The Indonesian Journal of Computer Science
www.ijcs.net
Volume 15, Issue 2, April 2026
https://doi.org/10.33022/ijcs.v15i2.5035

Adoption of Artificial Intelligence in Competitive Intelligence: A Systematic Literature Review

Alexander Maune[1,2]
alexandermaune6@gmail.com[1,2]
[1]University of South Africa (UNISA), South Africa
[2]Bindura University of Science Education (BUSE), Zimbabwe

Article Information

Received : 31 Oct 2025
Revised : 18 Mar 2026
Accepted : 26 Mar 2026

Keywords

Artificial Intelligence, Competitive Intelligence, Business Intelligence, Machine Learning, Deep Learning, Market Intelligence, Competitor Intelligence, Natural Language Processing

Abstract

The accelerating convergence of Artificial Intelligence (AI) and Competitive Intelligence (CI) represents a significant transformation in how organisations gather, analyse, and interpret strategic information. As global markets become increasingly dynamic and data-driven, understanding how AI enhances CI processes is critical for both scholars and practitioners. This study conducts a systematic literature review (SLR) using the PRISMA methodology to synthesise and critically evaluate existing research on the integration of AI into CI. Drawing from peer-reviewed articles published between 2000 and 2025, the review identifies four dominant thematic clusters: AI-enabled data acquisition and mining, predictive analytics and machine learning in market forecasting, natural language processing in sentiment and competitor analysis, and ethical, organisational, and interpretative challenges in AI-driven intelligence. Findings reveal that while AI enhances the accuracy, speed, and depth of intelligence analysis, the literature remains fragmented across disciplines, with limited empirical validation and theoretical coherence. Notably, few studies address the human–AI interface, data governance, and contextual applicability in emerging economies. The paper presents an integrative conceptual framework that links AI capabilities with the CI cycle, highlighting avenues for future research, including ethical AI governance, explainable intelligence models, and applications in small and medium-sized enterprises (SMEs). The synthesis underscores that AI does not replace human intelligence but rather augments it—transforming CI into a more anticipatory, adaptive, and strategic function.

A. Introduction

In an era characterised by hyper-competition, digital transformation, and data proliferation, organisations increasingly rely on timely and actionable intelligence to maintain strategic advantage. Competitive Intelligence (CI), defined as the systematic process of gathering, analysing, and interpreting information about competitors, markets, and industry trends, has long been recognised as a cornerstone of strategic decision-making [1]-[9]. Nevertheless, the exponential growth of data sources and technological advancements has dramatically altered the intelligence landscape. Traditional CI methods, which depend heavily on human analysts to collect and interpret data, are increasingly challenged by the sheer volume, velocity, and variety of information available today [10], [11], [6]. Within this evolving environment, Artificial Intelligence (AI) has emerged as a transformative force capable of automating data collection, uncovering hidden patterns, and enhancing analytical accuracy [12]-[15].

The convergence of AI and CI offers unprecedented opportunities for organisations to improve their strategic foresight and decision-making processes. AI technologies such as machine learning (ML), natural language processing (NLP), and deep learning can process vast amounts of structured and unstructured data, ranging from social media posts and news feeds to financial statements and patent databases, to generate actionable insights [12]-[15]. AI not only increases the efficiency of intelligence gathering but also introduces predictive and prescriptive capabilities that extend beyond traditional descriptive analytics [12]-[15]. Despite this potential, the academic literature on integrating AI into CI remains fragmented, conceptually underdeveloped, and empirically sparse. Most prior studies either focus broadly on business intelligence or analytics or address CI from a managerial perspective without engaging deeply with AI techniques and implications.

Studying AI in the context of CI is, therefore, both timely and necessary. From a practical standpoint, organisations face increasing pressure to navigate uncertain and rapidly changing competitive environments. AI-enabled CI promises to provide strategic agility by delivering real-time, data-driven insights. From a theoretical standpoint, this convergence challenges existing CI frameworks, demanding new conceptualisations of how intelligence is generated, validated, and applied in decision-making. Furthermore, the human–machine interface in intelligence work raises questions about trust, interpretability, and ethics that require scholarly attention.

What is currently known about the topic stems primarily from three strands of literature. First, the traditional CI scholarship provides conceptual foundations for intelligence cycles, organisational structures, and the role of information in strategic management [10], [2], [16], [6]. Second, the AI and business intelligence literature demonstrates how AI enhances analytics, decision support, and knowledge discovery [15], [17], [18]. Third, emerging interdisciplinary works have begun exploring AI applications in CI contexts, focusing on data automation, competitor tracking, and market sentiment analysis [19], [20]. However, what remains largely unknown is the extent, effectiveness, and ethical implications of AI integration into CI workflows. Few studies have examined the theoretical alignment between CI processes and AI-driven analytics,

and even fewer have assessed their empirical impact on organisational performance or competitive advantage.

This gap justifies the need for a systematic review to synthesise existing knowledge and chart a future research agenda. Accordingly, this study aims to answer three key research objectives:

- To map the existing literature on AI applications within competitive intelligence, identifying prevailing themes, methodologies, and disciplinary perspectives.
- To synthesise and critically evaluate findings regarding AI's role in enhancing CI processes—specifically in data acquisition, analysis, interpretation, and dissemination.
- To develop an integrative conceptual framework for AI-enabled CI and outline directions for future theoretical and empirical research.

The originality of this study lies in its comprehensive and systematic approach, employing the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) method to ensure transparency and reproducibility. By consolidating fragmented insights from both academic and practitioner sources, the paper advances understanding of how AI reshapes CI's traditional boundaries. Moreover, it emphasises underexplored issues such as human–AI collaboration, ethical data use, and the applicability of AI-based CI in small and medium enterprises (SMEs) and emerging economies—contexts often neglected in mainstream research.

In sum, this article addresses a critical gap at the intersection of technology and strategy. It argues that while AI offers immense promise for transforming CI, realising this potential requires more than technological adoption—it necessitates theoretical integration, ethical governance, and organisational readiness. The study, therefore, contributes to both scholarship and practice by clarifying what is known, what remains unknown, and what needs to be done to harness AI's transformative capacity in competitive intelligence.

The remainder of this article is structured as follows. Section B presents a comprehensive review of the existing literature, providing the theoretical and empirical foundations that frame the study. It explores key concepts, previous research findings, and gaps in current knowledge related to the integration of AI within CI processes. Section C outlines the research methodology adopted in the study, detailing the systematic review approach, data collection and analysis procedures, quality assessment criteria, and ethical considerations that guided the research process. Section D presents and discusses the results, highlighting the main themes, patterns, and insights derived from the reviewed studies while interpreting their implications for both theory and practice. Finally, Section E offers the conclusion, summarising the key findings, emphasising the study's contributions, acknowledging its limitations, and proposing directions for future research and policy development.

B. Literature Review

Overview of Competitive Intelligence

Competitive intelligence refers to the systematic process of collecting, analysing, and interpreting information about competitors, markets, and business

environments to support strategic decision-making [1]- [10], [21], [22]. CI has long been associated with the intelligence cycle, which comprises planning, data collection, analysis, and dissemination [10], [23], [24]. Traditional CI activities rely heavily on human expertise, intuition, and manual information gathering from secondary sources such as reports, trade publications, and news media. While such approaches provide contextual richness, they are often limited by cognitive bias, time constraints, and the inability to process large volumes of data [16].

In the early 2000s, the digitisation of business data and the emergence of big data analytics began to reshape the CI landscape [25]-[27]. Researchers emphasised the need to integrate information technology into CI processes to improve timeliness, accuracy, and comprehensiveness [28], [29], [22], [6]. This shift laid the groundwork for the subsequent incorporation of Artificial Intelligence (AI) into intelligence systems.

Artificial Intelligence in Business and Decision Support

Artificial intelligence, broadly defined as computer systems that can perform tasks typically requiring human intelligence [12], [13], [14], [15], has transformed how organisations gather, analyse, and use information. In the context of business intelligence and analytics, AI techniques, particularly machine learning (ML), natural language processing (NLP), and deep learning, enable pattern recognition, predictive modelling, and automation of data analysis [30].

Studies have shown that AI enhances business decision-making by improving data accuracy, reducing human bias, and accelerating analytical processes [12], [31], [15]. Rosa et al. [17] demonstrate that firms adopting AI-based analytics experience improved strategic information management and competitive advantage. Similarly, [33] argue that AI transforms information from a passive input into a strategic asset, creating new forms of dynamic capability. However, despite the growing body of research on AI in business analytics, relatively few studies focus explicitly on AI's role in Competitive Intelligence—a distinct yet related domain concerned with generating competitor-oriented and market-oriented insights.

AI and the Evolution of Competitive Intelligence

Recent years have witnessed a surge of interest in applying AI technologies within CI functions. Cekuls [18] identifies AI-driven CI as a mechanism that strengthens business strategy and decision quality by enabling the rapid synthesis of data from multiple sources. Similarly, [19] examine how AI tools enhance data collection, pattern recognition, and trend analysis in tourism intelligence. Their findings suggest that AI expands CI's scope by automating repetitive tasks, thereby allowing analysts to focus on strategic interpretation.

AI's contribution to CI can be classified into several domains:

- *Automated Data Collection* – AI web crawlers and intelligent agents harvest data from competitors' websites, product catalogues, and online reviews [34].

- *Text and Sentiment Analysis* – NLP techniques interpret qualitative data from news articles, press releases, and social media to assess competitor sentiment or reputation [35].
- *Predictive Analytics* – Machine learning models forecast competitor actions, pricing trends, and market shifts [36].
- *Decision Support and Visualisation* – AI dashboards summarise complex patterns into interpretable insights for executives [37].

Through these functions, AI enhances the accuracy and speed of intelligence generation while minimising cognitive overload for analysts. Nevertheless, empirical validation of these claims remains limited.

Theoretical and Conceptual Perspectives

Theoretically, the integration of AI into CI can be understood through several lenses. The Resource-Based View (RBV) posits that AI technologies represent valuable, rare, and hard-to-imitate resources that can enhance a firm's intelligence capabilities, leading to a sustained competitive advantage [38]-[45]. The Dynamic Capabilities Framework further suggests that AI augments a firm's ability to sense, seize, and reconfigure resources in response to environmental change [46].

Another perspective derives from Information Processing Theory [47], which views organisations as information-processing systems. In this view, AI reduces information asymmetry and improves processing capacity, allowing faster strategic adaptation. Meanwhile, Socio-technical Systems Theory [48] underscores the interdependence of human and technological subsystems, highlighting that effective AI-CI integration depends on balancing algorithmic capabilities with human interpretation and organisational culture.

However, the literature reveals limited empirical application of these theories to AI-CI contexts. Most existing studies lack a strong theoretical foundation, often remaining descriptive or tool-oriented in nature. Integrating AI and CI theory requires reconciling human cognitive processes with machine-learning systems, such as a complex and underexplored task.

Key Empirical Studies and Findings

A growing number of empirical studies have begun exploring how AI transforms CI processes. Cekuls [18] found that AI-enabled tools improved the speed and quality of intelligence gathering in Baltic firms. Rosa et al. [17] reported that 95% of surveyed Portuguese companies considered AI adoption a source of competitive advantage, particularly in strategic information processing. Taranu and Cioranu [19] identified improved analytical capacity and ethical concerns in AI-based tourism intelligence systems.

Other studies extend beyond traditional CI settings. For instance, [37] demonstrated that machine learning models can predict competitors' innovation strategies based on patent data, while [36] utilised neural networks to forecast competitors' pricing behaviour. Practitioners have also contributed insights: the Competitive Intelligence Alliance in 2023 emphasised AI's capacity to automate

monitoring and sentiment tracking, whereas [20] highlighted human judgment as irreplaceable in interpreting AI outputs.

Across these studies, common findings emerge: AI improves efficiency, enhances analytical depth, and broadens the scope of CI. Nevertheless, several limitations are repeatedly acknowledged—namely, insufficient theoretical grounding, a lack of longitudinal evidence, and minimal attention to ethical, governance, and contextual factors.

Limitations of Existing Literature

Despite the growing enthusiasm surrounding AI-driven CI, the existing literature suffers from multiple shortcomings.

- *Fragmentation and Lack of Synthesis*: Research on AI in CI remains dispersed across information systems, management, and marketing domains, with few systematic syntheses [36].
- *Methodological Weaknesses:* Many studies employ small sample sizes, cross-sectional designs, or case studies with limited generalizability [18]. Quantitative analyses measuring CI performance improvements remain scarce.
- *Neglect of Human–AI Collaboration:* Few studies investigate how analysts interact with AI systems, build trust in AI outputs, or balance human judgment with algorithmic recommendations [20].
- *Ethical and Governance Gaps:* Issues of privacy, algorithmic bias, data transparency, and responsible competitor monitoring are often mentioned but rarely examined empirically [19].
- *Contextual and Sectoral Bias:* Most research is conducted in developed economies and large enterprises, neglecting small and medium enterprises (SMEs) and emerging markets such as Africa or Latin America, where CI practices and resource constraints differ substantially [49].
- *Weak Theoretical Integration:* Few works attempt to unify CI frameworks with AI theories such as explainable AI (XAI) or human-machine teaming.

Contribution of the Present Study

The present study addresses these limitations by conducting a systematic literature review (SLR) of AI in CI using the PRISMA approach. Unlike previous narrative or conceptual reviews, this research applies explicit inclusion and exclusion criteria, ensuring transparency and replicability. By systematically identifying, screening, and synthesising relevant studies, the article contributes to:

- Providing a comprehensive map of how AI is applied across different CI processes and sectors.
- Critically evaluating methodological robustness and theoretical alignment within the literature;
- Developing an integrated conceptual framework linking data automation, AI analytics, human–machine collaboration, and ethical governance; and

- Highlighting future research directions, particularly in underrepresented contexts such as SMEs and emerging markets.

Through this synthesis, the paper advances understanding of how AI transforms not only the tools and techniques of CI but also its epistemological foundations—shifting from human intuition and static reports to algorithmic, dynamic, and predictive intelligence.

C. Methodology

Research Design

This study adopts a Systematic Literature Review (SLR) methodology to provide a comprehensive, transparent, and replicable synthesis of existing research on the intersection of Artificial Intelligence (AI) and Competitive Intelligence (CI) [50]-[53]. Systematic reviews are increasingly used in management and information systems research to integrate fragmented findings, evaluate the quality of evidence, and identify gaps for future inquiry [54]. The Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) framework was applied to structure the review process through four key phases: identification, screening, eligibility, and inclusion [55]-[58].

The SLR approach was chosen over a narrative review for three main reasons. First, it minimises researcher bias by following explicit inclusion and exclusion criteria. Second, it provides a reproducible method to evaluate the growing body of interdisciplinary literature spanning business, management, information systems, and computer science. Third, it enables the synthesis of both conceptual and empirical findings, facilitating the development of an integrative framework for AI-enabled CI.

Search Strategy and Data Sources

A comprehensive search strategy was designed to capture all relevant studies published between 2000 and 2025, covering the period during which AI technologies became increasingly relevant to business and competitive analysis. Searches were conducted across major academic databases, including Scopus, Web of Science, IEEE Xplore, ScienceDirect, Emerald Insight, and Google Scholar. To enrich the review with practical insights, relevant industry white papers, conference proceedings, and reputable practitioner sources (such as, Competitive Intelligence Alliance, Valona Intelligence, SCIP publications) were also considered.

The search combined Boolean operators and keywords derived from the study's conceptual focus. The main search string used was:

> ("Artificial Intelligence" OR "AI" OR "machine learning" OR "deep learning" OR "natural language processing") AND ("Competitive Intelligence" OR "CI" OR "business intelligence" OR "market intelligence" OR "competitor analysis")

Reference lists of selected papers were also reviewed through a backward and forward snowballing approach to ensure comprehensive coverage.

Inclusion and Exclusion Criteria

To ensure focus and relevance, the following inclusion and exclusion criteria were applied as shown in Table 1.

Table 1. Inclusion and exclusion criteria

Inclusion	Exclusion
The study explicitly examined AI or related technologies (such as, ML, NLP, and automation) within the context of competitive intelligence, business intelligence, or market intelligence.	Studies addressing AI or analytics without any connection to competitive or market intelligence.
The publication was peer-reviewed or a recognised practitioner report with substantial analytical content.	Purely technical computer science papers that do not discuss managerial or strategic implications.
The study was written in English and publicly accessible.	Opinion pieces lack substantive analysis or data.
The study provided conceptual, empirical, or methodological insights relevant to CI applications.	

Source: Author's compilation

These criteria ensured that only research directly addressing the role, implementation, or impact of AI in CI was retained.

PRISMA Review Process

Following the PRISMA protocol, the review process proceeded through four main stages as shown in Fig. 1. In the *identification* stage, the initial search yielded 312 studies across selected databases, and after removing duplicates, 248 unique records remained. During *the screening* process, titles and abstracts were reviewed for relevance, and papers unrelated to the intersection of AI and CI were excluded, resulting in a reduced number of articles to 116. In the *eligibility* stage, full-text articles were assessed against inclusion criteria, and studies lacking explicit discussion of AI technologies in CI workflows or theoretical alignment were removed, leaving 64 eligible studies. Finally, in the *inclusion* stage, 38 core studies were selected for synthesis, comprising 25 academic articles, seven conference papers, and six practitioner reports. A PRISMA flow diagram (Fig. 1) was developed to illustrate this process. Each included study was assigned a unique identification code and analysed for bibliographic details, AI technologies used, CI functions addressed, methods employed, and key findings.

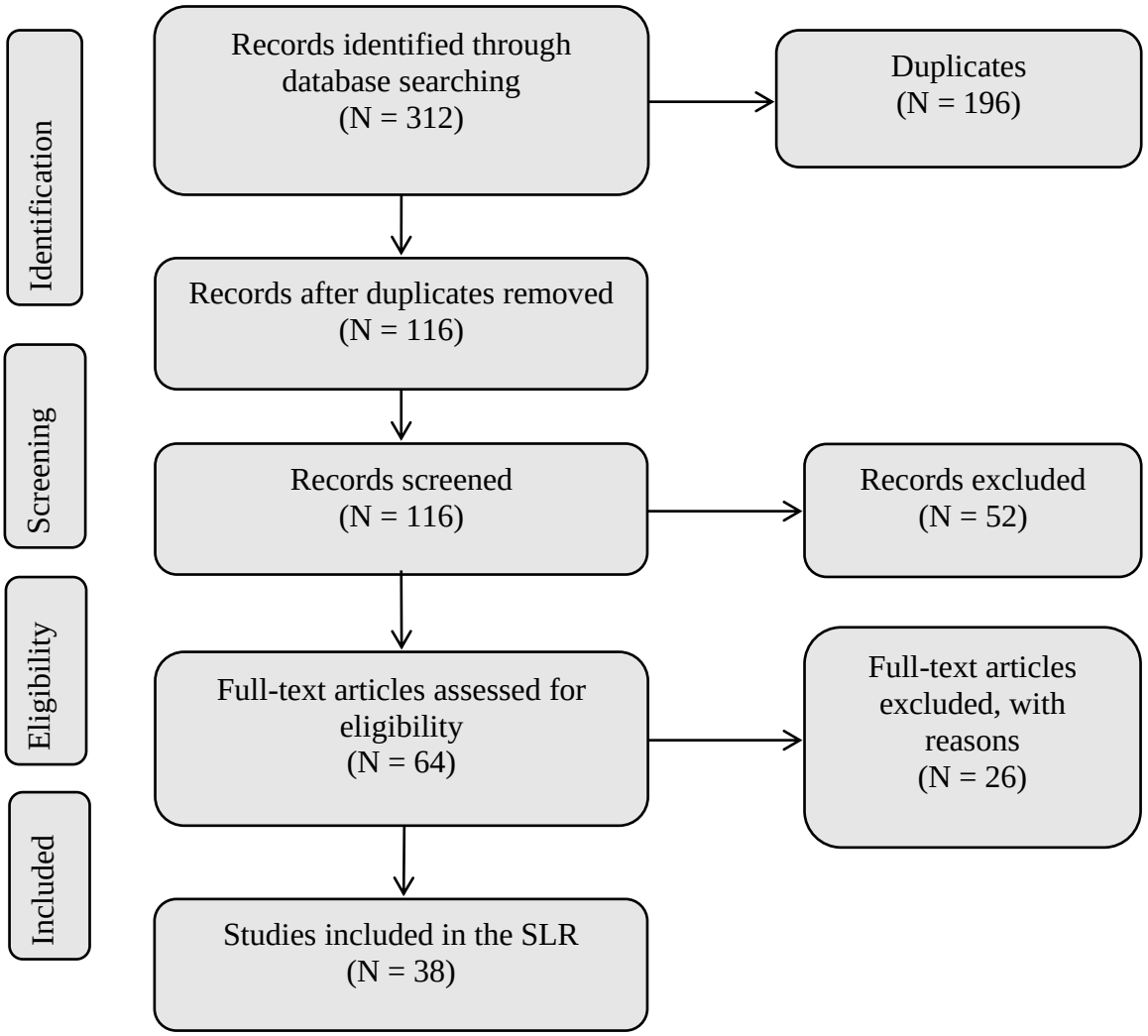

Figure 1. The PRISMA Diagram summarising literature identification, screening, eligibility, and inclusion

Data Extraction and Analysis

Data extraction followed a structured protocol using a predefined coding sheet. Each article was coded across several dimensions:

- *Bibliographic information:* author(s), year, journal/source, region.
- *Type of study:* empirical (quantitative, qualitative, mixed), conceptual, or review.
- *AI technology:* ML, NLP, deep learning, automation, big data analytics, or hybrid systems.
- *CI application:* data collection, competitor monitoring, market trend analysis, decision support, or strategic planning.
- *Theoretical foundation:* Resource-Based View, Dynamic Capabilities, Information Processing Theory.

Once extracted, data were subjected to thematic synthesis [59]-[62] to identify recurring themes and emerging trends through an inductive process of open coding, categorisation, and integration. The resulting thematic clusters were grouped into five broad categories: (1) AI-driven data automation; (2) unstructured data processing and NLP applications; (3) predictive and prescriptive intelligence models; (4) human–AI collaboration and interpretability; and (5) ethical, governance, and contextual considerations. These clusters form the foundation for the synthesis and discussion presented in the Results/Findings section.

Quality Assessment, Ethical Considerations, and Limitations

A quality appraisal was conducted to evaluate methodological rigour and relevance, with each study assessed on five criteria adapted from [63]: clarity of research objectives, transparency of methodology, validity and reliability of data, theoretical grounding, and practical relevance. Studies were classified as high, moderate, or low quality based on these criteria, with high-quality studies demonstrating transparent methodology, strong theoretical framing, and solid empirical evidence. Practitioner reports were categorised separately to ensure their insights were appropriately contextualised. Although this study did not involve primary data collection, ethical standards were maintained through accurate citation and intellectual acknowledgement. However, potential publication bias remains a limitation, as academic literature often overrepresents successful cases of AI adoption.

Additionally, the fast-paced evolution of AI technologies may render some findings quickly outdated, particularly regarding emerging tools such as generative AI. To mitigate these limitations, the review incorporated the most recent and reputable publications available up to 2025, including credible practitioner perspectives. Overall, the methodological approach adopted provides a transparent, replicable, and comprehensive foundation for mapping and analysing the role of Artificial Intelligence in Competitive Intelligence, ensuring that the findings and framework presented in Section D are grounded in a rigorous and systematic synthesis of the literature.

D. Discussion of Findings

Overview of the Reviewed Studies

From the final pool of 38 studies, approximately 65% were empirical (comprising case studies, surveys, or mixed-method analyses), 20% were conceptual or theoretical papers, and 15% were practitioner- or industry-based reports. The distribution across years indicates a significant growth trend: while only four studies appeared between 2000 and 2014, the number sharply increased after 2018, reflecting the global diffusion of Artificial Intelligence (AI) applications in business intelligence, data analytics, and strategic decision-making.

Sectorally, most studies were concentrated in information technology, manufacturing, and services, with emerging work in tourism, banking, and healthcare. Geographically, Europe (37%) and North America (34%) dominated,

followed by Asia (18%) and Africa (5%), indicating an underrepresentation of developing economies—an important gap this study later discusses.

Five dominant thematic clusters emerged from the synthesis, corresponding to recurring analytical patterns across studies. These clusters are presented below.

Theme 1: AI-Driven Automation and Data Collection in CI

A foundational contribution of AI in Competitive Intelligence (CI) lies in automating the data collection and monitoring process. Early CI approaches were limited by manual information retrieval, whereas AI now enables continuous, large-scale, and adaptive data gathering from heterogeneous digital sources [34].

Intelligent agents and web crawlers can automatically collect, categorise, and update data from news feeds, competitor websites, online forums, and social media. Taranu and Cioranu [19] demonstrated that AI-based systems reduced data-gathering time in tourism market monitoring by 60%, improving responsiveness to competitor moves. Similarly, [37] employed machine learning algorithms to mine patent databases and predict emerging innovation trends among competing firms.

These automation tools rely heavily on Natural Language Processing (NLP) and Machine Learning (ML) to extract meaning from unstructured textual data. As a result, organisations gain access to more complete, real-time information about market shifts, competitor strategies, and technological trajectories.

However, challenges persist. Automation may introduce information noise and algorithmic bias—for example, irrelevant data or misclassified competitor signals. Moreover, SMEs often face difficulties in integrating these systems due to cost and technical skill limitations [18]. Nevertheless, automation remains a transformative step in transitioning CI from reactive data collection to proactive environmental scanning.

Theme 2: NLP and Text Analytics for Intelligence Generation

The most frequently discussed AI technology in the reviewed literature is Natural Language Processing (NLP), which enables organisations to process vast amounts of unstructured textual data. NLP techniques are particularly valuable for sentiment analysis, topic modelling, and detecting semantic trends.

Liu et al. [35] employed sentiment analysis to evaluate competitors' brand perceptions across social media, uncovering correlations between online sentiment and market performance. Rosa et al. [17] found that NLP-enabled CI platforms allowed Portuguese firms to detect early warning signals from online reviews and news outlets, enhancing agility in product development and customer engagement.

Similarly, [19] found that tourism firms using NLP analytics could detect emerging travel trends weeks before conventional market reports. The ability to process both qualitative and quantitative signals positions NLP as a bridge between traditional human interpretation and automated analytics.

However, many NLP-based CI systems face limitations related to contextual understanding, sarcasm detection, and processing multilingual data. This is particularly problematic for firms operating across diverse linguistic and cultural markets. Thus, while NLP advances the analytical capacity of CI, its effective deployment requires careful calibration and human oversight.

Theme 3: Predictive and Prescriptive Analytics in Strategic Decision-Making

AI not only enhances descriptive intelligence but also extends CI into predictive and prescriptive domains. Predictive analytics uses historical and real-time data to forecast competitor actions, market dynamics, or technology disruptions, while prescriptive analytics suggests optimal strategic responses.

Rastogi et al. [36] employed neural networks to predict pricing behaviours in competitive markets, achieving 20% higher accuracy compared to traditional econometric models. Li et al. [37] developed AI-driven patent mapping systems that identify competitors' likely innovation trajectories. Cekuls [18] found that predictive intelligence helped managers identify emerging threats and opportunities faster, enabling data-driven decision-making.

Prescriptive analytics, though less developed in CI research, has gained attention for its potential to support automated strategy simulations. For example, [17] proposed a framework in which AI systems simulate the reactions of competitors to strategic moves, providing decision-makers with a range of possible outcomes.

However, the literature reveals several limitations. Many predictive models remain black-box systems, offering little interpretability. Decision-makers often struggle to trust AI recommendations without clear explanations [20]. This highlights the need for Explainable AI (XAI) frameworks within CI systems, striking a balance between accuracy and transparency.

Theme 4: Human–AI Collaboration and Interpretive Intelligence

A critical insight from the literature is that AI cannot fully replace human analysts; instead, effective CI emerges from human–AI collaboration. The integration of algorithmic and cognitive intelligence creates hybrid systems where machines handle data-intensive tasks while humans interpret, contextualise, and validate insights [33].

Valona Intelligence [20] highlighted that CI practitioners view AI as a “strategic assistant” rather than a decision-maker. Similarly, [18] found that organisations deriving the most benefit from AI-CI systems maintained a "human-in-the-loop" approach, combining algorithmic efficiency with strategic intuition.

From a theoretical perspective, this aligns with Socio-technical Systems Theory [48], which emphasises that technological innovation must be accompanied by organisational adaptation and skill development. AI augments human analytical capacity but also demands new competencies, such as data literacy and ethical reasoning.

Nevertheless, challenges remain in fostering trust between human analysts and AI systems. The absence of interpretability, fear of job displacement, and

ethical ambiguities about data use hinder adoption [19]. Consequently, future research must explore frameworks for effective human–machine teaming, ensuring complementarity rather than substitution.

Theme 5: Ethical, Governance, and Contextual Considerations

Ethical and governance issues emerged as recurring but underexplored themes across the reviewed literature. As AI enables large-scale data monitoring, questions of privacy, data ownership, algorithmic bias, and ethical surveillance arise.

Taranu and Cioranu [19] warned that AI-based CI may inadvertently breach ethical boundaries if competitor or customer data is collected without consent. Similarly, [17] emphasised that the lack of transparency in AI algorithms undermines accountability and stakeholder trust. The absence of standardised governance frameworks poses risks, particularly for SMEs lacking formal data governance structures.

Additionally, contextual disparities are evident across various regions and industries. Studies from developed economies highlight efficiency and profitability benefits, whereas those from developing regions [49] stress resource constraints, infrastructural gaps, and skills shortages. These contextual differences shape the feasibility and effectiveness of AI-driven CI systems.

Ethical and governance dimensions thus represent a frontier for future research—one that integrates responsible AI principles, transparency, and inclusivity into CI practice.

Integrative Conceptual Framework/AI–CI Convergence Model

Based on thematic synthesis, the study proposes an AI–CI Convergence Model, illustrating how AI technologies integrate across different stages of the CI process.

Table 2. AI-CI Convergence Conceptual Framework

CI Stage	AI Contribution	Key Benefits	Limitations/ Challenges
Planning and Direction	Predictive analytics, scenario simulation.	Improved foresight and strategic prioritisation.	Model opacity, data quality issues.
Data Collection	Web crawlers, NLP-based scraping, and automation tools.	Faster and broader data capture.	Information noise, privacy risks.
Data Analysis	ML, NLP, deep learning.	Enhanced accuracy, real-time insights.	Algorithmic bias, lack of interpretability.
Dissemination and Use	Dashboards, visualisation, decision-support	Timely and actionable intelligence.	Human resistance, trust deficits.

	systems.		
Feedback and Learning	Human–AI collaboration, reinforcement learning.	Continuous system improvement.	Organisational inertia, ethics concerns.

Source: Author's compilation

This framework conceptualises AI as an enabler of dynamic intelligence, where data is continuously collected, analysed, and fed back into the decision-making cycle. It underscores that sustainable AI–CI integration requires both technological sophistication and organisational readiness, including ethical safeguards, training, and adaptive leadership.

Summary of Key Findings

The systematic review reveals several overarching findings:

- AI significantly enhances the efficiency, accuracy, and timeliness of CI activities, transforming them from static and reactive to dynamic and predictive systems.
- NLP and ML are the most widely applied technologies, while deep learning and generative AI are emerging tools with high potential.
- Human–AI collaboration remains central; automation complements but does not replace human judgment.
- Ethical governance and interpretability are underdeveloped areas, posing risks to trust and legitimacy.
- There is a geographical and contextual research gap, particularly regarding SMEs and emerging economies.
- Future CI systems must integrate Explainable AI (XAI), ethical safeguards, and cross-functional collaboration to maximise strategic value.

Together, these findings underscore that AI does not merely automate Competitive Intelligence—it redefines its epistemology by enabling continuous, data-driven, and anticipatory strategic insight.

E. Conclusion

This study aimed to systematically review and synthesise the growing body of research at the intersection of AI and CI, utilising the PRISMA framework. The review revealed that AI is no longer a peripheral tool in intelligence activities but a transformative force redefining how firms collect, analyse, and act on competitive information.

The literature review established that CI has historically relied on human expertise, intuition, and manual processes that, while valuable, are constrained by cognitive and temporal limitations [2], [24]. The emergence of AI—through machine learning, natural language processing, deep learning, and automation—has radically enhanced the capacity to gather and interpret large, complex, and unstructured data [30], [17].

The findings from 38 reviewed studies converge on several key insights. AI enables data automation, text and sentiment analysis, and predictive modelling, thereby expanding CI's analytical scope. However, these advancements introduce challenges of interpretability, ethical governance, and organisational adaptation. The review also identified a gap between technical potential and practical implementation, particularly in small firms and emerging economies, such as those in Africa [49].

Thematically, five dominant clusters emerged: (1) automation and data collection, (2) NLP-based intelligence generation, (3) predictive and prescriptive analytics, (4) human–AI collaboration, and (5) ethical and governance issues. Together, these themes reflect a maturing but fragmented research field transitioning from descriptive accounts of AI tools to integrated frameworks that combine algorithmic intelligence with human strategic insight.

Theoretical Implications

From a theoretical standpoint, the integration of AI into CI supports and extends several established frameworks. The Resource-Based View (RBV) suggests that AI constitutes a strategic resource capable of generating a sustained competitive advantage when effectively embedded in CI systems [38]-[45]. The Dynamic Capabilities Theory explains how AI enables firms to sense and respond to market changes more rapidly [46]. Additionally, Information Processing Theory posits that AI enhances an organisation's information-processing capacity, thus improving strategic decision-making under uncertainty [47].

Empirical evidence indicates that AI enhances the speed, accuracy, and depth of intelligence processes, improving foresight and responsiveness. Nevertheless, AI alone does not guarantee strategic advantage—it must be complemented by human interpretation, organisational learning, and ethical governance. Therefore, AI-driven CI systems represent a socio-technical construct, where technological, human, and organisational components interact dynamically to create value.

In essence, AI transforms CI from a static, retrospective process into a dynamic, anticipatory, and data-driven discipline, shifting its epistemological base from human intuition toward algorithmically augmented intelligence. This transformation underscores a paradigm shift in how organisations perceive and manage competitive environments.

Practical Implications

The findings of this review have several implications for managers, analysts, and policymakers:

- *Strategic Integration:* Organisations should integrate AI tools directly into CI workflows—especially in data collection, analysis, and dissemination—while maintaining human oversight to interpret strategic meaning.

- *Skill Development:* Firms must invest in data literacy, AI competency, and analytical training to ensure that human analysts can effectively collaborate with AI systems.
- *Explainable and Ethical AI:* To build trust, CI systems should incorporate Explainable AI (XAI) mechanisms that make algorithmic outputs transparent and interpretable to decision-makers. Ethical guidelines should govern the use of data, ensuring privacy, fairness, transparency, and accountability.
- *Governance Frameworks:* Policymakers and industry associations (such as SCIP, Competitive Intelligence Alliance) should develop AI-CI governance standards to regulate data collection practices and promote responsible competitive monitoring.
- *Contextual Adaptation:* SMEs and emerging economies must adapt AI-CI systems to their specific contexts by using open-source tools, cloud-based analytics, and collaborative intelligence platforms to offset resource constraints.
- *Research–Practice Collaboration:* Universities, research institutions, and industry practitioners should establish collaborative innovation labs to co-develop, test, and refine AI-driven CI systems, bridging the gap between theory and practice.

Through these measures, organisations can transform AI from a technological novelty into a strategic enabler of intelligent, evidence-based decision-making.

Limitations and Future Research

Like any systematic review, this study has certain limitations. First, although the PRISMA framework minimised bias, the review may still suffer from publication bias, as positive AI adoption cases are more likely to be published. Second, the rapid evolution of AI tools means that findings may quickly become outdated, particularly with the rise of generative AI systems that were only recently introduced into competitive analytics. Third, while practitioner sources enriched the dataset, some lacked methodological rigour, limiting comparability with peer-reviewed studies. Future research should therefore:

- Conduct longitudinal studies to examine the evolution of AI-CI integration.
- Explore human–machine collaboration models that balance automation with creativity and ethics;
- Investigate sectoral and regional variations, particularly in Africa, Latin America, and Southeast Asia; and
- Develop and test Explainable AI frameworks that improve transparency, accountability, and user trust in CI systems.

Such inquiries would deepen understanding of how AI reshapes intelligence work and contribute to the ethical and sustainable deployment of AI-driven insights. The unique contribution of this study lies in providing the first comprehensive systematic review that maps, evaluates, and integrates the fragmented literature

on AI in CI. It develops an AI–CI Convergence Model, identifies thematic research trends, and bridges theoretical and practical perspectives. By doing so, it establishes a foundation for future empirical and conceptual work on AI-enabled intelligence ecosystems.

Ultimately, this research demonstrates that AI does not replace human intelligence, it augments it. CI, empowered by AI, evolves from passive information gathering to predictive strategic foresight, enabling organisations to sense the future rather than merely react to it. The fusion of AI and CI marks the dawn of a new era in strategic management, one where algorithms illuminate possibilities and human judgment turns them into advantage.

F. References

[1] W. Viviers, A. Saayman, & M-L. Muller, "Competitive intelligence in South Africa: 1999-2002 and beyond," *Africa insight,* Vol. 34(2/3), June, September, 2004.

[2] J. L. Calof, & S. Wright, "Competitive Intelligence: A Practitioner, Academic and Inter-disciplinary Perspective," *European Journal of Marketing,* Vol. 42(7/8), 717–730, 2008. https://doi.org/10.1108/03090560810877114.

[3] R. Bose, "Competitive Intelligence Process and Tools for Intelligence Analysis," *Industrial Management & Data Systems*, Vol. 108(4), 510-528, 2008.

[4] R. Pellissier, & T. E. Nenzhelele, "Towards a Universal Definition of Competitive Intelligence," *South African Journal of Information Management*, Vol. *15*(2), 1-7, 2013.

[5] T. Du Plessis, & M. Gulwa, "Developing a Competitive Intelligence Strategy Framework supporting the Competitive Intelligence needs of a Financial Institution's Decision-Makers," *South African Journal of Information Management*, Vol. *18*(2), 1-8, 2016.

[6] A. Maune, "Competitive Intelligence as a Game Changer for Africa's Competitiveness in the Global Economy," *Journal of Intelligence Studies in Business, Vol.* 9(3), 24-38, 2019.

[7] M. L. Maluleka, & B. Z. Chummun, "Competitive Intelligence and Strategy Implementation: Critical Examination of present Literature Review," *South African Journal of Information Management*, Vol. *25*(1), 1610, 2023.

[8] M. A. Fadhlurrahman, S. Riyanta, & A. R. Ras, "The Role of Competitive Intelligence in Strategic Decision-Making: A Literature Review," *Asian Journal of Engineering, Social and Health*, Vol. *3*(10), 2307-2324, 2024.

[9] S. S. A. Zaidi, S. Nagri, & S. I. H. Naqvi, "The role of Competitive Intelligence in Strategic Decision-Making," *Priority-The International Business Review*, Vol. *2*(2), 394-402, 2024.

[10] A. S. Juhari, & D. Stephens, "Tracing the Origins of Competitive Intelligence Throughout History," *Journal of Competitive Intelligence and Management,* 3(4), 2006.

[11] P. Johns, & D. C. Van Doren, "Competitive Intelligence in Service Marketing: A New Approach with Practical Application," *Marketing Intelligence & Planning*, *28*(5), 551-570, 2010.

[12] H. Henderson, *Artificial Intelligence: Mirrors for the Mind.* New York, Chelsea House, 2007.

[13] S. J. Russell, & P. Norvig, *Artificial Intelligence: A Modern Approach (3rd ed.),* Pearson, 2016.
[14] M. Chui, & B. McCarthy, "An Executive Guide to AI," *McKinsey*, October, 2018.
[15] A. Barnea, "How will AI Change Intelligence and Decision-Making?" *Journal of Intelligence Studies in Business*, Vol. 10(1), 75-80, 2020. https://ojs.hh.se/index.php/JISIB/article/view/521.
[16] W. Nasri, "Competitive Intelligence in Tunisian Companies," *Journal of Enterprise Information Management, Vol. 24*, 53–67, 2011. https://doi.org/10.1108/17410391111097429.
[17] P. Rosa, M. J. Sousa, & F. Martins, "Artificial Intelligence and Strategic Information Management: The Impact on Competitive Advantage," *Journal of Strategy and Management, Vol. 16*(2), 276–295, 2023. https://doi.org/10.1108/JSMA-04-2022-0079.
[18] A. Cekuls, "The role of Artificial Intelligence in Strengthening Business Strategy and Decision-Making, *Journal of Business Economics and Management, Vol. 23*(2), 201–219, 2022.
[19] A. Taranu, & I. Cioranu, "Artificial Intelligence in Competitive Intelligence: Insights from the Tourism Industry," *Tourism Management Perspectives, 49,* 2024. https://doi.org/10.1016/j.tmp.2023.101060.
[20] Valona Intelligence, "The State of Competitive Intelligence 2023: AI, Automation, and Human Insight," Valona Intelligence Research Report, 2023.
[21] N. Sewdass, & A. Du Toit, "Current State of Competitive Intelligence in South Africa," *International Journal of Information Management, Vol. 34*, 185–190, 2014. DOI:10.1016/j.ijinfomgt.2013.10.006.
[22] H. Tahmasebifard, "The role of Competitive Intelligence and its Sub-types on achieving Market Performance," *Cogent Business & Management,* Vol. 5(1), 1-16, 2018. DOI:10.1080/23311975.2018.1540073.
[23] J. E. Prescott, "The Evolution of Competitive Intelligence: Designing a Process for Action," *International Journal of Technology Management, Vol. 14*(1), 81–91, 1999. https://doi.org/10.1504/IJTM.1997.001638.
[24] S. Wright, D. W. Pickton, & J. Callow, "Competitive Intelligence in UK firms: A Typology," *Marketing Intelligence & Planning, Vol. 20*(6), 349–360, 2009. https://doi.org/10.1108/02634500210445400.
[25] W. Viviers, A. Saayman, & M-L. Muller, "Enhancing a Culture of Competitive Intelligence in South Africa," *International Journal of Social Economics, Vol. 32*(7), 576–589, 2005a. https://doi.org/10.1108/03068290510601175.
[26] W. Viviers, M-L. Muller, & A. Du Toit, "Competitive Intelligence: An Instrument to enhance South Africa`s Competitiveness," *SAJEMS*, NS, Vol. 8(2), pp. 247-254, 2005b.
[27] K. S. Solberg, "Why care about competitive intelligence and market intelligence? The case of Ericsson and the Swedish Cellulose Company," *Journal of Intelligence Studies in Business, Vol.* 7(2), 27-39, 2017.
[28] D. Heppes, & A. Du Toit, Level of Maturity of the Competitive Intelligence Function: Case Study of a Retail Bank in South Africa. *Aslib Proceedings, Vol. 61*(1), 48–66, 2009. https://doi.org/10.1108/00012530910932285.

[29] L. Degerstedt, "Social competitive intelligence: sociotechnical themes and values for the networking organization," *Journal of Intelligence Studies in Business*, Vol. 5(3), 5-34, 2015.
[30] T. H. Davenport, & R. Ronanki, "Artificial Intelligence for the Real World," *Harvard Business Review, 96*(1), 108–116, 2018.
[31] E. Brynjolfsson, & A. McAfee, *Machine, Platform, Crowd: Harnessing our Digital Future,* W.W. Norton & Company, 2017.
[33] A. Shollo, & R. D. Galliers, "Towards an Understanding of the role of Business Intelligence Systems in Organisational Knowing," *Information Systems Journal, Vol. 26*(4), 339–367, 2016. https://doi.org/10.1111/isj.12071.
[34] J. Marin, & S. Poulter, "Automating Competitive Intelligence: Web Mining and AI-driven Environmental Scanning," *Journal of Competitive Intelligence and Management, Vol. 16*(1), 45–62, 2020.
[35] B. Liu, L. Zhang, & Y. Zhang, "Social Media Sentiment Analysis for Competitive Intelligence: An NLP Perspective," *Information & Management, Vol. 59*(7), 103681, 2022. https://doi.org/10.1016/j.im.2022.103681.
[36] S. Rastogi, M. Sharma, & S. Sahu, "Predictive Analytics in Competitive Markets: Neural Network Approaches for Pricing Strategy," *Expert Systems with Applications,* Vol. 184, 115477, 2021. https://doi.org/10.1016/j.eswa.2021.115477.
[37] W. Li, Y. Zhao, & C. Wang, "Using Machine Learning to predict Competitors' Innovation Strategies based on Patent Data," *Technological Forecasting and Social Change,* 155, 119979, 2020. https://doi.org/10.1016/j.techfore.2020.119979.
[38] E. Penrose, *The Theory of the Growth of the Firm (4th ed.),* Oxford: Oxford University Press, 1959.
[39] B. Wernerfelt, "A Resource-Based View of the Firm," *Strategic Management Journal, Vol.* 5, 171-180, 1984.
[40] K. Conner, "Historical comparison of resource-based theory and five schools of thought within industrial organization economics: Do we have a new theory of the firm?" *Journal of Management, Vol. 17*(1), 121–154, 1991.
[41] R. M. Grant, "The Resource-Based Theory of Competitive Advantage: Implications for Strategy Formulation," *California Management Review,* Spring, 114-135, 1991.
[42] J. Barney, "Firm Resources and Sustained Competitive Advantage," *Journal of Management,* Vol. 17, 99–120, 1991. DOI:10.1177/014920639101700108.
[43] R. Amit, & P. J. Schoemaker, "Strategic Assets and Organizational Rent," *Strategic Management Journal, Vol.13*, 33-46, 1993.
[44] P. R. Dicksen, "The Static and Dynamic Mechanics of Competitive Theory," *Journal of Marketing,* 60(10), 102–106, 1996.
[45] A. Maune, "Competitive Intelligence as an enabler for Firm Competitiveness: An Overview," *Journal of Governance and Regulation, 3(*2), 29-42, 2014.
[46] D. J. Teece, "Business Models and Dynamic Capabilities," *Long Range Planning, Vol. 51*(1), 40–49, 2018. https://doi.org/10.1016/j.lrp.2017.06.007.
[47] J. R. Galbraith, *Designing Complex Organisations,* Addison-Wesley, 1973.

[48] R. P. Bostrom, & J. S. Heinen, "MIS Problems and Failures: A Socio-Technical Perspective, Part II: The application of socio-technical theory," *MIS Quarterly,* Vol. 1(4), 11–28, 1977. https://doi.org/10.2307/248710.
[49] A. Maune, "Competitive Intelligence and Firm Competitiveness: An Overview," *Journal of Corporate Ownership and Control, Vol. 12*(1), 533-542, 2022.
[50] R. Castro-Gil, & D. Correa, "Transparency in previous literature reviews about blended learning in higher education," *Education and Information Technologies*, Vol. *26*(3), 3399-3426, 2021.
[51] S. Ed-Dafali, Z. Adardour, A. Derj, A. Bami, & K. Hussainey, "A PRISMA-Based Systematic Review on Economic, Social, and Governance Practices: Insights and Research Agenda," *Business Strategy and the Environment*, Vol. *34*(2), 1896-1916, 2025.
[52] A. Polo, D. Morillo-Torres, & J. W. Escobar, "Toward adaptive and immune-inspired viable supply chains: A PRISMA systematic review of mathematical modeling trends," *Mathematics*, *13*(14), 2225, 2025.
[53] H. Carter-Templeton, M. H. Oermann, J. K. Owens, B. Vance, M. L. Mastorovich, M. Quazi, ... & F. Thurman, "Completeness of Systematic Reviews in Nursing Literature Based on PRISMA Reporting Guidelines," *Advances in Nursing Science*, Vol. 10-1097, 2025.
[54] D. Tranfield, D. Denyer, & P. Smart, "Towards a Methodology for Developing Evidence-informed Management Knowledge by means of Systematic Review," *British Journal of Management, 14*(3), 207–222, 2003. https://doi.org/10.1111/1467-8551.00375.
[55] D. Moher, A. Liberati, J. Tetzlaff, D. G. Altman, & PRISMA Group, "Preferred Reporting Items for Systematic Reviews and Meta-Analyses: The PRISMA Statement," *PLoS Medicine, Vol. 6*(7), 2009. https://doi.org/10.1371/journal.pmed.1000097.
[56] M. J. Page, J. E. McKenzie, P. M. Bossuyt, I. Boutron, T. C. Hoffmann, C. D. Mulrow,... & D. Moher, "Updating guidance for reporting systematic reviews: development of the PRISMA 2020 statement," *Journal of clinical epidemiology*, Vol. *134*, 103-112, 2021.
[57] R. E. O'Dea, M. Lagisz, M. D. Jennions, J. Koricheva, D. W. Noble, T. H. Parker,... & S. Nakagawa, "Preferred reporting items for systematic reviews and meta-analyses in ecology and evolutionary biology: a PRISMA extension," *Biological Reviews*, Vol. *96*(5), 1695-1722, 2021.
[58] S. Arya, A. H. Kaji, & M. A. Boermeester, "PRISMA reporting guidelines for meta-analyses and systematic reviews," *JAMA surgery*, Vol. *156*(8), 789-790, 2021.
[59] J. Thomas, & A. Harden, "Methods for the Thematic Synthesis of Qualitative Research in Systematic Reviews," *BMC Medical Research Methodology, Vol. 8*, 45, 2008. https://doi.org/10.1186/1471-2288-8-45.
[60] K. Dickson, "Systematic reviews to inform policy: institutional mechanisms and social interactions to support their production," Doctoral dissertation, UCL (University College London), 2019.

[61] G. Neta, D. A. Chambers, & L. Simpson, "Conference on the Science of Dissemination and Implementation in Health," *Implementation Science*, Vol. *19*(2), 42, 2024.
[62] K. Tiwari, D. Campus, & M. S. Shukla, "Asia Pacific Journal of Health Management," *Asia Pacific Journal of Health Management*, Vol. *20*(2), 2025.
[63] M. Petticrew, & H. Roberts, *Systematic Reviews in the Social Sciences: A Practical Guide,* Blackwell Publishing, 2006.