 2015), the social or institutional composition of the consortium (Wanzenböck et al., 2020), and the need to utilize the full value-creation potential of the firm's resources. Commitment, coordination, and communication are also crucial (Dodourova, 2009). The role of corporate governance in NFP organizations is significant, with cooperation being a key driver of wealth maximization (Romano, 2013).

With a foundational understanding of key factors influencing consortium formation across various industries and specifically the unique nature of the NREN consortium, this study will thus concentrate on only four critical areas: membership criteria, governance structure, financing mechanisms, and geopolitical dynamics.

Membership Criteria

Clear membership criteria are essential for maintaining the integrity and consistency of any organization. At the level of professional, totalitarian and bureaucratic organizations as social segments, membership is modified as "belonging status", organizational identity, subordination and involvement (Surovtseva, 2020). It can provide access to services, participation in a community, support for a cause, like-minded connections, prestige, special privileges, and networking opportunities (Weissman, 2014). "Setting Clear Membership Criteria for Nonprofit Organizations" emphasizes the importance of defined criteria for ensuring qualified membership and organizational mission alignment (*National Council of Nonprofits*, n.d.). American Society of Association Executives (ASAE) discusses the need for clear membership criteria to maintain integrity and reputation within corporate and professional organizations (*Welcome to ASAE — American Society of Association Executives*, n.d.).

Governance Structure

Inclusive governance structures are important for promoting diversity, equality, and inclusivity in various contexts, including higher education (Graham Wise Connie Dickinson & Gallegos, 2020), public administration (Emerson et al., 2011), and nonprofit organizations (Brown, 2002). Brown (2002) explains that nonprofit organizations need a better understanding of what inclusive governance looks like in practice. An inclusive board demonstrates awareness of the community and constituents who benefit from and contribute to the services of the organization (Barbero et al., 2019), seeks information from multiple sources (Daley & Angulo, 1994), and establishes policies and structures (such as committees) to foster stakeholder involvement (Duca, 1996).

Financing Mechanism

Financing mechanisms are essential for securing the necessary funds for any organization's operations. They can take multiple forms, such as loans, grants, equity investments, bonds, and public-private partnerships (Podyk, 2023). Various financial mechanisms are crucial for the sustainable development of not-for-profit organizations (NPOs) and non-governmental organizations (NGOs) (Pyanov et al., 2021). The economic and credit mechanism of an enterprise, a subset of the finance mechanism, is a set of interrelated financial processes, instruments, methods, and resources used to ensure the enterprise's activities, implement strategic goals, and achieve economic stability (Podyk, 2023).

Geopolitical Dynamics

When geopolitical relationships are stable, countries can engage in consistent and cooperative international policies, trade, and diplomatic relations. This stability reduces the risk of conflicts, encourages foreign investments, and enables long-term planning for development and security (Friedman, 2009). According to the World Bank Report, 2011, the relationships and interactions between countries and regions are relatively predictable and peaceful in the presence of stable geopolitical conditions. Geopolitical and geo-economic shifts in the region are ongoing, so, naturally, there is a process of adaptation that creates a bit of friction with domestic politics (Erlangga, 2018).

In summary, this literature review has identified and elaborated on four critical factors that influence the formation and success of NREN consortia: membership criteria, governance structures, financing mechanisms, and the impact of geopolitical dynamics.

Comparative analysis

Comparative analysis of organizations can reveal unexpected similarities and differences by examining cross-level, contextual factors (Whetten 2009). According to King et al. (2009), comparative analysis can be used to explain and describe organizational heterogeneity at varying levels and contexts. He

further explains that one advantage of comparative analysis is the ability to assess the observed differences between organizations and by examining differences between organizations, researchers can assess the sources of heterogeneity within fields and industries, offering a more comprehensive understanding of organizational phenomena.

Research methodology

Data Collection and Analysis

The research proceeded with a detailed literature review and secondary data collection to identify the existing global NREN consortiums. Through the secondary data collection, different NREN consortiums in different regions of the world were identified, and their form of establishment was based on membership criteria and participation guidelines, a financing mechanism, a governance structure, and a regional context.

When collecting details on regional NREN collaborations, it was identified that the details and publications available on the GÉANT website (https://geant.org) provide appreciable information on GÉANT itself and other regional collaborations worldwide. *Figure 3.1* visually represents regional NREN consortiums available worldwide and GÉANT's connection with them.

GÉANT is the pan-European data network for the research and education community. It interconnects national research and education networks across Europe and exerts appreciable effort in connecting with other regional collaborations.

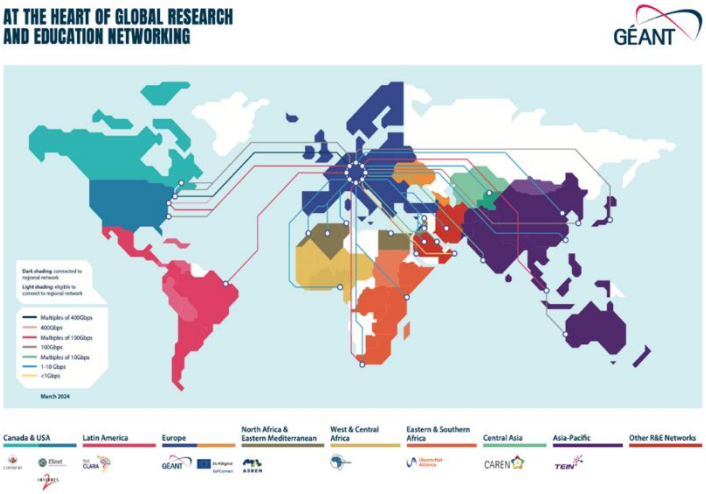
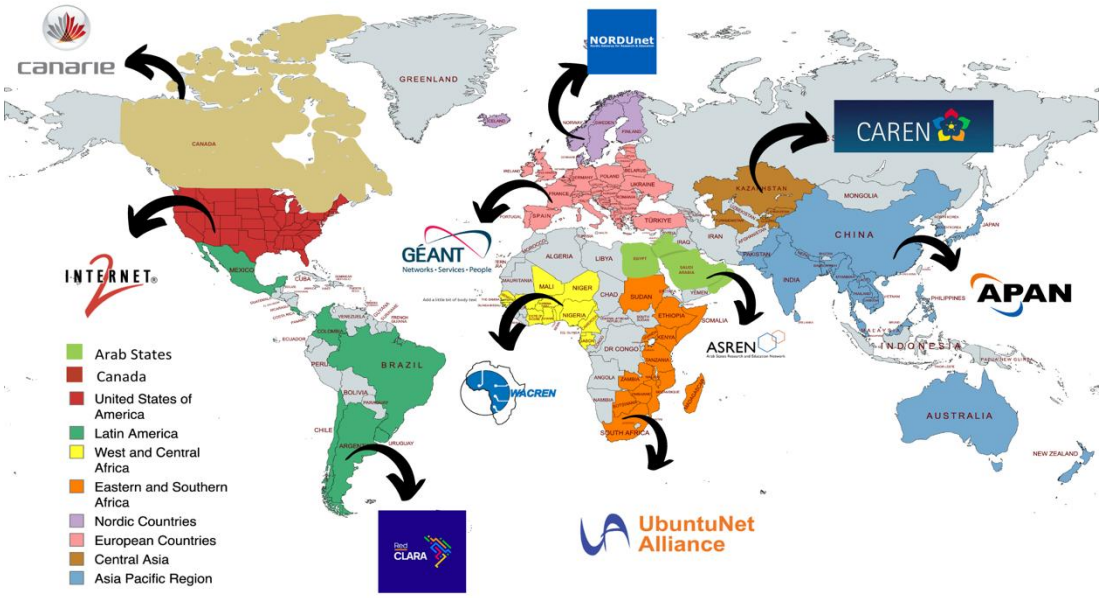


Fig 3.1: Global Connectivity Map of GÉANT

(Source: https://resources.geant.org/maps/)

Referring to the details in *Figure 3.1* and other online sources, worldwide regional NREN consortiums were identified, as shown in *Figure 3.2*. Table 3.1 shows a summary of those consortiums.

Figure 3.2: Regional NREN Consortiums



(Source: Developed by Author)

Table 3.1: Summary of regional NREN consortiums available worldwide

Region	NREN Consortium	Description	Source
America	CANARIE	"The Canadian NREN that supports advanced networks and technology to facilitate research and education. It connects 13 provincial and territorial R&E networks in Canada."	(*Canada's National Research and Education Network - CANARIE*, n.d.)
	Internet2	"A collaborative effort among regional and state education networks, universities, government agencies, and community anchor institutions in the United States of America working on advanced networking and technology initiatives."	(*Home - Internet2*, n.d.)
	RedCLARA	"A collaboration of Latin American NRENs in 13 Latin American countries connecting research and education	(*Home RedCLARA*, n.d.)

		networks across countries in the region."	
Africa	UbuntuNet Alliance	"An association of National Research and Education Networks in 13 countries in Eastern and Southern Africa. It works towards the establishment and management of a regional high-speed internet network dedicated to the research and education community."	(*Ubuntunet Alliance – For Research & Education Networking*, n.d.)
	WACREN	"A regional NREN consortium that aims to promote the deployment of advanced networks and technologies in 11 countries in West and Central Africa to support research and education."	(*Home - WACREN*, n.d.)
	ASREN	"It is an association of NRENs from the Arab region, along with strategic partners. ASREN's mission is to implement, manage, and expand sustainable Pan-Arab e-infrastructures dedicated to the research and education communities."	(*Arab States Research and Education Network*, n.d.)
Europe	GÉANT	"A pan-European data network dedicated to the research and education community. It interconnects national research and education networks, creating a high-performance, secure, and reliable communications infrastructure in the European region."	(*GÉANT*, n.d.)
	NORDUnet	"Supplies connectivity between the NRENs of the five Nordic countries and supports over 400 institutions."	(*Home - NORDUnet*, n.d.)
Asia and Asia Pacific	CAREN	"A project that was launched in 2009 with the goal of providing a high-capacity internet network for the research and education communities in Central Asia1. The network facilitates communication, information exchange, and collaboration between universities and research centers across the region."	(*CAREN Project – ICAREN*, n.d.)
	APAN	"Not-for-profit Association of Asia-Pacific NRENs incorporated in Hong	(*Asia Pacific Advanced Network*, n.d.)

		Kong as a company limited by guarantee."	

Comparative analysis is a valuable method in research that involves comparing two or more entities to identify similarities, differences, and patterns. The Qualitative Comparative Analysis (QCA) method introduced by Charles Ragin in 1980 was utilized in this research. Each criterion-membership, governance, financing, and regional context is analyzed across various NREN consortiums one by one. The comparison is structured around key variables: membership criteria, governance models, and financing mechanisms. A comparison of regional contexts (including political stability, economic strength, and technological infrastructure) was included to get a better understanding of regional behaviour.

Membership Criteria Analysis

After identifying the different NREN consortiums operating globally, the membership criteria of each were observed, and different membership categories were identified. The collected data on membership categories were summarized and presented in Table 3.2. The multi-value data coding method was used to code the data. Hence, only "Research and Education Network (REN) Members" were denoted by "0". Entities offering membership criteria for REN members and other associate/affiliate members excluding Industry partners were denoted by "1". Entities offering membership criteria for all REN members, associate/affiliate members and Industry partners were denoted by "2".

Table 3.2: Summary of membership categories

Network	Membership Criteria	Membership Category	Code
CANARIE	Offer membership to the leading research, education, and innovation organizations and contribute to evolving Canada's digital research infrastructure. Applications are subject to the approval of the CANARIE Board of Directors. Source: CANARIE website (www.canarie.ca/nren/)	1. Research and Education Network Members 2. Higher education institutes (colleges, universities, research institutes) 3. Other innovative organizations	1
Internet2	Membership is divided into four levels based on annual operating budgets for Affiliate members, and annual revenues for Industry members. The member's level determines its annual membership dues and network participation fees. Source: Internet2 website (https://internet2.edu/)	1. Higher Education Members 2. Affiliate Members 3. Industry Members 4. Research and Education Network Members	2

RedCLARA	To become a full associate, an entity must manage an academic, scientific and/or research network at a national level in a country, have support from the Government of the country represented, and request its incorporation into the Association through a formal letter addressed to the Directing Council. Only one NREN per country can be a RedCLARA member. Source: RedCLARA website (https://www.redclara.net/en/)	Research and Education Network Members	0
UbuntuNet Aliance	The UbuntuNet Alliance is a membership organization of National Research and Education Networks (NRENs) in Eastern and Southern Africa. They collectively seek to facilitate access by the region's knowledge communities to their global research and educational resources. Source: UbuntuNet Alliance website (https://ubuntunet.net/)	Research and Education Network Members	0
WACREN	WACREN offers membership to organizations in education and research. Members of WACREN play a critical role in the governance and evolution of the organization, helping ensure West and Central Africa remains at the forefront of research and innovation. Source: WACREN website (https://wacren.net/en/)	1. NREN Member 2. Associate Member 3. Premium Associate Member 4. Corporate Member 5. Premium Corporate Member 6. Partner Member	2
ASREN	Coordinates Arab region National Research and Education Networks (NRENs) and strategic partners, aiming to build, manage, and expand sustainable Pan-Arab e-Infrastructures. Source: ASREN website (https://www.asren.net/)	Research and Education Network Members	0
GÉANT	Owned by its core membership, including 36 National Members which are European NRENs, and one Representative Member – NorduNET. Associates include commercial organizations and multi-national research infrastructures and projects	1. Research and Education Network members 2. Associates	1

	Source: GÉANT website (https://geant.org/)		
NorduNET	Primarily serves the Nordic countries, connecting research and education networks to the rest of the world. Membership is based on being part of the Nordic research and education networks. Source: NorduNET Website (https://nordu.net/)	Research and Education Network Members	0
CAREN	Membership details are not explicitly stated, but it appears to be focused on NRENs in Central Asia, aiming to be part of a large user group representing academic institutions in the region Source: CAREN website (https://icaren.org/)	Research and Education Network Members	0
APAN	APAN has one category of Voting Member, also known as Primary Member, which is typically an entity that coordinates advanced research and education network provisioning within a country/economy. There are also four categories of Non-voting Members: Associate, Affiliate, Liaison, and Industry Members, with each having different roles and interests aligned with APAN's objectives. Source: APAN website (https://apan.net)	1. Primary Members 2. Associate Members 3. Affiliate Members 4. Liaison Members 5. Industry Members	2

Governance Structure Analysis

The governance structures of NREN consortia vary, with some similarities and distinct models across entities. The gathered data on each consortium's governance model are summarized and presented in Table 3.3. The multi-value data coding method was used to code the data. Hence," Board of Directors" was denoted by "0." Entities having a "Board of Trustees" were denoted by "1." "Community Governance" was denoted by "2," and if data was unavailable, it was denoted by "3."

Table 3.3: Summary of Government Structures

Consortium	**Governance Structure**	**Governance Model**	**Code**
CANARIE	Governed and managed by the NREN Governance Committee, including the president of CANARIE and leaders of provincial and territorial networks. Source: CANARIE website (www.canarie.ca/nren/)	Board of Directors	0
Internet2	Internet2 is governed by members of the Internet2 community, including university presidents, chancellors, CIOs, industry and regional representatives. The Board of Trustees provides strategic direction, leadership, and oversight for Internet2. Source: Internet2 website (https://internet2.edu/)	Community Governance	2
RedCLARA	Governed by an Assembly, Board of Directors, and Technical Commission. Members include various Latin American countries' national research and education networks. Source: RedCLARA website (https://www.redclara.net/en/)	Board of Directors	0
WACREN	The Board of Directors comprises six members including the Chair and CEO. Directors are nominated for three-year renewable terms. Source: WACREN website (https://wacren.net/en/)	Board of Directors	0
Ubuntunet Alliance	Governed by a Council of Members, a Management Board, and a Secretariat. It operates with a three-tier structure. Source: UbuntuNet Alliance website (https://ubuntunet.net/)	Board of Trustees	1
ASREN	No specific governance structure details were found.	Not Available	3
NorduNET	Managed by a Board consisting of members from five partnering countries. The Board resolves overall political and strategic issues. Source: NorduNET Website (https://nordu.net/)	Board of Directors	0
GEANT	The highest governing body is the General Assembly, which elects members to the Board of	Board of Directors	0

	Directors. The Board manages and administers the organization. Source: GÉANT website (https://geant.org/)		
CAREN	No specific information found on the governance structure.	Not Available	3
APAN	Comprises a Board of Directors, General Meeting of Members/Council of Primary Members, and various committees and working groups. Source: APAN website (https://apan.net)	Board of Directors	0

Financing Mechanism Analysis

The study observed the financing mechanisms of each NREN consortium selected. This included the financing received for the consortium's initial establishment and the methods of revenue generation for operational activities and long-term sustainability. The summarized data are presented in Table 3.4. The multi-value data coding method was used to code the data, and coding was done as follows,

Membership fees and service fees only – "0"
Membership fees and project grants – "1"
Membership fees, Service fees and corporate partners – "2"
Membership fees, service fees and grants – "3"
Membership fees, service fees and corporate partners – "4"
Membership fees, service fees and funds and corporate partners – "5"

Table 3.4: Summary of Financing Mechanisms

Consortium	**Initial Establishment Funding**	**Revenue generation**	**Code**
CANARIE	Initially funded by the Government of Canada. Source: CANARIE website (www.canarie.ca/nren/)	From membership fees, government grants, partnerships and service fees	5
Internet2	Started with various sources including government grants. Source: Internet2 website (https://internet2.edu/)	From member fees, corporate partners, and service fees.	4
RedCLARA	Received initial funding from the European Union and Latin American NREN community. Source: RedCLARA website (https://www.redclara.net/en/	From membership fees, project funds, Partnerships and service fees	5

UbuntuNet Alliance	Substantial initial funding from the European Union under the Africa Connect Programme. Source: UbuntuNet Alliance website (https://ubuntunet.net/)	From membership fees and service provision to members.	0
WACREN	Incubation started with support from the Africa Network Operation Group (AfNOG) and the Association of African Universities (AAU). Source: WACREN website (https://wacren.net/en/)	From membership fees and possibly project grants.	1
ASREN	Established with the support of member NRENs and strategic partners. Source: ASREN website (https://www.asren.net/)	From membership fees and project funding.	1
GEANT	Funded under the Horizon Europe framework by the European Commission. Source: GÉANT website (https://geant.org/)	From membership fees and project funds.	1
NorduNET	Receives public financing for specific projects like the Arctic gateway to Asia. Source: NorduNET Website (https://nordu.net/)	Membership fees from Nordic NRENs and service fees.	0
CAREN	Jointly funded by the EU and Central Asian NREN partners for initial establishment. Source: CAREN website (https://icaren.org/)	Membership fees and service fees from participating countries.	0
APAN	The total budget for regional operations is USD 2.5 million per annum, not exclusive to loss and damage but covering all activities. Source: APAN website (https://apan.net)	From membership fees and possible project grants.	1

Regional Context Analysis

This study conducted a comprehensive analysis of regions worldwide based on predefined criteria, as shown in Table 3.5.

Table 3.5: Summary of Regional Context

Factors		America	Africa	Europe	Asia
Political Stability and Governance	Political Stability	Usually high, with vigorous democratic institutions and steady governance	Varies widely; some countries experience substantial instability (e.g., conflicts, coups), while others (e.g., Botswana, Ghana) are comparatively stable	Normally, very high, with robust democratic institutions and a history of steady governance	Varied; East Asia (e.g., Japan, South Korea) is very stable, while South Asia (e.g., India, Pakistan) and parts of Southeast Asia (e.g., Myanmar) face more challenges
	Governance	Robust legal frameworks and regulatory systems facilitate business operations and consortium formations	The quality of governance varies, with factors like corruption and weak institutions affecting the formation of consortiums	Inclusive legal and regulatory frameworks support consortium operations. The European Union offers an additional layer of governance and care for cross-border collaborations	Differs significantly; countries like Japan and South Korea have strong governance, while others brawl with fraud and regulatory inadequacies
Economic Factors	Economic Strength	Robust economies, mainly in the US and Canada, with high GDP and substantial investment potential	Usually lower GDP, but with some fast-growing economies (e.g., Nigeria, South Africa)	Robust and varied economies, with high GDP and well-known markets	Mixed, with highly advanced economies (e.g., Japan, South Korea) and developing ones (e.g.,

					India, Bangladesh)
	Market Size and Openness	Large and open markets, enabling large-scale consortiums	Emerging markets with important growth potential but also high risks	Extremely combined markets, especially within the EU, offering a huge and reachable market for consortiums	Large markets with important growth potential, but also fluctuating degrees of market openness
Cultural and Social Factors	Cultural Diversity	Massive cultural diversity, nurturing innovation and collaboration	Enormously varied cultures and languages	Varied but with a robust prominence on collaboration and integration, especially within the EU	Extremely diverse, with substantial cultural differences between countries
	Social Acceptance	Usually, high acceptance of consortiums and collaborative business models	Differs, with some societies being more public and others more individualistic, impacting consortium dynamics	High acceptance of collaborative projects and consortiums	Differs; some cultures highlight hierarchical structures which can impact collaborative efforts
Technological Infrastructure	Technological Advancements	Very advanced, with important investments in R&D and technology infrastructure	Differs extensively; some countries are progressing rapidly, while others lag significantly	Vastly advanced, especially in Western and Northern Europe	Diverse; countries like Japan, South Korea, and China are leaders in technology, while others are developing
	Digital Connectivity	High internet penetration and advanced digital	Usually lower internet penetration, though mobile connectivity is growing fast	High levels of internet penetration and advanced digital	High in East Asia, but lower in parts of South and Southeast Asia

		infrastructure		infrastructure	
Educational and Research Capabilities	Educational Institutions	Housing numerous world-leading universities and research institutions	Differs, with a few robust universities but usually lower global rankings	Several top-ranking universities, especially in Western Europe	Diverse; world-class universities in Japan, China, and South Korea, with others developing
	Research Output	High levels of research and innovation, maintained by considerable funding	Limited by funding and infrastructure, though improving in some regions	High research output, maintained by EU funding and collaborative frameworks	Increasing quickly, particularly in East Asia, with substantial investments in R&D

Sources:

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Results

The following results were obtained from the analysis. Presented in Table 4.1

Table 4.1: Results of the analysis

Consortium	Region	Membership criteria	Governance structure	Financing mechanism
CANARIE	North America	1	0	5
Internet2	North America	2	2	4
RedCLARA	South America	0	0	5
UbuntuNet Alliance	Africa	0	0	0
WACREN	Africa	2	1	1
ASREN	Asia	0	3	1
GEANT	Europe	1	0	1

NorduNET	Europe	0	0	0
CAREN	Asia	0	3	0
APAN	Asia	2	0	1

- Some consortiums offer membership only to NRENs, while others offer a range of membership categories, such as associate membership, industry partner membership, and Partner membership other than the NREN membership. The majority of regional NREN consortiums offer membership only to NRENs

- NREN consortiums are governed by a Board of Directors, a Board of Trustees, or Community Governance. Of these three models, the Board of Directors is the most popular and most practiced.

- A common mechanism of generating operating finance for all the NREN consortiums was collecting membership fees. Not limited to membership fees, on top of that, service fees are collected for the services provided among the consortium members. Some of the Consortiums formed with low and middle-income countries in Asian and African regions were formed with a grant received.

- When considering the regional context,
  - The Political Stability and Governance of American and European regions are comparatively highly stable, and the governance is favourable for consortium establishment, while it's varied in African and Asian regions because some countries of these regions have highly stable situations while some are very unstable.

  - In terms of economic factors, the American and European regions demonstrate strong economies with high-GDP countries. Asia shows a mix of low and high-GDP countries, while Africa has predominantly low-GDP countries. The American region boasts a large and open market. Asia's market size is significant, but its openness varies. The European region is composed of combined markets within the EU region, and the African region has an emerging market but with a high risk.
  - Cultural and Social Factors vary greatly across American, Asian, and African regions, with notable diversity. Diversity exists in the European region but is well integrated within the European Union. Social acceptance is usually high among the American and European regions. In Asian and African regions, it varies as some nations are more public and some are more individualistic.

  - Technological Advancement and Digital Connectivity are high in America and Europe. Asian region varies: some nations lead in technology, others are developing. East Asia has high digital connectivity; Southeast and South Asia have low connectivity. Some countries in the African region show rapid progress in technological advancement, and some show very little advancement and progress. Hence, technological advancements differ in the region, and digital connectivity is low overall.

  - When comparing Educational and Research Capabilities, leading universities are housed in the American and European regions. Hence, research output is higher in these two regions. Certain countries in the Asian region have many world-class universities, and there has been a rapid

increase in research output from this region. The situation in the African region is that there are only a few robust universities and research output is low.

Recommendations and conclusion

Providing membership for NREN members is more practical and crucial, but allocating space for a wide range of stakeholders, including NRENs, associate members, industry partners, and relevant entities, promotes a more dynamic consortium by encouraging a diverse exchange of knowledge and resources.

The Board of Directors model has proven to be the most effective and practised governance structure for NREN consortiums. It provides strategic oversight, ensures accountability, and supports decision-making processes that reflect the consortium's diverse membership.

A sustainable financial model is essential for the longevity of NREN consortiums. Collecting membership fees from member institutions and service fees for specific services provided ensures a steady revenue stream. This model can be supplemented with grants and external funding, particularly for consortiums in low and middle-income countries. Actively seeking grants from international organizations and development agencies can provide essential funding for initial setup and specific projects. This is especially important for consortiums in regions with limited financial resources.

Recognising the unique political, economic, and social contexts of different regions is critical. Consortiums should develop tailored strategies considering regional stability, economic strength, market openness, and cultural factors.

In conclusion, the success and sustainability of NREN consortiums require flexible membership options, robust governance models, and diversified financing mechanisms. Tailoring strategies to regional contexts, investing in technological and educational capacity, and fostering inclusive and participatory governance are essential to enhance research and education networks. These efforts will strengthen the consortiums and contribute to regional and global development by facilitating advanced research, education, and technological progress.

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