Structured Knowledge Quality for Reliable Intelligence in the Post-Truth Era

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Abstract: Organisations continue to invest in Agentic AI and advanced analytics, yet the conversion of extensive knowledge resources into sustained innovation remains uneven. This difficulty is amplified in the post-truth era, where misinformation, synthetic content, and algorithmic hallucinations undermine information reliability. Within Knowledge Management (KM) research, substantial attention has been given to knowledge creation, sharing, and organisational learning. Less attention has been paid to the structured regulation of knowledge quality as a necessary condition for dependable intelligence production. This paper argues that innovation in digitally mediated environments depends not simply on knowledge availability, but on disciplined management of knowledge quality across the data-information-knowledge-intelligence-wisdom (DIKIW) continuum. The study is grounded in a pragmatist philosophy and adopts an abductive Design Science Research approach, supported by a Systematic Literature Review. It develops a model that links structured knowledge quality to organisational intelligence production. The model comprises three interconnected elements. The first element is a foundational knowledge infrastructure governing data and information organisation. The second element is explicit knowledge quality criteria - validity, authenticity, reliability, currency, and sufficiency, intended to safeguard epistemic integrity. The third element is a structured mechanism for transforming validated knowledge into prioritised organisational intelligence relevant to both human decision-makers and Agentic AI. By clarifying the transition from organised information to prioritised intelligence, the paper extends DIKIW within KM theory to address contemporary challenges of information instability. It shows how structured quality regulation stabilises explicit knowledge repositories and supports more coherent internalisation and organisational learning. Innovation is therefore understood as contingent upon epistemic governance rather than technological capability alone. The paper contributes by conceptualising structured knowledge quality as a distinct KM capability, articulating a formalised pathway between KM and organisational intelligence, and offering a design-oriented framework derived through abductive movement between the reviewed literature, established KM theory and the identified organisational problem.

Keywords: Agentic AI, Design science research, Epistemic control, Innovation, Knowledge management, Knowledge quality, Organisational intelligence, Post-truth

1. Introduction

Organisations increasingly operate in environments defined by information overload, rapid technological change, and growing uncertainty about the reliability of what they know. Data systems, analytics platforms and Agentic AI are often adopted on the assumption that more information will produce better decisions and stronger innovation, reflecting the broader analytics-driven view that organisations can compete through superior use of data and analytical capability (Davenport and Harris, 2017). In practice, however, the route from available knowledge to dependable intelligence remains uneven. Agentic AI intensifies both the opportunity and the risk because agentic systems can coordinate multi-step workflows, retrieve information across sources and act with bounded autonomy, while still requiring oversight, governance and safeguards (World Economic Forum, 2026).

The difficulty is sharpened by the post-truth condition because organisational decisions may increasingly draw on content that is persuasive in form but uncertain in origin, accuracy or context. Digital environments facilitate the rapid circulation of misinformation, disinformation, synthetic media and AI hallucinations. Williamson and Prybutok (2024) describe AI hallucinations as plausible but incorrect outputs that create risks in domains requiring precision and dependability. Palese (2026) similarly argues that algorithmic systems increasingly shape what is recognised as credible, authoritative and true. For KM, this means that unverified content can enter repositories, be shared as organisational knowledge and later influence decisions. Knowledge quality therefore becomes a strategic governance problem rather than a technical afterthought. This aligns with the view of Floridi (2019), that information must be understood not merely as content, but as a structured object of philosophical and conceptual design.

Knowledge Management (KM) has made substantial contributions to understanding knowledge creation, sharing, transfer and organisational learning (Alavi and Leidner, 2001; Davenport and Prusak, 1998). Yet many KM frameworks do not explicitly specify how knowledge should be evaluated before it is used for intelligence production. This paper responds to that gap by conceptualising knowledge quality as the central unit of analysis and as a managerial capability that regulates the transformation of information into knowledge and knowledge into organisational intelligence.

This study also builds on prior Nominal Ranking Technique (NRT) related work in Information and Knowledge Management (IKM). NRT is a structured methodology for transforming large volumes of unstructured data into prioritised intelligence through inclusion criteria, data cleansing, ranking and quality validation. Earlier work introduced the NRT as a methodology within IKM (De Koker and Du Plessis, 2024), while subsequent work expanded the NRT methodology - as a structured approach for transforming big data into strategic intelligence under volatile, uncertain, complex, and ambiguous (VUCA), and brittle, anxious, nonlinear, and incomprehensible (BANI) conditions (De Koker, 2025; De Koker and Du Plessis, 2025a). In related work on AI-driven business models in the data-information-intelligence economy, the NRT methodology was further positioned as a solution for managing big data towards strategic intelligence and innovation (De Koker and Du Plessis, 2025b). Across these studies, the NRT methodology emphasises inclusion criteria, data cleansing, prioritisation and VARCS principles as quality checks. The VARCS principles speaks to the validity, authenticity, reliability, currency and sufficiency of data, information, and intelligence. This paper will extend the VARCS principles into the DIKIW continuum. This paper does not reapply the NRT methodology outrightly, instead, this paper extends the methodological logic into the KM domain by positioning knowledge quality as the unit of analysis and as the validation capability required for dependable organisational intelligence production. For this paper, only the VARCS principles from the NRT methodology is considered.

The paper makes three contributions. First, the paper specifies structured knowledge quality as a distinct KM capability. Second, the paper extends the DIKIW continuum by treating the movement from data to intelligence as a governed transformation, rather than a natural progression. Third, the paper offers a design-oriented model that links; 1) knowledge infrastructure, 2) knowledge quality validation, and 3) intelligence production - to be considered in environments managed by humans and supported by AI.

2. Theoretical Foundations

2.1 Knowledge Management, Digital Transition and Innovation

KM traditionally focuses on how organisations create, store, share and apply knowledge. The knowledge-based view positions knowledge as a strategic resource and a basis for competitive advantage (Grant, 1996; Stoian, Tardios and Samdanis, 2024). Current digital transition changes the conditions under which knowledge is produced and used. Cerchione et al. (2024) shows that digital transition reshapes KM processes and requires renewed theorisation of knowledge creation. Mkhize (2026) similarly finds that 4IR technologies such as AI, blockchain, the Internet of Things and big data have reshaped organisational knowledge creation, sharing and application. These studies support the argument that KM is no longer only about knowledge flow, but also about the reliability and governance of digital knowledge.

2.2 DIKIW and the Problem of Transition

Rowley (2007) explains the DIKW hierarchy as a staged progression in which data are transformed into information, information into knowledge, and knowledge into wisdom. DIKW extends into the DIKIW continuum, with intelligence added after knowledge and before wisdom (Liew, 2013), which is useful for this paper, as the DIKIW continuum describes the movement from data to information, information to knowledge, knowledge to intelligence and intelligence to wisdom. However, the transition between these stages is not automatic. Data may be incomplete, information may be misinterpreted, knowledge may be decontextualised and intelligence may be poorly prioritised. This paper therefore treats DIKIW as a transformation process requiring explicit validation. Intelligence is understood as prioritised, decision-ready knowledge rather than merely accumulated information.

2.3 SECI, Internalisation and Digital Knowledge Creation

The SECI model remains a central KM framework because it explains how tacit and explicit knowledge interact through socialisation, externalisation, combination and internalisation (Nonaka and Takeuchi, 1995; Dalkir, 2011, Adesina and Ocholla, 2019). It captures the dynamic nature of knowledge conversion and organisational learning and has been applied to innovation-oriented contexts where KM supports entrepreneurial learning and knowledge creation (Bandera et al., 2017). Recent work demonstrates that SECI requires extension in digital and AI-mediated environments. Cerchione et al. (2024) proposed the WISED model to rethink the knowledge-creating company under digital transition, which considers 1) webification - transformation of explicit knowledge into digital knowledge, 2) informatisation - transformation of digital knowledge into tacit knowledge, 3) systematisation - transformation of tacit knowledge into digital knowledge, 4) explicitation - transformation of digital knowledge into explicit knowledge, and 5) digitalisation - transformation of digital knowledge into other digital knowledge (Cerchione et al., 2024). Böhm and Durst (2026) argue that generative AI changes the assumptions of the SECI model and proposes the Generative, Receptive Artificial Intelligence (GRAI) framework as a revised perspective for KM in the age of generative AI. Li, Liu and Zhou (2018) showed, through the Grey SECI (G-SECI) model, that internalisation by practice is central to knowledge creation and innovation performance. These contributions support the need to stabilise explicit knowledge before it is combined and internalised. This is consistent with Tsoukas' (2009) dialogical view of knowledge creation, where new organisational knowledge emerges through interpretation, interaction and the disciplined articulation of meaning.

2.4 Post-truth, Hallucination and Epistemic Risk

Post-truth conditions make epistemic control a KM concern because inaccurate or manipulated content can be captured, shared and institutionalised as organisational knowledge. Lewandowsky, Ecker and Cook (2017) explain the cognitive and social difficulty of coping with misinformation, while Ecker et al. (2022) identify its psychological drivers and the need for corrective strategies. Bender et al. (2021) warn that large language models can produce fluent but unreliable outputs, and Williamson and Prybutok (2024) show that AI hallucinations require quality assurance, transparency and human review. In this paper, epistemic governance refers to the organisational rules, roles and validation routines used to determine which knowledge claims may enter repositories and inform intelligence. Epistemic control is the operational application of those rules to preserve trustworthy intelligence under uncertainty.

2.5 Knowledge Quality as a Capability

Quality has long been examined in information systems and data-quality research. Wang and Strong (1996) show that information quality and user satisfaction are important dimensions in evaluating information-system success, and that quality extends beyond accuracy to include attributes such as timeliness, precision, reliability, currency, completeness, relevance, accessibility and interpretability. Their empirical framework further demonstrates that high-quality data should be intrinsically sound, contextually appropriate for the task, clearly represented and accessible to the user. Quality is therefore not determined by a single technical attribute, but by whether data are fit for use within a specific decision context. This paper extends this multidimensional quality logic from data and information into the KM domain. Knowledge quality concerns whether interpreted and organised knowledge is sufficiently trustworthy, contextually appropriate and complete to support intelligence production. The VARCS principles provide the validation logic for this purpose: validity, authenticity, reliability, currency and sufficiency (De Koker, 2025; De Koker and Du Plessis, 2025a; De Koker and Du Plessis, 2025b). Validity and reliability reflect the need for knowledge to be sound and dependable; authenticity addresses the credibility and provenance of the source; currency addresses temporal relevance; and sufficiency addresses whether the available knowledge is adequate for the intended purpose. The contribution of this paper is not to replace established data- and information-quality frameworks, but to extend their multidimensional and fitness-for-use logic by positioning VARCS as a knowledge-quality validation layer within the DIKIW continuum.

3. Research Design and Method

This study is a conceptual, abductive Design Science Research (DSR) paper supported by a structured Systematic Literature Review (SLR) using Scopus and the PRISMA protocol. The SLR supplied the evidence base, while DSR supplied the artefact-development logic. The unit of analysis is knowledge quality, examined as a conceptual and managerial capability that regulates movement across the DIKIW continuum. Pragmatism was adopted because the research problem is both theoretical and practical: organisations require a defensible way to evaluate knowledge quality in highly digital environments. Abductive reasoning, illustrated in Figure 1, was applied by moving iteratively between the literature review findings, existing theory and the developing artefact. The literature-derived themes were compared with the DIKIW continuum, the SECI model and established data and information quality literature to determine what these perspectives explained about knowledge transformation and where conceptual gaps remained. The themes were then translated into design requirements for the three model layers. The model was refined by positioning VARCS as a knowledge-quality validation layer and was checked against the literature to ensure conceptual coherence, theoretical alignment and relevance to the research problem.

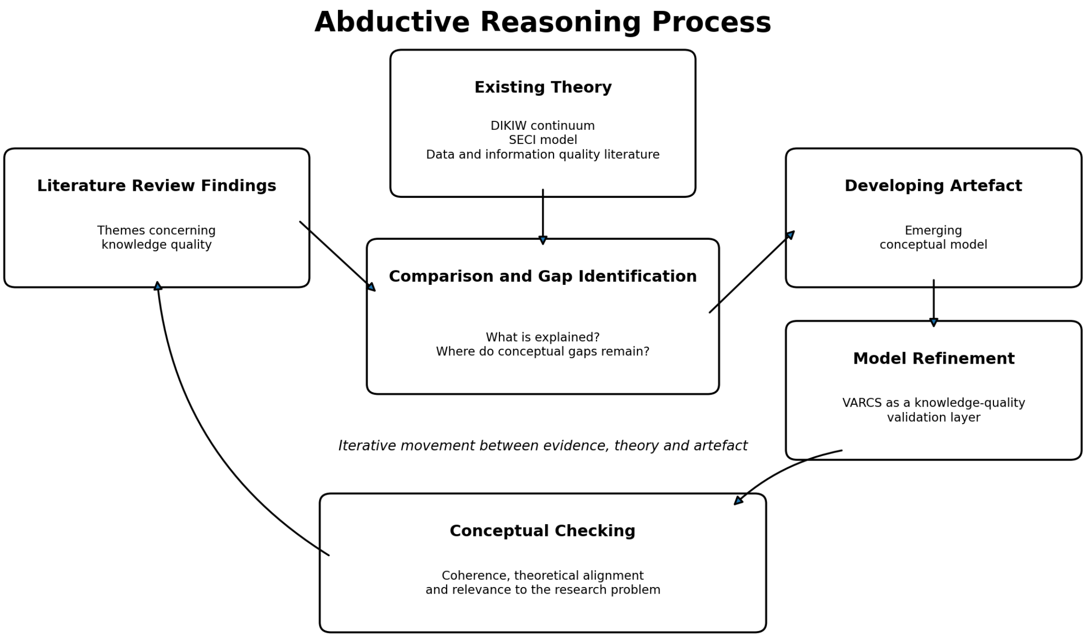

Figure 1: Abductive reasoning process used to develop and refine the conceptual artefact (Author's own compilation, 2026. Developed using ChatGPT for visual rendering)

DSR is appropriate because the paper develops a conceptual artefact: the Knowledge Quality Model for reliable intelligence production. Hevner et al. (2004) position DSR as a problem-solving paradigm for creating and evaluating artefacts, while Van der Merwe, Gerber and Smuts (2020) emphasise the need to clarify the artefact, philosophical position, method and communication logic. Structurally, the SLR functions as the knowledge-base component of the DSR process: it identifies the problem environment, establishes design requirements and provides theoretical justification for the three model layers. DSR then integrates those requirements into the artefact and evaluates it conceptually through internal coherence, alignment with the literature and explanatory value. The paper does not claim empirical validation.

Scopus was selected as the single indexing database because of its broad multidisciplinary coverage of KM, information systems, AI and organisational research. No publication-year restriction was applied; the search covered all records indexed in Scopus at the time of the 2026 search. The search used the following string: TITLE-ABS-KEY ("knowledge quality" AND ("structured knowledge" OR "knowledge management" OR "reliable intelligence" OR "post-truth era*" OR "post-truth*" OR "post truth" OR "artificial intelligence" OR "epistemic governance" OR "epistemic control" OR "VARCS" OR "misinformation" OR "disinformation" OR "synthetic media" OR "algorithmic hallucinations" OR "hallucination*")). Agentic AI was not used as a separate search term because it was treated as a contemporary application context within the broader artificial intelligence category, supported by supplementary literature used to interpret the artefact rather than to determine corpus inclusion.

The search returned 170 records. Two duplicates were removed, leaving 168 records for screening. Following title, abstract and keyword screening, 61 studies were retained for review.

Records were included when they directly addressed knowledge quality, knowledge validation, knowledge infrastructure, KM systems, decision-oriented knowledge use, intelligence production or AI-related knowledge reliability. Records were excluded where they had no clear link to quality, validation, infrastructure or intelligence (n = 60), where the focus was non-KM (n = 27), or where there was no clear organisational KM or epistemic-governance relevance (n = 20). The PRISMA protocol is shown in Figure 2 below.

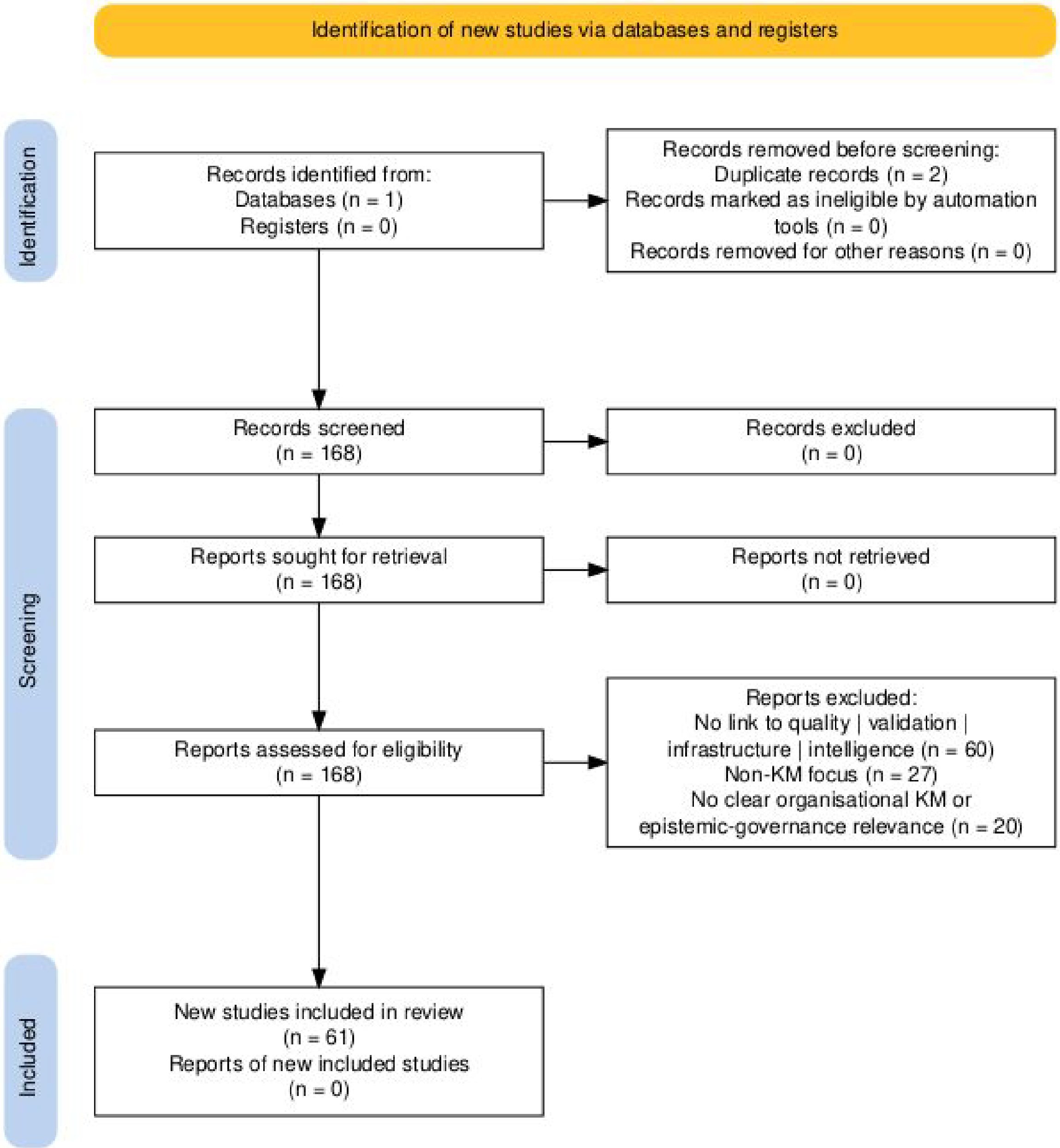

Figure 2: PRISMA flow diagram for the Scopus screening process (Author's own compilation, 2026. Developed using Haddaway et al., 2022)

4. Bibliometric and Thematic Findings

The VOSviewer keyword co-occurrence map in Figure 3 below, shows that the Scopus corpus is strongly centred on knowledge management, with prominent links to knowledge sharing, knowledge-based systems, system quality, quality control, learning systems and knowledge transfer. This confirms that the literature contains a substantial KM and information systems base. However, the map also shows that knowledge quality, reliable intelligence, epistemic control and post-truth are not dominant organising concepts.

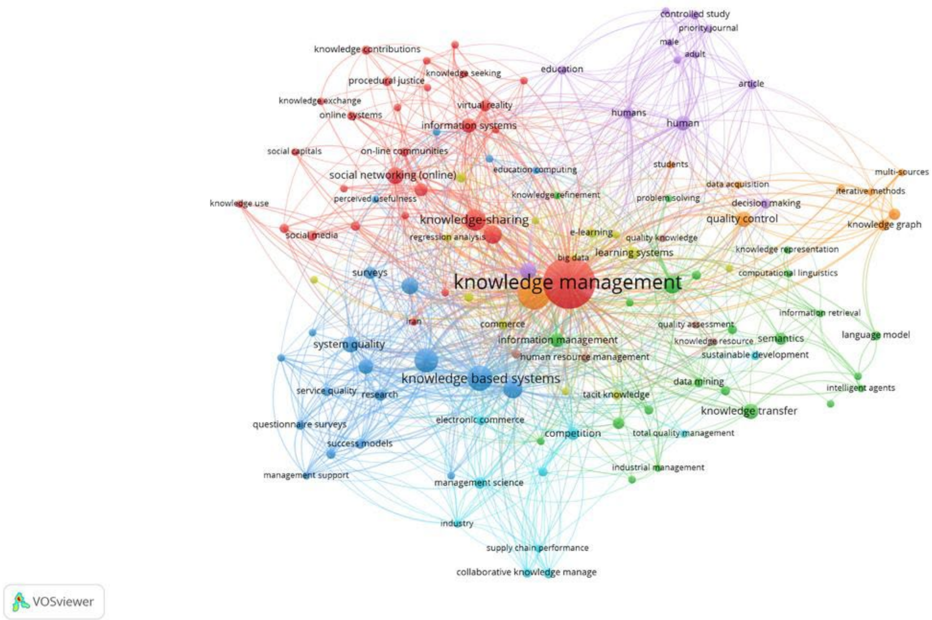

Figure 3: Keyword co-occurrence network (Author's own compilation, 2026. Developed using VOSviewer)

The visual structure of the knowledge-quality and KM corpus suggests a broad but fragmented field. One cluster is oriented towards knowledge sharing and online communities; another towards systems quality and knowledge-based systems; another towards knowledge transfer, semantics and intelligent agents; and another towards quality control, knowledge graphs and multi-source integration. These clusters were interpreted as design requirements rather than merely descriptive findings: infrastructure-related themes informed Layer 1, quality and control themes informed Layer 2, and decision-oriented knowledge-use themes informed Layer 3. Table 1 makes this relationship explicit.

Table 1: Relationship between the SLR evidence base and the model layers

SLR theme / evidence	Representative literature	Model layer and design implication
Knowledge creation, sharing, repositories and digital KM	Alavi and Leidner (2001); Cerchione et al. (2024); Mkhize (2026)	Layer 1: establish people, processes, technologies, structures and culture for organising knowledge.
Information quality, validation, misinformation and hallucination risk	Wang and Strong (1996); Bender et al. (2021); Williamson and Prybutok (2024)	Layer 2: apply explicit VARCS quality gates before knowledge informs intelligence.
Knowledge conversion, internalisation, decision use and organisational intelligence	Nonaka and Takeuchi (1995); Li, Liu and Zhou (2018); Knudsen, Catasús and Kaarbøe (2025)	Layer 3: transform validated knowledge through comparison, synthesis, prioritisation and human judgement.

5. Knowledge Quality Model for Reliable Intelligence

The proposed model illustrated in Figure 3, integrates three layers; 1) knowledge infrastructure, 2) knowledge quality validation, and 3) intelligence production. It does not replace existing KM frameworks. Instead, it adds a quality-control architecture that conditions whether knowledge is sufficiently reliable to support intelligence production.

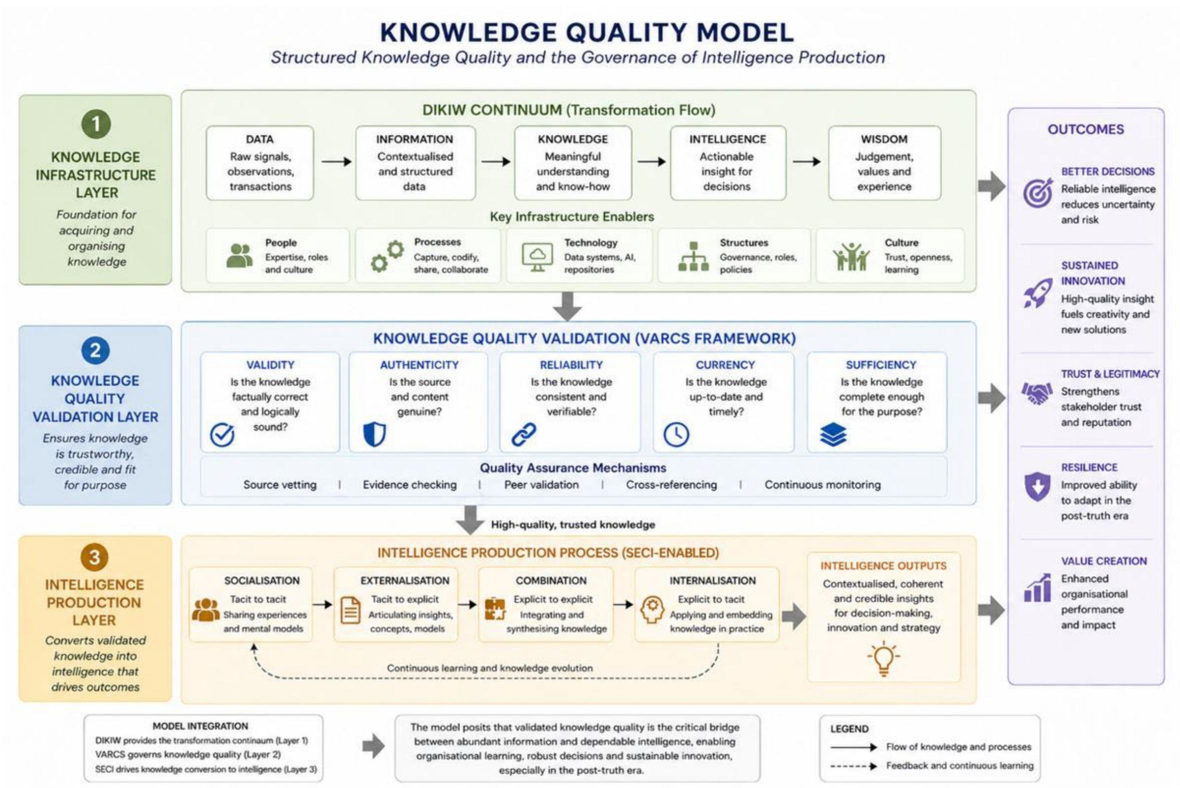

Figure 3: Conceptual Knowledge Quality Model (Own source - developed for this study, 2026)

The Knowledge Quality Model links the DIKIW continuum, the SECI model and the VARCS principles. The DIKIW continuum provides the transformation logic. The SECI model explains how knowledge moves through socialisation, externalisation, combination and internalisation. The VARCS principles provides the validation logic required before knowledge is combined, internalised and converted into intelligence.

5.1 Knowledge Infrastructure Layer

The first layer provides the foundation for acquiring and organising knowledge. It includes people (expertise, roles and culture), processes (capture, codify, share, collaborate), technology (data systems, AI, repositories), structures (governance, roles, policies) and culture (trust, openness, learning). This layer speaks to the movement of, and from data to information to knowledge to intelligence to wisdom.

5.2 Knowledge Quality Validation Layer

The second layer is the core of the model. It applies the VARCS principles. Validity asks whether knowledge is factually and logically sound. Authenticity asks whether the source and content are genuine. Reliability asks whether knowledge is consistent and verifiable. Currency asks whether it is current enough for the decision context. Sufficiency asks whether it is complete enough for the purpose. This layer operates as a gate between data, information and knowledge, governing and protecting intelligence production from low-quality inputs.

5.3 Intelligence Production Layer

The third layer converts validated knowledge into prioritised organisational intelligence. It includes comparison, synthesis, ranking, interpretation and narration. In human environments supported by AI, this layer is important as agentic AI systems may act across workflows and process multiple sources at speed. The model therefore treats intelligence production as headed and inspired by humans and only supported by AI. Intelligence production is not merely a mechanical output of automation.

6. Discussion

6.1 Theoretical Contribution

The paper offers three conceptual contributions to KM. First, it frames knowledge quality as a distinct managerial capability rather than a peripheral information-systems feature. Second, it treats DIKIW as a regulated transformation process by placing quality gates at critical transition points. Third, it links KM and organisational intelligence by explaining how validated knowledge becomes prioritised, decision-ready intelligence. These contributions arise from the integration of the SLR evidence base, established theory and DSR artefact design; the paper does not claim that the SLR alone is sufficient to validate or rewrite theory.

6.2 Implications for SECI and Digital KM

Recent SECI extensions show that digital transition, generative AI and distorted knowledge environments require renewed attention to how knowledge is created and internalised (Cerchione et al., 2024; Böhm and Durst, 2026; Cegarra-Navarro et al., 2026). The present model contributes by specifying the validation layer that should condition combination and internalisation. This is important because internalising low-quality knowledge can institutionalise error, while internalising validated knowledge can support organisational learning and innovation.

6.3 Implications for Agentic AI and Epistemic Resilience

Agentic AI refers here to AI systems that can pursue bounded goals, coordinate multi-step tasks, retrieve information and initiate actions across workflows while remaining subject to human oversight (World Economic Forum, 2026). This makes knowledge quality more important, not less. When AI outputs are plausible but unverified, organisations require governance routines to establish validity, authenticity, reliability, currency and sufficiency. Recent evidence from digital learning environments similarly shows that generative AI increases the importance of source evaluation, critical reasoning and information competence (Yrymbayeva et al., 2026). Epistemic control is therefore not only the filtering of poor-quality information; it is the managerial process through which organisations shape how knowledge is produced, validated and institutionalised (Knudsen, Catasús and Kaarbøe, 2025). Although Agentic AI was treated within the broader AI category in the SLR, it is used in the model as a contemporary application context supported by supplementary literature. Ethical decision-making remains a uniquely human skill (Evans, Akrong and Wensley, 2025); accordingly, the model retains human responsibility for judgement, accountability and action.

6.4 Practical Contribution

For practice, the model suggests that organisations should not focus only on larger repositories, more dashboards or stronger AI tools. They should establish explicit rules for source vetting, evidence checking, peer validation, triangulation and continuous monitoring. KM solutions should therefore ask not only what the organisation knows, but how it knows and whether that knowledge satisfies the VARCS criteria before it is transformed into intelligence and applied as wisdom.

7. Limitations and Future Research

This paper is limited by its conceptual and design-oriented nature. Although the model is supported by a structured Scopus SLR and relevant literature, it has not been empirically tested in an organisation. The review was limited to one indexing database and one search string, so relevant studies outside the search scope may have been missed. Future research should test the model through case studies, expert evaluation, practitioner surveys or formal design evaluation in AI-supported environments. It could also operationalise metrics for each VARCS principle and investigate whether knowledge-quality capability improves intelligence reliability and innovation outcomes. Future studies may further apply the model within the expanded data-information-knowledge-intelligence-wisdom-impact (DIKIWI) continuum, in which impact represents the measurable consequence of applied intelligence and wisdom.

8. Conclusion

This paper argued that reliable intelligence in the post-truth era depends on structured knowledge quality. It developed a Knowledge Quality Model linking knowledge infrastructure, VARCS-based validation and intelligence production. The model responds to a central KM problem: knowledge abundance does not automatically produce reliable intelligence or innovation. By treating knowledge quality as a managerial and epistemic capability, the paper reframes DIKIW as a governed transformation, strengthens the quality conditions surrounding SECI knowledge conversion, and offers a design-oriented path for human controlled, AI-supported decision-making. Innovation is not produced by technological capability alone; it depends on disciplined governance before knowledge is transformed into intelligence. Structured knowledge quality is therefore a strategic condition for trust, resilience and innovation in complex organisations.

Ethics Declaration: Ethical clearance for the research project was obtained from the University of Johannesburg. The paper uses secondary data, published scholarly literature and publicly available non-

identifiable sources. No human participants, interviews, surveys, observations, personal data or sensitive data were used.

AI Declaration: AI tools were used in a supportive capacity for language refinement, structuring, formatting and the visual rendering of Figures 1 and 4. The author developed the conceptual logic represented in both figures, designed the Knowledge Quality Model's architecture, selected its constructs and relationships, verified the visual outputs, conducted the literature selection and interpretation, and retained responsibility for the final argument, source verification and all manuscript decisions.

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