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AI-Driven Knowledge Management and Decision-Making Quality in Medium-Sized Technology Companies: A Critical Integrative Review

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Abstract

This paper presents a critical integrative review of how artificial intelligence-driven knowledge management may support decision-making quality in medium-sized technology companies. It argues that generative AI shifts the central knowledge management challenge from retrieval to trustworthiness. While generative AI improves access to dispersed organisational knowledge, its outputs may lack traceable sources, contain confident errors, or blur the boundary between reliable knowledge and probabilistic text. Drawing on classical knowledge management theory, recent AI and generative AI research, decision-making literature and regional implementation evidence, the paper develops a conceptual framework in which knowledge management practices mediate the relationship between AI-driven knowledge management and decision-making quality. Perceived challenges such as poor data quality, weak governance, limited skills and overreliance on AI may weaken this relationship. The paper identifies provenance, validation, governance and human review as core practices for trustworthy AI-supported decision-making.

Keywords: artificial intelligence; generative AI; knowledge management; decision-making quality; medium-sized technology companies; integrative review; organisational knowledge.

1. Introduction

Knowledge management has been discussed for more than three decades as a central issue in organisational work. Classical studies showed that knowledge is not only stored information. It includes experience, interpretation and the ability to use what is known in action (Davenport & Prusak, 1998). Nonaka and Takeuchi (1995) also showed that organisational knowledge is created through the movement between tacit and explicit knowledge. These ideas remain important because many companies still struggle to turn individual experience into knowledge that can be reused.

The issue is more visible in technology companies. A single decision may require technical knowledge, supplier history, project experience, client requirements and financial judgement. Choo (1998) explained that organisations use information to construct meaning and guide decisions. This means that decision-making is not a mechanical process. It depends on organisational memory and on the ability to interpret knowledge in context.

Medium-sized technology companies represent a useful context for this discussion. They often have rich practical knowledge gained from projects, suppliers and technical work. At the same time, their knowledge systems may be less formal than those of large corporations. Important files may be spread across emails, project folders, technical documents and personal memory. This creates a gap between what the company has learned and what it can use when a decision is needed.

This context requires separate attention because medium-sized technology companies occupy a position between start-ups and large corporations. Unlike start-ups, they usually have accumulated project experience, supplier records, client histories and technical knowledge.

Unlike large corporations, they may not have mature knowledge management systems, specialised data teams or formal governance structures. This creates a specific organisational condition in which valuable knowledge exists, but its use in decision-making may remain uneven. For this reason, AI-driven knowledge management may be especially relevant to such firms, provided that it is connected to clear routines for documentation, retrieval, sharing and human review.

Artificial intelligence has created new possibilities for reducing this gap. It can support search, classification, summarisation and the comparison of previous cases. Yet the value of these tools should not be assumed. Davenport and Ronanki (2018) warned that organisations gain more from artificial intelligence when it is attached to clear business problems rather than treated as a general technology fashion. The same logic applies to knowledge management. An intelligent tool can only work well when the knowledge base and organisational routines are prepared.

This review uses the term medium-sized technology companies as an organisational category referring to technology-related firms with approximately 50 to 250 employees. This numerical benchmark follows the European Commission definition of a medium-sized enterprise (European Commission, 2003), while the paper uses it as a practical guide rather than a universal legal threshold. The analytical focus is on firms that have accumulated project, supplier and client knowledge but lack the mature knowledge management infrastructure, specialised data teams or formal governance systems found in larger corporations. Definitions and thresholds vary across countries and sectors, particularly in the Arab region; accordingly, organisational complexity and the degree of knowledge-system formalisation remain more important here than headcount alone.

The literature on this topic remains distributed across several related streams. Classical knowledge management studies provide the foundation for understanding knowledge creation, knowledge sharing and organisational memory. However, much of this work was developed before the current expansion of AI and before the rise of generative AI in organisational knowledge work. Recent studies on AI and knowledge management explain how intelligent tools may support search, classification, retrieval, summarisation and decision support. Yet many of these studies still discuss AI as a general digital capability or focus mainly on large organisations and broad digital transformation. Less attention is given to medium-sized technology companies, where practical knowledge is often rich but not always formally organised.

The recent development of generative AI makes this gap more important. Earlier knowledge systems mainly helped organisations store and retrieve what was already documented. Generative AI can also produce summaries, combine previous material and create knowledge-like outputs. This does not remove the need for knowledge management. It increases the need for stronger knowledge practices. In AI-supported organisations, knowledge must not only be captured and shared. It must also be checked, traced to its source, governed and reviewed by people who understand the organisational context.

Regional and emerging-economy implementation evidence adds contextual insight on readiness, skills, infrastructure and governance barriers — though it rarely explains how AI-driven knowledge management may influence decision-making quality through knowledge management practices specifically.

The research gap addressed in this paper therefore lies in the limited integration of these streams. Existing literature does not yet provide a focused conceptual explanation of how AI-driven knowledge management, knowledge management practices, decision-making quality and perceived challenges work together in medium-sized technology companies. The gap is not only about whether AI supports knowledge work, but about how generative AI changes the conditions under which organisational knowledge can be trusted and used in decisions.

The theoretical contribution of this paper rests on a specific claim about what generative AI changes in knowledge management. Before generative AI, retrieval was often experienced as the most visible bottleneck in medium-sized technology companies because employees struggled to find relevant knowledge dispersed across files, emails, project records and individual memory. Generative AI can reduce the salience of that bottleneck by making access faster and more conversational, but it does not eliminate the underlying problems of retrieval, grounding or source selection. Instead, it adds a verification burden: employees may obtain fast and fluent answers without knowing where those answers came from, whether they are accurate, or who is responsible if they are wrong. This paper therefore argues that generative AI shifts the principal organisational emphasis from retrieval alone to trustworthiness. Provenance, validation, governance and human review become central knowledge management practices alongside documentation and retrieval. This argument extends classical knowledge management theory and gives particular attention to medium-sized technology companies, where practical knowledge is often rich but informally organised and where ungoverned AI use may have consequential effects on decisions.

What this paper adds to existing work

Storey (2025) is an important recent contribution, proposing a framework for knowledge management in the generative AI era and examining how generative artificial intelligence (GenAI) affects novice and expert knowledge workers. The present paper complements that work by focusing on medium-sized technology companies and by specifying provenance, validation, governance and human review as the practices required to make AI-supported knowledge trustworthy. However, the mediation structure itself is not new. Leoni et al. (2022) empirically showed, in a sample of 120 senior executives from Italian manufacturing firms, that knowledge management processes mediate the effects of AI on supply-chain resilience and firm performance. The novelty claimed here therefore rests not on proposing mediation in the abstract, but on identifying how the content and priority of the mediator change under generative AI: from an emphasis on documentation and retrieval toward organisational routines for provenance, validation, governance and human review. Table 1 summarises this positioning.

Table 1
How this paper extends Storey (2025)

Dimension	Storey (2025)	This paper
Organisational scope	All organisations and knowledge workers	Medium-sized technology companies specifically
Central argument	GenAI affects novice vs expert workers differently; risks include knowledge loss and over-automation	GenAI shifts the central KM challenge from retrieval to trustworthiness
Role of KM practices	Contextual background; general framework	Mediator whose distinctive content under GenAI is provenance, validation, governance and human review
New KM practices identified	Quality evaluation by expert workers	Provenance, validation, governance and human review as core organisational practices
Empirical testing path	Not specified	Six propositions for future empirical testing in medium-sized technology firms
Closest mediation precedent	Not the paper's focus	Leoni et al. (2022) tested KMP mediation for AI effects on manufacturing outcomes; this paper re-anchors novelty in the trustworthiness content of the mediator

Before presenting the research problem, it is useful to clarify how the main concepts are used in this review. The definitions below are not intended as universal definitions. They are working definitions developed to support the logic of the present paper and the proposed conceptual framework. Table 2 presents the working definitions used throughout the review.

Table 2

Working definitions of the main concepts

Concept	Working definition in this paper
AI-driven knowledge management	The organisational use of artificial intelligence tools to support the acquisition, classification, storage, retrieval, sharing and application of knowledge in a way that improves access to relevant organisational experience during work and decision-making.
Knowledge management practices	The organisational routines and procedures through which knowledge is identified, documented, validated, stored, shared, updated and applied in operational and managerial decision situations.
Decision-making quality	The extent to which organisational decisions are informed by relevant knowledge, made in a timely manner, consistent with organisational objectives and supported by evidence, experience and professional judgement.

Perceived challenges	The organisational and technical barriers that may weaken AI-supported knowledge work, including poor documentation, limited infrastructure, skill gaps, resistance and governance concerns.
Critical integrative review	A review approach that connects related bodies of literature, evaluates their contribution and uses them to develop a conceptual argument or framework.

These definitions are used to connect the reviewed literature with the proposed conceptual framework. They also clarify that the paper treats artificial intelligence as part of a wider knowledge process rather than as an isolated technical tool.

2. Research Problem and Review Questions

The issue addressed in this paper is not the weakness of the existing literature, but its fragmentation across several related research streams. Classical studies explain knowledge creation, knowledge sharing and knowledge systems. Recent studies explain the role of artificial intelligence and generative AI in knowledge work. Regional and emerging-economy implementation evidence adds contextual insight into readiness, skills, governance and implementation barriers. What is still missing is an integrated explanation of how artificial intelligence-driven knowledge management can improve decision-making quality in medium-sized technology companies.

This review asks how the existing literature explains the relationship between artificial intelligence-driven knowledge management and decision-making quality in medium-sized technology companies, and whether knowledge management practices can be understood as the main pathway through which this relationship takes place.

The review is guided by four supporting questions. First, what theoretical foundations do classical knowledge management studies provide for understanding organisational knowledge and decision-making? Second, how does recent AI, generative AI and knowledge management literature explain the role of intelligent tools in knowledge acquisition, sharing and application?

Third, what contextual insights does regional and emerging-economy implementation evidence add regarding readiness, skills, governance and implementation barriers? Fourth, how can these streams of literature be integrated into a conceptual framework linking AI-driven knowledge management, knowledge management practices, decision-making quality and perceived challenges?

3. Methodology of the Review

This paper adopts a purposive critical integrative review. Torraco (2005) and Whittemore and Knafl (2005) provide the main methodological basis for using an integrative review to connect heterogeneous evidence and develop conceptual insight. More general literature-review guidance supports transparent synthesis of fragmented research streams and the development of conceptual contributions (Fisch & Block, 2018; Paul & Criado, 2020; Snyder, 2019; Tranfield et al., 2003). The approach is appropriate here because the research problem sits between knowledge management, artificial intelligence, generative AI and decision-making quality.

The review followed a purposive and staged search process. The first stage focused on identifying foundational studies in knowledge management and organisational knowledge. The second stage focused on recent studies linking artificial intelligence, generative AI, knowledge management and decision-making. The third stage focused on regional and emerging-economy implementation evidence that could provide contextual insight into readiness, skills, infrastructure, acceptance and governance. This staged search was used because the paper does not examine one isolated literature area. It brings together theoretical, technological and contextual streams that are usually discussed separately. Arabic-language studies were identified through combinations of English and Arabic search terms in Google Scholar and regional journal portals, followed by backward citation tracing; their bibliographic details were checked against the journal or DOI record.

The search used Scopus, Web of Science, Google Scholar and the AIS electronic library. Searches combined terms such as knowledge management, artificial intelligence, generative AI, decision-making quality, organisational knowledge, AI-driven knowledge management and medium-sized companies. Classical studies were also identified through backward citation tracing because many foundational works were published before recent database filters would normally capture them. During final revision, a targeted verification search on large-language-model hallucination identified one additional peer-reviewed survey (Huang et al., 2025). Because this source was added during revision rather than through the original staged screening process, it is reported separately in Table 3.

The selection process was guided by conceptual relevance rather than numerical exhaustiveness. Titles and abstracts were reviewed first to remove studies that were unrelated to organisational knowledge, decision-making or AI-supported knowledge work. The remaining studies were then reviewed more closely to assess their relevance to the research problem, their conceptual or empirical contribution and their usefulness for framework development. Studies were retained when they helped explain one of the main components of the review: AI-driven knowledge management, knowledge management practices, decision-making quality, automation and augmentation, generative AI or perceived implementation challenges. Table 3 summarises the search process and retained sources.

Table 3

Search transparency summary for the purposive review

Database / Source	Key search terms	Date range	Records screened	Sources retained
Scopus	AI, knowledge management, decision-making quality, generative AI, AI governance	1990–2026	~160	19

Database / Source	Key search terms	Date range	Records screened	Sources retained
Web of Science	AI, KM practices, organisational knowledge, human-AI collaboration, decision quality	1990–2026	~130	14
Google Scholar	Classical KM, AIKM, decision-making quality, generative AI, hallucination, AI trustworthiness	1990–2026	~210	18
AIS electronic library	Information systems, knowledge management, AI in organisations, LLMs and organisational systems	1990–2026	~45	5
Backward citation tracing	Foundational KM and organisational knowledge works	Foundational works retained regardless of date	~25	5
Targeted revision search	LLM hallucination; peer-reviewed survey	2025	Not separately logged	1
Total			~570	62

Note: figures are approximate and reflect the purposive nature of this review. Counts across Scopus, Web of Science and Google Scholar include overlap and should not be read as unique records. Google Scholar was used primarily as a supplementary source for citation-chasing and locating regional or otherwise difficult-to-index material, rather than as a primary bibliographic database. The original staged search retained 61 sources. One additional peer-reviewed source was added during final revision through a targeted hallucination-verification search and is reported separately; the review therefore contains 62 retained sources. The approximate screening total refers to the original purposive search and does not include a separately reconstructed count for the revision search.

Table 4 sets out the inclusion and exclusion criteria applied in the review.

Table 4

Inclusion and exclusion criteria used in the review

Criterion	Inclusion criteria	Exclusion criteria
Topic relevance	Studies addressing knowledge management, artificial intelligence, generative AI, decision-making, organisational knowledge or review methodology	Studies dealing with AI only as a technical issue, unless directly relevant to an organisational risk or framework component
Type of contribution	Theoretical, empirical or review-based studies that support the research problem or framework	Exclude studies that do not address at least one framework component or provide a usable theoretical, empirical or review contribution.
Contextual relevance	International, regional and emerging-economy studies relevant to organisations, knowledge work, AI implementation or decision-making	Studies focused on unrelated sectors or purely technical applications
Methodological clarity	Studies with clear argument, method or conceptual contribution	Studies lacking sufficient methodological or conceptual clarity
Use in synthesis	Studies that help explain AIKM, KM practices, decision-making quality, generative AI or perceived challenges	Exclude studies whose findings cannot be mapped to AIKM, KM practices, decision quality, generative AI or implementation challenges.
Publication period	Main search period 1990–2026, with earlier foundational works retained where theoretically necessary	Earlier works excluded unless they are foundational to the theoretical framework

These criteria were used to maintain the focus of the review and to ensure that the selected studies contributed directly to the synthesis and the development of the proposed framework. The review does not claim to be an exhaustive systematic review. Instead, it uses selected literature from knowledge management, artificial intelligence in organisational contexts, generative AI, decision-making, review methodology and regional implementation evidence to build a conceptual argument.

The synthesis procedure followed a thematic logic. Selected studies were not treated only as separate findings. They were grouped according to the role they played in the argument of the paper. Classical knowledge management studies were used to explain the theoretical basis of organisational knowledge. Contemporary AI and generative AI studies were used to explain how intelligent tools may support and reshape knowledge work. Decision-making studies were used to connect knowledge processes with decision quality. Regional and emerging-economy implementation evidence was used to identify contextual barriers and implementation conditions.

The selected studies were assessed through four dimensions: methodological clarity, theoretical contribution, relevance to the research problem and originality. The review was then analysed thematically. This allowed the discussion to move from foundations of knowledge management to artificial intelligence and generative AI in knowledge work, and then to contextual evidence on implementation challenges. This procedure allowed the review to move from description toward conceptual integration.

4. Review of the Literature

4.1. Classical Foundations

The classical literature provides the theoretical base for this paper. Nonaka and Takeuchi (1995) remain important because their work explains a problem that still appears in many companies. Practical experience is often held by engineers, managers and project staff before it becomes part of organisational knowledge. When this experience is not documented, the organisation may lose part of what it has already learned.

Grant (1996) viewed the firm as an institution that brings specialised knowledge together. This view supports the argument that knowledge is not just an administrative record. It is a strategic resource. Choo (1998) also moved the discussion beyond access to information. His work is useful here because it shows that decisions require interpretation and sense-making before information can guide action.

Organisational memory and organisational learning studies also support this view. They show that organisations do not retain knowledge through documents alone, but through routines, individuals, culture, structures and stored information. This is important for medium-sized technology companies because practical experience may remain available only when it is connected to organisational routines and not left as personal memory (Huber, 1991; Walsh & Ungson, 1991).

The knowledge-based view also helps explain why knowledge should be treated as an organisational capability. Firms create value not only by possessing knowledge, but by combining, transferring and reusing specialised knowledge in ways that support action and adaptation (Kogut & Zander, 1992; Spender, 1996; Teece et al., 1997).

Davenport and Prusak (1998) described knowledge as experience, values, context and expert insight. This helps avoid a narrow technical view of artificial intelligence. Alavi and Leidner (2001) later explained knowledge management systems as socio-technical systems that support knowledge creation, storage, transfer and application. Gold et al. (2001) added that technology, structure and culture need to work together. These studies point to the same general lesson. Knowledge has little value when it remains only in individual memory or scattered across files that are difficult to use. Zack (1999) also linked knowledge management with organisational strategy, which supports the view that companies should know which knowledge is most important for their work. Mills and Smith (2011) found that some knowledge management resources—notably organisational structure and knowledge application—were directly related to organisational performance, whereas other resources were not directly related.

Although these classical studies provide a strong theoretical foundation, their main limitation is that they were developed before the current use of artificial intelligence in organisational knowledge work. They explain why knowledge creation, sharing, memory and application matter, but they do not explain how intelligent tools may change the way knowledge is searched, retrieved and reused in decision situations. This limitation is important for the present paper because it shows the need to extend classical knowledge management thinking into an AI-supported organisational context.

4.2. Contemporary Studies on Artificial Intelligence and Knowledge Management

Contemporary literature updates the classical discussion by showing how artificial intelligence may support knowledge work. Davenport and Ronanki (2018) identified practical organisational uses of artificial intelligence, including automation, cognitive insight and cognitive engagement. Their work is useful, although much of their discussion is based on larger organisations.

Other studies have examined the relationship between artificial intelligence and knowledge management more directly. Taherdoost and Madanchian (2023) reviewed how artificial intelligence can support knowledge discovery, storage, retrieval and analysis. Pai et al. (2022) also showed that the value of artificial intelligence in knowledge management depends on the relationship between people and technology. Jarrahi et al. (2023) made a similar point through the idea of human and artificial intelligence partnership in knowledge work.

More recent research treats artificial intelligence as part of organisational knowledge work rather than as a purely technical tool. This view is important because AI affects how people search, interpret, organise and use knowledge inside organisations. It also draws attention to the relationship between intelligent systems, human expertise, organisational routines and governance (Berente et al., 2021; Faraj et al., 2018; Jarrahi, 2018; Raisch & Krakowski, 2021; von Krogh, 2018).

Other studies add that the relationship between AI and knowledge management should not be separated from tacit knowledge, implementation challenges and the recent development of generative AI. These issues are relevant to the present review because medium-sized technology companies often depend on practical experience that is difficult to capture fully in formal systems (Rezaei, 2025; Sanzogni et al., 2017; Storey, 2025).

Nakash and Bolisani (2024) also show that research between knowledge management and artificial intelligence is still developing and needs more focused organisational studies.

Recent work has extended these insights into the generative AI era. Dwivedi et al. (2023) provided a multidisciplinary assessment of generative AI's opportunities and challenges across research, practice and policy, including risks involving accuracy, bias, transparency and credibility. Kirchner et al. (2025) examined generative AI adoption among software developers as knowledge workers, finding that developers valued GenAI for solving simpler programming tasks efficiently and rapidly, while knowledge exchange with fellow programmers was partly—but not entirely—replaced by exchange with GenAI. This pattern is directly relevant to medium-sized technology companies, where informal knowledge exchange is often a primary channel for transmitting project experience and tacit expertise. He and Yang (2026) combined literature analysis with Chinese manufacturing case studies to develop a five-stage GenAI-enhanced knowledge management framework covering acquisition, sharing, integration, application and optimization. Alavi et al. (2024) examined generative AI through a knowledge management lens, identifying opportunities and challenges across knowledge creation, storage, transfer and application, including risks such as AI bias, reduced human socialization and overreliance on AI.

The trustworthiness of AI-generated knowledge outputs has emerged as a specific concern. Hallucinations—instances in which generative AI systems produce fluent but nonfactual or unsupported content—create a risk for organisations that use AI-supported knowledge without adequate validation routines (Huang et al., 2025; Xu et al., 2024). Huang et al. (2025) provide a peer-reviewed survey of hallucination principles, causes, detection and mitigation, while Xu et al. (2024) argue that hallucination is an inherent limitation of large language models. Retrieval-augmented generation can improve grounding by connecting a model to external sources, but the recent literature also shows that retrieval quality, source selection and faithful use of retrieved material remain open technical problems with important organisational implications (Fan et al., 2024; Huang & Huang, 2026; Mombaerts et al., 2024). These limitations reinforce the need for provenance tracking, validation procedures and human review. Chau and Xu (2025) identify major organisational issues and challenges in the use of large language models and call for further information-systems research on their business and management impacts. Leoni et al. (2024), based on semi-structured interviews with KM and AI experts from 52 mostly large, private and for-profit organisations, found that AI adoption in knowledge management has both linear and retroactive relationships with organisational decision-making. The study is useful as exploratory evidence about organisational processes, but it does not test decision-making quality as a construct or establish the mediation proposed in this paper; its large-firm sample also limits direct transfer to medium-sized firms.

Many contemporary studies explain the potential of artificial intelligence, but they do not always show how medium-sized technology companies can adopt it under limited resources and less formalised knowledge structures. This is an important gap because medium-sized firms may need practical and gradual adoption rather than large-scale transformation programmes.

Gelashvili-Luik et al. (2025) conducted a systematic literature review on integrating emerging AI technologies into knowledge management systems, highlighting governance, data quality and organisational readiness among the recurring implementation concerns identified across sectors. These findings are particularly relevant to medium-sized technology companies, which typically lack the specialised teams or formal governance frameworks used by larger corporations to address such concerns. Oldemeyer et al. (2025) similarly reviewed AI implementation in small and medium enterprises and identified lack of knowledge, costs and inadequate infrastructure as the most commonly perceived implementation barriers.

Recent studies also show that generative AI changes the skills, governance arrangements and validation routines required for organisational knowledge work. Kaczorowska-Spychalska et al. (2024) describe generative AI as a potential source of change in the knowledge management paradigm, highlighting its capacity to automate tasks and generate insights while also identifying challenges involving data quality, human oversight and ethical considerations. Korzynski et al. (2023) identify prompt engineering as a new digital competence, which is relevant because employees need the ability to question, refine and evaluate AI-supported outputs rather than accept them passively. Wach et al. (2023) further emphasise the risks and controversies surrounding ChatGPT, including misinformation and misuse, which reinforces the need for validation and human review in organisational settings. Studies on retrieval-augmented generation also show that connecting language models to external knowledge sources can improve grounding but does not remove technical problems of source selection and evaluation; in organisational use, these limitations create a continued need for governance (Fan et al., 2024; Huang & Huang, 2026; Mombaerts et al., 2024). These studies strengthen the present paper's argument that the value of AI-driven knowledge management depends not only on retrieval capability, but also on the organisational practices that make AI-supported knowledge traceable, verifiable and decision-ready.

The contemporary literature is useful because it shows that artificial intelligence can support knowledge discovery, retrieval, analysis and decision support. However, much of this literature still treats AI adoption as a general organisational or technological issue. It does not always explain the knowledge management routines that must exist before AI can produce value. It also gives limited attention to medium-sized technology companies, where knowledge may be rich in practical terms but less formally organised. This leaves an important gap between the promise of AI and the organisational conditions needed for its effective use.

4.3. Regional and Emerging-Economy Implementation Evidence

Regional and emerging-economy implementation evidence adds a useful contextual layer to the review. Abu Al-Nasr (2021) discussed knowledge management and knowledge-based management in Arab institutions, which is useful for linking the topic with regional organisational contexts. More recent regional studies address AI in organisational and educational decision and knowledge-management settings (Al Azzam & Al Dafra, 2023; Al-Dosari & Al-Nouh, 2024; Al-Qarni, 2024), while Masameh et al. (2025) provide complementary public-sector evidence on knowledge management and institutional development.

The value of this literature for the present paper is mainly contextual. It draws attention to practical implementation conditions such as digital readiness, skills, infrastructure, acceptance, governance and institutional support. These issues are important because AI-driven knowledge management cannot work effectively through technology alone. It also depends on the organisational environment in which knowledge is documented, reviewed, shared and used.

At the same time, much of this regional evidence remains concentrated in public and educational sectors rather than medium-sized technology companies. It also tends to discuss artificial intelligence and decision-making as a relatively direct relationship, without giving enough attention to knowledge management practices as the pathway through which AI may influence decision-making quality. The present paper therefore uses this literature as implementation evidence rather than as the main theoretical foundation. It supports the argument that AI-supported knowledge work is shaped by readiness, governance and human capability, especially in organisations where formal knowledge systems are still developing.

The relevance of this evidence to medium-sized technology companies can be justified through the similarity of the organisational bottlenecks involved. Public and educational institutions often face bureaucratic routines, fragmented data, weak governance arrangements and uneven digital readiness when they introduce AI-supported systems. Medium-sized technology firms may operate in a more commercial and project-based environment, but they can face comparable structural constraints when knowledge is dispersed across departments, individual expertise, supplier files, project records and client histories. For this reason, regional implementation evidence is used here not as direct sector evidence, but as a theoretical bridge for understanding how data silos, governance gaps and human capability constraints may also shape AI-driven knowledge management in medium-sized technology companies.

4.4. Summary of the Literature Streams

Table 5

Summary of the literature streams used in the review

Literature stream	What it explains well	Main limitation	Use in this paper
Classical knowledge management	Knowledge creation, sharing, strategy and socio-technical systems	Most works predate current artificial intelligence tools	Provides the theoretical foundation
Contemporary international studies	Artificial intelligence in knowledge work and decision support	Often focused on large organisations or broad digital transformation	Updates the discussion with recent intelligent tools
Regional and emerging-economy implementation evidence	Readiness, skills, infrastructure, governance and implementation conditions	Often focused on public and educational sectors rather than medium-sized technology companies	Adds contextual evidence on readiness, governance and implementation challenges

Table 5 shows that the three streams are complementary. Classical studies explain why knowledge matters. Contemporary studies show how artificial intelligence and generative AI may support and reshape knowledge processes. Regional and emerging-economy implementation evidence shows that digital readiness, skills, governance and institutional challenges matter in organisational settings. The gap lies in bringing these streams together for medium-sized technology companies.

5. Synthesis and Research Gap

The reviewed literature can be synthesised around one main point. AI can support knowledge work, but it does not remove the need for knowledge management. Earlier knowledge systems mainly helped organisations store, classify and retrieve what had already been documented. Generative AI adds a new issue because it can also summarise, combine and produce knowledge-like outputs. This makes AI-supported knowledge work more powerful, but also more dependent on validation, provenance, governance and human review.

Classical knowledge management studies show that knowledge must be created, shared, stored and applied before it can become useful for organisational action. Contemporary AI studies show that intelligent tools can support retrieval, classification, summarisation, analysis and decision support. Decision-making research highlights the role of information and decision processes (Citroen, 2011; Dean & Sharfman, 1996), examines decision speed in high-velocity environments (Eisenhardt, 1989), documents the rapid adoption of data-driven decision-making (Brynjolfsson & McElheran, 2016), and develops alternative human–AI decision structures intended to benefit organisational decision quality (Shrestha et al., 2019). Regional and emerging-economy implementation evidence also points to skills, infrastructure, readiness, governance and acceptance as practical implementation conditions.

Taken together, these streams suggest that AI-driven knowledge management should not be examined only as a technical capability. It should be examined as a socio-technical knowledge process. If a company has weak documentation, scattered files and poor sharing routines, AI may only make weak material easier to find or reproduce. If the company has stronger knowledge practices, AI can make previous experience more visible, searchable and usable. In the case of generative AI, this point becomes more important because generated outputs may look coherent even when they require checking against reliable organisational sources.

The research gap can therefore be stated as follows: existing literature has not yet explained how generative AI changes the knowledge management practices that matter most for decision-making quality in medium-sized technology companies. Prior research focused on whether AI improves access to knowledge. The present paper argues that the more important and less examined question is whether organisations can make AI-supported knowledge trustworthy enough to use in decisions. This requires a shift in theoretical focus from retrieval-oriented knowledge management practices to trustworthiness-oriented ones, specifically provenance, validation, governance and human review. This gap is especially consequential for medium-sized technology companies, where formal knowledge governance is often limited and where the risks of acting on ungoverned AI outputs are high.

These firms may hold valuable project experience, supplier history, technical expertise and client knowledge, but this knowledge may remain dispersed across files, people and previous decisions. For such companies, AI-driven knowledge management may create value only when it is connected to clear practices for documenting, validating, retrieving, sharing and reviewing knowledge before decisions are made.

This synthesis is informed by several converging lines of research. Shrestha et al. (2019) develop a framework for combining human and AI-based decision-making across different contingency conditions, with the aim of benefiting organisational decision quality. Berente et al. (2021) frame artificial intelligence as a distinct organisational management challenge rather than a technology that can be adopted passively. Raisch and Krakowski (2021) conceptualise automation and augmentation as interdependent rather than mutually exclusive, highlighting the need to manage their paradoxical relationship. Together, these studies motivate—but do not empirically establish—the mediating logic of the present framework: AI-driven knowledge management is expected to create value for decisions through knowledge management practices that structure how knowledge is captured, validated and used, rather than through technical deployment alone.

6. Proposed Conceptual Framework

The proposed framework is built on the synthesis above. It links four main components: AI-driven knowledge management, knowledge management practices, decision-making quality and perceived challenges. The framework does not treat AI as an automatic solution. It treats AI as an enabling condition whose value depends on how it is connected to organisational knowledge practices.

The framework is informed by the automation-augmentation view of artificial intelligence. AI can automate some knowledge tasks, such as searching, classifying, summarising and comparing previous cases. At the same time, AI can augment human work by helping managers and employees interpret knowledge, notice patterns and review previous experience before decisions are made. This distinction is important for the present paper because decision-making quality in medium-sized technology companies cannot be improved by automation alone. It also requires human judgement, validation and contextual understanding.

Generative AI makes this issue more important. It can produce knowledge-like outputs that appear useful and coherent, but these outputs still need to be checked against reliable organisational sources. For this reason, the framework gives knowledge management practices a central position. Practices such as documentation, validation, provenance, retrieval, sharing, application, governance and human review are treated as the pathway through which AI-supported knowledge can become useful for decision-making.

The position of the variables in the framework follows this logic. AI-driven knowledge management is placed as the independent variable because it represents the organisational use of intelligent tools to acquire, organise, retrieve, generate, summarise and apply knowledge. Knowledge management practices are placed as the mediating variable because the value of AI is expected to pass through organisational routines rather than through technical presence alone. Decision-making quality is placed as the dependent variable because it represents the expected organisational outcome of better knowledge use. Perceived challenges are included as moderating conditions because weak documentation, limited skills, poor data quality, resistance, unclear governance and overreliance on AI may reduce the expected value of AI-supported knowledge work.

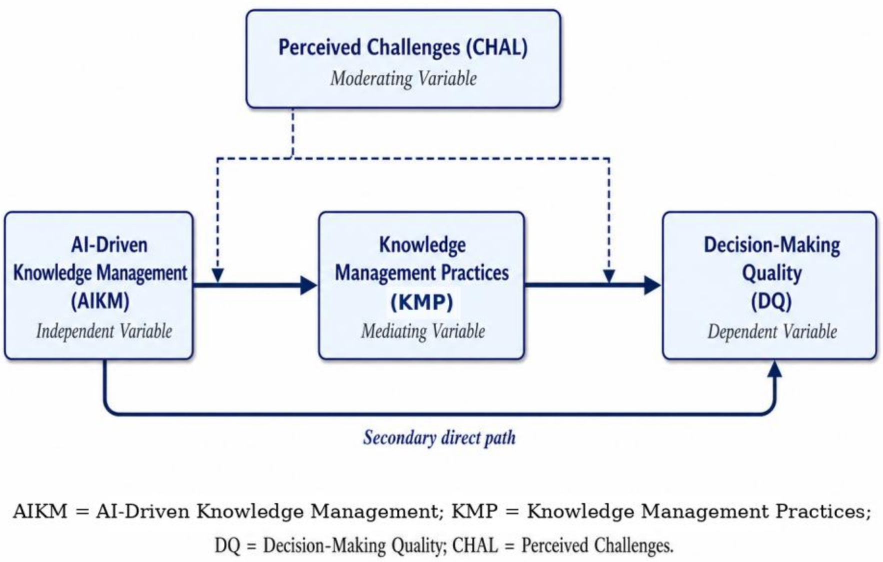
Figure 1 presents the proposed conceptual framework. The main path moves from AI-driven knowledge management to knowledge management practices and then to decision-making quality. A secondary direct path from AI-driven knowledge management to decision-making quality is also shown. This path recognises that AI tools may sometimes support decisions directly through search, summarisation or analytical support. However, the framework assumes that this direct path is weaker and less stable than the mediated path through knowledge management practices. Perceived challenges are shown as moderating conditions because they may weaken both the use of AI in knowledge practices and the translation of those practices into decision-making quality.

The logic of the framework is therefore based on partial rather than full mediation. AI-driven knowledge management may have some direct value for decision-making, but its more reliable contribution is expected to occur through knowledge management practices. This is especially important in medium-sized technology companies, where valuable knowledge may exist but remain dispersed across people, documents, projects and previous decisions.

Figure 1

Proposed conceptual framework

Note. Solid arrows indicate direct or mediated paths. Dashed moderation paths indicate that perceived challenges may weaken both the AI-driven knowledge management → knowledge management practices path and the knowledge management practices → decision-making quality path.



6.1. Research Propositions

Based on the proposed framework, the review develops six conceptual propositions for future empirical testing. These propositions are not presented as tested hypotheses in this paper. They are derived from the automation-augmentation view of AI and from the argument that provenance, validation, governance and human review are the new core knowledge management practices in AI-supported organisations. They are intended to clarify how AI-driven knowledge management may influence decision-making quality through these practices, and how perceived challenges may weaken these relationships.

AI-driven knowledge management can support knowledge practices by automating and augmenting parts of knowledge work. It may help organisations search previous records, classify documents, summarise project experience and retrieve relevant knowledge more quickly. In medium-sized technology companies, this can be useful because valuable knowledge is often dispersed across emails, reports, supplier files, technical documents and individual experience. However, AI contributes to knowledge management only when it is connected to organisational routines that make knowledge visible, usable and reviewable.

Proposition 1: AI-driven knowledge management positively influences knowledge management practices in medium-sized technology companies.

Knowledge management practices are expected to influence decision-making quality because decisions depend on the quality and usability of the knowledge available at the time of decision. When knowledge is documented, validated, shared and applied through clear routines, managers and employees can make decisions that are better informed, more timely and more consistent with organisational objectives. In this sense, knowledge management practices form the organisational route through which knowledge becomes useful for decision-making.

Proposition 2: Knowledge management practices positively influence decision-making quality.

The relationship between AI-driven knowledge management and decision-making quality is expected to operate mainly through knowledge management practices. AI may improve access to knowledge, but access alone is not enough. Knowledge must be checked, interpreted, traced to its source and applied to the decision context. This is especially important with generative AI, because generated outputs may appear coherent even when they require validation against reliable organisational sources.

Proposition 3: Knowledge management practices mediate the relationship between AI-driven knowledge management and decision-making quality.

A secondary direct effect may also exist. AI tools can sometimes support decision-making directly by providing faster search, summarisation, comparison of previous cases or analytical support. However, this direct effect is expected to be weaker and less stable than the mediated effect through knowledge management practices, because direct AI outputs still require human judgement and organisational validation before they can safely support decisions.

Proposition 4: AI-driven knowledge management may have a secondary direct positive influence on decision-making quality, but this effect is expected to be weaker than the mediated pathway through knowledge management practices.

Perceived challenges may weaken the relationship between AI-driven knowledge management and knowledge management practices. Poor data quality, weak documentation, limited technical skills, unclear governance and resistance to change can reduce the ability of AI tools to support knowledge work. In such conditions, AI may retrieve or generate outputs faster, but those outputs may not become reliable organisational knowledge.

Proposition 5: Perceived challenges weaken the relationship between AI-driven knowledge management and knowledge management practices.

Perceived challenges may also weaken the relationship between knowledge management practices and decision-making quality. Even when knowledge practices exist, their value may be reduced if employees do not trust the system, if governance rules are unclear, if knowledge is not updated, or if decision-makers over-rely on AI outputs without sufficient human review. These challenges may reduce the ability of knowledge practices to support timely, evidence-based and contextually appropriate decisions.

Proposition 6: Perceived challenges weaken the relationship between knowledge management practices and decision-making quality.

7. Discussion

The review supports a balanced understanding of AI-driven knowledge management. AI can make knowledge easier to search, summarise and compare, but this does not automatically improve decision-making quality. Its value appears when connected to knowledge management practices that make organisational knowledge visible, reliable and usable — which is why the proposed framework places knowledge management practices as the main pathway between AI-driven knowledge management and decision-making quality. In the generative AI context, outputs that appear clear and coherent may still need to be checked against reliable organisational sources. Validation, provenance, governance and human review are therefore the core knowledge management practices through which AI-supported knowledge becomes trustworthy enough to use in decisions.

The framework also reflects the automation-augmentation view of AI. Some AI functions may automate knowledge work, such as classification, retrieval and summarisation. Other functions may augment human work by helping managers and employees interpret previous cases, compare alternatives and prepare for decisions. The present review argues that decision-making quality depends more on augmentation than automation alone. Medium-sized technology companies may gain value from automation, but reliable decisions still require human judgement and contextual understanding.

This argument extends classical knowledge management theory. Classical knowledge management studies were written before the current rise of AI, but their ideas remain useful because knowledge still needs to be captured, shared, interpreted and applied (Alavi & Leidner, 2001; Davenport & Prusak, 1998; Nonaka & Takeuchi, 1995). What has changed is that AI, especially generative AI, can now participate in the production and reformulation of knowledge-like outputs. This makes the old knowledge management problem more complex rather than less important.

The framework also differs from studies that treat AI mainly as a direct driver of decision quality or performance. A direct path may exist because AI tools can support search, summarisation and analysis. However, this direct effect is expected to be weaker and less stable than the mediated path through knowledge management practices. For medium-sized technology companies, the main issue is not only whether AI tools are available. It is whether the organisation has the routines needed to document, validate, retrieve, share and review knowledge before decisions are made.

Regional and emerging-economy implementation evidence adds an important reminder. AI-supported knowledge work is shaped by readiness, skills, infrastructure, governance and institutional context. These issues matter for medium-sized technology companies because they may operate with limited formal knowledge systems and fewer specialised data or AI teams than large corporations. The framework therefore treats perceived challenges as active conditions that can weaken the value of AI-driven knowledge management.

7.1. Implementation Challenges

Implementation challenges are central to the proposed framework. Data quality is the first concern: if project records, supplier information and previous decisions are incomplete or poorly organised, AI tools may retrieve information faster without improving its usefulness. In the case of generative AI, poor data quality may also lead to outputs that appear coherent but are not reliable enough for decision-making.

Skills are also important. Employees need enough digital awareness to use AI-supported systems correctly, interpret results and recognise their limits. Without these skills, AI may be treated either as a complete substitute for professional judgement or as a tool that employees avoid, both of which reduce its value.

Governance is another challenge. Medium-sized technology companies need clear rules about who can add, update, approve and use knowledge inside the system. They also need rules for checking AI-generated summaries and tracing important outputs back to reliable organisational sources. Without such governance, the knowledge base may become inconsistent and difficult to trust.

Resistance to change may also weaken adoption when employees feel their practical experience is being replaced rather than supported. AI implementation should therefore be presented as a way to preserve practical knowledge, not remove human expertise. Human judgement remains essential throughout: AI can support retrieval and analysis, but it cannot carry organisational responsibility for the final decision. Managers and specialists must still assess whether previous knowledge fits the new case, client requirement or regulatory context.

A further challenge is over-reliance on AI outputs. When AI-generated answers appear clear and confident, decision-makers may give them more trust than they deserve. This risk is higher when the source of the output is not clear or when employees do not check the information against reliable organisational records. Provenance, validation and human review are therefore necessary safeguards for AI-driven knowledge management. Technical research characterises hallucination as a persistent reliability problem in large language models: Xu et al. (2024) argue that hallucination is an inherent limitation, while Huang et al. (2025) synthesise the main causes, detection approaches and mitigation strategies. These sources do not by themselves establish organisational failure rates; rather, they show why fluent AI outputs require verification before they are treated as organisational knowledge. For medium-sized technology companies without formal AI governance teams, this creates a specific risk: confident AI outputs may be accepted as reliable organisational knowledge without adequate human verification. Dwivedi et al. (2023) likewise emphasise that generative AI introduces substantive accuracy, transparency, ethical and organisational risks, reinforcing the need for careful human validation when such outputs are used in knowledge work. These concerns reinforce the need for provenance tracking and structured human review as practical governance mechanisms, not merely theoretical safeguards.

The need for human review is also supported by recent evidence on human-AI collaboration. Vaccaro et al. (2024) show that human-AI combinations do not automatically outperform humans or AI alone, and that performance depends on task type and the way collaboration is structured. This finding is important for AI-driven knowledge management because it suggests that human oversight must be designed into the knowledge process rather than assumed. Reuel and Undheim (2024) similarly argue that generative AI requires adaptive governance because its capabilities, uses and risks change quickly. For medium-sized technology companies, this means that governance cannot be treated only as a formal policy. It must operate through practical routines for checking outputs, assigning responsibility, tracing sources and deciding when human judgement should override AI-supported recommendations. Hosanagar and Ahn (2024), in a creative-writing experiment, likewise show that collaboration design matters: configurations that preserved substantive human input produced higher quality and satisfaction than designs that limited humans largely to confirming AI output. Although the task context differs from organisational knowledge work, the result supports treating role design as an empirical question rather than assuming that more AI involvement is always better.

8. Theoretical Implications

This review offers four theoretical implications. First, it extends classical knowledge management theory by showing that AI-driven tools do not reduce the need for knowledge management practices. In the context of generative AI, these practices become more important because knowledge may now be summarised, combined and reformulated by intelligent systems. Validation, provenance, governance and human review therefore become central parts of AI-supported knowledge management.

Second, the paper contributes to AI and knowledge management literature by positioning knowledge management practices as the main pathway through which AI-driven knowledge management may influence decision-making quality. The framework follows a partial mediation logic. AI may have some direct value through search, summarisation and analytical support, but its more reliable contribution is expected to occur through knowledge management practices.

Third, the paper adds to decision-making research by linking decision-making quality to the condition of organisational knowledge. Better decisions depend not only on access to AI tools, but also on whether the knowledge used is reliable, traceable, timely and reviewed in context. This is especially important for medium-sized technology companies, where useful knowledge may be practical, project-based and dispersed across people, files and previous decisions.

Fourth, the paper contributes to the growing body of work on AI governance in knowledge-intensive organisations. Rezaei (2025) identified a broad set of technological, organisational and ethical challenges associated with AI-enabled knowledge management. The study highlights job security and privacy as prominent cross-process concerns, while transparency, accountability and explainability are also identified as important implementation issues influencing trust in AI-supported knowledge systems. These concerns are amplified in the generative AI context because outputs may be produced without clear attribution to verifiable organisational sources. The present framework addresses this by positioning provenance and governance as core knowledge management practices, rather than as compliance add-ons.

Gelashvili-Luik et al. (2025) reached a complementary conclusion, finding that successful AI-enabled knowledge management depends on strong leadership commitment, adaptable governance structures, context-sensitive technology selection and an appropriate balance between automation and human oversight. Together, these contributions suggest that the theoretical framework proposed in the present paper is consistent with emerging research on what makes AI-supported knowledge work reliable and organisationally useful.

9. Practical Implications

For managers, the framework suggests beginning with a specific knowledge risk rather than with the purchase of an AI tool. In a 120-person technology firm without a dedicated data team, a workable first step is to choose one bounded repository—such as completed project files, supplier assessments or technical incident reports—assign an owner, define which documents are authoritative, and record the source and date of every AI-generated summary. The purpose is not merely to make search faster, but to ensure that an employee can trace a recommendation back to the organisational evidence on which it relies.

A simple provenance routine can operate through four controls. First, the AI output should display or attach the source documents used. Second, a named subject-matter reviewer should verify material claims against those sources. Third, the reviewer should record approval, correction or rejection in the project record. Fourth, any approved summary should carry a review date and an expiry or revalidation point. For high-impact decisions—such as regulatory compliance, safety, client commitments or major expenditure—the accountable manager, not the AI user alone, should sign off before the output enters the decision process.

Governance should also specify who may upload, update, approve and reuse organisational knowledge; which categories of information may not be entered into external AI systems; and when professional judgement must override an AI-supported recommendation. These controls respond to the finding that human–AI combinations do not automatically outperform the better of humans or AI working alone (Vaccaro et al., 2024). The framework therefore favours selective augmentation, not an assumption that collaboration is always superior: human review adds value only when roles, expertise, escalation rules and accountability are deliberately designed.

10. Limitations and Future Research

This review has several limitations. It is a purposive critical integrative review and does not claim to be an exhaustive systematic review. Screening, selection and synthesis were carried out by the author. Fully independent dual screening was not undertaken, which may introduce selection and interpretive bias; explicit inclusion and exclusion criteria were used to reduce it. The inclusion of public-sector and educational evidence provides contextual insight, but transferability to medium-sized technology companies remains partly analogical and should be tested empirically. The proposed framework is conceptual and has not yet been tested.

Future research should test the framework with data from medium-sized technology companies. Quantitative studies could use structural equation modelling to examine the mediating role of knowledge management practices and the moderating role of perceived challenges; established procedural-rationality measures, including those developed by Dean and Sharfman (1996), provide a starting point for operationalising decision-making quality. The perceived-challenges construct is intentionally broad at this conceptual stage, but it combines data quality, documentation, skills, governance, resistance and overreliance, which have different causal logics. Empirical studies should therefore disaggregate these dimensions before testing moderation on the two framework paths. Qualitative and mixed-methods studies could then explain how managers and technical employees apply provenance, validation and human-review routines in daily work.

Future work may also examine additional conditions such as leadership support, organisational culture, data governance and the risks of over-reliance on generative AI. These factors may influence whether AI-driven knowledge management becomes a real organisational capability or remains only a technical tool. Table 6 summarises the suggested directions for future research.

Table 6

Suggested directions for future research

Future research area	Suggested method
Testing how provenance, validation, governance and human review shape the AIKM → KMP → decision-making pathway	Structural equation modelling (PLS-SEM) with separate measures for trustworthiness practices
Examining the moderating role of perceived challenges	Quantitative survey with moderation analysis
Understanding employee acceptance of AI-supported knowledge systems	Qualitative interviews
Comparing AIKM adoption in medium-sized and large firms	Comparative case study
Measuring decision-making quality in technology sectors	Survey-based empirical study
Studying governance, provenance and ethical risks of generative AI in AIKM	Mixed-methods research
Operationalising decision-making quality and framework propositions	Survey measures based on procedural rationality, evidence use, timeliness and goal consistency

11. Conclusion

This review concludes that AI-driven knowledge management can support decision-making quality, but not as an isolated technical solution. Its value depends on whether AI tools are connected to knowledge management practices that make organisational knowledge visible, reliable, traceable and usable. This is especially important in medium-sized technology companies, where useful knowledge is often practical, project-based and dispersed across people, files and previous decisions.

The review also shows that generative AI changes the conditions of knowledge work. AI can now summarise, combine and produce knowledge-like outputs, but these outputs still require validation, provenance, governance and human review. For this reason, knowledge management practices remain the main pathway through which AI-driven knowledge management may influence decision-making quality. This logic is reflected throughout the framework in the central role assigned to provenance, validation, governance and human review as organisational safeguards rather than optional additions.

The proposed framework therefore treats knowledge management practices as a mediating mechanism and perceived challenges as limiting conditions. It also recognises a secondary direct path from AI-driven knowledge management to decision-making quality, but this path is expected to be weaker than the mediated pathway through organised knowledge practices. The paper provides a conceptual basis for future empirical testing in medium-sized technology companies and contributes to a more cautious understanding of AI-supported decision-making.

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Generative AI Use Statement

Generative AI tools were used to support the readability, language refinement and text editing of the manuscript. The author developed the research question, conceptual framework and scholarly argument, appraised and interpreted the literature, and made all final academic decisions. The author reviewed and verified the final content and takes full responsibility for the accuracy and integrity of the manuscript.

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The author discloses that Dr. Ibrahim Al Souleiman, acknowledged for supervisory guidance on earlier drafts, has an active role in directing operations and global strategy for the U7Y Academic Journal. No other conflicts of interest are declared.

Data Availability Statement

This article is based on a critical integrative review of published literature. No new empirical dataset was generated or analysed for this paper.

Ethics Approval Statement

This study did not involve human participants, personal data collection or experimental procedures. Therefore, formal ethics approval was not required.

Originality Statement

This manuscript is original, not previously published, and not currently under review elsewhere.

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