DOCTORAL THESIS

Knowledge Management for AI-Augmented Decision-Making: A Multi-Level Analysis of Organisational Maturity, Capabilities, and Socio-Technical Conditions

Teona Gelashvili-Luik

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Declaration:
Hereby I declare that this doctoral thesis, my original investigation and achievement, submitted for the doctoral degree at Tallinn University of Technology has not been submitted for doctoral or equivalent academic degree.

Teona Gelashvili-Luik

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Teadmusjuhtimine tehisintellektiga toetatud otsustusprotsessides: organisatsioonilise küpsuse, võimekuste ja sotsiaal-tehniliste tingimuste mitmetasandiline analüüs

TEONA GELASHVILI-LUIK

TALTECH KIRJASTUS

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List of Publications

The publications are presented in the order of their analytical contribution to the research questions.

I Pappel, I., Gelashvili, T. & Pappel, I. (2022). Maturity model for automatization of service provision and decision-making processes in municipalities. In *Lecture Notes in Networks and Systems* (pp. 399–409). Springer.

II Gelashvili, T., & Pappel, I. (2021). Challenges of transition to paperless management: Readiness of incorporating AI in decision-making processes. In L. Terán, J. Pincay, & E. Portmann (Eds.), *Proceedings of the 2021 Eighth International Conference on eDemocracy & eGovernment (ICEDEG)* (pp. 41–46). IEEE.

III Gelashvili-Luik, T., Vihma, P., & Pappel, I. (2025). Navigating the AI revolution: Challenges and opportunities for integrating emerging technologies into knowledge management systems. *Frontiers in Artificial Intelligence*, 8, Article 1595930.

IV Gelashvili-Luik, T., Vihma, P., Pappel, I., & Ferreira, F. A. (under second-round review). AI-augmented knowledge management in FinTech: Dynamic capabilities for strategic decision-making in complex and uncertain environments. *Journal of Modelling in Management*.[1]

V Weck, M., Gelashvili, T., Pappel, I., & Ferreira, F. (2022). Supporting collaboration and knowledge sharing in building smart living environments for ageing well: Using cognitive mapping in KMS design. *Knowledge Management Research & Practice*, 22(6), 865–877.

[1] Publication IV has undergone peer review and received a decision of major revisions. The revised manuscript was resubmitted in December 2025 and is currently under second-round review.

Author’s Contribution to the Publications

Contribution to the papers in this thesis are:

I The author was the second author of the publication. The author contributed to the refinement of the maturity model, supported the literature review and contextual framing, and collaborated on the methodological approach and interpretation of findings. The author also contributed to writing and editing the manuscript and served as the corresponding author.

II The author was the lead and corresponding author of the publication. The author conceptualised the study, developed the research questions and methodology, conducted the interviews and survey, analysed the data, and wrote the manuscript.

III The author was the lead and corresponding author of the publication. The author designed and conducted the systematic literature review, performed the coding and analysis of selected studies, and wrote most of the manuscript, including the research framing and methodological design.

IV The author was the lead and corresponding author of the publication. The author developed the research design, formulated the research questions, conducted the interviews and document analysis, coded and analysed the data, and wrote the majority of the manuscript.

V The author was a second author of the publication. The author contributed to the conceptualisation of the study, conducted the literature review, wrote the Estonian case analysis, and supported the interpretation of findings and drafting of key sections of the article.

Abbreviations

ADR	Action Design Research
AI	Artificial Intelligence
CASP	Critical Appraisal Skills Programme
DCF	Dynamic Capabilities Framework
DEMATEL	Decision-Making Trial and Evaluation Laboratory
EDRMS	Electronic Document and Records Management System
FinTech	Financial Technology (sector/organisation type)
KM	Knowledge Management
PICOS	Population, Intervention, Comparison, Outcomes, Study Design
PRISMA	Preferred Reporting Items for Systematic Reviews and Meta-Analyses
PSM	Problem Structuring Method
RQ	Research Question
SLR	Systematic Literature Review
SODA	Strategic Options Development and Analysis
SPSS	Statistical Package for the Social Sciences
SQ	Sub-Research Question
STS	Socio-Technical Systems
TAM	Technology Acceptance Model
UTAUT	Unified Theory of Acceptance and Use of Technology

Terms

AI-Augmented Knowledge-Management	AI-augmented knowledge management refers to the use of artificial intelligence to support core knowledge management processes such as knowledge retrieval, structuring, and reuse, particularly in decision-relevant contexts, while retaining human oversight and governance (Edwards & Dwivedi, 2019). In this thesis, AI augments organisational knowledge practices by improving the availability and interpretability of knowledge used in decision-making, rather than replacing human judgement.
AI-Augmented Decision-Making	Scholars distinguish AI automation, where decisions are delegated to algorithms, from AI augmentation, where AI supports human judgement while decision authority remains with humans (Davenport & Kirby, 2016; Jarrahi, 2018). In this thesis, AI-augmented decision-making refers to decision processes in which AI provides analytical inputs that are integrated into organisational knowledge practices, with humans retaining responsibility for interpretation and final decisions.
Dynamic Capabilities	Higher-order organisational abilities to sense opportunities and threats, seize them through strategic action, and transform structures and routines accordingly (Teece, Pisano & Shuen, 1997; Teece, 2007).
Knowledge Management	Organisational processes for creating, storing, sharing and applying knowledge to support action and performance (Alavi & Leidner, 2001).
Knowledge Management System	An information system that supports KM processes by enabling the capture, structuring, storage and retrieval of organisational knowledge (Alavi & Leidner, 2001).
Mediation Structure	A unit that facilitates communication and integration across functional or knowledge domains (e.g., between data teams, knowledge management staff and operational decision-makers).
Microfoundations	Microfoundations are the individual actions, social processes, and structural conditions that together explain how organisational routines and capabilities arise and change over time (Felin et al., 2012).

Sensing–Seizing–Transforming	A three-part model describing how dynamic capabilities are enacted at each capability tier/level (Teece, 2007).
Socio-Technical System	A system in which social elements (people, norms, roles) and technical elements (technologies, infrastructures) are interdependent and jointly shape organisational outcomes (Trist & Bamforth, 1951; Mumford, 2000).

1 Introduction

Digital transformation has reshaped how organisations create, manage, and use knowledge in decision-making (Grant, 1996; Chierici et al., 2019). As organisational services become more data-intensive and interconnected, artificial intelligence (AI) is introduced to support the analysis of information, assist with routine judgement tasks, and inform decision processes within existing organisational workflows (Al-Okaily & Al-Okaily, 2025; Khan et al., 2025). In this context, knowledge management (KM) provides the organisational structures and practices through which knowledge is created, maintained, and applied (Nonaka & Takeuchi, 1995; Von Krogh et al., 2000). AI systems rely on reliable and well-structured knowledge resources while also affecting how these resources are produced and interpreted within organisational work practices (Jarrahi et al., 2022).

This gives the raise to the AI-augmented knowledge management in which AI supports the structuring, retrieval or interpretation of organisational knowledge and lays the foundations for AI-augmented decision-making. The latter refers to organisational decision processes such as risk assessment, operational planning, or customer analytics in which human judgement remains the final authority while analytical outputs produced by AI systems (predictive analytics, anomaly detection, or natural language processing tools) are incorporated into routine decision workflows (Lui & Lamb, 2018). In this research, AI augmentation refers to systems that support human decision processes rather than fully automated algorithmic decision systems. These developments expand the role of KM systems from storage and access toward more analytical and predictive functions (Chierici et al., 2019).

Despite increasing investments in AI, many organisations struggle to translate digital tools into meaningful improvements in decision quality (Bérubé et al., 2021; Kerschbaum & Dachs, 2024). These weaknesses often originate at the level of data and information infrastructures. When organisational data remain fragmented or poorly governed, information cannot be consistently integrated across workflows. This limits the development of organisational knowledge (Dulipovici & Robey, 2013; Jarrahi et al., 2023). In this thesis, data refer to structured organisational records, information to contextualised data integrated into workflows, and organisational knowledge to the shared interpretive capacity through which decision-makers apply information within organisational routines. These knowledge environments also shape the development of organisational capabilities required to integrate AI outputs into decision routines.

This thesis approaches these issues through a multi-level analytical perspective, examining how knowledge structures, organisational capabilities and collaborative and institutional conditions influence the emergence of AI-augmented KM.

This thesis is structured as follows. Chapter 2 introduces the theoretical framework. Chapter 3 outlines the methodological approach and study design. Chapter 4 presents the empirical findings in relation to the research questions. Chapter 5 discusses the theoretical and practical contributions. Chapter 6 concludes with limitations and directions for future research.

The following section outlines the specific problem that motivates the research.

1.1 Research Problem

Although existing research examines technological, organisational, and socio-technical factors influencing AI adoption, these perspectives often treat such factors separately and give limited attention to the organisational knowledge environments through which AI outputs are integrated into decision processes (Bérubé et al., 2021; Kerschbaum & Dachs, 2024). As a result, current scholarship provides only limited explanation of how organisations develop the knowledge infrastructures, routines, and capabilities required to incorporate AI into everyday decision-making practices. This gap makes it difficult to explain why organisations with comparable technological resources achieve different outcomes when implementing AI, or how organisational maturity, capability development, and socio-technical conditions jointly shape the integration of AI into decision work.

1.2 Aim and Research Questions

The aim of this doctoral thesis is thus to understand how organisations develop the knowledge and capabilities required to integrate AI into decision-making while maintaining human decision authority. To investigate this, the thesis examines:

- micro-level knowledge environments that shape how individual decision-makers access, interpret, and apply information in decision processes
- meso-level organisational capabilities through which routines, governance structures, and practices are adapted to incorporate AI into decision-making
- macro-level socio-technical conditions that shape collaboration, governance arrangements, and regulatory environments influencing AI adoption

The analysis draws on five peer-reviewed studies conducted between 2019 and 2025 across Estonian, Georgian and Finnish public-sector organisations and a multinational financial-technology company. The empirical settings were selected to examine how AI-augmented knowledge management operates under clearly different organisational conditions.

Estonia and Georgia were chosen to compare public administrations at different stages of digital and knowledge management maturity. In Estonia and Finland, electronic document and records management systems (EDRMS) are widely standardised, metadata practices are formalised, and interoperability between institutions is institutionally embedded. This provides a setting in which structured digital data already supports traceability and workflow integration. Georgia, by contrast, represents a transitional environment where digital systems exist but metadata consistency, cross-departmental integration, and ownership of data governance remain uneven. While EDRMS represent only one component of organisational knowledge infrastructures, their maturity provides a visible indicator of how digital information is structured and governed within organisational workflows. Although these countries do not constitute a fully systematic comparison of national digital maturity, they provide analytically useful variation in organisational knowledge infrastructures and governance environments.

The FinTech case was selected to extend the analysis into a private-sector organisation operating at scale, with a large customer base and continuous data flows. Unlike the public-sector cases, where AI integration was largely prospective, this organisation had already embedded AI in operational processes such as risk assessment and customer analytics. This made it possible to observe how routines are adapted when AI outputs directly affect real-time decisions and customer outcomes.

The research is guided by the following questions:

RQ1 (Micro level). How can organisational maturity of knowledge environments supporting AI-augmented decision-making be defined and assessed?

RQ2 (Meso level). How do organisations adapt their capabilities to integrate AI into decision-making?

- **SQ2.1** What opportunities and challenges arise when AI is introduced into decision-making processes?
- **SQ2.2** How do dynamic capabilities influence organisational adaptation?

RQ3 (Macro level). How do socio-technical conditions shape an organisation's ability to implement AI-augmented decision-making?

Table 1 summarises the alignment between the research questions, publications, and author contributions.

Table 1. Alignment of research questions, publications and author contributions.

Publication	RQ1	RQ2	SQ2.1	SQ2.2	RQ3	Author Role
I	X					Co-author: Conceptualisation, model refinement, writing
II	X					Lead author: Design, data collection, analysis, writing
III		X	X		X	Lead author: Design, coding, synthesis, writing
IV		X		X		Lead author: Design, interviews, analysis, writing
V					X	Co-author: Conceptualisation, writing

2 Theoretical Framework

Research on AI integration in organisational contexts can be approached through multiple theoretical perspectives, including technology acceptance models, institutional theory, diffusion frameworks, and resource-based approaches. Technology adoption models such as TAM (Davis, 1989) and UTAUT (Venkatesh et al., 2003) primarily address individual-level behavioural intention and user acceptance, offering limited explanatory depth for organisational capability development or structural knowledge transformation. Institutional (DiMaggio & Powell, 1983) and diffusion-based perspectives (Rogers, 2003) highlight regulatory pressures and legitimacy dynamics but provide less insight into internal organisational adaptation processes. Similarly, the Resource-Based View (Barney, 1991) conceptualises capabilities as strategic assets but provides limited explanation of how organisational capabilities develop and evolve under conditions of technological disruption.

Given the focus of this thesis on organisational maturity (RQ1), capability adaptation (RQ2), and socio-technical conditions (RQ3), a multi-level analytical framework was required.

The multi-level framing adopted here follows established approaches in organisational research that distinguish between knowledge environments shaping individual work practices, organisational capability development, and broader institutional contexts (Klein & Kozlowski, 2000). In this thesis, the micro level refers to the organisational knowledge environments that shape how individual decision-makers access, interpret, and apply information in their daily work practices. These environments include the structuring of organisational data, metadata practices, and workflow integration that determine how information can be retrieved and interpreted during decision-making. The meso level concerns organisational routines, governance structures, and capability development through which organisations integrate analytical tools and AI technologies into decision processes. The macro level captures the broader socio-technical and institutional conditions, including regulatory environments, collaboration networks, and technological ecosystems, that influence organisational adoption and scaling of AI-enabled knowledge systems.

In line with microfoundational perspectives (Felin et al., 2012), organisational capabilities are understood as emerging from structured knowledge environments and routine configurations rather than existing independently of them. Organisational decision-making capabilities therefore develop through the interaction between the conditions that structure information use, the organisational routines that integrate analytical technologies, and the institutional contexts that shape technological adoption.

This thesis is therefore grounded in three complementary theoretical perspectives that address these analytical levels. Maturity and organisational readiness models are used to assess the structural conditions of organisational knowledge environments that shape decision practices (micro level). The Dynamic Capabilities Framework explains how organisations adapt and reconfigure routines in response to emerging technologies such as AI (meso level). Socio-technical systems theory accounts for the interaction between organisational practices, technological infrastructures, and institutional environments shaping the adoption of AI-enabled knowledge systems (macro level). Figure 1 illustrates how these analytical levels interact in the development of AI-augmented decision-making capabilities.

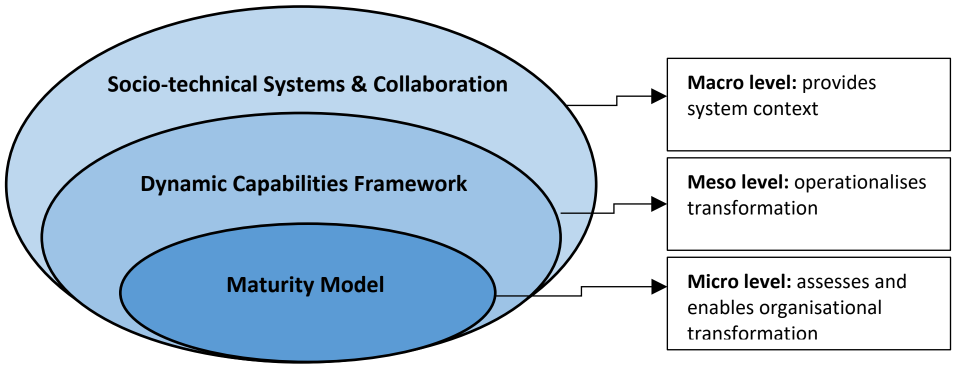

Figure 1. Complementary theoretical lenses.

2.1 Maturity Model and Organisational Readiness

At the micro level, maturity and organisational readiness models are used to analyse the foundational conditions that make AI-augmented knowledge management and decision-making feasible. These models conceptualise organisational development as a progression toward increasing standardisation of information structures, integration of workflows, and formalisation of governance practices (Becker et al., 2009; De Bruin & Rosemann, 2005). Rather than assuming ad hoc digital transformation, maturity models emphasise path dependency, where earlier design choices constrain or enable later technological use (Kohlegger et al., 2009).

In this thesis, the maturity lens is used to examine how organisational knowledge infrastructures evolve from fragmented, document-centric practices toward more structured and machine-readable configurations that enable AI-supported analysis. Across the empirical studies, insufficient data coherence, inconsistent metadata practices, and weak workflow formalisation repeatedly emerge as barriers to meaningful AI integration. In this sense, the maturity model captures micro-level readiness conditions of the organisational knowledge environment that shape how individual decision-makers can access and interpret information in their daily work practices.

Important to note that maturity model does not describe the maturity of AI technologies themselves, but rather the organisational readiness of knowledge environments that enable AI-supported decision-making. In this sense, maturity models help identify structural conditions that enable or constrain the development of organisational capabilities for AI-supported decision processes.

However, while maturity models clarify what organisational conditions must be in place, they do not explain how organisations mobilise, coordinate, or reconfigure these conditions once they exist. Addressing that question requires a process-oriented, meso-level perspective, which is examined through the lens of dynamic capabilities.

2.2 Dynamic Capabilities Framework

The Dynamic Capabilities Framework (DCF) is employed to explain how organisations actively adapt their knowledge practices and decision routines once foundational conditions are present. Dynamic capabilities refer to the organisational abilities to sense emerging opportunities, seize them through coordinated action, and transform existing structures to sustain adaptation over time (Teece et al., 1997; Teece, 2007). Unlike operational routines, these capabilities enable organisations to respond to uncertainty and technological change (Eisenhardt & Martin, 2000).

Applied to AI-augmented knowledge management, the DCF lens explains how organisations interpret the potential of AI technologies, reorganise task allocations between human actors and automated systems, and establish new coordination and governance routines to support human–AI collaboration (Shrestha et al., 2019). In the empirical material, these processes are visible in the development of intermediary roles, iterative alignment practices, and mechanisms for maintaining knowledge integrity as AI tools are introduced.

The DCF perspective complements the maturity lens by explaining how structural readiness is translated into organisational action. While maturity captures whether AI integration is possible, dynamic capabilities explain how it is operationalised, stabilised, and adjusted in practice. Yet these adaptation processes do not occur in isolation; they are shaped by broader socio-technical arrangements that extend beyond organisational boundaries.

2.3 Socio-technical Conditions and Collaboration

Socio-Technical Systems (STS) theory is used to situate organisational adaptation within the broader systems in which AI-augmented decision-making is embedded. STS theory emphasises that technological effectiveness depends on its alignment with social arrangements, including coordination structures, governance mechanisms, and shared interpretive frameworks (Trist & Bamforth, 1951; Mumford, 2000; Baxter & Sommerville, 2011).

The STS lens is applied narrowly here to explain how AI-supported decision-making is shaped by cross-organisational coordination requirements, interoperability of information infrastructures, and institutional expectations for accountability and transparency (Orlikowski, 1992). These conditions are particularly critical in the empirical studies, where AI use is constrained by internal capabilities as well as by regulatory frameworks, data-sharing arrangements, and dependencies between organisational units or external actors.

The STS perspective therefore explains why organisational adaptation does not scale uniformly, even when maturity and dynamic capabilities are present. It highlights how socio-technical dependencies enable or limit the stabilisation and expansion of AI-supported decision processes.

Although each of these perspectives offers important insights, none alone fully explains how AI-augmented knowledge management develops as an integrated organisational capability. Maturity models clarify structural readiness but provide limited insight into ongoing adaptation. The Dynamic Capabilities Framework explains organisational reconfiguration but pays less attention to underlying knowledge infrastructures and cross-organisational dependencies. Socio-technical systems theory situates AI integration within broader systemic conditions but does not specify how internal capabilities evolve over time. By combining these perspectives, this thesis develops an integrated analytical framework.

3 Research Methodology

The empirical design of the thesis combines several organisational and institutional contexts in order to examine how AI-augmented knowledge management develops under different organisational conditions. The research does not aim to produce statistically comparable sectoral or national comparisons.

The research design adopts a multi-method approach aligned with the multi-level nature of the research questions and the cumulative structure of the thesis. Different methodological strategies are combined to develop complementary forms of empirical and analytical understandings. Action Design Research (ADR) supports the development of a maturity model, case study methods enable in-depth analysis of organisational adaptation, a systematic literature review synthesises existing conceptual and empirical knowledge, and problem structuring methods capture shared representations of complex socio-technical conditions. As the thesis is based on a series of related publications addressing different analytical levels of the research problem, empirical contexts and datasets vary across studies. Rather than forming a single comparative dataset, the publications provide complementary perspectives on organisational maturity, capability adaptation, and socio-technical conditions shaping AI-augmented decision-making. An overview of methods and data sources for each publication is provided in Table 2.

Table 2. Overview of research methods.

Publication	Methodological approach	Data Sources
I	Action Design Research	Expert consultations, existing maturity models, municipal documents
II	Comparative Case Study	5 semi-structured interviews (Estonia, Georgia); survey (n = 101, Georgia)
III	Systematic Literature Review	40 peer-reviewed studies (from 1,568 screened records)
IV	Qualitative Case Study	10 semi-structured interviews; internal company documents
V	Cognitive Mapping	Stakeholder panels (Finland n = 8; Estonia n = 7), Quadruple Helix actors

3.1 Action Design Research

Action Design Research was employed to develop and evaluate an artefact that operationalises micro-level readiness for AI-augmented decision-making (Sein et al., 2011). Publication I applies an ADR approach to construct a five-stage maturity model that captures the progression of municipalities from paper-based routines toward structured, digital and AI-ready decision environments.

The model was developed through iterative cycles of problem framing, conceptualisation, empirical grounding, and refinement. Empirical input was drawn from long-term collaboration with Estonian local governments and from the deployment of the Amphora electronic records management system. Data sources included expert workshops, observational material, and municipal documentation. Iterative feedback from IT managers, records officers, and administrative leaders informed successive revisions of the model.

Validation of the maturity model took place through its development and use in real municipal settings. The model was refined through workshops, stakeholder discussions, and its application within the Amphora platform. Feedback from practitioners was incorporated into successive iterations of the model.

Instead of being tested in a controlled or experimental setting, the model was evaluated through practical use and continuous adjustment in collaboration with users. Its validity therefore rests on repeated application, stakeholder feedback, and alignment with actual administrative processes.

3.2 Case Study

Case study research allows organisational phenomena to be examined within their real-life context and supported by multiple forms of evidence (Yin, 2014; Eisenhardt, 1989). Publication IV applies an embedded single-case design within a multinational financial-technology organisation to analyse how AI-supported analytics are integrated into operational and compliance-related decision routines.

Data were collected through ten semi-structured interviews with employees working in analytics, compliance, and operational decision-making, supplemented by internal strategy documents and regulatory materials. The interview protocol was explicitly structured around the sensing, seizing, and transforming dimensions of the Dynamic Capabilities Framework. Data were analysed using reflexive thematic analysis (Braun & Clarke, 2006) in Atlas.ti. Triangulation across interviews and documentation reduced reliance on a single data source and enhanced analytical depth (Patton, 1999).

Publication II adopts a comparative case design to examine public-sector readiness for more structured and automated decision processes in Georgian and Estonian institutions. The empirical material comprises five expert interviews, a survey of 101 public servants, and supporting legislative and implementation documents. While the survey component focuses on Georgian public servants, the interview material includes experts from both Estonian and Georgian institutions. The survey was used primarily to capture broader perceptions of readiness conditions in a transitional administrative environment, while interviews provided comparative qualitative insights across both countries. The combination therefore supports analytical triangulation rather than strict statistical comparison. Interview data were thematically analysed in NVivo, while survey responses were examined using descriptive and correlational techniques in SPSS. The selection of Estonia and Georgia follows the theoretical sampling logic outlined in Chapter 1. Estonia represents a digitally mature administrative environment with standardised metadata practices and interoperable EDRMS infrastructures, while Georgia reflects a transitional setting where workflow integration, user adoption and governance alignment remain uneven. The comparative design enabled identification of recurring human, technical, and organisational factors shaping readiness, rather than producing geographical representations.

3.3 Systematic Literature Review

A systematic literature review (publication III) was conducted to synthesise existing research on AI-augmented knowledge management and decision-making and to identify conceptual gaps addressed by the empirical studies (Kitchenham, 2004; Moher et al., 2009). Following PRISMA guidelines (Moher et al., 2009), the review applied the PICOS framework to define inclusion criteria and guide database searches in Scopus, Web of Science, ScienceDirect, and Google Scholar.

Of 1,568 records initially identified, 40 peer-reviewed studies met the criteria for full inclusion. Study quality was assessed using a CASP-informed evaluation matrix. Thematic synthesis (Nowell et al., 2017) was applied to identify recurring technological, organisational, and human dimensions of AI integration. The review provides a consolidated analytical baseline that informs the positioning of the empirical findings and highlights areas where existing research remains conceptually underdeveloped. The PRISMA flow diagram is presented in Figure 2.

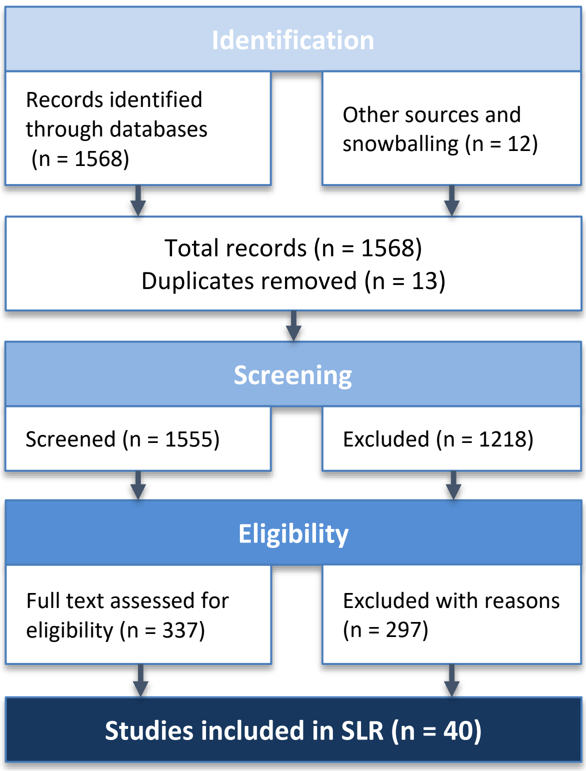

Figure 2. PRISMA flow diagram of the study selection process.

3.4 Multi-Criteria Decision-Making and Problem Structuring

Problem structuring methods (PSMs) are used to analyse socio-technical conditions characterised by multiple stakeholders, interdependent factors, and competing priorities (Ackermann & Eden, 1998; Belton & Stewart, 2002). Publication V applies cognitive mapping within the Strategic Options Development and Analysis (SODA) tradition to elicit and structure stakeholder perceptions of barriers and enablers shaping digital transition and AI-related decision processes.

In facilitated stakeholder panels, participants identified relevant factors and articulated perceived causal relationships, producing collective cognitive maps that represent shared problem understandings. To complement this qualitative structuring, the Decision-Making Trial and Evaluation Laboratory (DEMATEL) method was applied to assess the relative influence and dependence of identified factors. This combined approach enabled a systematic examination of interaction patterns within complex socio-technical systems, without reducing stakeholder perspectives to purely quantitative indicators.

The use of PSMs is exploratory and explanatory rather than predictive, providing insight into how socio-technical dependencies shape the feasibility and scaling of AI-augmented decision-making.

4 Results

The results are organised around the three research questions and synthesise findings from the five publications.

4.1 Organisational Maturity

Publications I and II show that maturity in this thesis is not treated as a general label for digitalisation, but as the structural configuration of the organisational knowledge environment. In the empirical context, electronic document and records management systems provide observable indicators of how organisational knowledge infrastructures are structured. These indicators include (1) the consistency of metadata practices, (2) the integration of workflows, (3) the traceability of information and decisions, and (4) the extent to which information is organised in a form that can be processed and reused by analytical systems. Publication I consolidates these patterns into a five-stage maturity model that describes the progression from paper-based information handling toward structured, machine-readable knowledge environments capable of supporting analytical and AI-assisted decision processes. In this thesis, the maturity model therefore operationalises micro-level organisational readiness conditions that shape how decision-makers access and interpret information within organisational workflows. The model differentiates maturity stages according to the dominant information carrier (paper, hybrid, or digital) and the degree of standardisation and integration achieved across organisational processes. the maturity stages presented in Table 3 illustrate how the structuring of organisational knowledge infrastructures creates the conditions under which individual decision-makers can retrieve, interpret, and apply information in decision processes.

Table 3. Five-stage maturity model of organisational knowledge infrastructure readiness.

Maturity Phase	Information Carrier	Core Characteristics	Implications for Decision-Making
Phase 1	Paper-based originals	Information unstructured, paper-only	Decisions are fully human, with long manual circulation and archiving, so outcomes take weeks or months
Phase 2	Paper originals with digital copies	Digital copies added; information still unstructured	Decisions are still human, though digital circulation shortens workflows to days, while parallel paper use limits impact
Phase 3	Digital texts with metadata + legalized paper	Digital metadata appears; some paper persists	Humans decide, but searchable metadata enables faster retrieval, reducing decisions to days or hours
Phase 4	Structured digital data with partial AI support	Digital, structured data; mix of paper	Decisions blend human and AI support, cutting delays to nearly real-time, though oversight is still required
Phase 5	Data and AI integration	Fully structured, machine-readable data; AI–human co-decision	Decisions occur in real-time or proactively, shifting from reactive to predictive

Publication II applies the maturity logic in Estonia and Georgia and shows that progression is constrained when the knowledge environment is treated primarily as a compliance repository rather than shared infrastructure. In the Georgian cases, misalignment between data structures, workflow practices, and governance roles limited the extent to which EDRMS enabled reuse, coordination, and decision traceability. In the Estonian cases, more coherent interoperability arrangements, standardised data practices, and coordinated workflow design supported more advanced maturity patterns.

These study results show that organisational maturity varies as a function of alignment between information structures, workflow integration, and governance routines. Where one element remains fragmented (e.g., inconsistent metadata or unclear ownership), overall maturity stalls even when digital tools are in place.

4.2 Dynamic Capabilities in Practice

The second research question concerns how organisations adapt routines and capabilities to integrate AI into decision processes. Findings are drawn from Publication III (systematic literature review) and Publication IV (FinTech case study) and interpreted through the Dynamic Capabilities lens.

4.2.1 Evidence from the Literature

Publication III identified a set of recurring organisational challenges and opportunities that influence how AI becomes embedded into knowledge management and decision processes. The challenges relate primarily to organisational and human factors, data quality and integration, governance and ethical issues, tensions between legacy and emerging practices, and the technological complexity of scaling AI systems.

In opposite, several opportunities and enabling conditions were observed, including improved data management strategies, organisational and cultural interventions that strengthen interpretive alignment, leadership and workforce development, technological solutions that support incremental AI adoption, and ethical or governance mechanisms that ensure responsible deployment.

These themes are summarised in Figure 3, which consolidates the main barriers and enablers affecting AI-augmented KM processes across the literature reviewed.

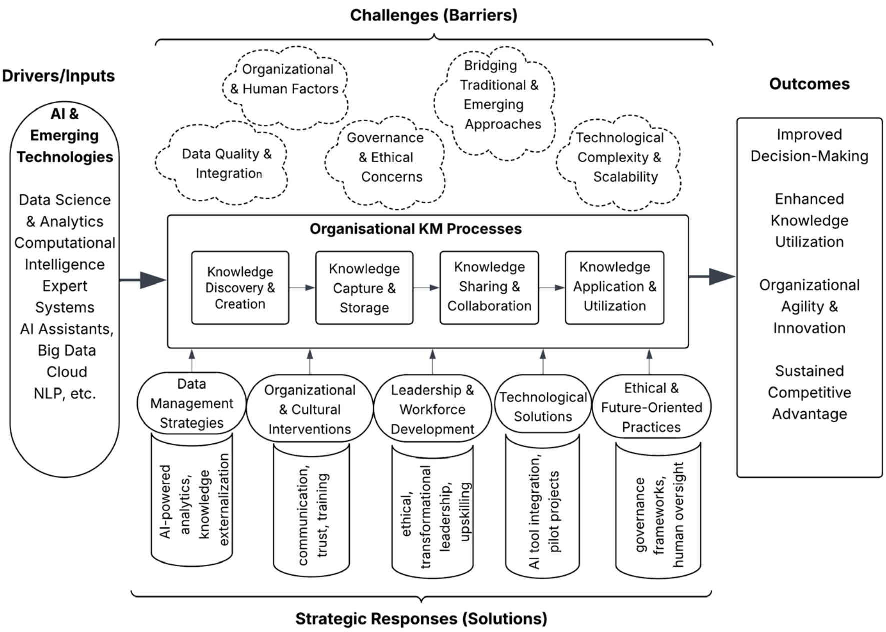

Figure 3. Conceptual framework for integrating AI into organisational knowledge management.

Three additional recurring patterns were also revealed:

(1) AI introduces new coordination demands across socio-technical layers

As AI systems increase knowledge retrieval and analysis, underlying weaknesses in data governance, metadata practices and validation routines become more visible. Organisations respond by strengthening data flows, establishing clearer governance arrangements and revising documentation standards.

(2) Trust and interpretive consistency influence adoption outcomes

Studies repeatedly emphasised that effective AI use depends on shared understanding of how model outputs should be interpreted. Interpretive misalignment between teams reduced the usefulness of AI-generated insights, even when models performed adequately.

(3) Variation in absorptive and learning capacity affects adaptation

The review identified substantial differences across organisations. Those with well-developed learning routines and stronger KM foundations were better able to embed AI into routine decision work, while others stagnated despite similar technological investments.

Therefore, the findings demonstrate that organisational adaptation is not solely technological but relies on recursive alignment of people, processes and knowledge structures.

4.2.2 Case Study Findings

Publication IV analysed how a multinational financial-technology organisation adapted its knowledge practices and routines for an early stage of AI integration. The findings show that organisational adaptation unfolded through the interplay of several enabling conditions, constraining factors and external pressures, which collectively shaped the sensing, seizing and transforming activities captured in the extended Dynamic Capabilities Framework for AI-augmented knowledge management.

Several internal enablers supported the development of these capabilities. The organisation had established governance structures for managing knowledge assets and demonstrated leadership commitment to exploring AI-based solutions. Documentation practices and metadata structures, while not fully standardised, provided a sufficient foundation for experimentation. Collaboration between data specialists, KM practitioners and operational teams was already strong, supported by a culture familiar with analytical tools and business-intelligence systems. These conditions created organisational readiness for AI-related initiatives and gave teams the confidence to test new approaches.

At the same time, internal barriers constrained the adaptability of existing routines. Ownership of decision logic and knowledge assets uneven distribution across units could make it difficult to ensure consistency when integrating AI-generated outputs into workflows. Knowledge bases containing gaps and inconsistencies, and the volatility of regulatory information would likely place pressure on existing validation routines. In addition, uneven analytical proficiency and misalignment between existing tools and emerging AI capabilities could potentially limit the ability to scale early prototypes.

The sensing activities thus centred on diagnosing the organisation’s readiness for AI-supported knowledge work. This included examining the integrity and currency of regulatory knowledge, assessing whether AI-generated analysis could be meaningfully embedded into existing decision pathways and evaluating whether available tools could operate reliably at scale. External developments were monitored systematically, informing assessments of where AI might provide value or introduce risk.

Seizing activities involved mobilising organisational structures that could support early AI adoption. The business-intelligence function played a critical boundary-spanning/mediating role, between data teams, KM practitioners and operational decision-makers. This mediation improved interpretive alignment and ensured that experimentation remained connected to practical decision needs. Seizing also required clarifying resource commitments and role expectations, alongside the use of pilot projects that allowed safe, incremental testing of AI models within controlled environments.

And the transforming activities reflected deeper changes to how decision work was organised. AI tools could began reducing the cognitive load associated with routine information retrieval and synthesis, enabling employees to focus on higher-order interpretive and evaluative tasks. Workflow adjustments were introduced to preserve oversight, including additional review checkpoints, updated documentation practices and distributed responsibility for validating AI-supported outputs. Feedback from AI use would inform continuous updates to knowledge assets and adjustments to decision routines, reinforcing an iterative cycle of capability refinement.

The extended framework (Figure 4) synthesises these elements, illustrating how sensing, seizing and transforming activities in AI-augmented KM are grounded in the interaction between structural conditions, cross-functional coordination and organisational learning processes. Therefore, adaptation depends on microfoundational routines that stabilise interpretation and accountability (e.g., mediation roles, validation checkpoints, iterative updating of knowledge assets), not only on building or buying AI tools.

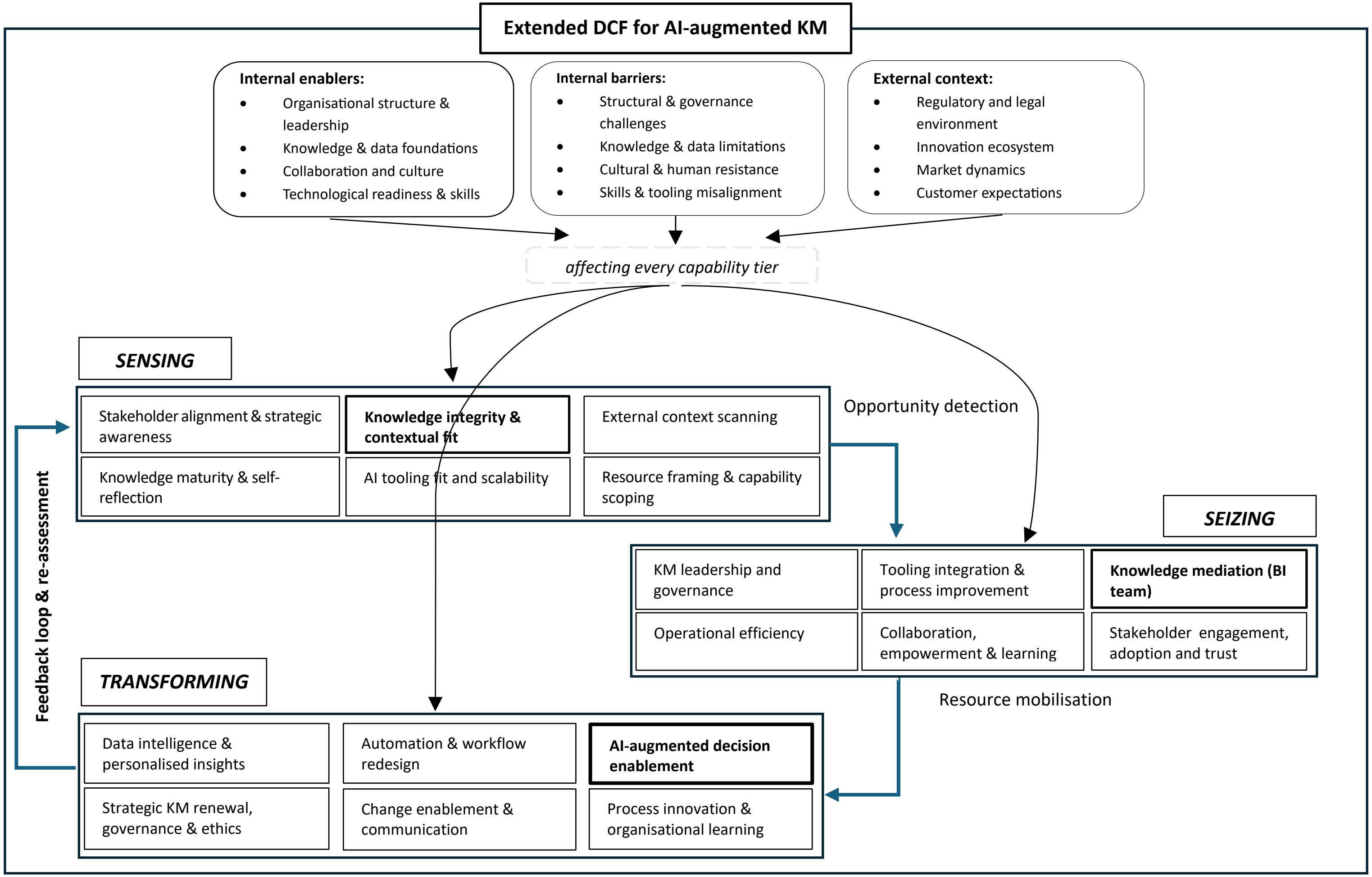

Figure 4. Framework for knowledge management enabling AI-augmented decision-making.

4.3 Socio-Technical Conditions

RQ3 examines the conditions beyond single organisations that shape whether AI-augmented KM can be implemented and sustained. Across Publications III, IV, and V, three socio-technical conditions recur:

4.3.1 Shared Meaning

Publication V, which examined the co-design of smart living environments, showed that multi-stakeholder settings require mechanisms for establishing shared meaning before integrated knowledge practices can function. Stakeholders from public, private, civic and academic sectors relied on representational tools such as cognitive mapping to align interpretations, terminology and expectations regarding data, processes and outcomes. The findings demonstrate that collaboration and interpretive alignment were necessary for constructing coherent knowledge environments, particularly in contexts where responsibilities and expertise were distributed across organisational boundaries.

4.3.2 Governance and Accountability

Publication III identified governance and accountability as recurring constraints in the adoption of AI-augmented decision-support tools. The systematic review showed that unclear decision rights, fragmented responsibilities and inconsistent validation procedures limited organisations' ability to rely on AI-generated outputs. Studies frequently reported gaps in oversight mechanisms, difficulties in coordinating updates to knowledge assets and uncertainty about how accountability should be assigned when decisions were supported by automated analysis. These patterns indicate that governance structures significantly condition how decision technologies can be introduced, monitored and integrated into existing organisational routines.

4.3.3 Infrastructure and Regulation

Publication IV provided evidence that infrastructural and regulatory environments directly shape the feasibility of AI augmentation in knowledge-intensive work. The financial-technology case revealed that interoperability constraints, inconsistent data standards and dependencies on external regulatory updates influenced how knowledge was maintained and how AI tools could be embedded into operational workflows. Regulatory volatility required continuous monitoring and adjustment of knowledge assets, while industry norms influenced expectations for explainability, documentation and human oversight. These factors created conditions under which internal capability development had to be aligned with external infrastructural and legal requirements.

In summary, scaling AI-augmented KM depends on socio-technical alignment across (i) shared interpretive frameworks, (ii) governance and accountability mechanisms, and (iii) infrastructural and regulatory coherence. These conditions determine whether micro-level maturity and meso-level adaptation routines can stabilise over time.

5 Discussion

Rather than treating AI as a discrete technological intervention, the findings across the five publications show that AI-augmented decision-making emerges as a cumulative organisational achievement. Knowledge infrastructure readiness alone does not produce effective AI use, nor do adaptive capabilities operate independently of broader infrastructural and governance arrangements. These elements should be aligned across levels. The discussion below interprets these findings in relation to the research questions, situates them within existing theory, and considers their implications across sectors and for practice.

5.1 Theoretical Contributions

This thesis advances theoretical understanding in the following ways.

First, extending organisational readiness perspectives to AI-augmented decision-making. Organisational readiness and digital maturity have long been conceptualised as multidimensional phenomena, typically encompassing technological infrastructure, leadership, organisational culture and governance arrangements (PwC, 2019; Gartner, 2020; Holmström, 2021). This thesis does not redefine organisational readiness, but extends these perspectives to the context of AI-augmented decision-making. The findings show that readiness for AI-supported decision processes depends on the alignment of three conditions: the structural maturity of organisational knowledge infrastructures, the organisational capabilities required to integrate AI into decision routines, and the broader socio-technical conditions that shape governance and collaboration.

Second, it repositions Knowledge Management in AI-augmented decision-making. The results extend KM theory by demonstrating that KM is the organisational arena where human–AI collaboration is operationalised. Classical KM literature conceptualises KM as enabling knowledge creation and organisational learning (Nonaka & Takeuchi, 1995; Von Krogh et al., 2000), but this thesis shows that KM also provides the microfoundations of dynamic capabilities in AI contexts. KM-based mechanisms such as continuous knowledge-updating, interpretive alignment routines and mediation structures, shape how organisations enact sensing, seizing and transforming activities (Shrestha et al., 2019). These findings show that organisational adaptation to AI is inseparable from the management of knowledge integrity and cross-functional coordination.

And lastly, Dynamic capabilities conditioned by socio-technical environments. While dynamic capabilities literature emphasises sensing, seizing and transforming as internal organisational routines (Teece et al., 1997; Teece, 2007), this thesis shows that these routines are significantly constrained or enabled by external system-level conditions. Interoperability limitations, regulatory volatility and distributed accountability restrict the scope of organisational adaptation (Vial, 2019). Their advancement is also non-linear and as framework (figure 4) demonstrates, each stage is achieved through ongoing feedback loop.

This highlights the boundary conditions of dynamic capabilities: they are necessary but not sufficient for AI-augmented decision-making in contexts with fragmented infrastructures or unclear governance.

5.2 Cross-sector Insights

The thesis examined public-sector organisations and a financial-technology company, revealing both distinct sectoral pressures and several recurring organisational conditions influencing AI-augmented decision-making.

Public organisations operate within formalised governance regimes and standardisation mandates, yet face persistent fragmentation of legacy systems and varying levels of interoperability (Publication I; Publication II). Their central challenge lies in coordinating multiple agencies and stabilising decision pathways across historically siloed infrastructures (Publication I; Publication II).

The FinTech case, by contrast, is characterised by rapid product evolution, dynamic regulatory environments and strong market responsiveness (Publication III; Publication IV). Here, the dominant challenge is maintaining knowledge integrity and alignment under continuous change, rather than overcoming infrastructural fragmentation.

Despite these sectoral differences, several enabling conditions appeared across the cases examined:

1. reliable and well-maintained knowledge assets that provide consistent inputs for analytical systems (Publication I; Publication II; Publication IV);
2. interpretive alignment across teams to ensure shared understanding of AI-generated outputs (Publication II; Publication IV);
3. mediation structures linking data work, knowledge management and operational decision processes (Publication IV; Publication V);
4. socio-technical environments that support the stabilisation and scaling of AI-supported practices (Publication I; Publication II; Publication IV).

These observations should be interpreted as analytical patterns rather than sector-wide generalisations, as the empirical material covers a limited number of organisations and contexts.

These cross-sector observations suggest that, despite differences in organisational context, similar enabling conditions appeared across the cases examined. Although the empirical material does not support broad generalisation across all sectors, the recurrence of these patterns across public administration and financial-technology settings indicates that reliable knowledge assets, interpretive alignment across teams, mediation structures linking data work and operational decisions, and coherent socio-technical environments may represent important conditions for integrating AI into organisational decision processes.

5.3 Practical Implications

The findings suggest several practical considerations for organisations seeking to integrate AI into decision processes.

First, organisations may benefit from formalising routines for maintaining knowledge integrity. AI systems require current and verified knowledge assets; this can be achieved through scheduled content reviews, explicit ownership of knowledge domains, and traceable update mechanisms integrated into their knowledge management platforms.

Second, organisations may need structured mechanisms for interpretive alignment. To avoid inconsistent decisions, managers should establish cross-functional review practices, shared documentation standards and clear governance roles that make interpretive assumptions transparent and consistent.

Third, organisations may consider establishing mediation roles. Boundary-spanning functions, such as Business Intelligence units (in Publication IV) or knowledge mediators, should be embedded into workflows to link data work, KM practices and operational decision-making, ensuring that AI outputs remain interpretable and usable.

Lastly, AI initiatives are more likely to succeed when they are aligned with broader socio-technical conditions. Interoperability standards, shared data semantics and transparent governance arrangements form the systemic environment that allows organisational AI developments to first stabilise and then scale.

6 Conclusion

This thesis demonstrates that AI-augmented decision-making develops incrementally and is shaped by organisational conditions rather than by technological sophistication alone. Across the five publications, AI integration was shown to depend first on the structural configuration of knowledge environments, second on the organisation's ability to adapt routines and redistribute decision authority, and third on the socio-technical conditions that enable or constrain coordination.

The maturity analysis of public-sector organisations revealed that fragmented data structures, inconsistent metadata practices, and document-centric workflows significantly limit the feasibility of AI-supported decision processes. The dynamic capabilities perspective further demonstrated that even where structural readiness exists, organisations must actively reorganise roles, routines, and governance mechanisms to translate AI potential into operational practice. Finally, the socio-technical analysis showed that cross-organisational interoperability, regulatory frameworks, and accountability requirements shape whether AI-supported decision processes can stabilise and scale.

The findings together indicate that AI-augmented knowledge management is not a discrete implementation phase but a cumulative organisational transformation. The multi-level perspective developed in this thesis provides an integrated explanation of how readiness, adaptation, and systemic conditions interact in practice.

6.1 Limitations

Several limitations should be considered when interpreting these findings.

First, the empirical material is primarily derived from public-sector organisations in Estonia, Georgia, and Finland, alongside a single multinational FinTech organisation. While this enabled comparative analysis across differing institutional and maturity contexts, the results reflect specific governance and regulatory environments and should be understood as analytically rather than statistically generalisable.

Second, the maturity model was developed and refined through ADR-based engagement in municipal and state-level settings. Although this ensured contextual validity, the model has not yet been systematically tested across broader organisational populations or private-sector domains.

Third, comparative design also relied on different types of empirical material across countries, including interviews in both Estonia and Georgia but survey data only from Georgian organisations.

And lastly, much of the empirical evidence captures organisations in transitional stages of AI adoption. Fully automated, large-scale AI decision environments remain limited in practice, and therefore long-term stabilisation dynamics could not be observed directly.

These limitations do not invalidate the findings but define the scope within which they should be interpreted.

6.2 Future Research

Several directions for future research emerged.

The maturity dimensions identified in the public-sector studies could be operationalised into measurable indicators and examined across a broader cross-sector sample. Such work would enable systematic assessment of progression patterns beyond the case-based contexts analysed here.

Longitudinal research could further explore how dynamic capabilities for AI adaptation evolve over time, particularly in organisations transitioning from structured data environments to AI-supported decision systems. Observing these shifts across extended periods would clarify how sensing, seizing, and transformation processes stabilise or change. Such studies could also examine more explicitly the mechanisms through which knowledge infrastructures, organisational routines and institutional conditions interact to shape capability development.

Further comparative research across sectors would also help clarify how organisational knowledge environments and capability development differ between public administration and private-sector organisations, particularly in contexts with varying regulatory pressures and decision accountability requirements.

Additional research is also needed on human–AI interpretive practices in operational decision settings, especially in highly regulated domains. Examining how accountability, explainability, and trust are negotiated within everyday organisational routines would extend the socio-technical insights developed in this thesis.

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References

Ackermann, F., & Eden, C. (1998). Making Strategy: The Journey of Strategic Management. London: Sage.

Alavi, M., & Leidner, D. E. (2001). Knowledge management and knowledge management systems: Conceptual foundations and research issues. MIS Quarterly, 25, 107–136.

Bertin, J. (1981). *Graphics and Craphic Information Processing.* Berlin: Walter de Gruiter.

Shih, S. A. (2015). Towards and Interactive Learning Approch in Cybersecurity Education. *Proceedings of the 2015 Information Security Curruculum Development Conference* (p. 11). New York: SCM.

Al-Okaily, M., & Al-Okaily, A. (2025). Financial data modeling: An analysis of factors influencing big data analytics-driven financial decision quality. Journal of Modelling in Management, 20(2), 301–321.

Barney, J. (1991). Firm resources and sustained competitive advantage. *Journal of Management*, 17(1), 99–120.

Baxter, G., & Sommerville, I. (2011). Socio-technical systems: From design methods to systems engineering. Interacting with Computers, 23(1), 4–17.

Becker, J., Knackstedt, R., & Pöppelbuß, J. (2009). Developing maturity models for IT management. Business & Information Systems Engineering, 1(3), 213–222.

Belton, V., & Stewart, T. J. (2002). Multiple Criteria Decision Analysis: An Integrated Approach. Boston: Springer.

Bérubé, M., Giannelia, T., & Vial, G. (2021). Barriers to the implementation of AI in organizations: Findings from a Delphi study. Proceedings of the 54th Hawaii International Conference on System Sciences, 6702–6711.

Braun, V., & Clarke, V. (2006). Using thematic analysis in psychology. Qualitative Research in Psychology, 3(2), 77–101.

Chierici, R., Mazzucchelli, A., Garcia-Perez, A., & Vrontis, D. (2019). Transforming big data into knowledge: The role of knowledge management practice. Management Decision, 57(8), 1902–1922.

Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS Quarterly*, 13(3), 319–340.

De Bruin, T., & Rosemann, M. (2005). Towards a business process management maturity model. In Proceedings of the 13th European Conference on Information Systems (ECIS).

Davenport, T. H., & Kirby, J. (2016). Only humans need apply: Winners and losers in the age of smart machines. *Harvard Business Review*, 94(6), 58–65.

DiMaggio, P. J., & Powell, W. W. (1983). The iron cage revisited: Institutional isomorphism and collective rationality in organizational fields. *American Sociological Review*, 48(2), 147–160.

Duan, Y., Edwards, J. S., & Dwivedi, Y. K. (2019). Artificial intelligence for decision making in the era of big data: Evolution, challenges and research agenda. International Journal of Information Management, 48, 63–71.

Dulipovici, A., & Robey, D. (2013). Strategic alignment and interpretive challenges in knowledge management. Information Systems Research, 24(4), 969–991.

Eisenhardt, K. M. (1989). Building theories from case study research. Academy of Management Review, 14(4), 532–550.Eisenhardt, K. M., & Martin, J. A. (2000). Dynamic capabilities: What are they? Strategic Management Journal, 21(10–11), 1105–1121.

Felin, T., Foss, N. J., Heimeriks, K. H., & Madsen, T. L. (2012). Microfoundations of routines and capabilities: Individuals, processes, and structure. *Journal of Management Studies, 49*(8), 1351–1374.Gartner. (2020). AI Maturity Model. Gartner Research.

Gill, A., & Delahaye, J. (2020). Organizational readiness for digital transformation: A knowledge-based view. Journal of Management & Organization, 26(3), 331–344.

Grant, R. (1996). Toward a knowledge-based theory of the firm. Strategic Management Journal, 17(Special Issue), 109–122.

Holmström, J. (2021). From AI readiness to AI maturity: A capability maturity model for AI adoption. Journal of Business Research, 129, 902–912.

Jarrahi, M. H. (2018). Artificial intelligence and the future of work: Human–AI symbiosis in organizational decision making. *Business Horizons*, 61(4), 577–586.

Jarrahi, M., Askay, D., Eshraghi, A., & Smith, P. (2022). Artificial intelligence and knowledge management: A partnership between human and AI. Business Horizons, 65(4), 549–559.

Jarrahi, M. et al. (2023). Trust and interpretability in AI-supported organisational decision-making. Business Horizons.

Kerschbaum, C., & Dachs, R. (2024). Challenges in AI implementation: Perspectives from practice and research. ICAIR Conference Proceedings.

Khan, F., Bartáková, G., Almadhor, A., Qayyum, A., Abeer, K., & Durrani, A. (2025). Evaluating the capacity and limitations of generative AI in financial decision making. Computer Standards & Interfaces, 93, Article 103965.

Kitchenham, B. (2004). Procedures for Performing Systematic Reviews. Keele University Technical Report TR/SE-0401.

Klein, K. J., & Kozlowski, S. W. J. (2000). Multilevel theory, research, and methods in organizations. San Francisco: Jossey-Bass.

Kohlegger, M., Maier, R., & Thalmann, S. (2009). Understanding maturity models: Results from a structured literature review. In Proceedings of the I-KNOW ’09 Conference.

Lui, S. M., & Lamb, R. (2018). Understanding human–AI collaboration in organisational decision-making. Information Systems Journal, 28(3), 435–469.

Moher, D., Liberati, A., Tetzlaff, J., Altman, D. G., & The PRISMA Group. (2009). Preferred reporting items for systematic reviews and meta-analyses: The PRISMA statement. PLoS Medicine, 6(7), e1000097.

Mumford, E. (2000). A socio-technical approach to systems design. Requirements Engineering, 5(2), 125–133.

Nonaka, I., & Takeuchi, H. (1995). The Knowledge-Creating Company. Oxford University Press.

Nowell, L. S., Norris, J. M., White, D. E., & Moules, N. J. (2017). Thematic analysis: Striving to meet the trustworthiness criteria. International Journal of Qualitative Methods, 16(1), 1–13.

Orlikowski, W. J. (1992). The duality of technology: Rethinking the concept of technology in organizations. Organization Science, 3(3), 398–427.

Patton, M. Q. (1999). Enhancing the quality and credibility of qualitative analysis. *Health Services Research*, 34(5), 1189–1208.

PwC. (2019). AI Readiness Model. PwC Research.
Sein, M. K., Henfridsson, O., Purao, S., Rossi, M., & Lindgren, R. (2011). Action design research. MIS Quarterly, 35(1), 37–56.
Teece, D. J. (2007). Explicating dynamic capabilities. Strategic Management Journal, 28(13), 1319–1350.
Teece, D. J. (2018). Business models and dynamic capabilities. Long Range Planning.
Teece, D. J., Pisano, G., & Shuen, A. (1997). Dynamic capabilities and strategic management. Strategic Management Journal, 18(7), 509–533.
Trist, E., & Bamforth, K. (1951). Some social and psychological consequences of the longwall method of coal-getting. Human Relations, 4(1), 3–38.
Tushman, M., & Scanlan, T. (1981). Boundary spanning individuals: Their role in information transfer and their antecedents. Academy of Management Journal, 24(2), 289–305.
Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User acceptance of information technology: Toward a unified view. *MIS Quarterly*, 27(3), 425–478.
Von Krogh, G., Ichijo, K., & Nonaka, I. (2000). Enabling Knowledge Creation. Oxford University Press.
Warner, K. S. R., & Wäger, M. (2019). Building dynamic capabilities for digital transformation. Long Range Planning, 52(3), 326–349.
Yin, R. K. (2014). Case Study Research: Design and Methods (5th ed.). Thousand Oaks, CA: Sage.

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Abstract

Knowledge Management for AI-Augmented Decision-Making: A Multi-Level Analysis of Organisational Maturity, Capabilities, and Socio-Technical Conditions

Organisations in both the public and private sectors are increasingly expected to consider the use of artificial intelligence (AI) in knowledge-intensive decision-making. While AI tools can support the analysis of information and routine judgement tasks, their effective use depends on how organisational knowledge is structured, how capabilities develop, and how governance and socio-technical arrangements are aligned. In practice, fragmented information systems, unstable knowledge practices and unclear governance arrangements often limit organisations' ability to integrate AI into everyday decision processes.

This thesis investigates how organisations progress towards AI-augmented knowledge management and decision-making through five complementary studies. The empirical work spans municipal administrations in Estonia and Georgia, multi-stakeholder initiatives in Estonia and Finland, and a multinational financial-technology (FinTech) organisation. Together, these settings allow examination of organisational readiness and adaptation across contrasting institutional environments while maintaining a consistent focus on knowledge-intensive work.

The research draws on maturity and organisational readiness models, the Dynamic Capabilities Framework and socio-technical systems theory. Methodologically, the thesis combines Action Design Research, comparative case studies with interviews and survey data, a PRISMA-guided systematic literature review and problem-structuring methods.

The findings show that the integration of AI into decision processes depends on three interacting conditions. First, the structure of organisational knowledge environments such as metadata practices, workflow integration and information traceability, shapes whether AI-generated insights can be interpreted and reused in decision processes. Second, organisations must develop capabilities that adapt routines, roles and governance arrangements as AI becomes embedded in operational workflows. Third, broader socio-technical conditions, including interoperability infrastructures and regulatory requirements, influence whether AI-supported decision practices can stabilise and scale.

Overall, the thesis suggests that AI-augmented knowledge management is better understood as a cumulative organisational transformation rather than a discrete technological implementation. The proposed multi-level perspective helps explain how knowledge infrastructures, organisational capabilities and socio-technical environments interact in the integration of AI into decision-making.

Future research could test and extend these findings across broader organisational contexts, examine quantitative relationships between knowledge management mechanisms and decision outcomes, and further explore governance and accountability challenges in AI-supported decision environments.

Lühikokkuvõte

Teadmusjuhtimine tehisintellektiga toetatud otsustusprotsessides: organisatsioonilise küpsuse, võimekuste ja sotsiaal-tehniliste tingimuste mitmetasandiline analüüs

Avaliku ja erasektori organisatsioonid seisavad üha enam silmitsi ootusega kasutada tehisintellekti (TI) teadmuspõhistes ja keerukates otsustusprotsessides. Kuigi TI-l põhinevad tööriistad võimaldavad toetada andmete analüüsi ja rutiinseid hindamisülesandeid, sõltub nende tulemuslik rakendamine sellest, kuidas organisatsioonis on teadmised struktureeritud, kuidas arenevad organisatsioonilised võimekused ning kuidas on kujundatud juhtimis- ja sotsiaal-tehnilised korraldused. Praktikas piiravad TI kasutuselevõttu sageli killustunud infosüsteemid, ebastabiilsed teadmushalduse praktikad ning ebaselged juhtimis- ja vastutusstruktuurid.

Käesolev doktoritöö uurib, kuidas organisatsioonid liiguvad tehisintellekti toetatud teadmushalduse ja otsustamise suunas viie omavahel seotud uuringu kaudu. Empiiriline materjal hõlmab kohalikke omavalitsusi Eestis ja Gruusias, mitme osapoole koostööalgatusi Eestis ja Soomes ning rahvusvahelist finantstehnoloogia (FinTech) ettevõtet. Need juhtumid võimaldavad analüüsida organisatsioonilist valmisolekut ja kohanemisprotsesse erinevates institutsionaalsetes kontekstides, säilitades samal ajal keskse fookuse teadmuspõhisel tööl.

Teoreetiliselt ühendab töö küpsus- ja valmisolekumudelid, dünaamiliste võimekuste käsitluse ning sotsiaal-tehniliste süsteemide teooria. Metoodiliselt kasutatakse tegevuspõhist disainiuuringut (Action Design Research), võrdlevaid juhtumiuuringuid intervjuude ja küsitlusandmetega, PRISMA-juhistest lähtuvat süstemaatilist kirjanduse ülevaadet ning probleemistruktureerimise meetodeid (kognitiivne kaardistamine ja DEMATEL).

Tulemused näitavad, et tehisintellekti integreerimine otsustusprotsessidesse sõltub kolme omavahel seotud tingimuse koostoimest. Esiteks määrab organisatsiooni teadmuskeskkonna struktuur — sealhulgas metaandmete praktikad, töövoogude integratsioon ja info jälgitavus — selle, kas TI loodud analüüse on võimalik otsustusprotsessides mõtestatult kasutada. Teiseks peavad organisatsioonid arendama võimekusi, mis võimaldavad kohandada rolle, tööpraktikaid ja juhtimisrutiine TI kasutuselevõtu käigus. Kolmandaks mõjutavad laiemad sotsiaal-tehnilised tingimused, näiteks infrastruktuurne koostalitlusvõime ja regulatiivsed nõuded, seda, kas TI-toetatud otsustuspraktikad saavad organisatsioonides püsivalt toimima hakata ja laieneda.

Töö tulemused viitavad, et TI-toetatud teadmushaldust on otstarbekam käsitleda kumulatiivse organisatsioonilise muutusena, mitte üksiku tehnoloogilise rakendusetapina. Töös esitatud mitmetasandiline lähenemine aitab selgitada, kuidas teadmuse infrastruktuurid, organisatsioonilised võimekused ja sotsiaal-tehnilised tingimused koos mõjutavad tehisintellekti kasutuselevõttu otsustusprotsessides.

Töö piiranguks on kvalitatiivsete ja juhtumipõhiste meetodite kasutamine konkreetsetes riiklikes ja sektoripõhistes kontekstides ning keskendumine organisatsioonilistele ja sotsiaal-tehnilistele tingimustele, mitte algoritmilisele disainile või mudelite tehnilisele tulemuslikkusele. Edasised uuringud võiksid testida ja laiendada esitatud küpsus- ja võimekusraamistikke laiemates võrdlevates valimites, uurida teadmushalduse mehhanismide ja otsustustulemuste kvantitatiivseid seoseid ning käsitleda põhjalikumalt TI-toetatud otsustamise eetilisi ja vastutuse küsimusi.

Appendix 1

Publication I

Pappel, I., Gelashvili, T. & Pappel, I. (2022). Maturity model for automatization of service provision and decision-making processes in municipalities. In *Lecture Notes in Networks and Systems* (pp. 399–409). Springer.

Maturity Model for Automatization of Service Provision and Decision-Making Processes in Municipalities

Ingmar Pappel, Teona Gelashvili, and Ingrid Pappel

Abstract Citizens expect local governments to provide high-quality public services quickly and without hidden additional costs. Today, public service provision takes place mainly through e-services, using various document and information management systems. In this paper, we present the five-stage maturity model describing the automatization of service provision and decision-making processes in the back offices of municipalities. The model is developed after 20 years of continuous work in the field of e-governance. The process has been backed up by a scientific research method called Action Design Research (ADR) together with existing maturity model development methods. This model makes it possible to assess the level of maturity of local governments based on the carrier and format of data, as well as introducing other criteria and various easy-to-apply KPIs.

Keywords Maturity model · e-Governance · Action design research · Service provision · e-Service · Artificial intelligence · Local government · EDRMS

1 Introduction

This paper is based on the authors' experience in implementing digital administration and developing document management software (Amphora) in Estonia over the past 20 years. Today, digital records management and digital workflows are used in most organizations; nevertheless, the information processed in digital records management systems is still not machine-readable. The extreme importance of document management at the municipal level in connection with the state's e-governance level has been

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highlighted numerously [1, 2]. Therefore, having the model which enables measurement of maturity levels of advanced service provisioning and decision-making in the local municipalities is crucial for Estonia, as one of the leading countries in e-governance [3, 4].

The maturity model presented in this paper has been created based on a five-step maturity model development framework [5], which consists of the following phases: scope, design, populate, test, and deploy and proposes three levels for models: descriptive, prescriptive, and comparative. The general principles of the Action Design Research (ADR) and Agile methodology have been followed during the creation process. The first cycle of model development was a theoretical and unvalidated prototype based on the authors' experience, and it is covered by this paper. The second cycle is planned as the further advancement of the model, promoting it to the prescriptive level and piloting in five municipalities. The third cycle is the development of the model to the highest, comparative level and the compilation of a comparison of Estonian local governments.

1.1 Development of Amphora

In 2003, when Amphora was created, document management in Estonia was handled on paper, and there was almost no usage of a digital signature. One of the biggest challenges in municipalities was the loss of citizens' applications and letters. Development of the TWAIN interface in 2005 enabled Amphora to work with document scanners and transition to the use of digital copies in the workflows; to a small extent, letters were signed digitally. When Amphora was introduced outside the clerical offices, support for digital signatures was developed, and the first digitally signed documents began to emerge. In 2008, measurement of an organizational development process in municipalities became vital, thus the first Key Performance Indicators (KPIs) were developed and monitored.

Administrative processes in local governments to be efficient, the digitization of the input of public services started with a creation of e-forms on the portal eesti.ee (Estonian gateway to government information and e-services). In 80 local governments (of 237 in total at this time), the first two new e-services have been implemented. Later, a package of additional 25 new e-services (e-forms) was developed. Even though municipalities increased introducing e-forms and implementing e-services, a broader use remained low. In 2010 et seq., the transition to digitally signed documents was significant, and Amphora was increasingly used for digital workflows.

By 2018, signing the letters and documents digitally was predominant, but the information was still managed in the "A4" format. Soon a self-service portal and the machine-readable XML legislation system in Amphora started to develop. Interfaces for other popular self-service portal providers (SPOKU, KOVMEN), business rule-based automatic registration and distribution of input documents from self-service portals, and data exchange with council information system VOLIS were introduced.

During 2020, several of these systems have been implemented by approximately 30 percent of local governments, but none of them have reached fully automatic processes.

Prediction is that over the next 5 years, the transition to machine-processed information will take place, and most activities will be automated. It is also expected that in the next 5 years, the first municipalities in Estonia will begin to implement rules for making automated decisions that are approved by humans. From 2025 onwards, it is likely that AI (Artificial Intelligence) will be introduced for simpler (discretionary) decisions, and the role of the individual will be a random check of accuracy. By 2030, AI could make an initial (discretionary) decision that will be validated by humans. Further steps would encompass giving AI greater legal power.

1.2 Digital Records Management in Municipalities

Three leading digital records management processes can be distinguished in municipalities: the correspondence handling process, the decision-making process, and the rule-making process. The correspondence process consists of registering an incoming application, forwarding it to a person responsible for preparing a draft of decision or answer, formulating a draft of the decision or answer, signing or passing (on town government meeting), and lastly, sending the answer back to the applicant. The decision-making process consists of preparing a draft of the decision, adding a draft to the agenda of the meeting, approving the agenda before the meeting, presenting the draft decision at the meeting, formal or substantive decision-making at the meeting, post-meeting formalization, digital signing of the decision, and sending the decision to the applicant. The rule-making process consists of drafting the terms of regulation, drafting the legislation (regulation) in the government, submitting the draft to the government meeting, passing the regulation on the meeting, submitting the draft to the council meeting, adopting (or rejecting) the regulation on the meeting, post-meeting formulation, and sending the formulated regulation to the Riigi Teataja (Estonian state portal for legal acts) for publishing and entering into force.

During the development of the model, careful attention has been paid to the integration of these three processes. The internal and personnel management processes have been eliminated from the model as nonsignificant in the context of service provisioning and decision-making.

2 Literature Review

Maturity models have been widely used in various disciplines, and their definition varies accordingly [6, 7]. In the Information System (IS) discipline, the term "maturity" is defined as "a measure to evaluate the capabilities of an organization" [8]. Nevertheless, on a large scale, the idea behind it is similar; they define the evolution path of a certain artifact or process within the organization and it can be displayed either through a top-down or bottom-up approach [5, 9]. Maturity models are grouped into two categories: fixed-level maturity models and focus area maturity models [10]. Irrespective of what the scheme when describing the evolution path is, Utterback and Abernathy argue that the progress of an innovation follows an S-curve [11, 12] and can be represented in four stages: emerging, pacing, disruptive, and mature.

Maturity Model in Information Governance. The development and usage of maturity models have been significant in Information Governance (IG) discipline. Proenca and Borbinha develop how to create an IG maturity model through Design Science Research [13]. The following three maturity models belong to five fixed-level category schemes and focus on different areas: Information Governance Maturity Model through which organizations are able to grasp IG characteristics and advance across the levels [14]; Asset Management Maturity Model developed in the Netherlands for the asset managers, helping them to make better investment decisions [15]; Digital Asset Management (DAM) Maturity Model with a rather broad focus and including people, systems, information, and processes [16].

Maturity Model in IT Service Delivery. IT Service delivery maturity models presented below consist of five levels [17] and assess various aspects. The Control Objects for Information and related Technology (COBIT) represents a framework for IT management and identifies IT processes; Service Management Process Maturity Framework (PMF) focuses on assessing the maturity of each of the Service Management processes; IT Service Capability Maturity Model (IT Service CMM) is oriented to assess the maturity of IT service processes and identify a direction for improvement, and its target is to help service organizations improve service quality [17].

*Enterprise Content Management (ECM) Maturity Model. T*he concept of ECM is widely spread in various disciplines and has been used interchangeably with other related terms such as Electronic Document Management Systems (EDMS), Electronic Records Management Systems (ERMS), and Electronic Document and Records Management Systems (EDRMS) [18]. The core idea of ECM software applications and strategies is to allow the organization to manage its information effectively [19, 20]. The Enterprise Content Management Maturity Model (ECM3) was launched in March 2009 [19] and has five levels of maturity.

Maturity Model for IT Management. Improvement of IT performance in connection with economic efficiency is one of the main goals of introducing a maturity model in IT management. The role of the maturity model here is to assess the as-is position of the organization, identify the existing maturity state, and assign improvement measures to be implemented for further progress [21].

Business Process Management (BPM) Maturity Models. The Software Engineering Institute at Carnegie Mellon University has developed the Capability Maturity Model (CMM) which is the foundation for most of the Business Process Management maturity measurement models [22]. Among others, Harmon developed a Business Process Management Maturity (BPMM) model based on the Capability Maturity Model [23, 24]. Similarly, Fisher [25] combines five "levers of change" with five states of maturity. And lastly, the Infrastructure Management Maturity Matrix

(IM^3) has a stronger focus on organizational communication reflected in the columns internal and external communication [26].

3 Maturity Model of Service Provisioning and Decision-Making Processes

3.1 Methodology

The authors of the presented maturity model have been active participants in the projects of the document exchange center of Estonia, contributing to conceptualizing a paperless management approach at the national level and involving in the state digitization processes. Therefore, the development of the suggested maturity model has been in close cooperation with state entities and ongoing digital advancements at the national level. The very first iteration of the model started in 2004 with the creation of Amphora. From then on, the process has been continued, with Amphora being an excellent platform where the implementation of all the existing hypotheses became possible together with testing their validity and applicability. The development process included a plethora of workshops in which the participants have been experts in the fields together with the actual users (from various municipalities, governmental entities, and citizens). Therefore, the methodology through which the model has been developed is based mainly on the qualitative approach. For building the model offered in this paper, together with their own practical experience, authors have conducted a thorough review of the existing maturity models in different fields and the methodologies which have enabled their development. Action Design Research, according to which "IT artifacts are ensembles shaped by the organizational context during development and use" [27, 28], has been chosen to apply the development process of the model. Application of ADR has enabled to deal with two challenges: firstly, it allowed to address the problem in the organizational setting and provided evaluation possibility and secondly, after identifying the existing problem, respective IT artifact could have been constructed which mitigated typified difficulty [27]. Consequently, the immense value offered by this maturity model has been in the fact that it has enabled authors to involve the dimension beyond the technological and incorporate all the feedback, reviews, experience, and opinions received from the users in the form of data and build an artifact based on the contextual framework. The active engagement with the stakeholders has been the foundation for the co-creation aspect [29, 30], which has also guided through the model formation process.

Maturity Model for Automatization of Service Provision and Decision-making Processes in Municipalities is represented in Table 1 below, followed by the description of each phase.

First Phase. In the first phase, the original application is copied several times on paper and all correspondence is delivered using postal service or hand-to-hand. There are

Table 1 Maturity model of service provisioning and decision-making processes

No.	Phase name	Information mode	Information carrier	Decision-making	Time for deciding
1	Paper original/paper copy	Unstructured	Paper/paper	Human	Weeks or months
2	Paper original/digital copy	Unstructured	Paper/digital	Human	Days
3	Digital free text + metadata/legalized paper copy	Unstructured	Digital/paper	Human	Days/hours
4	Data/(legalized) digital or paper copy	Structured	Digital	Human/AI	Nearly real-time
5	Data and AI	Structured	Digital	AI/human	Realtime/proactive

two main problems identified at this level: documents are getting lost when processed, and since the documents must be moved physically, workflows are time-consuming. The decision-making act is formalized and signed on paper. This the first and most basic level, and there is no transitioning path to this level. The most distinctive difference between this and the next phase is that at this level, there is no digital information used on any step of the processes and paper is only a "data carrier". The main flaw at this level is that documents are lost when processed, and the circulation of original documents is not controlled.

Maturity at this level can be detected through observation, interviews, and questionnaires. Exit criteria to the next are every paper document to be scanned, digital copies to be used for processing, and digital records management system to be implemented. Detecting this phase can be done by observations or using questionnaires and interviews.

Second Phase. At this stage, applications are scanned and archived, digital copies are used in workflows, EDRMS is handling digital copies, and digital channels are being used for digital copies. Decisions are formulated and signed still on paper, and then scanned. Archiving and preserving are happening on paper. There are three significant problems identified at this level: scanning a document is time-consuming and costly, only paper documents are accepted and sent because only paper documents are trusted outside of ERDMS, and formulation of the decision on a paper is time-consuming and cannot be automated. However, there is an advantage compared to the previous stage: digital copies in ERDMS can be trusted, workflows are faster than in the previous phase, and most importantly, because of no physical delivery of documents, paper originals are not lost anymore. The transitioning path from level 1 is to follow the rule: everything must be digitized.

The list of the challenges to be mitigated includes technical capabilities (ERDMS must be implemented, scanners must be in places where papers appear), human capabilities, and change management (how to work with digital copies). The distinctive characteristic of this phase from others is that the data carrier is now a hybrid of paper/digital with two main criteria of progress: the percentage of digital copies in ERDMS and the percentage of digital workflows.

In order to initiate the transition from the previous phase, every document must be scanned, digital copies must be used in workflows, and paper originals must be stored in a controlled place. For exiting from this phase, digitally signed documents and e-forms over a trusted channel (self-service portals) should be accepted, as well as decision-making acts should be signed digitally or be delivered to the self-service portal. Maturity at this level can be detected through data acquired from EDRMS, observation, interviews, and questionnaires when there is no direct access to data.

Third Phase. During this phase, applications are accepted in digitally signed form or from trusted channels like self-service portals, decisions are formulated and signed digitally or delivered to trusted channels, and all documents are handled and processed in ERDMS. Archiving is also done in digital format. Because of the usage of unstructured free-text, it is hard to implement automated processing and decision-making. Moreover, human work is needed because of the unstructured and non-machine-readable format of data, which makes it time-consuming and error-prone. Identified advantages compared to the previous level are that some processes can be automated based on metadata or based on the processing of free-text, delivery of digital originals is nearly real-time, and every "copy" of the digitally signed document has the same legal power. There is no more distinction between copy and original. To transition from level 2, every signature must be digital, no more signing of paper documents.

The list of the main challenges occurring at this level consists of technical capability—servers, digital signing, document formats, archiving of digital documents, tendency of creating more "copies", and lastly, human capability and change management. A crucial aspect at this stage is the implementation of a digital archive. A distinctive feature of this phase is the fact that the data carrier is now digital, but the format is still unstructured, with the two main progress criteria being the percent of digitally signed documents and the percent of digitally signed decisions in ERDMS.

To transition from the previous phase, everything must be digitally signed, digitally signed documents or e-forms from self-service portals should be accepted (and preferred), and digital documents should be processed faster than paper. For exiting from this phase, IS working with structured and machine-readable data, registries, and databases should be implemented, or ERDMS must have this functionality. Maturity at this level is measured through data from ERDMS, observation, interviews, and questionnaires only when there is no direct access to data.

Fourth Phase. At this phase, applications are accepted from self-service portals using e-forms or inserted directly into IS, decisions are formulated in IS, and generated, signed digitally, or stamped as an extract of the state of data. Delivered over trusted channels, all documents are handled and processed in ERDMS or IS. Changes in data are archived when a change in data has different legal power and consequences in comparison with the previous state of the data. There are no papers preserved anymore except receiving the paper original from the external party. The list of the main problems existing at this level include the development of IS capable of working with unstructured data to be more expensive than implementing EDRMS, changes in the structure of data, business rules and workflows may be costly to implement, decisions are still made by humans, time-consuming, error-prone, and open to corruption.

Advantages over the previous level include the workflows to be nearly real-time and automated, some decisions can be automated, delivery of digital data happens in real-time, the system is interoperable with other IS, registries, and databases, and data can be re-used. The biggest challenge during the transition from level 3 lies within the technical capability—development and implementation of specialized IS. Distinctive characteristics of this phase are that the data carrier is now digital and format is unstructured with the new main criterion of progress—percent of decisions done in IS.

To initiate the transition from the previous phase, data should be in the re-usable format, and there should be interfaces to other interconnected information systems directly or over data exchange layers like X-road (Estonian official data exchange layer). For exiting from this phase, implementation of the AI-assisted decision-making system is crucial, and AI should be used for decision making; there must be strict rules and procedures to prove and validate decisions made by AI. Maturity at this level is measured through data from IS, observation, interviews, and questionnaires when there is no direct access to data.

Fifth Phase. In the fifth phase, only structured and machine-readable data is used; most of the decision-making is done by AI, and humans must be able to validate AI decisions. The main problems at this level include trust in AI, decisions are not "humanly soft" anymore, AI has no compassion, changing business rules may be costly, laws and regulations are not machine-understandable, and AI may be non-ethical and discriminating. Advantages over the previous level are that decisions are automated and real-time, proactive service can be provided.

The transitioning path from level 4 every decision is prepared or supported by AI. Main challenges include technical capability—development and implementation of AI as well as trust in AI. A distinctive characteristic from others is that decisions are made by AI and the main progress criterion is the percent of decisions done by AI.

Transition factors from the previous phase are AI does not make mistakes (if rules are correct), and AI is honest and non-corruptible. Since this is the highest level on this maturity model, there is no exit. Maturity at this level is measured through the percentage of automated decisions.

4 Discussion and Shortcomings

Firstly, understanding how convenient the implementation of the proposed maturity model is, and secondly, whether it is more beneficial than those which already exist will become apparent after the testing stage followed shortly after the current development phase. Nevertheless, it is still possible to identify a few expected shortcomings, even without having tangible post-implementation results. The challenges can be divided into several categories, such as technical, financial, legal, and human-related. When it comes to technical limitations, the main issue could be archiving problems of hybrid case files as well as archiving problems of structured data. Transitioning between the phases includes the advancement of technology, and thus, the development of EDRMS and IS capable of working with unstructured data might be costly. When it comes to the challenges of the legal aspects, continuous translation of legal acts to machine-readable rules will also be something to consider beforehand and think about possible mitigations. One of the very important aspects of the transition is the human factor, and the challenges related to change management are expected to be identified at each transitional phase. Furthermore, at the levels when decision-making is supported by AI, another important factor to consider is trust—trust in AI.

5 Future Work

The current paper where the development of the model has been presented belongs to the first cycle of model development. The result of this cycle is a theoretical and unvalidated prototype, which is based on the authors' experience, consultations (with experts in the field as well as customers and users), and existing literature. The second development cycle is planned as the further advancement of the model, promoting it to the prescriptive level and piloting in five municipalities. The third cycle is the additional improvement of the model to the highest, comparative level and the compilation of a comparison of Estonian local governments on the basis of the model. The maturity model is scalable and can be applied to different cases. It should be highlighted that the transition to each cycle is a result of thorough research, design, and consultation with all of the stakeholders. As already mentioned, an integral part of this development process is a collaborative aspect, which enables authors to keep the right track and progress.

References

1. Pappel I, Pappel I (2011) Methodology for measuring the digital capability of local governments. In: 5th international conference on theory and practice of electronic governance, Tallinn

2. Pappel I, Pappel I, Tampere T, Draheim D (2017) Implementation of e-invoicing principles in Estonian local governments. In: Proceedings of the 17th European conference on digital government (ECDG). Military Academy, Lisbon
3. Pappel I, Tsap V, Draheim D (2020) The e-LocGov model for introducing e-Governance into local governments: an Estonian case study. In: IEEE transactions on emerging topics in computing
4. Pappel I, Tsap V, Pappel I, Draheim D (2018) Exploring e-services development in local government authorities by means of electronic document management systems. In: 5th international conference on electronic governance and open society challenges in Eurasia, St. Petersburg
5. De Bruin T, Freeze R, Kulkarni U, Rosemann M (2005) Understanding the main phases of developing a maturity assessment model. In: Proceedings of the ACIS 2005
6. Mettler T (2011) Maturity assessment models: a design science research approach. Int J Soc Syst Sci 81–98
7. Peffers K, Tuunanen T, Rothenberger M, Chatterjee S (2007) A design science research methodology for information systems research. J Manag Inf Syst 45–78
8. Rosemann M, De Bruin T (2005) Towards a business process management maturity model.In: Proceedings of the thirteenth European conference on information systems ECIS 2005
9. Proença D, Vieira R, Borbinha J (2016) A maturity model for information governance. In: 2016 11th Iberian conference on information systems and technologies (CISTI), Lisbon
10. Utterback J, Abernathy W (1975) A dynamic model of process and product innovation. Omega, p 639–656
11. Van Steenbergen M, Bos R, Brinkkemper S, Van de Weerd I (2010) The design of focus area maturity models. In: International conference on design science research in information systems
12. Lahrmann G, Marx FMT, Winter R, Wortmann F (2011) Inductive design of maturity models: applying the Rasch algorithm for design science research. In: International conference on design science research in information systems
13. Proença D, Borbinha J (2018) Maturity models for data and information management. In: 22nd international conference on theory and practice of digital libraries
14. ARMA international. https://www.arma.org/page/principles
15. Lei T, Volker L, Herder P, Ligtvoet A (2011) Evaluating asset management maturity in the Netherlands: a compact benchmark of eight different asset management organizations.In: 6th world congress of engineering asset management
16. DAM foundation. What is the DAM maturity model? https://www.dammaturitymodel.org/.
17. Flores J, Rusu L, Johannesson P (2011) A maturity model of IT service delivery. In: Proceedings of the CONF-IRM 2011
18. Katuu S (2016) Assessing the functionality of the enterprise content management maturity. Records Manag J
19. Pelz-Sharpe A, Durga A, Smigiel D, Hartman E, Byrne T, Gingras J (2010) ECM3 maturity model
20. Milenković DS (2016) Determining the maturity level of business organizations for ICT implementation in the case of electronic content management. Military Technical Courier, p 1119–1131
21. Becker J, Knackstedt R, Pöppelbuß J (2009) Developing maturity models for IT management—a procedure model and its application. Business & Information Systems Engineering, pp 213–222
22. Paulk M, Curtis B, Chrissis M (1993) Capability maturity model for software, version 1.1. Software Engineering Institute, CMU/SEI-93-TR-24
23. Harmon P (2003) Business process change: a manager's guide to improving, redesigning, and automating processes (The Morgan Kaufmann series in data management systems), 1st edn. Morgan Kaufmann
24. Harmon P (2004) Evaluating an organization's business process maturity
25. Fisher D (2004) The business process maturity model: a practical approach for identifying opportunities for optimization. Business Process Trends

26. Volker L, Van der Lei T, Van den Boomen M, Van der Velde J (2012) Continued learning in asset management for the Dutch transport network. In: Third international engineering systems symposium CESUN 2012
27. Sein M, Henfridsson O, Purao S, Rossi M, Lindgren R (2011) Action design research. MIS Q 35(1):37–56
28. Petersson ALJ (2016) Applying action design research (ADR) to develop concept generation and selection methods. Elsevier, p 222 – 227
29. Ind N (2013) The meanings of co-creation. Eur Bus Rev 25(1)
30. Bhalla G (2011) Collaboration and co-creation. Springer-Verlag, New York

Appendix 2

Publication II

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Challenges of Transition to Paperless Management: Readiness of Incorporating AI in Decision-making Processes

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***Abstract* — National governments are eager to design innovative ways of altering traditional service delivery. Nevertheless, the transition from legacy systems to digital is challenging. A crucial aspect of e-Governance is paperless management which facilitates seamless data exchange and digitalised workflows. Remote access to documents and files has become an absolute necessity based on the current Covid pandemic, especially in relation to internal workflows. The whole lifecycle of the records should be secure, traceable, and immutably archived for future access. The purpose of this research was to investigate the challenges of implementing Electronic Documents and Records Management Systems (EDRMS) in Georgian public entities, with a focus on user acceptance. In addition, the goal was to determine the current EDRMS maturity level and possibility of implementing virtual assistants in decision-making processes. Estonia, as a tech-savvy country and highflyer in e-Governance, was taken as a successful model. Comparison was made between Georgia and Estonia based on EDRMS maturity model. In combination with thorough literature review, primary data was also collected by conducting semi-structured interviews with government institutions, experts in this field and questionnaires disseminated among users. The result of the study showed that the major hinderances among users were fears of losing jobs, increased accountability and insufficient computer literacy. Lack of automated decision-making processes indicated that the application of Artificial Intelligence (AI) in the EDRMS is not yet possible. In order for Georgia to initiate transition from existing maturity phase, various advancements should be made. An initial implementation plan has been derived from this research.**

Keywords— Electronic Document and Records Management Systems, User Acceptance, AI, Virtual Assistants, Maturity Model, Decision-making

I. Introduction

e-Governance - "The use of IT by public sector organizations" [1], means efficient service delivery, increased interaction of government to citizens and businesses and the application of ICT (Information and Communication Technologies) in service provision [2], [3]. A crucial mechanism for altering traditional service delivery with innovative ways can be facilitated through the implementation of Electronic Documents and Records Management Systems (EDRMS) in public organisations. However, according to Adam: "Implementing EDRMS is not just about technology — that is the easy part! It is more about people, organizations, organizational culture, cultural change, and good, strong, yet flexible project management." [4]. Thus, an integral part of this chain is peoples' readiness since interaction with technology also includes emotional factors [5], [6], [7].

In 2012, the Government of Georgia issued the Decree according to which public organizations across the country should have started implementing EDRMS [8]. However, a transformation from traditional to electronic document management systems was challenging for most of the organisations. This study aims to identify the challenges when transitioning to paperless management and peoples' readiness to incorporate Artificial Intelligence (AI) in the decision-making process. To do so, together with interviews and survey, EDRMS implementation experiences shared by different countries and various technology acceptance theories have been investigated and based on this accumulated knowledge, the impediments of EDRMS implementation in Georgian governmental institutions were analysed. A paperless approach through the usage of EDRMS has been widely applied in the Estonian public sector [9], [10]. Despite all the obstacles, the country managed to reach high digital document exchange level. Therefore, Estonia is taken as a successful model.

The structure of this paper is organised as follows. The next section provides a theoretical background of the studied phenomenon: theories about implementation and adoption of ICT and related case studies. The research methodology is described in the next section. This continues with a presentation and discussion of findings. Assessment of EDRMS maturity in Georgia and Estonia are provided in Section V. We proceed with the discussion and outline the prospects of future work in the following section. The paper is ended by introducing conclusion.

II. Literature Review

A. *Theories About ICT Implementation and Adoption*

For a better understanding of human nature when it comes to adopting technology, a thorough analysis of various technology acceptance theories has been conducted. This section briefly summarises ICT implementation and adoption theories with identified factors when accepting technology. Studied theories are Theory of Reasoned Action (TRA), IT Implementation Process Model (IT IPM), Diffusion of Innovations (DOI), Technology Acceptance Model (TAM), Theory of Planned Behavior (TPB), Unified Theory of Acceptance and Use of Technology (UTAUT). Table I is divided into three columns, where identified factor (1st column), respective theory it has been detected (2nd column) and the source (3rd column) has been indicated.

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TABLE I. MAIN FACTORS AFFECTING ICT ACCEPTANCE

Identified factors	*Theory*	*Source*
Personal attitudes and perceptions	TRA, TAM, DOI	[11], [12], [13], [14]
Organisational change	IT IPM	[15]
Role of leadership	DOI, UTAUT	[13], [14], [16]
Perceived usefulness & ease of use	TRA, TAM, TPB	[5], [11], [17], [18], [19]
Social pressure and sense of control	TPB	[18], [19]
Importance of expectances	UTAUT	[16]

B. Country-Specific Case Study Examples (Challenges)

After gaining knowledge of the fundamental aspects of technology acceptance described in theories, we researched to learn more about country-specific EDRMS and ICT implementation scenarios. Experiences described by the scholars of different countries allowed us to make comparisons and point out those occurrences which happened to be rampant. Identified challenges, obstacles and lessons learned are displayed in Tables II and III below.

TABLE II. CHALLENGES RELATED TO EDRMS IMPLEMENTATION

Challenges	*Country*	*Source*
User-resistance	Australia, USA, Turkey, Malaysia, Taiwan	[20], [21], [22], [23], [24]
Management support	Australia, New Zealand	[25], [26]
User interface	New Zealand, USA, Malaysia	[26] , [21], [23]
Cultural change	Australia	[25]
Standardisation of work routines and service descriotions	UK, Estonia	[27], [28]

Country Specific Case Study Examples (Benefits)

TABLE III. ACHIEVED BENEFITS

Achieved benefits	*Country*	*Source*
Improved internal records management	UK, New Zealand, Turkey, Taiwan, Estonia	[29], [27], [26], [22], [24], [28]
Improved information quality and access	UK	[27]
Safe repository	New Zealand	[26]
Cost-effectiveness	New Zealand	[26]
Increased transparency and accountability	New Zealand, Estonia	[26], [28]
Determined workflows	Estonia	[28]

III. METHODOLOGY

As Kincheloe and Berry emphasized, the unilateral perspective is not enough to cover the complexity of the subject matter [30]. Thus, a combination of qualitative research methods such as case study, semi-structured interviews and survey has been adopted for a thorough investigation since the knowledge acquired through the observation of reality facilitates the understanding of social phenomenon [31]. Empirical method, inductive case study - “an examination of a specific phenomenon” [32], has allowed us to investigate a contemporary phenomenon in depth and within its real-world context. Furthermore, it provided the possibility of explaining complex causal links in real-world interventions and described the response and context in which it occurred [33]. Comprehensive insight into the study subject has been achieved through conducting the research in its setting and exploring the case with the different stakeholders’ perspective.

Five interviewees were chosen based on their expertise and competence regarding the subject matter. The list included ex-Minister of the Education and Science of Georgia, who was in office when the first official government decree about the standardization of the EDRMS was published. Within the framework of the Ministry, he was leading the projects in collaboration with other public entities aiming to achieve improved communication between the organizations and better service delivery; Head of the Document Management of the Ministry of Culture and Monument Protection of Georgia, who has been working in the Ministry since 2010. She was actively engaged in the implementation of the EDRMS in 2012, and her direct duty was to select the system which would suit the entity the most. Therefore, she gave excellent insight and described all the struggles they have been through during the implementation; Chairman of the Municipality City Council of Georgia, who initiated acceleration of the EDRMS implementation at the local government level. Before becoming the Chairman, he was a Governor of the Municipality for a few years, and he implemented the system there as well. His input was valuable not only for a better understanding of the situation at the local government level but also to recognise the role of the leadership when initiating such a significant change.

As mentioned in the introduction, the Estonian case is discussed in this study as the model of successful practice. The first Estonian interviewee is a prominent professional with the background in ICT and currently employed in the Ministry of Economic Affairs and Communications. The second Estonian interviewee is a PwC Advisors IT Senior Consultant, who provided input regarding Estonian experience and discussed some common challenges, pitfalls and shortcomings that are usually encountered during the EDRMS implementation.

Due to current pandemic, interviews were conducted online. They were recorded and later transcribed for thematic analysis and mind mapping, which was accomplished by using NVIVO. Patters (“themes“) were identified through coding and making different notes, which allowed us to come to certain conclusions (See Appendix 1 for Mindmap).

To study this matter from another – employees’ perspective, the survey (using Survey Monkey) has been drafted and distributed among Georgian public servants through social network and other electronic channels of communication. The survey consisted of 10 multiple-choice as well as open-ended questions, intending to understand their perceptions about the EDRMS implementation and to detect correlations between variables. The software SPSS was used for gathering descriptive statistics, identifying correlations and analysing survey results. An overall number of the survey participants was 101 from 36 Georgian public institutions and the survey was conducted from mid-March till mid-April 2020. The content of the questions was designed to identify the EDRMS features employees would perceive useful or vice versa, the provision of system training, need for assistance when using their system, and their attitude towards this innovation, in general. The survey was anonymous, and participants' personal information has not been collected.

IV. Results of the EDRMS Implementation Study

Analysis of the conducted interviews and survey displayed the correlation between the EDRMS implementation challenges, as well as benefits, Georgia experienced and those presented in the ICT acceptance theories and country-specific studies.

A. *Resistance to the Change*

Interviewees highlighted personal attitudes and perceptions as an initial barrier, by providing a detailed description of the stuff resistance they were facing. These factors are also highlighted in the Theory of Reasoned Action and Diffusion of Innovation. Moreover, the resistance of accepting the technology was enhanced by the scepticism and distrust they expressed towards it. Description of such a scenario also resonates with the stipulation made by Dent (1999) about systems of social roles, with their associated patterns of attitudes, expectations, and behaviour norms, share tendencies to resist change, to restore the previous state after a disturbance [34]. Inclination towards stability can be justified through this concept.

The results of the Survey gave different perspective towards the challenge of system usage. Pearson's Correlation revealed a positive correlation between system training and system's daily usage meaning that employees with EDRMS training were using the system in their daily activities compared to those with lack or no training at all (Fig. 1). Davis argues in TAM that crucial criteria for people to use technology is perceived usefulness of the system and also, how easy it is to be used. Therefore, providing training to the employees is the core aspect of the implementation policy. In the case of Estonia, there were Records Managers and IT personnel mutually delivering training to the employees thus the results were respective.

		Training	System Daily Usage
Training	Pearson Correlation	1	.295**
	Sig. (2-tailed)		0.003
	N	101	101
System Daily Usage	Pearson Correlation	.295**	1
	Sig. (2-tailed)	0.003	
	N	101	101
**. Correlation is significant at the 0.01 level (2-tailed).			

Fig. 1. Pearson Correlation between training and daily usage of the system

B. *IT Literacy*

Another positive correlation depicted by the survey is between the working experience, daily usage of the system and needed system assistance (Fig. 2). It means that those employees who were working with EDRMS for a longer time than others were more likely to use the system for their tasks. On the other hand, Pearson's correlation is negative for the cases of variable "needed system assistance" meaning that those employees with longer EDRMS working experience are less likely to ask help from their managers or co-workers (Fig, 3). These findings can also be justified through the Unified Theory of Acceptance and Use of Technology as the theory stipulates it as once of the most significant determinants.

		Work Experience	System Daily Usage
Work Experience	Pearson Correlation	1	.283**
	Sig. (2-tailed)		0.004
	N	101	101
System Daily Usage	Pearson Correlation	.283**	1
	Sig. (2-tailed)	0.004	
	N	101	101
**. Correlation is significant at the 0.01 level (2-tailed).			

Fig. 2. Pearson Correlation between work experience and system daily usage

		Work Experience	Assistance Needed
Work Experience	Pearson Correlation	1	-.264**
	Sig. (2-tailed)		0.008
	N	101	101
Assistance Needed	Pearson Correlation	-.264**	1
	Sig. (2-tailed)	0.008	
	N	101	101
**. Correlation is significant at the 0.01 level (2-tailed).			

Fig. 3. Pearson Correlation between work experience and system assistance needed

C. *Fear of Failure*

The barrier such as being afraid to fail to accomplish a certain task has been rampant among Georgian public servants, hindering them from incorporating EDRMS in their daily activities. As the representative of the Ministry of Culture of Georgia described, staff members were also concerned and sceptical about possible risks regarding storing documents, preserving their work and performing certain tasks. Although using the EDRMS was mandatory, there were specific procedures, which were "voluntary" to be accomplished digitally. In such scenarios, apprehension was apparent as employees would prefer a traditional, paper-based method instead. Additional factor hampering system usage and encourages traditional method is fear of system errors meaning that employees would rather spend more time on performing the task manually just to be sure that they would be error-free from failures caused by a digital workflow.

D. *System Interoperability and Standardization*

Together with identifying the most useful elements of EDRMS such as repository, version control, auditing and so on, interviewees and survey respondents pointed out integral features, especially the standardization and measures for the future archiving processes. Besides, public organizations are using software provided by different vendors which leads to failure to system interoperability. The study showed that this does not hinder employees of the different teams within the same organization to work on the documents simultaneously but when it comes to collaborating and sharing data with other entities, then the obstacle appears, which also adds resistance to their willingness to use the system more frequently.

E. *Organizational Change and the Role of the Leadership*

Organizational change, which occurred in the studied organizations, has greatly affected the implementation processes, which could have transformed into a barrier. Despite the interviewees not specifically mentioning the concept of the leadership, their discussions have revealed and confirmed its presence and essence. UTAUT Theory emphasises the fact that managers must understand what the drivers of the technology acceptance among employees are and what leads to subsequent successful usage [16]. Active participation of the interviewees themselves, which can be deduced from their discussions, can be considered as one of the facilitating factors. Furthermore, implementing EDRMS at the municipality level has been relatively more complicated and as the Chairman of City Council described, he initiated the implementation process and fully engage in it through conducting meetings with his staff members for better conveying the message of its positive effect and necessity of this change.

V. Assessing EDRMS Maturity

A. EDRMS Maturity Model

After learning about various aspects of the EDRMS implementation, it is possible to move to the next stage and define their maturity level. Even though the number of existing maturity models is quite high, they address various domains and finding the one that would match the needs of this particular case is challenging. Nevertheless, considering the importance of document management and decision-making processes achieved through EDRMS in the service provision has encouraged us to develop a five-level maturity model framework, with identifiable characteristics of each phase (Table IV).

The methodology used for constructing the model is based on combinations of over twenty years of authors' experience in working in implementing digital administration and developing document management software, expert interviews and user workshops, a thorough analysis of existing maturity models and Action Design Research (ADR), according to which "IT artefacts are ensembles shaped by the organizational context during development and use" [35], [36]. ADR enabled us to address the problem in an organizational setting and constructing respective IT artefact to combat against typified difficulty. The significance of the suggested maturity model is enhanced by the fact that it enabled us to expand the scope from technology and combine feedback received from the stakeholders in the form of data. Maturity Model for Automatization of Service Provision and Decision-making Processes in Municipalities is represented in Table IV below.

TABLE IV. EDRMS Maturity Model

No	*Phase name*	*Information mode*	*Information carrier*	*Decision-making*	*Time for deciding*
1	Paper original/paper copy	Unstructured	Paper/ paper	Human	Weeks or months
2	Paper original/ digital copy	Unstructured	Paper/ digital	Human	Days
3	Digital free text + metadata/ legalised paper copy	Unstructured	Digital/ paper	Human	Days/ hours
4	Data/ (legalised) digital or paper copy	Structured	Digital	Human/ AI	Nearly Realtime
5	Data & AI	Structured	Digital	AI/ Human	Realtime/ proactive

Maturity model for automatization of service provision and decision-making processes in municipalities. Source [37]

B. EDRMS Maturity Level in Georgia

The study has shown that EDRMS usage and maturity is different at the municipality level, compared to the capital Tbilisi. It also varies among public institutions. Nevertheless, it is still possible to assess them based on the criteria described in the maturity model and identify the respective phase. It can be stated that Georgia is between the second (paper original/digital copy) and third (digital free text + metadata/legalised paper copy) phase. It is revealed in the following characteristics:

Paper copies of applications and documents are scanned and then used in the digital workflow using digital channels and decisions are still drafted on the paper and signed manually. Same applies to their archival and preservation practices – happening on paper copies. All these paper-based workflows are time-consuming. However, the clear improvement is depicted through the trust towards digital copies in EDRMS, workflow makes decision-making process faster (days instead of months) and since documents are not carried around manually, the problem of losing them is significantly reduced. This second phase is the most widespread among municipalities, as for the ones in Ministries located in the capital city, a level can be close to the third phase.

Characteristics assuring us to attribute part of the EDRMS in Georgian public sector to third phase include acceptance of digitally signed applications and documents, decisions are now formulated and delivered digitally, and all the documents are being held in digital format. The critical differentiating factor here is the existence of metadata or free-text, which allows automation of several processes and thus the delivery of digital originals is nearly Realtime. Nevertheless, we may say that the full transition to the third phase is not accomplished yet.

C. EDRMS Maturity in Estonia

Despite the existing similarities, interviewing Estonian experts in this field has shown that the aspects they were focusing on were different from the insights received from Georgia. Before defining maturity level, we will provide a brief overview of the EDRMS implementation process.

After introducing EDRMS in Estonia in 1999, the Public Information Act was launched, requiring all the documents and records to be standardised. By that time, Estonian public entities were using different systems with X-Road (Estonian official data exchange layer). This challenging transition process was facilitated with extensive system training focusing on system features, procedures to follow and principles of data privacy. The obstacle at that stage was the Usability and UX (User-experience). One of the current challenges highlighted by the interviewee (employed in Estonian Ministry of Economic Affairs and Communications) was the excessive amount of the EDRMS systems. The goal Ministries aim to achieve is having two-three systems only country-wide, to reduce interoperability issues.

When it comes to defining the EDRMS maturity level in Estonian public institutions, the study [37] shows it to be also transitional from third to the fourth phase. Applications and documents are accepted in digitally signed form from self-service portals and e-forms, decision-making acts are also signed digitally, workflow consists of digital copies only and the same applies to a repository and archiving. The only paper exception is those paper originals, which are received from external parties. Because most of the processes are automated, which enables decisions to be made almost in Realtime. However, decisions are still made by humans, thus is error-prone.

VI. Discussion and Future Work

A. AI-incorporation Readiness

Georgia. Incorporating AI in the decision-making process is greatly connected with finances, technical capabilities as well as legal and human aspects. From studying Georgian context one can say that the challenges related to the EDRMS implementation in particular and trust towards ICT in general, is still not mature enough. Even though most of the public institutions are at the transitional level from second to third phases, the overall situation is not advanced. For Georgia to reach the level when AI makes decision and humans are only checking its validity, the country should pass third and fourth levels and achieve fifth – Data & AI, where information mode is structured, information carrier is only digital, the decision is made by AI and checked by human and time for deciding is Realtime and even proactive. And as said earlier, even the country accomplishes technically and legally to achieve that state, human (ethical) readiness will take longer time to be achieved.

Estonia. Taking into consideration the fact that Estonia is transitioning from third to the fourth phase and from 2018 self-service portals and machine-readable XML system started to be incorporated in EDRM systems, it can be said that even though fully automated processes has not been achieved yet, the country is on the right path. Prediction is that during the next decade the full transition to machine-readable information will occur and most of the activities will be automated, meaning that AI will decide yet still to be approved by humans. It can be taken to the next stage of granting AI right to make simple decisions where humans will make random check for the sake of accuracy.

Even though the discussion of incorporating AI in decision-making systems is at a very initial stage and we have not piloted the project yet, some of the possible challenges which are likely to appear can already be predicted. From the technical viewpoint, key obstacle hybrid case files as well as archiving problems of structured data. Moreover, reaching the level which enabled AI to make a decision, requires respective advanced technology, which will be expensive and here comes a financial part. And last but not least, taking into consideration the legal aspect - continuous translation of legal acts to machine-readable rules and human factor – change management and trust to AI, the transition should occur in both of the domains.

This paper is part of ongoing research to investigate the readiness of modern-day citizens to use AI-enabled governmental services. Based on the Estonian Next Generation Government Architecture [38], the future agenda of the government is to provide services using virtual assistants. Our research has started with the focus on investigating the current situation in the public sector, as a basis of incorporating AI and applying to the decision-making routines. The current plan is to pilot suggested maturity model in five Estonian municipalities, advance the model based on the lessons learned through the implementation process and promote it to the larger scale. Simultaneously, the focus will expand to user studies and inquiring those human aspects, which will play a crucial role in accepting AI-enabled services.

VII. Conclusion

In this paper, we have assessed the challenges of EDRMS implementation in Georgia. For a thorough investigation of the matter, different technology acceptance theories and ICT implementation practices of countries were analysed. Interview, as well as survey examination, presented the key factors affecting system implementation, user acceptance and their performance, which includes resistance to change, (insufficient) IT literacy, fear of failure (and increased accountability), organisational change and role of leadership as well as standardisation and system interoperability. Causal links between variables have also been displayed.

Lack of automated decision-making processes indicated that the application of AI in the EDRMS is not yet possible. For Georgia to initiate a transition from the existing maturity phase, various advancements should be made. Estonia was taken as a successful model. A comparison was made between Georgia and Estonia based on EDRMS maturity model. Based on the existing maturity level, it is likely Estonia to manage to enable the virtual assistant to be part of the decision-making process. Prospects of piloting hypothetical model and subsequent study have also been described.

References

[1] R. Heeks, Implementing and Managing eGovernment, An International Text, London: SAGE Publications Ltd, 2006.

[2] B. Gupta, S. Dasgupta and A. Gupta, "Adoption of ICT in a government organization in a developing country: An empirical study," *Science Direct,* p. 140–154, 2008.

[3] Y. K. Dwivedi, N. P. Rana, M. J. Banita Lal, M. D. Williams and M. Clement, "An empirical validation of a unified model of electronic government adoption (UMEGA)," *Government Information Quarterly,* no. 34, p. 211–230, 2017.

[4] A. Adam, Implementing Electronic Document and Record Management Systems, Boca Raton: Auerbach Publications, 2008.

[5] M. A. Wimmer and R. Traunmüller, "Electronic Government," in *4th International Conference, EGOV 2005*, Copenhagen, 2005.

[6] A. A. Aziz, Z. M. Yusof, U. A. Mokhtar and D. I. Jambari, *The Determinant Factors of Electronic Document and Records Management System (EDRMS) Adoption in Public Sector: A UTAUT-based Conceptual Model,* Universiti Kebangsaan Malaysia, 2017.

[7] A. Tough, "Accountability, open government and record keeping: time to think again?," *Records Management Journal,* vol. 21, no. 3, pp. 225-236, 2011.

[8] *Decree №64 of the Government of Georgia on the Implementation of the Minimal Standarts of the Electronic Document and Management Systems in the Governmental Entities,* Tbilisi: Legislative Herald of Georgia, 2012.

[9] I. Pappel, V. Tsap and D. Draheim, "The e-LocGov Model for Introducing e-Governance into Local Governments: an Estonian Case Study," in *IEEE Transactions on Emerging Topics in Computing*, 2021. Forthcoming

[10] H. Gunaratne and I. Pappel, "Enhancement of the e-invoicing systems by increasing the efficiency of workflows via disruptive technologies," in *7th International Conference, EGOSE 2020, St. Petersburg, Russia, November 18-19, 2020, Proceedings*. pp. 60–74, 2020

[11] K. Eija, *Theories of ICT System Implementation and Adoption - A Critical Review,* Helsinki: Aalto University, 2011.

[12] P. Surendran, "Technology Acceptance Model: A Survey of Literature," *International Journal of Business and Social Research (IJBSR),* vol. 2, no. 4, pp. 175-178, 2012.

[13] I. Sahin, "Detailed review of Rogers' diffusion of innovations theory and educational technology-related studies based on Rogers' theory," *The Turkish Online Journal of Educational Technology – TOJET,* pp. 14-23, 2006.

[14] G. C. B. I. Moore, *Development of an Instrument to Measure the Perceptions of Adopting an Information Technology InnovationAdopting an Information Technology Innovation,* Vancouver: Information Systems Research, 1991.

[15] R. B. Cooper and R. W. Zmud, "Information Technology Implementation Research: A Technological Diffusion Approach," *Management Science,* p. 123–139, 1990.

[16] V. Venkatesh, M. G. Morris, G. B. Davis and F. D. Davis, "User Acceptance of Information Technology: Toward a Unified View," *MIS Quarterly,* pp. 425-478, 2003.

[17] F. D. Davis, "Perceived Usefulness, Perceived Ease of Use, and User Acceptance of InformationTechnology," *MIS Quarterly,* vol. 13, no. 3, pp. 319-340, 1989.

[18] I. Ajzen, "The Theory of Planned Behavior," *ORGANIZATIONAL BEHAVIOR AND HUMAN DECISION PROCESSES ,* pp. 179-211, 1991.

[19] S. Taylor and P. A. Todd, "Understanding Information Technology Usage: A Test of Competing Models," *Information Systems Research ,* p. 144–176, 1995.

[20] L. T. Nguyen, P. M. Swatman, B. Fraunholz and S. Salzman, "EDRMS Implementations in the Australian Public Sector," in *20th Australasian Conference on Information Systems*, Melbourne, 2009.

[21] L. Carter and F. Bélanger, "The utilization of e-government services: citizen trust, innovation and acceptance factors," *Info Systems J,* pp. 5-25, 2005.

[22] Ö. Sebetci, "A TAM-based model for e-government: A case for Turkey," *International Journal of Electronic Governance,* pp. 113-135, 2015.

[23] A. A. Hamid, F. Z. A. Razakb, A. Abu Bakarc and W. S. W. Abdullah, "The Effects Of Perceived Usefulness And Perceived Ease Of Use On Continuance Intention To Use E-Government," *Procedia Economics and Finance,* pp. 644-649, 2016.

[24] S.-Y. Hung, C.-M. Chang and T.-J. Yu, "Determinants of user acceptance of the e-Government services: The case of online tax filing and payment system," *Government Information Quarterly,* p. 97–122, 27 January 2006.

[25] L. Wilkins, D. Holt, P. M. C. Swatman and E. S. K. Chan, "Implementing Information Management Strategically: An Australian EDRMS Case Study," in *BLED 2007 Proceedings*, Bled, 2007.

[26] B. Yin, *An analysis of the issues and benefits in EDRMS Implementation - A case study in a NZ public sector organisation,* Wellington: Victoria University of Wellington, 2014.

[27] R. Maguire, "Lessons learned from implementing an electronic records management system," *Records Management Journal,* pp. 150-157, 2005.

[28] I. Pappel, V. Tsap and D. Draheim, "The e-LocGov Model for Introducing e-Governance into Local Governments: an Estonian Case Study," *IEEE Transactions on Emerging Topics in Computing,* 2020.

[29] Z. A. Smyth, "Implementing EDRM: has it provided the benefits expected?," *Records Management Journal,* pp. 141-149, 2005.

[30] J. L. Kincheloe and K. S. Berry, Rigour & Complexity in Educational Research (Conducting Educational Research), Open University Press, 2004.

[31] G. Scott and R. Garner, Doing Qualitative Research - Designs, Methods, and Techniques, New Jersey: Pearson Education, Inc., 2013.

[32] J. W. Willis, Foundations of Qualitative Research - Interpretive and Critical Approaches, California: Sage Publications, Inc., 2007.

[33] R. K. Yin, Case Study Research and Applications - Design and Methods, Los Angeles: SAGE Publications, Inc., 2018.

[34] E. B. Dent, "Challenging “Resistance to Change”," *THE JOURNAL OF APPLIED BEHAVIORAL SCIENCE,,* vol. 35, no. 1, pp. 25-41, 1999.

[35] M. Sein, O. Henfridsson, S. Purao, M. Rossi and R. Lindgren, "Action Design Research," *MIS Quarterly,* vol. 35, no. 1, pp. 37-56, 2011.

[36] A. L. J. Petersson, "Applying action design research (ADR) to develop concept generation and selection methods," *Elsevier,* p. 222 – 227, 2016.

[37] I. Pappel, T. Gelashvili and I. Pappel, *Maturity Model for Automatization of Service Provision and Decision-making Processes in Municipalities,* In Progress: Springer, 2021. Forthcoming

[38] K. Vaher, *Next Generation Government Architecture,* Tallinn: Republic of Estonia GCIO Office, 2020.

Appendix 1 - Mindmap of Interview Outcome

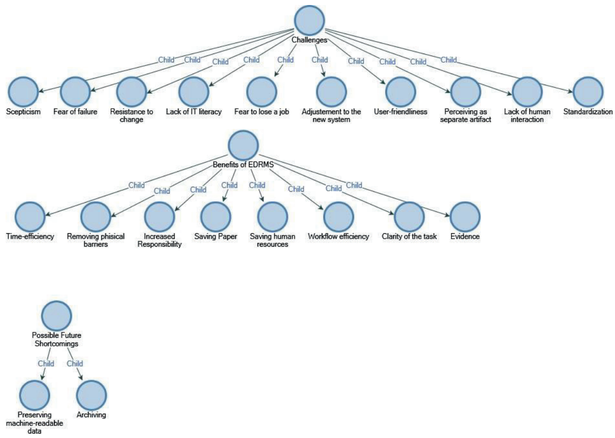

Fig. 4. Mindmap

Appendix 3

Publication III

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Navigating the AI revolution: challenges and opportunities for integrating emerging technologies into knowledge management systems. Systematic literature review

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Introduction: Artificial intelligence (AI) is transforming organizational knowledge management (KM) by leveraging techniques such as machine learning, neural networks, and fuzzy logic to enhance knowledge discovery, capture, storage, and sharing. While this shift promises improved efficiency and personalization, it also poses challenges related to data quality, employee resistance, and alignment with existing workflows.

Methods: This study presents a systematic literature review (SLR) of 40 peer-reviewed publications focused on the integration of AI in KM. The review follows PRISMA guidelines and includes thematic coding to identify patterns, critical success factors, and knowledge gaps.

Results: Findings indicate that successful AI-enabled KM depends on strong leadership commitment, adaptable governance structures, and context-sensitive technology selection. AI's role is evolving from supporting routine tasks to enabling dynamic, real-time knowledge flows. The review also highlights a critical need to balance automation with human oversight.

Discussion: Key gaps were identified in understanding cost–benefit trade-offs, ethical implications, and governance mechanisms. These insights suggest directions for future research focused on practical, accountable, and empirically validated KM strategies. As part of an ongoing research project, the synthesized findings will inform the design of future empirical studies. The evidence suggests that, when strategically implemented, AI can serve as a competitive enabler in knowledge-driven organizations.

KEYWORDS

artificial intelligence, emerging technologies, knowledge management, organizational performance, digital transformation

1 Introduction

Knowledge Management (KM) has long been recognized as critical to organizational performance and long-term competitiveness (Harrington et al., 2019; Manesh et al., 2020; Foli, 2022). Contemporary KM extends beyond intra-firm activities to encompass regional and multi-stakeholder ecosystems, fostering innovation across diverse sectors (Weck et al., 2022; Muzzio and Gama, 2024). Recent research has expanded its focus to include organizations of various sizes, external knowledge flows, and broader geographic contexts (Shekhar and Valeri, 2023; Castagna et al., 2020).

Knowledge Management Systems (KMS) form the technological and organizational infrastructure for capturing, storing, sharing, and applying knowledge. In the digital era, KMS convert dispersed data into actionable insights, enabling collaboration and innovation (Alavi and Leidner, 2001; Davenport and Prusak, 1998). The integration of artificial intelligence (AI), big data analytics, and cloud computing has further advanced these capabilities, helping organizations manage complexity and pursue strategic objectives (Jarrahi et al., 2023; Georgiev and Antonova, 2024). Nevertheless, many firms still struggle to realize the full potential of these technologies, highlighting a persistent research and practice gap (Herrero et al., 2016; Kaplan and Haenlein, 2019).

The rise of Industry 4.0—the digital transformation of industrial processes—has further increased interest in the intersection of KM and emerging technologies (Li et al., 2019; Babkin et al., 2019). To remain competitive, organizations increasingly focus on knowledge lifecycle management, digital infrastructure, and human-centered strategies (Gupta et al., 2022).

AI is playing a growing role in optimizing business processes and generating data-driven insights (Beheshti et al., 2021; Esposito et al., 2024). Applications such as data mining, predictive analytics, and supply chain optimization illustrate this trend (Mahmood, 2019; Khan and Vorley, 2017; Hashem et al., 2024; Torres-Dela Cruz et al., 2019). However, the broader strategic and organizational implications of AI integration into KM remain underexplored.

While several systematic reviews have examined IT and AI impacts on KM (Al Mansoori et al., 2021; Ofosu-Ampong, 2024; Samuels, 2025), gaps remain regarding the specific technologies involved, their organizational consequences, and the implementation barriers encountered. This review seeks to address these gaps by synthesizing current literature on the integration of AI and emerging technologies into KMS, assessing their impact on KM practices, and identifying challenges and strategies for effective implementation.

Accordingly, this study is guided by the following research questions:

- RQ1: How do AI and emerging technologies impact organizational KM practices?
- RQ2: What are the primary challenges in updating existing KM processes to match current trends?
- RQ3: How can AI and emerging technologies be leveraged to address these challenges?

To answer these questions, a Systematic Literature Review (SLR) methodology was employed, following established guidelines to ensure methodological rigor and minimize bias (Kitchenham, 2004). The SLR enables a structured synthesis of key trends, insights, and gaps across diverse scholarly sources.

The article is structured as follows: Section 2 reviews KM development and identifies key research gaps; Section 3 outlines the methodology; Section 4 presents the findings and discussion; and Section 5 concludes with limitations and directions for future research.

2 State of the art

This chapter reviews key developments in knowledge management research. It traces the field's evolution from foundational concepts through the impacts of digitalization and AI, ending with a summary of literature gaps that motivate this study.

2.1 Early discussions and principles of KM implementation

Organizational performance has long been a central focus in management research, emphasizing leadership (Bass and Riggio, 2005), organizational culture (Cameron and Quinn, 2011), and innovation adoption (Damanpour, 1998; Rogers, 2003; Pacheco and Paul, 2023). Knowledge management emerged as a critical factor for enhancing performance by managing information, knowledge, and experience to extend organizational capabilities (Nerney, 1997; Skyrme and Amidon, 1997; Mayo, 1998; Bassi, 1997).

Early KM research identified key organizational and technical challenges in implementation (Lloyd, 1996; Davenport, 1997), emphasizing the importance of integrating human networks with technology. Davenport et al. (1998) highlighted several pillars of successful KM: operational foundations such as infrastructure and flexible knowledge structures; cultural facilitators including a knowledge-friendly environment and motivational practices; optimized knowledge flow through multiple transfer channels supported by leadership; and economic integration. Bennett and Gabriel (1999) further linked formal KM procedures to increased innovation, adaptability, and improved access to knowledge.

From the 2000s onward, technological advances inspired research into digitalization's impact on enterprise knowledge networks and lifecycle management (Vladova et al., 2018; Babkin et al., 2019). Open innovation perspectives expanded KM systems to incorporate emerging technologies like the Internet of Things (Santoro et al., 2018) and frameworks for organizational knowledge visualization were also proposed (Smuts and Scholtz, 2020). This progression reflects a shift from foundational KM concepts toward integrating innovation, digitalization, and organizational dynamics.

2.2 Digitalization and human-centric approaches in modern KM research

During this time, knowledge management has developed in two main ways: advances in technology and a focus on people. Digital tools have changed organizational operations by enabling quicker decisions and supporting new ideas (Radavičius and Tvaronavičienė, 2022; Vladova et al., 2018). Using digital systems for knowledge management helps make workflows more efficient and can improve overall organizational results (Schäffer et al., 2021).

At the same time, human-centered approaches focus on the role of people, social interactions, and organizational culture in creating, sharing, and using knowledge. Supporting ongoing learning that meets different employee needs is key to effective knowledge management (Viterouli et al., 2023; Castellani et al., 2021; McIver and Lepisto, 2017). Encouraging active knowledge sharing based on teamwork and human judgment plays an important part in fostering innovation (Muzzio and Gama, 2024). Social and relational aspects of knowledge transfer—which cannot be fully captured by digital tools—remain essential to success (Nguyen et al., 2023; Retkowsky et al., 2024). Sharing tacit knowledge through face-to-face interaction and communities of practice continues to support learning and innovation within organizations (Kamasak et al., 2017; Obembe and Obembe, 2020).

Effective knowledge management combines technology with attention to people's experience and insights. Digital tools help organize and share information efficiently, while human involvement is essential to capture the knowledge that cannot be easily documented. Balancing these aspects is important as organizations adopt new technologies without losing expertise held by their employees (Malik et al., 2021).

2.3 Advancements in AI-driven knowledge management

Recent advances in artificial intelligence have led organizations to adopt more sophisticated technologies in knowledge management. Data mining methods—such as neural networks and decision trees—are now used to reveal hidden knowledge, improve forecasting, and support decision-making (Bandaru et al., 2017; Tsai, 2013; Natek and Zwilling, 2014). AI also enhances knowledge transfer and sharing, and contributes to building expert systems through machine learning and semantic technologies (Jia et al., 2012; Abubakar et al., 2019; Alonso et al., 2012; López-Cuadrado et al., 2012; Herrero et al., 2016).

Research has expanded from focusing solely on organizational performance to also considering wider societal issues. Organizations increasingly acknowledge how digital knowledge management tools affect employee well-being, job performance, and access to knowledge (Babkin et al., 2019; Ferraris et al., 2017; Castellani et al., 2021). Recent studies examine human factors like trust, attitudes toward information technology, interpersonal behaviors, and leadership's influence on knowledge sharing (Castellani et al., 2021). Additionally, research investigates how technology adoption impacts mental health and well-being, with organizational support, such as training and leadership, playing a moderating role (Nguyen et al., 2023). Sustainability has also become an important topic, with knowledge management framed as a strategy to secure and sustain competitive advantage (Gupta et al., 2022).

2.4 Emerging trends in knowledge management research

The evolution of knowledge management is reflected in academic research, with literature reviews adapting to new developments. Studies such as Inkinen (2016) and Radavičius and Tvaronavičienė (2022) have focused on KM digitalization, while others examine knowledge creation, transfer, and digital innovation (Smuts and Scholtz, 2020; Di Vaio et al., 2021). Research has also highlighted links between KM, digital transformation, and Industry 4.0 (De Bem Machado et al., 2022). Recent reviews have broadened their scope beyond technology to include human-centered topics, such as cognitive support (Li et al., 2019) and adult learning theories within organizational culture (Viterouli et al., 2023).

Despite the extensive discussion on KM digitalization, integrating AI into traditional KM is still underexplored. Some scholars propose AI-focused KM frameworks that combine human and technological elements (Fteimi and Hopf, 2021), while others investigate KM challenges in remote and hybrid work environments (Taherdoost and Madanchian, 2023). However, research remains limited, and recent systematic literature reviews highlight the need for further research (Al Mansoori et al., 2021; Ofosu-Ampong, 2024).

Many existing reviews examine these topics from a narrow angle, often relying on a single database. For example, Inkinen (2016) and Radavičius and Tvaronavičienė (2022) used Scopus, Li et al. (2019) used Web of Science, and Shekhar and Valeri (2023) and Al Mansoori et al. (2021) relied on ScienceDirect. While these databases are reputable, focusing on only one may miss relevant studies found elsewhere.

This review aims to provide a thorough analysis of themes, concepts, and findings across the KM field by searching multiple databases and applying no restrictions on time, publication type, or source. This approach seeks to reduce the risk of overlooking important research.

2.5 Theoretical foundations of knowledge management

The empirical and technological advances discussed above are grounded in established theoretical frameworks that explain how knowledge is created, shared, and utilized within organizations. Understanding these foundational models is essential for interpreting the evolution of KM practices and the impact of emerging technologies.

The evolution of knowledge management has been shaped by several influential theories. The SECI model (Nonaka and Takeuchi, 1995) conceptualizes knowledge creation as a dynamic process involving socialization, externalization, combination, and internalization, emphasizing the interplay between tacit and explicit knowledge. The Dynamic Capabilities Framework (Teece, 2007) highlights an organization's ability to sense, seize, and reconfigure resources in response to change, positioning knowledge as a key dynamic asset. Furthermore, Distributed Cognition (Hutchins, 1995) and Organizational Learning (Argyris and Schön, 1978) focus from individual or centralized knowledge to systems where knowledge is constructed and enacted through ongoing interaction among people and technologies. These frameworks provide a lens for analyzing how successive technological paradigms in KM (from expert systems to generative AI) reflect changing assumptions about how knowledge is created, shared, and leveraged in organizations.

3 Methodological applications

This systematic literature review (SLR) follows established guidelines from Kitchenham (2004) and Webster and Watson (2002), ensuring transparency, rigor, and reproducibility. The review process included: (1) formulation of research questions, (2) development of a comprehensive search strategy, (3) application of predefined inclusion and exclusion criteria, (4) data extraction, and (5) thematic synthesis. The Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) framework (Liberati et al., 2009) guided the reporting of the study selection process.

3.1 Search strategy and resources

Search terms were developed in direct alignment with the research questions and study objectives. To ensure comprehensive

TABLE 1 Inclusion and exclusion criteria.

Inclusion criteria	Exclusion criteria
Relevance: Studies focusing on the relationship between KM and organizational performance.	Relevance: Studies not directly relevant to the intersection of KM, AI, and emerging technologies in organizational settings.
Impact on knowledge processes: Studies addressing the impact of digitalization, AI, and emerging technologies on KM practices.	Focus: Studies focusing solely on the public sector or government organizations.
Challenges and strategies: Studies examining the challenges and strategies for updating existing KM processes to align with current trends.	Specificity: Studies do not address the specific research questions outlined in the Introduction section.
Variability across industries/sizes: Studies exploring variations across industries and organizational sizes.	Non-English literature: Non-English studies.
Language: Studies published in English language.	

coverage, the search strategy incorporated a broad set of keywords and their commonly used synonyms, including variations in terminology used across disciplines. This approach was designed to reduce the risk of omitting relevant studies that may use different descriptors for knowledge management, artificial intelligence, or related emerging technologies. The search string was refined through an iterative process involving preliminary testing and adjustment, ensuring both sensitivity and specificity in capturing pertinent literature. Boolean operators (AND, OR, NOT) were applied to structure the search logic and to connect key concepts effectively. The final search string used was: ("knowledge management technology" OR "knowledge management tools" OR "knowledge management processes") AND ("intelligent systems" OR "emerging technologies" OR "digitalization" OR "artificial intelligence") AND "organization" AND ("adoption" OR "drivers" OR "strategies" OR "challenges" OR "success factors") AND "innovation" NOT ("public sector" OR "government").

To maximize coverage and minimize bias, we searched four major academic databases: Scopus, Web of Science, ScienceDirect, and Google Scholar. No restrictions were applied regarding publication date, type, or language. Reference lists of selected papers were manually screened to capture additional relevant studies. Where direct export was not possible (e.g., Google Scholar), bibliographic details were manually entered into a master spreadsheet.

3.2 Study selection

The PICOS framework, which is widely recognized for structuring eligibility criteria in systematic reviews (Higgins and Green, 2011; Schardt et al., 2007), informed inclusion and exclusion criteria:

- Population: Organizations using or implementing KM systems
- Intervention: AI, digitalization, or emerging technologies applied to KM
- Comparison: Traditional KM or alternate technological approaches (where applicable)
- Outcomes: Impact on KM processes, organizational challenges, and strategic responses
- Study Design: Empirical studies, SLRs, and theoretical papers published in peer-reviewed journals or conferences

Study selection proceeded in two phases: (1) screening of titles and abstracts, and (2) full-text assessment. Inclusion and exclusion criteria are summarized in Table 1.

3.3 Data analysis and quality assessment

A total of 1,568 records were identified through searches in Scopus (266), Web of Science (21), Google Scholar (1100), ScienceDirect (169), and additional manual searches (12). After removing duplicates, identified based on matching titles, authors, and publication years, 1,555 records remained. The screening process involved two stages: initial title and abstract screening, which reduced the pool to 337 records, followed by a full-text review based on predefined eligibility criteria. Ultimately, 40 studies are included in the review. The detailed selection process is illustrated in the PRISMA flow diagram (Figure 1).

The selected articles were subjected to thematic analysis following the approach outlined by Nowell et al. (2017). During the coding phase, key concepts and findings relevant to the research questions were identified and organized into categories. These categories were then synthesized into overarching themes reflecting the impact of AI and emerging technologies on knowledge management practices, associated challenges, and strategic responses. The inclusion of studies from diverse geographic regions, publication years, and disciplinary perspectives helped mitigate potential biases related to narrow focus or source reliance.

Study quality was assessed using a customized matrix based on the CASP checklists (Critical Appraisal Skills Programme, 2018) and adapted for mixed-methods studies. The matrix included seven criteria as presented on the Table 2, each scored on a 0–2 scale (2 = fully met; 1 = partially met; 0 = not met). Studies were classified as high (scores of 12–14), medium (8–11), or low quality (0–7), using thresholds informed by CASP-based scoring approaches and the Mixed Methods Appraisal Tool (MMAT) framework (Hong et al., 2019).

Quality assessment was conducted in accordance with the predefined criteria outlined in the quality assessment matrix. Based on these criteria, 80% of the studies were rated as high quality, 15% as medium quality, and 5% as low quality (for quality scores for each study see Supplementary Appendix B). The final selection of studies included in the review was reached by consensus among all authors.

Studies rated as relatively low quality (overall score of 7) were early-stage conceptual papers. While these studies are vital for understanding the development of the field, the primary analysis and outcomes presented in the following chapters are based on the high-quality publications.

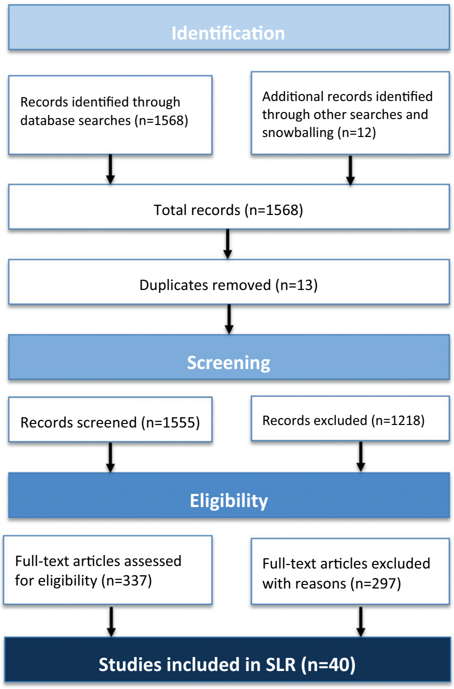

FIGURE 1
PRISMA flow diagram illustrating the study selection process.

TABLE 2 Quality assessment criteria.

Criterion	Description
1. Clarity of aims	Are the research objectives clearly stated and aligned with the study design?
2. Methodology appropriateness	Is the methodology (qual/quant/mixed) justified and suitable for the aims?
3. Data collection transparency	Are data collection methods described in sufficient detail?
4. Analysis rigor	Is the analysis process transparent, systematic, and reproducible?
5. Bias consideration	Does the study address potential biases or limitations?
6. Relevance to SLR focus	How directly does the study address AI/emerging tech in KM?
7. Technological context	Does the study adequately describe the AI/emerging technology used (e.g., NLP, machine learning)?

3.4 Methodological limitations

This review only includes peer-reviewed, published literature in English, which may introduce publication and language bias. Although multiple databases were searched, some relevant studies may have been missed due to terminology variation or manual data entry errors.

The search string was designed to capture a broad spectrum of relevant studies. However, its complexity may have inadvertently excluded articles using alternative or less common terms. Balancing comprehensiveness and precision in search strategies remains an inherent challenge in systematic reviews.

Screening, coding, and thematic analysis involve elements of subjective judgment. While clear criteria and established methods were applied to minimize bias, some degree of interpretive subjectivity is unavoidable. The heterogeneity in study designs, contexts, and methodologies among the included articles may also influence the comparability and generalizability of the findings.

4 Results and discussion

This chapter addresses research questions, with each sub-section focused on a specific question. Table 3 provides a summary of the main technology categories and their contributions to knowledge management, based on the 40 studies included in this review (for detailed study-level information see Supplementary Appendix A). Following the summary, a more in-depth analysis of the publications is presented, exploring each AI or emerging technology and its associated research area within knowledge management.

4.1 AI and emerging technologies impact on organizational KM practices

This sub-section answers the first research question by analyzing how artificial intelligence and emerging technologies are changing core knowledge management functions. To explore this transformation of how knowledge is created, distributed, and applied within organizations, the section is divided into thematic sub-categories, each focused on a distinct technological domain.

4.1.1 Data science and analytics

The rapid growth of organizational data presents both strategic opportunities and operational challenges. Big Data Analytics (BDA) provides powerful tools to process this data, but without mechanisms to convert it into actionable knowledge, its strategic value remains limited (Rialti et al., 2020). Knowledge management serves as a critical bridge between data and decision-making, ensuring that insights translate into informed organizational decisions. Artificial intelligence and machine learning are central to this process. Automated data mining and real-time extraction tools support the generation of knowledge in action. For example, Finogeev et al. (2017) demonstrate how AI, integrated with distributed computing infrastructures such as cloud and fog systems, processes sensor data in real time to support operational decisions. Likewise, Ristoski and Paulheim (2016) show how Semantic Web technologies connect heterogeneous datasets to create integrated, context-aware knowledge systems.

Data science reshapes each phase of the KM lifecycle. In creation, machine learning uncovers patterns that would be difficult for humans to detect (Nguyen et al., 2014). For storage and retrieval, semantic technologies and classification algorithms enhance organization and accessibility. Knowledge sharing is becoming personalized through analytics that tailor content to user needs,

TABLE 3 Summary of technology categories and their contributions to knowledge management.

Technology/ category	Representative studies (Year)	Study type(s)	Main KM process(es)	Key insights
Generative AI and AI	Retkowsky et al. (2024), Stollberg et al. (2004), Iaia et al. (2024), Stohr et al. (2024), Safadi and Watson (2023), Leoni et al. (2022), Schäffer et al. (2021), and Jia et al. (2012)	Empirical, conceptual, technical	Knowledge transfer, sharing, creation, retention, collaboration, structuring	AI and generative models (e.g., ChatGPT) transform knowledge work, collaboration, and sharing, frameworks and empirical studies highlight risks, mechanisms, and implementation guidance.
Neural networks and hybrid AI	Liebowitz (2001), Kawonga et al. (2023), Sanders et al. (2019), Herrero et al. (2016), and Miradi et al. (2009)	Empirical, conceptual, technical	Knowledge capture, discovery, diagnosis, integration, competitiveness	Neural networks and hybrid AI support knowledge discovery, scaling, and decision support across industries.
Fuzzy logic and machine learning (ML)	Yadegari and Mohammadi (2024), Grzeszczyk (2021), Anshari et al. (2023), and Vladova et al. (2018)	Empirical, conceptual, technical	KM system modeling, collecting, sharing, discovery	Fuzzy logic and ML enhance KM system modeling, knowledge collection, and automation
Big data and data mining	Shaqrah and Alzighaibi (2023), Abualoush (2025), Sumbal et al. (2021), Thomas and Chopra (2020), Safhi et al. (2019), Khan and Vorley (2017), Depeige and Doyencourt (2015), Gullo (2015), Mahmood (2019), Natek and Zwilling (2014), Nguyen et al. (2014), and Alonso et al. (2012)	Empirical, conceptual, technical	Acquisition, sharing, discovery, application, workflow optimization	Big data and data mining drive knowledge acquisition, discovery, and application, especially in healthcare, and education.
Other digital technologies	Wielgórka (2023), Kane (2017), Bandaru et al. (2017), Ristoski and Paulheim (2016), Bianchi et al. (2016), Braun et al. (2016), Santoro et al. (2018), Pisoni et al. (2024), and (Leoni et al., 2024)	Empirical, conceptual	KM capacity, innovation, collaboration, knowledge integration	Internet of Thing (IoT), cloud, social media, and analytics tools foster innovation, collaboration, and digital knowledge integration in diverse sectors.

while application is supported by dashboards and predictive models embedded directly into workflows. More than enhancing each KM phase, BDA reconfigures the entire process. Rather than a linear sequence—create, store, share, apply—KM becomes a dynamic feedback loop. Knowledge is treated as provisional, continuously updated based on new data. This recursive model allows past applications to inform future knowledge through real-time monitoring and learning mechanisms.

One forward-looking approach is Knowledge-Driven Optimization (KDO), which uses knowledge generated during processes to improve future performance (Bandaru et al., 2017). This supports adaptive, self-correcting systems. It reflects a shift from knowledge-as-asset—a static, codified resource—to knowledge-as-flow, where value lies in relevance and responsiveness. In this flow-based KM model, knowledge is continuously generated, revised, and embedded in real-time interactions among systems, algorithms, and decision environments.

This shift challenges traditional frameworks such as Nonaka and Takeuchi (1995) SECI model, which emphasizes human-centric knowledge creation, particularly through socialization and tacit knowledge exchange. In contrast, flow-based KM repositions the human actor as peripheral, privileging algorithmic pattern recognition and system-level feedback. While SECI views knowledge as emerging through reflection and conversion, flow-based KM treats it as emergent, iterative, and embedded in automated systems.

This transformation also introduces significant governance challenges. When knowledge is continuously evolving, how can organizations ensure its trustworthiness, accuracy, and accountability? Algorithmic decision-making often obscures the origin and rationale behind knowledge outputs, raising both technical and epistemological concerns. Consequently, KM must now incorporate real-time processes for curating, validating, and explaining knowledge.

AI, data science, and analytics extend beyond operational functions to challenge traditional assumptions about knowledge itself. Is knowledge objective and stable, or inherently dynamic and distributed? While these questions warrant further exploration, these technologies clearly elevate knowledge as a strategic organizational asset. They facilitate real-time insights, tailor knowledge flows to individual needs, and embed intelligence directly into processes, while simultaneously demanding new approaches to knowledge governance and understanding.

4.1.2 Computational intelligence

Computational Intelligence (CI), which includes neural networks, fuzzy logic, and evolutionary algorithms, supports knowledge management by allowing systems to learn from data, adjust to new information, and function in uncertain conditions. In contrast to traditional AI approaches that rely on predefined rules, CI is better equipped to address the complexity and ambiguity often present in organizational knowledge systems.

A key contribution of Computational Intelligence in knowledge management is its alignment with the Dynamic Capabilities Framework. This framework outlines three core capabilities necessary for organizations operating in uncertain environments: sensing opportunities and threats, learning from experience, and responding effectively (Teece, 2007). CI techniques support sensing by analyzing diverse and incomplete data to identify relevant patterns; they enable learning through the iterative refinement of knowledge models; and they support response by integrating decision-making tools into organizational processes. In this way, CI helps shift KM from a primarily static repository function toward a more adaptive, real-time process of organizational learning and informed action.

Herrero et al. (2016) illustrate this shift with their Hybrid Artificial Intelligence System (HAIS), which identifies KM weaknesses and generates adaptive insights, supporting flexible and ongoing KM assessment. Similarly, Delen et al. (2013) emphasize how CI enhances knowledge utilization by learning from user behavior to recommend contextually relevant content, ensuring timely and effective application within daily decision-making.

CI supports the integration of fragmented and tacit knowledge across organizational functions. For example, Grzeszczyk (2021) presents a fuzzy logic framework for processing unstructured documents, illustrating how CI can enable automated knowledge extraction and targeted dissemination. Such approaches support more adaptive and flexible knowledge management systems, moving beyond static repositories and enabling real-time responsiveness to evolving informational needs.

Collectively, these developments suggest that CI extends the Dynamic Capabilities Framework by making knowledge itself a continuously evolving capability—one that is sensed, learned, and enacted in real time through intelligent systems embedded within organizational processes. However, the adoption of CI in KM presents challenges. Issues such as algorithmic interpretability, bias in training data, data quality, and lack of transparency can undermine trust and accountability. These risks highlight the need for governance structures to ensure ethical, explainable, and responsible CI use in KM, balancing technological potential with critical oversight.

4.1.3 From expert systems to AI assistants

The development of artificial intelligence in knowledge management reflects a shift from static, rule-based systems toward more flexible and adaptive approaches. Early KM technologies operated on fixed logic and emphasized codified knowledge, whereas current AI-enabled systems support more personalized access, the use of tacit knowledge, and decisions that respond to contextual nuances. This section introduces a four-stage framework that outlines how successive waves of AI technologies have shaped and redefined KM practices over time.

4.1.3.1 Stage 1. Rule-based expert systems (1980s–1990s)

Expert systems relied on explicitly coded "if–then" rules to simulate expert-level decision-making within defined domains (Liebowitz, 2001). These systems supported basic automation and were effective in environments where knowledge could be clearly articulated and structured. However, they lacked adaptability and were unable to deal with uncertainty, change, or the nuanced, tacit knowledge that characterizes many organizational processes. As a result, their applicability remained narrow and domain-specific.

4.1.3.2 Stage 2. Ontology-driven and NLP-enabled KM (2000s)

The early 2000s introduced systems that integrated ontologies and natural language processing to enable more sophisticated, user-friendly knowledge retrieval. Platforms such as h-TechSight (Stollberg et al., 2004) reflected a move toward semantic KM, improving flexibility in categorizing and accessing knowledge assets. While these systems enhanced the organization and discoverability of knowledge, they still relied on largely static architectures with limited capacity for real-time learning or adaptation.

4.1.3.3 Stage 3. Predictive and adaptive KM systems (2010s)

Advancements in machine learning, big data analytics, and user modeling enabled KM platforms to become more predictive and adaptive. These systems could analyze behavior patterns, infer user intent, and deliver personalized knowledge recommendations. As Delen et al. (2013) noted, even sophisticated infrastructures fail if knowledge is not usable. Predictive systems helped overcome this by contextualizing content and enhancing knowledge applicability. The adaptive nature of these systems made them increasingly valuable in dynamic environments, where relevance and timeliness are essential.

4.1.3.4 Stage 4. Interactive and generative KM systems (2020s)

The current generation of KM technologies is characterized by real-time, interactive platforms operated by conversational and generative AI. Tools such as ChatGPT and IBM Watson engage users in natural language dialog, facilitate the extraction of tacit insights, and support collaborative knowledge creation (Retkowsky et al., 2024). These systems embed knowledge directly into workflows, reduce users' cognitive load, and promote sensemaking across organizational contexts. Their capacity to learn from interaction and adapt to context reflects a major shift toward human–AI co-production of knowledge.

As outlined in the State of the Art (Section 2.5), these technological shifts reflect evolving theoretical perspectives in KM. Table 4 presents a summary of each stage's technological paradigm, knowledge focus, and organizational role, building on these foundational frameworks. This theoretical progression highlights how the dominant knowledge focus and organizational impact have evolved alongside underlying KM theories.

4.2 Primary challenges in updating existing KM processes

This next part answers second research question by examining the challenges preventing organizations from effectively updating their KM processes in response to emerging AI technologies. Instead of treating these challenges as separate issues, the analysis highlights how technical constraints, organizational resistance, and poor strategic alignment often interact and reinforce one another.

4.2.1 Data quality and integration

The increase in organizational data volume and diversity places considerable pressure on KM systems and exposes critical

TABLE 4 Evolution of AI in knowledge management: technological and theoretical shifts.

Period	Technological paradigm	Knowledge focus	Organizational impact	Theoretical orientation
1980s–1990s	Expert systems (Rule-based KM)	Explicit, codified knowledge	Task automation, decision support	Codified knowledge, stability, SECI
2000s	Ontology and NLP (Semantic KM)	Metadata, structured texts	Structured access, retrieval improvement	SECI, early dynamic capabilities
2010s	Machine learning and predictive analytics (Adaptive KM)	Tacit and contextual knowledge	Adaptive reasoning, real-time feedback	Dynamic capabilities, organizational learning
2020s	Conversational AI and generative models (Embedded KM)	Cognitive processes, interaction, tacit and explicit knowledge	Human–AI collaboration, embedded knowledge assistance	Dynamic capabilities, organizational learning, distributed cognition

vulnerabilities in data quality, consistency, and integration. While heterogeneous data sources ranging from structured databases to unstructured social media content offer rich knowledge potential, they simultaneously complicate seamless knowledge flow (Kawonga et al., 2023; Ristoski and Paulheim, 2016). This fragmentation complicates the process of turning raw data into practical knowledge, increasing the risk of inefficiency and poor strategic coordination. Therefore, the growth in data volume might become a liability instead of an asset. As data volumes increase, it often becomes more difficult to maintain clarity and practical usability, which can hinder effective interpretation and decision-making. This highlights the importance of determining whether there is a practical limit to the amount of data that can meaningfully contribute to insight before it leads to information overload or misalignment.

Legacy IT systems often reinforce data silos, where knowledge remains locked within departments or platforms, making it difficult to access or reuse across the organization (Kawonga et al., 2023). This fragmentation limits the ability of AI-driven KM tools to deliver value, as these tools depend on integrated, high-quality data to function effectively. Efforts to improve interoperability, such as using Semantic Web technologies like Linked Open Data (LOD), offer potential solutions, but their practical application faces significant barriers. In many cases, organizations rely too heavily on a few central knowledge bases, limiting coverage and relevance. Additionally, inconsistent standards and uneven adoption across systems reduce the benefits of these technologies (Ristoski and Paulheim, 2016). This reflects on a critical challenge in knowledge management when new tools are often introduced without fully addressing the constraints of the existing IT environment. It can leading to partial solutions that fail to scale and result in an ongoing tension between technological ambition and infrastructural capacity.

The high speed and diverse formats of big data present challenges for maintaining quality throughout the knowledge discovery process (Safhi et al., 2019). In practice, organizations often struggle to validate, clean, and standardize incoming data quickly enough for it to be useful. Choosing the right analytics tools is not just a technical matter, it directly affects how well knowledge can be extracted and applied. Poorly chosen frameworks or weak sensor data management can lead to processing errors, misinterpretations, and unreliable outputs (Kawonga et al., 2023; Finogeev et al., 2017). If these issues are not resolved, they affect the entire knowledge management system by reducing the reliability and relevance of the insights produced. In this context, data quality and integration are not just technical concerns but directly influence the trustworthiness and timeliness of decisions.

4.2.2 Organizational and human factors

Technological upgrades to KM systems often encounter friction coming from human and organizational dynamics. Resistance toward AI-based tools is often caused by fears of job displacement and skepticism toward automation which reveals deeper cultural and psychological barriers to change (Herrero et al., 2016; Lei, 2022). This resistance slows adoption and hinders organizations from successfully applying KM to support learning, knowledge exchange, and innovation.

A misalignment between an organization's knowledge management maturity and the complexity of new technologies can further complicate the adoption process (Herrero et al., 2016). Without a clear assessment of organizational readiness and a tailored change management approach, implementations are more likely to underperform or fail. Gaps in digital literacy and limited training opportunities may hinder user engagement and reduce the effective use of new technologies, adding to these challenges (Miradi et al., 2009; Obembe and Obembe, 2020).

Tacit knowledge capture which is embedded in individual experience and to codify it remains one of the most persistent challenges in knowledge management. AI-enabled tools, such as natural language processing systems or conversational agent, offer potential solutions, but their success depends heavily on user trust, participation, and alignment with organizational culture (Obembe and Obembe, 2020). One-size-fits-all KM strategies often overlook sector-specific and cultural variations, leading to uneven adoption and ineffective knowledge sharing (Delen et al., 2013).

For organizations aiming to improve their readiness for knowledge management initiatives, it is important to evaluate cultural absorption capacity alongside technological infrastructure and financial resources. Human factors, such as attitudes toward change, openness to collaboration, and engagement with new systems, should not be viewed merely as barriers. Instead, they represent key enablers that can significantly influence the long-term effectiveness and adaptability of KM efforts.

4.2.3 Organizational size and resource constraints

Organizational size, its structural capacity and resource availability influences the implementation and outcomes of knowledge management initiatives. Larger organizations, including multinational corporations (MNCs), often operate with complex hierarchies, departmental segmentation, and legacy information systems that inhibit efficient knowledge flow (Harrington et al., 2019). In such contexts, KM interventions typically require formal governance structures and comprehensive technical frameworks to ensure integration across divisions and geographies. In contrast, small and medium-sized enterprises (SMEs) may benefit from flatter organizational structures and more flexible decision-making processes, which can facilitate the adoption of KM practices (Kianto et al., 2018; Harrington et al., 2019). However, SMEs frequently face limitations in digital infrastructure, technical expertise, and financial capacity, which restrict their ability to implement and sustain advanced AI-based KM systems as well as their long-term maintenance and user-training (Wielgórka, 2023).

Given these differences, KM strategies must be adapted to organizational scale and resource profiles. In larger firms, the emphasis lies in system interoperability, data governance, and cross-functional alignment. In smaller firms, effective KM requires low-cost, user-friendly tools that do not exceed existing operational capacity. A uniform approach to AI integration across organizations of varying size is therefore unlikely to produce equitable outcomes.

4.2.4 Governance and ethical concerns

As AI and big data become more central to knowledge management systems, questions of governance and ethics become core concerns. One of the main challenges is the lack of transparency in how AI systems make decisions. When algorithms produce results that users cannot explain or understand, it becomes difficult to trust the system (Safadi and Watson, 2023). Without clear rules for how data is used, and decisions are made, people's resistance in adopting increases which in the end limits tools' usefulness in knowledge management.

In addition to trust, legal and ethical risks must be considered. Organizations are responsible for protecting sensitive data, complying with regulations, and ensuring that data is not misused (Schäffer et al., 2021; Leoni et al., 2022). A failure to do so can result in more than legal fines, it can lead to reputational damage, employee resistance, or even financial losses. Strong governance structures must therefore go beyond compliance and promote a shared understanding of ethical data use across the organization.

What complicates these challenges further is the rapid pace of technological innovation. Emerging tools frequently introduce capabilities that existing governance models were not designed to address. In many cases, ethical shortcomings arise not from deliberate misconduct but from outdated policies or ambiguous accountability structures. This emphasizes a critical issue: whether static governance frameworks remain adequate in contexts where technologies evolve continuously. There is a growing need to consider whether governance mechanisms themselves must become more dynamic and responsive, capable of evolving in parallel with the tools and risks they aim to regulate.

If governance is to become adaptive, it raises questions regarding the assignment of responsibility. Determining who is accountable for updating governance frameworks and ensuring the ethical and transparent use of new technologies is essential. In the absence of clearly defined roles and processes, oversight risks becoming fragmented, inconsistent, or altogether overlooked. Thus, governance should not be viewed merely as a compliance function, but as a continuous, distributed responsibility that shapes how knowledge management systems are implemented, trusted, and sustained within organizational contexts.

4.2.5 Technological complexity, scalability and integrating KM approaches

Integrating AI and big data tools into knowledge management is rarely straightforward. Many existing KM systems were built around traditional methods focused on storing and retrieving explicit knowledge, rather than handling the volume and speed of new data sources or supporting AI-driven analysis (Rialti et al., 2020; Sumbal et al., 2021). Updating these systems involves complex technical choices about architecture, data infrastructure, and ongoing maintenance that directly affect how reliable and usable the KM system is day-to-day (Kawonga et al., 2023).

A common issue is that organizations often treat traditional KM processes and emerging AI-driven methods as separate, which limits their ability to combine the strengths of both (Rialti et al., 2020; Sumbal et al., 2021). Traditional KM usually follows linear steps of capturing, storing, and sharing explicit knowledge while big data analytics works through iterative, exploratory processes aimed at discovering patterns and creating knowledge in real time (Sumbal et al., 2021). This difference means organizations need integrative frameworks that balance the steady, controlled flow of traditional KM with the flexible, dynamic nature of AI-based knowledge discovery.

The ability to implement and scale these complex solutions varies widely. Large organizations typically have the technical expertise and resources to adapt and expand AI-enhanced KM systems. Smaller or less digitally mature organizations often lack these resources, leading to a "scalability gap" where some firms move forward while others lag behind, potentially increasing inequality in knowledge capabilities for (Shaqrah and Alzighaibi, 2023; Abualoush, 2025).

This gap makes it essential the KM tools to be designed for different organizational contexts. For example, machine learning algorithms can speed up data mining and knowledge creation (Nguyen et al., 2014), but their effectiveness depends on how well they are adapted to the specific context highlighting that automation cannot fully replace human judgment or domain expertise.

Addressing technological complexity and scalability goes beyond technical fixes. It requires organizations to rethink how they integrate traditional KM and AI-driven approaches, and to plan for different levels of capacity and maturity. Failing to do so risks fragmented knowledge flows, underused data assets, and missed out innovation opportunities.

4.2.6 Technological complexity, scalability and integrating KM approaches

To better understand the interdependencies highlighted in the previous sections shaping AI-enabled knowledge management systems, this study incorporates a Causal Loop Diagram (CLD) (see Figure 2). The CLD visualizes the dynamic feedback relationships among key technological, human, organizational, and governance variables that influence the performance, scalability, and sustainability of KM initiatives. It maps elements such as data quality, legacy IT systems, resistance to change, AI adoption, trust, digital literacy, and

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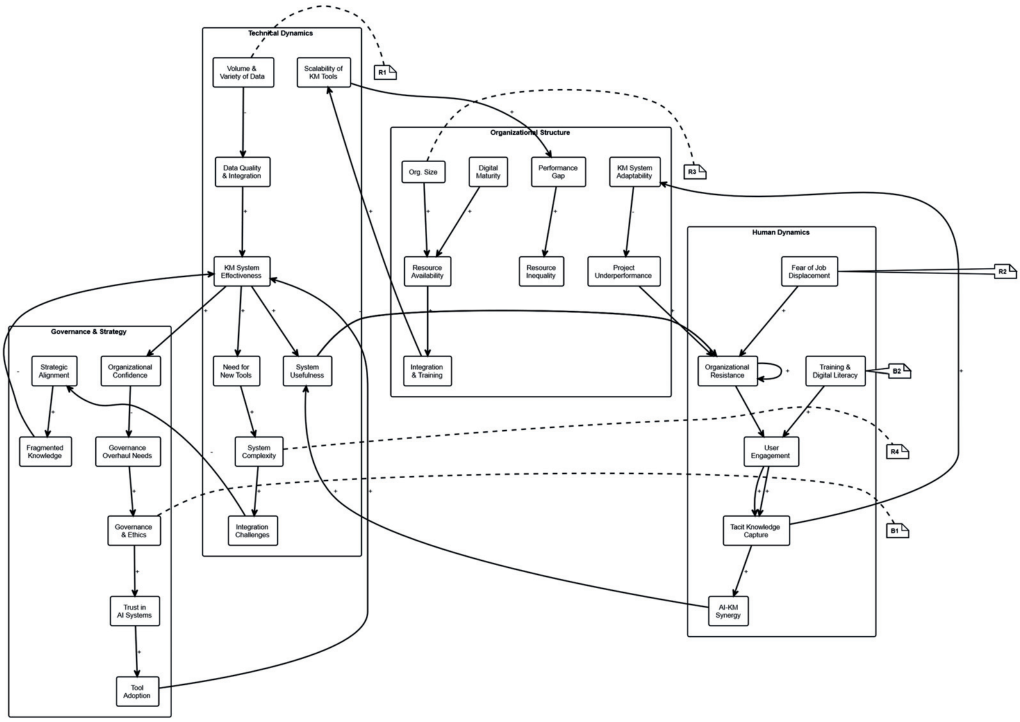

FIGURE 2
Causal loop diagram.

governance capacity, showing how these interact through reinforcing and balancing feedback loops.

At its core, the model reveals several critical systemic dynamics:

- The Data Chaos Loop (R1) illustrates how rapidly increasing data volume and heterogeneity—when inadequately integrated—can erode data quality. This in turn weakens AI tool performance and KM effectiveness, leading to misinterpretation of outputs, organizational distrust, and resistance. These responses further hinder data integration, perpetuating a self-reinforcing negative cycle.
- The Governance Stabilizer Loop (B1) shows how effective governance frameworks and ethical oversight enhance user trust in AI, encouraging adoption and improving system reliability. Greater confidence reduces resistance and the need for reactive governance changes, creating a stabilizing feedback mechanism.
- The Resistance Spiral Loop (R2) captures how fears around job displacement and skepticism toward automation intensify resistance to AI-KM initiatives. Reduced engagement limits the capture of tacit knowledge and adaptability, further compounding resistance in a downward spiral.
- The Training & Engagement Loop (B2) offers a counterbalancing dynamic, where investment in digital literacy and user training increases engagement, enhances trust, and improves the effectiveness of KM tools, especially those reliant on tacit knowledge inputs.
- The Capability-Scalability Loop (R3) highlights systemic disparities. Larger or more digitally mature organizations can dedicate greater resources to integration, training, and innovation, accelerating AI-KM benefits. However, this widens the capability gap between firms, reinforcing structural inequality.
- The Complexity Trap Loop (R4) underscores how increasing technological complexity, when poorly managed, leads to fragmented knowledge flows, reduced usability, and rising demand for new tools. Without strategic alignment, this leads to further complexity in a vicious cycle.

To clarify these interactions and identify leverage points, the CLD organizes variables into four subsystems:

- Technical Dynamics: Data quality, integration, and system complexity
- Human Dynamics: Resistance, training, and tacit knowledge engagement
- Organizational Structure: Size, resource availability, and digital maturity
- Governance & Strategic Alignment: Trust, ethics, and policy responsiveness

This systems-based perspective helps explain why isolated interventions, whether technical upgrades or training initiatives, often fail without coordinated attention to broader feedback dynamics. By identifying key loops and leverage points, the CLD provides a practical framework for designing more adaptive, equitable, and resilient AI-enabled KM strategies.

4.3 Leveraging AI and emerging technologies to address imposed challenges

This section of the chapter addresses the third research question by critically examining how organizations can leverage AI and emerging technologies to overcome the challenges identified in updating KM processes. The analysis highlights both technological solutions and socio-organizational dynamics and concludes with a practical implementation roadmap.

4.3.1 Data and knowledge management strategies

Effectively managing large volumes of organizational knowledge depends on tools that go beyond manual or traditional information systems. Automated data processing such as categorization algorithms and filtering techniques plays a critical role in ensuring that relevant and timely information reaches decision-makers. Vladova et al. (2018) and Wielgórka (2023) emphasize that such automation supports more efficient identification of information gaps, helping organizations act on incomplete or overlooked knowledge. However, these systems primarily address explicit knowledge. Capturing tacit knowledge which is rooted in employee experience and often difficult to articulate remains a significant challenge. According to Schäffer et al. (2021), AI-based extraction tools and collaborative digital platforms can support the articulation of experiential knowledge by facilitating interaction, reflection, and annotation.

4.3.2 Organizational and cultural interventions

Organizational culture can either support or hinder knowledge management (KM) transformation. Kianto et al. (2018) emphasize that trust and open communication are essential for reducing knowledge silos and encouraging collaboration across teams. While AI-based tools such as cross-functional collaboration platforms or network analysis algorithms can help surface hidden knowledge flows and support interaction across units, they cannot replace the need for planned, organization-specific efforts to shift cultural norms around sharing and learning. Practical challenges, including geographically dispersed teams, language barriers, and differences in local practices (Harrington et al., 2019; Gupta et al., 2022), require flexible approaches to knowledge adaptation and localization. Addressing these issues highlights the need to align technological solutions with human and contextual factors, rather than treating culture as an afterthought in KM initiatives.

4.3.3 Leadership and workforce development

Leadership plays a critical role in integrating AI into knowledge management. Studies by Castellani et al. (2021) and Chang et al. (2017) highlight that transformational and ethical leadership help build a culture of knowledge sharing and reduce resistance to new technologies. The introduction of AI tools such as ChatGPT brings new challenges: excessive reliance on these tools may lead to skill loss among employees, while a lack of proper oversight can compromise the quality of knowledge produced (Retkowsky et al., 2024). Addressing these issues requires ongoing training and adjustments in job roles that combine human expertise with AI support. Therefore, leadership development initiatives should focus on fostering ethical decision-making and transparency to ensure responsible and effective use of AI in knowledge management.

4.3.4 Technological solutions and AI integration

Building on the importance of leadership and workforce development, effective integration of AI technologies is essential to realize improvements in knowledge management. AI can streamline routine tasks, tailor knowledge delivery to users' needs, and support real-time collaboration across teams. For example, Lei (2022) shows how cognitive computing can enhance knowledge transfer by identifying collaboration barriers, while Retkowsky et al. (2024) find that AI assistants improve information retrieval and help generate content efficiently. However, these benefits rely heavily on selecting appropriate tools, aligning AI capabilities with existing workflows, and ensuring systems can work together smoothly (Kawonga et al., 2023). To manage these complexities, organizations should implement AI solutions gradually and iteratively, allowing time to adjust processes and minimize operational disruption. Ultimately, the technical sophistication of AI tools must be balanced with flexible, adaptable processes to achieve meaningful gains in knowledge management.

Yet the effectiveness of such integration depends not only on internal readiness but also on the sectoral context shaping how AI and KM converge. In healthcare, for instance, Torres-Dela Cruz et al. (2019) describe how AI supports clinical decision-making by dynamically managing patient knowledge, though always under human supervision due to ethical and contextual considerations. By contrast, in energy-intensive manufacturing, Sanders et al. (2019) observe a more autonomous model, where AI-driven systems embedded with real-time sensing technologies optimize operational processes with minimal human input. These divergent patterns illustrate that AI–KM integration is not uniform: the degree of automation, the locus of decision-making, and the role of human expertise all shift according to domain-specific imperatives. Retkowsky et al. (2024) further complicate this picture by showing how generative AI tools are integrated bottom-up in office-based environments, reshaping individual workflows without formalizing KM processes at the organizational level. These variations highlight that realizing the benefits of AI in KM is not only a matter of tool selection or implementation strategy, but also of aligning technological possibilities with the epistemic and operational logic of the domain in which they are deployed.

4.3.5 Ethical governance and sustainable KM

Ethical governance becomes essential as AI keeps re-shaping KM systems. Schäffer et al. (2021) and Leoni et al. (2022) highlight the importance of frameworks that promote transparency, fairness, and accountability to maintain trust among users and stakeholders. Protecting data privacy is a fundamental requirement. Algorithmic transparency allows stakeholders to audit AI decision-making, helping to uncover and address hidden biases (Safadi and Watson, 2023), while ongoing human oversight is necessary to ensure accountability in critical decision. Without these safeguards, organizations risk reputational damage and operational harm.

A forward-looking KM strategy integrates continuous learning and adaptability, recognizing that technological innovation alone cannot drive transformation (Retkowsky et al., 2024). The organizations to succeed must combine advanced data capabilities, organizational change management, leadership commitment, and ethical governance. They should balance automation with human expertise, appreciating that effective KM is as much about people and culture as it is about technology. This integrative approach positions organizations to build KM systems that are effective, accountable, and resilient during an ongoing technological and environmental shift.

Building on the analysis above, the following roadmap (see Figure 3) translates these findings into a structured, phased implementation plan. Each phase addresses core challenges identified in knowledge strategy, infrastructure, culture, leadership, governance, and continuous improvement. The roadmap reflects both technical and human dimensions of AI-enhanced KM, offering a practical guide for organizations to navigate transformation with clarity and accountability.

4.3.5.1 Objectives

Phase 1	Phase 2	Phase 3	Phase 4	Phase 5	Phase 6
Assessment and strategic alignment	Infrastructure readiness and data preparation	Technology selection and pilot deployment	Cultural and workforce enablement	Governance, ethics, and scaling	Continuous improvement

4.3.5.2 Key activities

Phase 1	Phase 2	Phase 3	Phase 4	Phase 5	Phase 6
- Audit KM maturity. - Map critical knowledge processes. - Align KM with organizational strategy.	- Upgrade IT systems for interoperability. - Clean and organize existing data. - Add metadata and tags to improve searchability.	- Match AI tools to tasks (e.g., NLP, chatbots). - Run small pilots to assess fit. - Track usage, quality, and business value.	- Provide digital literacy training. - Set up KM communities or champions. - Facilitate open discussions about AI and job roles.	- Define ethical AI and data policies. - Use audits and feedback to monitor use. - Scale pilots thoughtfully across the org.	- Use AI to find gaps and outdated knowledge. - Adjust KM based on analytics and user input. - Foster a culture of ongoing learning.

4.3.5.3 Expected outcomes

Phase 1	Phase 2	Phase 3	Phase 4	Phase 5	Phase 6
Clear understanding of needs and priorities to guide focused KM efforts.	A reliable system with well-structured, accessible knowledge assets.	AI tools with demonstrated value and practical use cases.	Staff are engaged, informed, and ready to contribute to KM.	KM practices are consistent, ethical, and scalable.	KM remains relevant, efficient, and supports innovation.

This phased roadmap provides a practical structure for organizations to implement AI-enhanced KM in a manageable and adaptive way. Grounded in both technical feasibility and organizational readiness, it offers flexibility for sector-specific challenges while maintaining a consistent focus on strategic alignment, ethical governance, and continuous learning.

4.4 Theoretical contribution and propositions

This section introduces a conceptual framework based on the earlier analysis of how AI and emerging technologies influence organizational knowledge management. The framework integrates five core dimensions: technological drivers, KM processes, implementation challenges, strategic organizational responses, and anticipated outcomes. It positions AI as a transformative input that reshapes KM activities such as knowledge discovery, capture, sharing, and application, while emphasizing the sociotechnical factors that moderate this transformation.

The following propositions operationalize this framework, translating its dimensions into empirically testable or practically actionable statements. Specifically, Propositions 1 and 2 address the technological drivers and data-related challenges depicted in the model. Propositions 3 and 4 correspond to the human and governance barriers, highlighting organizational culture and ethical oversight. Finally, Propositions 5 and 6 focus on strategic responses and structural adaptations that organizations can leverage to overcome these challenges, such as scalable AI solutions and hybrid knowledge management architectures. Figure 4 visually summarizes the framework, offering a reference point for researchers and practitioners seeking to design, implement, or evaluate AI-enabled KM strategies.

> Proposition 1: Organizations with a culture open to innovation, strong real-time data capabilities, and mature digital infrastructure can use AI to turn static knowledge into a dynamic, evolving resource—making them more responsive and agile.
>
> Proposition 2: When data is poor, systems are fragmented, and information comes in fast and varied forms, AI struggles to deliver useful insights. However, investing in data quality and system integration can significantly improve decision-making.
>
> Proposition 3: If employees distrust AI, fear job loss, or lack digital skills (and the culture does not support change) AI-based KM systems are unlikely to succeed. Overcoming this requires targeted training and cultural support to encourage adoption.
>
> Proposition 4: Transparent and inclusive AI governance within KM helps prevent bias, protect privacy, and avoid reputational harm. This builds trust and encourages long-term, responsible use of AI in organizations.
>
> Proposition 5: When AI tools are scalable, easy to use, and fit specific industry needs, even smaller or less-resourced firms can benefit, if they also invest in digital skills, change readiness, and external support.
>
> Proposition 6: Blending traditional KM methods, like communities of practice, with AI tools such as machine learning and NLP creates a hybrid system. This supports both structured and experience-based knowledge sharing—especially in a collaborative learning culture.

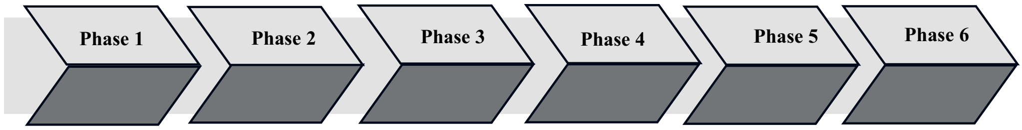

FIGURE 3
Phased implementation roadmap for AI-driven KM.

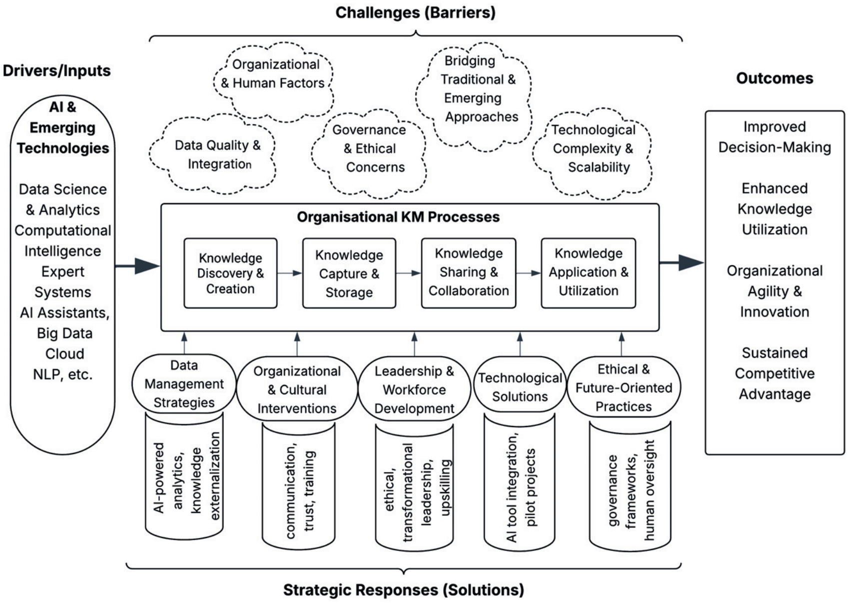

FIGURE 4
Conceptual framework for integrating AI and emerging technologies into organizational KM.

5 Conclusion and future work

The evolving relationship between organizational knowledge and technological innovation is reshaping the field of knowledge management. This systematic review has critically examined how AI and related technologies are influencing KM practices, drawing on evidence from 40 studies. The findings indicate that while AI enhances core KM activities including knowledge discovery, capture, sharing, and application, it also introduces new modes of collaboration, personalization, and decision support. However, the review also highlights that the integration of AI into KM is not straightforward. Significant challenges persist, including managing data quality and integration, overcoming organizational and human barriers, navigating governance and ethical complexities, and aligning emerging technologies with existing KM practices. These challenges can substantially limit the realization of AI's potential benefits in organizational contexts. Addressing these barriers requires a multidimensional strategy: rigorous data management, attention to organizational culture and leadership, investment in workforce development, careful technology selection, and the implementation of robust ethical and governance frameworks. The conceptual framework proposed in this review (see Figure 4) offers an initial roadmap, though it requires further empirical validation.

Notably, the findings caution against viewing AI as a substitute for human expertise or established KM approaches. Instead, AI should be seen as a complement to human judgment, one that, when integrated thoughtfully, can strengthen organizational learning and adaptability. Ethical concerns, particularly around data privacy, algorithmic accountability, and human oversight, must remain central to both research and practice if AI-enabled KM is to advance in responsible and sustainable ways. This review is not without limitations. Its reliance on published literature may introduce selection bias and potentially overlooks emerging or practice-based innovations. Moreover, the diversity of organizational contexts and AI applications limits the generalizability of some findings.

To advance understanding in this area, future research should focus on several key topics identified in this review: First, as this study shows, knowledge management is evolving alongside how advanced systems access and process information in real time. Future research should examine knowledge flow models that balance real-time knowledge creation, validation, and application within operational settings. Second, the analysis highlighted the need for ethical governance frameworks that are flexible and continuously evolving to ensure responsible AI-KM practices. A key question to explore would be: how can organizations develop adaptive governance models that clearly define accountability and keep pace with rapidly changing technologies to provide ethical, transparent, and effective oversight? Third, there is a lack of research on the measurable costs and benefits of AI-enabled knowledge management, including investment needs and return on investment (ROI). Future studies should analyze these financial aspects by examining productivity, decision-making speed, and innovation outcomes.

Methodologically, these future studies should adopt mixed methods approaches that combine qualitative depth (e.g., case studies in diverse sectors, in-depth interviews) with quantitative validation (e.g., system analytics, performance metrics) and design science (model development and testing).

Together, these directions aim to deepen practical and theoretical understanding of AI-enabled knowledge management, guiding organizations toward more effective, responsible and sustainable implementations.

Data availability statement

The raw data supporting the conclusions of this article will be made available by the authors, without undue reservation.

Author contributions

TG-L: Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Validation, Writing – original draft, Writing – review & editing. PV: Conceptualization, Supervision, Validation, Writing – review & editing. IP: Conceptualization, Supervision, Validation, Writing – review & editing, Methodology.

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Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

Generative AI statement

The authors declare that no Gen AI was used in the creation of this manuscript.

Correction note

A correction has been made to this article. Details can be found at: 10.3389/frai.2025.1664837.

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Supplementary material

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References

Abualoush, S. (2025). The nexus of knowledge management processes and innovation performance: the moderates of big data analytical. *Kybernetes* 54, 1716–1735. doi: 10.1108/K-01-2023-0056

Abubakar, A. M., Behravesh, E., Rezapouraghdam, H., and Yildiz, S. B. (2019). Applying artificial intelligence technique to predict knowledge hiding behavior. *Int. J. Inf. Manag.* 49, 45–57. doi: 10.1016/j.ijinfomgt.2019.02.006

Al Mansoori, S., Salloum, S. A., and Shaalan, K. (2021). "The impact of artificial intelligence and information technologies on the efficiency of knowledge management at modern organizations: a systematic review" in Recent advances in intelligent systems and smart applications. Studies in systems, decision and control. eds. M. Al-Emran, K. Shaalan and A. Hassanien, vol. *295* (Cham: Springer).

Alavi, M., and Leidner, D. E. (2001). Knowledge management and knowledge management systems: conceptual foundations and research issues. *MIS Q.* 25, 107–136. doi: 10.2307/3250961

Alonso, F., Martínez, L., Pérez, A., and Valente, J. P. (2012). Cooperation between expert knowledge and data mining discovered knowledge: lessons learned. *Expert Syst. Appl.* 39, 7524–7535. doi: 10.1016/j.eswa.2012.01.133

Anshari, M., Syafrudin, M., Tan, A., Fitriyani, N. L., and Alas, Y. (2023). Optimisation of knowledge management (KM) with machine learning (ML) enabled. *Information* 14:35. doi: 10.3390/info14010035

Argyris, and Schön (1978). Organizational learning: A theory of action perspective. Reading, MA: Addison-Wesley.

Babkin, E., Poletaeva, T., and Ulitin, B. (2019). Knowledge life cycle management as a key aspect of digitalization. Cham: Springer, 429–452.

Bandaru, S., Ng, A. H. C., and Deb, K. (2017). Data mining methods for knowledge discovery in multiobjective optimization: part A—survey. *Expert Syst. Appl.* 70, 139–159. doi: 10.1016/j.eswa.2016.10.015

Bass, B. M., and Riggio, R. E. (2005). Transformational leadership. *2nd* Edn. New York, NY: Psychology Press.

Bassi, L. J. (1997). Harnessing the power of intellectual capital. *Train. Dev.* 51, 25–30.

Beheshti, A, Benatallah, B, Sheng, QZ, Casati, F, Motahari-Nezhad, HR, and Yang, J. (2021). AI-enabled processes: the age of artificial intelligence and big data. In: Hacid, H., et al. (eds) *Service-oriented computing – ICSOC 2021 workshops. ICSOC, Lecture Notes in Computer Science.* Cham: Springer. 13236. 321–323. doi: 10.1007/978-3-031-14135-5_29

Bennett, R., and Gabriel, H. (1999). Organisational factors and knowledge management within large marketing departments: an empirical study. *J. Knowl. Manag.* 3, 212–225. doi: 10.1108/13673279910288707

Bianchi, F. M., Rizzi, A., Sadeghian, A., and Moiso, C. (2016). Identifying user habits through data mining on call data records. *Eng. Appl. Artif. Intell.* 54, 49–61. doi: 10.1016/j.engappai.2016.05.007

Braun, P., Cuzzocrea, A., Leung, C. K., Pazdor, A. G., and Tran, K. (2016). Knowledge discovery from social graph data. *Procedia Comput. Sci.* 96, 682–691. doi: 10.1016/j.procs.2016.08.250

Cameron, K. S., and Quinn, R. E. (2011). Diagnosing and changing organizational culture: Based on the competing values framework. *Rev* Edn. San Francisco: Jossey-Bass.

Castagna, F., Centobelli, P., Cerchione, R., Esposito, E., Oropallo, E., and Passaro, R. (2020). Customer knowledge management in SMEs facing digital transformation. *Sustain. For.* 12:3899. doi: 10.3390/su12093899

Castellani, P., Rossato, C., Giaretta, E., and Davide, R. (2021). Tacit knowledge sharing in knowledge-intensive firms: the perceptions of team members and team leaders. *Rev. Manag. Sci.* 15, 125–155. doi: 10.1007/s11846-019-00368-x

Chang, Y.-Y., Chang, C.-Y., and Chen, C.-W. (2017). Transformational leadership and corporate entrepreneurship: Cross-level mediation moderation evidence. *Leadership & Organization Development Journal* 38, 812–833. doi: 10.1108/LODJ-10-2015-0219

Critical Appraisal Skills Programme. (2018). CASP cohort study checklist. Available online at: https://casp-uk.net/casp-tools-checklists/ (Accessed 01 June 2025).

Damanpour, F. (1998). Organizational innovation. *1st* Edn. London: John Wiley & Sons.

Davenport, T. H. (1997). Ten principles of knowledge management and four case studies. *Knowl. Process. Manag.* 4, 187–208. doi: 10.1002/(SICI)1099-1441(199709)4:3<>3.0.CO;2-A

Davenport, T. H., De Long, D. W., and Beers, M. C. (1998). Successful knowledge management projects. *MIT Sloan Manag. Rev.* 39:43.

Davenport, T. H., and Prusak, L. (1998). Working knowledge: How organizations manage what they know. Boston, MA: Harvard Business School Press.

De Bem Machado, A., Secinaro, S., Calandra, D., and Lanzalonga, F. (2022). Knowledge management and digital transformation for industry 4.0. *Knowl. Manag. Res. Pract.* 20, 320–338. doi: 10.1080/14778238.2021.2015261

Delen, D., Zaim, H., Kuzey, C., and Zaim, S. (2013). A comparative analysis of machine learning systems for measuring the impact of knowledge management practices. *Decis. Support. Syst.* 54, 1150–1160. doi: 10.1016/j.dss.2012.10.040

Depeige, A., and Doyencourt, D. (2015). Actionable knowledge as a service (AKAAS): leveraging big data analytics in cloud computing environments. *J. Big Data* 2:12. doi: 10.1186/s40537-015-0023-2

Di Vaio, A., Palladino, R., Pezzi, A., and Kalisz, D. E. (2021). The role of digital innovation in knowledge management systems: A systematic literature review. *J. Bus. Res.* 123, 220–231. doi: 10.1016/j.jbusres.2020.09.042

Esposito, M., Sarbazvatan, S., Tse, T., and Silva-Atencio, G. (2024). The use of artificial intelligence for automatic analysis and reporting of software defects. *Front. Artif. Intellig.* 7:1443956. doi: 10.3389/frai.2024.1443956

Ferraris, A., Santoro, G., and Dezi, L. (2017). How MNC'S subsidiaries may improve their innovative performance? The role of external sources and knowledge management capabilities. *J. Knowl. Manag.* 21, 540–552. doi: 10.1108/JKM-09-2016-0411

Finogeev, A. G., Parygin, D. S., and Finogeev, A. A. (2017). The convergence computing model for big sensor data mining and knowledge discovery. *Hum. Cent. Comput. Inf. Sci.* 7:11. doi: 10.1186/s13673-017-0092-7

Foli, S. (2022). Total interpretive structural modelling (TISM) and MICMAC approach in analysing knowledge risks in ICT-supported collaborative project. *Vine J. Inf. Knowl. Manag. Syst.* 52, 394–410. doi: 10.1108/VJIKMS-09-2021-0205

Fteimi, N, and Hopf, K. (2021). Knowledge management in the era of artificial intelligence – developing an integrative framework. In: ECIS 2021 Research-in-Progress Papers (No. 20). Available online at: https://aisel.aisnet.org/ecis2021_rip/20

Georgiev, D., and Antonova, A. (2024). "Enhancing knowledge sharing processes via automated software documentation management systems using Gen AI software tools" in *2024 XXXIV International Scientific Symposium Metrology and Metrology Assurance (MMA)*, 07–11 September 2024 (Sozopol, Bulgaria: IEEE) doi: 10.1109/MMA62616.2024.10817681

Grzeszczyk, TA. (2021). Fuzzy logic driven technological knowledge collecting and sharing. ECKM 2021 22nd European Conference on Knowledge Management, *(ECKM 2021)*, Virtual, Online, 2–3 September 2021. Reading, UK: Academic Conferences International Limited, 310–316.

Gullo, F. (2015). From patterns in data to knowledge discovery: what data mining can do. *Phys. Procedia* 62, 18–22. doi: 10.1016/j.phpro.2015.02.005

Gupta, A., Singh, R., Kamble, S., and Mishra, R. (2022). Knowledge management in industry 4.0 environment for sustainable competitive advantage: a strategic framework. *Knowl. Manag. Res. Pract.* 20, 878–892. doi: 10.1080/14778238.2022.2144512

Harrington, T. S., Srai, J. S., and Kumar, M. (2019). Knowledge management in SMEs and MNCs: matching knowledge mobility mechanisms to supply network configuration profiles. *Prod. Plan. Control* 30, 971–994. doi: 10.1080/09537287.2019.1582103

Hashem, G., Aboelmaged, M., and Ahmad, I. (2024). Proactiveness, knowledge management capability and innovation ambidexterity: an empirical examination of digital supply chain adoption. *Manag. Decis.* 62, 129–162. doi: 10.1108/MD-02-2023-0237

Herrero, Á., Sáiz-Bárcena, L., Manzanedo, M. A., and Corchado, E. (2016). A hybrid proposal for cross-sectoral analysis of knowledge management. *Soft. Comput.* 20, 4271–4285. doi: 10.1007/s00500-016-2293-9

Higgins, JPT, and Green, S. (eds.) (2011). Cochrane handbook for systematic reviews of interventions. Version 5.1.0 [updated March 2011]. London: The Cochrane Collaboration. Available at: https://training.cochrane.org/handbook/archive/v5.1/ (Accessed April 30, 2025).

Hong, Q. N., Pluye, P., Fàbregues, S., Bartlett, G., Boardman, F., Cargo, M., et al. (2019). Improving the content validity of the mixed methods appraisal tool: a modified e-Delphi study. *J. Clin. Epidemiol.* 111, 49–59.e1. doi: 10.1016/j.jclinepi.2019.03.008

Hutchins, E. (1995). Cognition in the wild. Cambridge, MA: MIT Press.

Iaia, L., Nespoli, C., Vicentini, F., Pironti, M., and Genovino, C. (2024). Supporting the implementation of AI in business communication: the role of knowledge management. *J. Knowl. Manag.* 28, 85–95. doi: 10.1108/JKM-12-2022-0944

Inkinen, H. (2016). Review of empirical research on knowledge management practices and firm performance. *J. Knowl. Manag.* 20, 230–257. doi: 10.1108/JKM-09-2015-0336

Jarrahi, M. H., Lutz, C., Boyd, K., Oesterlund, C., and Willis, M. (2023). Artificial intelligence in the work context. *Journal of the Association for Information Science and Technology* 74, 303–310. doi: 10.1002/asi.24730

Jia, Z., Shi, Y., Jia, Y., and Li, D. (2012). A framework of knowledge management systems for tourism crisis management. *Procedia Eng.* 29, 138–143. doi: 10.1016/j.proeng.2011.12.683

Kamasak, R., Yozgat, U., and Yavuz, M. (2017). Knowledge process capabilities and innovation: testing the moderating effects of environmental dynamism and strategic flexibility. *Knowl. Manag. Res. Pract.* 15, 356–368. doi: 10.1057/s41275-017-0068-4

Kane, G. C. (2017). The evolutionary implications of social media for organizational knowledge management. *Inf. Organ.* 27, 37–46. doi: 10.1016/j.infoandorg.2017.01.001

Kaplan, A., and Haenlein, M. (2019). Siri, Siri, in my hand: Who's the fairest in the land? On the interpretations, illustrations, and implications of artificial intelligence. *Bus. Horiz.* 62, 15–25. doi: 10.1016/j.bushor.2018.08.004

Kawonga, T., Kumar, T. A., and Jerin, G. (2023). Scaling enterprise knowledge management with big data neural network using apache Hadoop and apache spark for efficient processing and analysis. *Int. J. Adv. Eng. Manag* 5, 313–322. doi: 10.35629/5252-0504313322

Khan, Z., and Vorley, T. (2017). Big data text analytics: an enabler of knowledge management. *J. Knowl. Manag.* 21, 18–34. doi: 10.1108/JKM-06-2015-0238

Kianto, A., Hussinki, H., Vanhala, M., and Nisula, A.-M. (2018). The state of knowledge management in logistics SMEs: evidence from two Finnish regions. *Knowledge Management Research Practice* 16, 477–487. doi: 10.1080/14778238.2018.1488523

Kitchenham, B. (2004). Procedures for performing systematic reviews, Joint Technical Report TR/SE-0401. Software Engineering Group, Department of Computer Science, Keele University, UK and National ICT. Australia Ltd. 33, 1–26. Available at: https://www.inf.ufsc.br/~aldo.vw/kitchenham.pdf (Accessed September 12, 2024).

Leoni, L., Ardolino, M., El Baz, J., Gueli, G., and Bacchetti, A. (2022). The mediating role of knowledge management processes in the effective use of artificial intelligence in manufacturing firms. *Int. J. Oper. Prod. Manag.* 42, 411–437. doi: 10.1108/IJOPM-05-2022-0282

Leoni, L., Gueli, G., Ardolino, M., Panizzon, M., and Gupta, S. (2024). AI-empowered KM processes for decision-making: empirical evidence from worldwide organisations. *J. Knowl. Manag.* 28, 320–347. doi: 10.1108/JKM-03-2024-0262

Lei, A. (2022). Knowledge transfer analysis and management of virtual enterprises based on structured cognitive computing. *Computational Intelligence and Neuroscience* 2022:Article ID 4858434, 1–12. doi: 10.1155/2022/4858434

Li, D., Landström, A., and Fast-Berglund, Å. A. P. (2019). Human-centred dissemination of data, information and knowledge in industry 4.0. *Procedia CIRP* 84, 380–386. doi: 10.1016/j.procir.2019.04.261

Liberati, A., Altman, D. G., Tetzlaff, J., Mulrow, C., Gøtzsche, P. C., Ioannidis, J. P. A., et al. (2009). The PRISMA statement for reporting systematic reviews and meta-analyses of studies that evaluate health care interventions: explanation and elaboration. *Ann. Intern. Med.* 151, 65–94. doi: 10.7326/0003-4819-151-4-200908180-00136

Liebowitz, J. (2001). Knowledge management and its link to artificial intelligence. *Expert Syst. Appl.* 20, 1–6. doi: 10.1016/S0957-4174(00)00044-0

Lloyd, B. (1996). Knowledge management: the key to long-term organizational success. *Long Range Plan.* 29, 576–580. doi: 10.1016/0024-6301(96)00052-0

López-Cuadrado, J. L., Colomo-Palacios, R., González-Carrasco, I., García-Crespo, Á., and Ruiz-Mezcua, B. (2012). Sabumo: towards a collaborative and semantic framework for knowledge sharing. *Expert Syst. Appl.* 39, 8671–8680. doi: 10.1016/j.eswa.2012.01.198

Mahmood, Z. (2019). "Data mining and knowledge management application to enhance business operations: an exploratory study" in Advances in information and communication networks. FICC 2018. eds. K. Arai, S. Kapoor and R. Bhatia, vol. *886* (Cham: Advances in Intelligent Systems and Computing, Springer).

Malik, A., De Silva, M. T., Budhwar, P., and Srikanth, N. R. (2021). Elevating talents' experience through innovative artificial intelligence-mediated knowledge sharing: evidence from an IT-multinational enterprise. *J. Int. Manag.* 27:100871. doi: 10.1016/j.intman.2021.100871

Manesh, M. F., Massimiliano, M. P., Giacomo, M., and Dabic, M. (2020). Knowledge management in the fourth industrial revolution: mapping the literature and scoping future avenues. *IEEE Trans. Eng. Manag.* 68, 289–300. doi: 10.1109/TEM.2019.2963489

Mayo, A. (1998). Memory bankers. *People Manag.* 22, 34–38.

McIver, D., and Lepisto, D. A. (2017). Effects of knowledge management on unit performance: examining the moderating role of tacitness and learnability. *J. Knowl. Manag.* 21, 796–816. doi: 10.1108/JKM-08-2016-0347

Miradi, M., Molenaar, A. A., and van de Ven, M. F. (2009). "Knowledge discovery and data mining using artificial intelligence to unravel porous asphalt concrete in the Netherlands" in Intelligent and Soft Computing in Infrastructure Systems Engineering: Recent Advances (Berlin, Heidelberg: Springer), 107–176.

Muzzio, H., and Gama, M. (2024). Collaborative idea generation: an experience of open creativity in the public sector. *Vine J. Inf. Knowl. Manag. Syst.* 54, 176–194. doi: 10.1108/VJIKMS-07-2021-0112

Natek, S., and Zwilling, M. (2014). Student data mining solution—knowledge management system related to higher education institutions. *Expert Syst. Appl.* 41, 6400–6407. doi: 10.1016/j.eswa.2014.04.024

Nerney, C. (1997). Getting to know knowledge management. *Netw. World* 14:101.

Nguyen, P., Hilario, M., and Kalousis, A. (2014). Using meta-mining to support data mining workflow planning and optimization. *J. Artif. Intell. Res.* 51, 605–644. doi: 10.1613/jair.4377

Nguyen, M., Rundle-Thiele, S., Malik, A., and Budhwar, P. (2023). Impact of technology-based knowledge sharing on employee outcomes: moderation effects of training, support, and leadership. *J. Knowl. Manag.* 27, 2283–2301. doi: 10.1108/JKM-07-2022-0552

Nohuddin, P. N., and Zainol, Z. (2020). Discovering explicit knowledge using text mining techniques for peacekeeping documents. *Int. J. Bus. Inf. Syst.* 35, 152–166. doi: 10.1504/IJBIS.2020.10016191

Nonaka, I., and Takeuchi, H. (1995). The knowledge-creating company: How Japanese companies create the dynamics of innovation. New York: Oxford University Press.

Nowell, L. S., Norris, J. M., White, D. E., and Moules, N. J. (2017). Thematic analysis: striving to meet the trustworthiness criteria. *Int J Qual Methods* 16, 1–13. doi: 10.1177/1609406917733847

Obembe, F, and Obembe, D. (2020). Deep learning and tacit knowledge transfer: an exploratory study. In: *Proceedings of the European Conference on Knowledge Management (ECKM 2020)*, Kidmore End. 172–179. Available at: https://irep.ntu.ac.uk/id/eprint/49738 (Accessed September 21, 2024).

Ofosu-Ampong, K. (2024). Artificial intelligence research: a review on dominant themes, methods, frameworks, and future research directions. *Telematics Informatics Reports* 14:100127. doi: 10.1016/j.teler.2024.100127

Pacheco, C., and Paul, B. (2023). Applying complexity theory perspective to knowledge management in the innovation context. *Vine J. Inf. Knowl. Manag. Syst.* 55, 421–444. doi: 10.1108/VJIKMS-08-2022-0279

Pisoni, G., Molnár, B., and Tarcsi, Á. (2024). Knowledge management and data analysis techniques for data-driven financial companies. *J. Knowl. Econ.* 15, 13374–13393. doi: 10.1007/s13132-023-01607-z (Accessed September 20, 2024).

Radavičius, T., and Tvaronavičienė, M. (2022). Digitalisation, knowledge management and technology transfer impact on organisations' circularity capabilities. *Insights Reg. Dev.* 4, 76–95. doi: 10.9770/IRD.2022.4.3(5)

Retkowsky, J., Hafermalz, E., and Huysman, M. (2024). Managing a ChatGPT-empowered workforce: understanding its affordances and side effects. *Bus. Horiz.* 67, 511–523. doi: 10.1016/j.bushor.2024.04.009

Rialti, R., Marzi, G., Caputo, A., and Mayah, K. A. (2020). Achieving strategic flexibility in the era of big data: The importance of knowledge management and ambidexterity. *Manag. Decis.* 58, 1585–1600. doi: 10.1108/MD-09-2019-1237

Ristoski, P., and Paulheim, H. (2016). Semantic web in data mining and knowledge discovery: a comprehensive survey. *J. Web Semant.* 36, 1–22. doi: 10.1016/j.websem.2016.01.001

Rogers, E. M. (2003). Diffusion of innovations. *5th* Edn. New York: Free Press.

Safadi, H., and Watson, R. T. (2023). Knowledge monopolies and the innovation divide: a governance perspective. *Inf. Organ.* 33:100466. doi: 10.1016/j.infoandorg.2023.100466

Safhi, H. M., Frikh, B., and Ouhbi, B. (2019). Assessing reliability of big data knowledge discovery process. *Procedia Comput. Sci.* 148, 30–36. doi: 10.1016/j.procs.2019.01.005

Samuels, A. (2025). Examining the integration of artificial intelligence in supply chain management from industry 4.0 to 6.0: a systematic literature review. *Front. Artif. Intell.* 7, 1–17. doi: 10.3389/frai.2024.1477044

Sanders, D., Robinson, D. C., Hassan Sayed, M., Haddad, M. J. M., Gegov, A., and Ahmed, N. (2019). "Making decisions about saving energy in compressed air systems using ambient intelligence and artificial intelligence" in Intelligent systems and applications: Proceedings of the 2018 intelligent systems conference (IntelliSys) volume 2. Advances in intelligent systems and computing. eds. K. Arai, S. Kapoor and R. Bhatia, vol. *869* (Cham, Switzerland: Springer), 1229–1236. doi: 10.1007/978-3-030-01057-7_92

Santoro, G., Vrontis, A., Thrassou, I., and Dezi, L. (2018). The internet of things: building a knowledge management system for open innovation and knowledge management capacity. *Technol. Forecast. Soc. Change* 136, 347–354. doi: 10.1016/j.techfore.2017.02.034

Schäffer, E., Mayr, A., Reichenstein, T., Shafiee, S., and Franke, J. (2021). Four independent knowledge domains to enable an agile, distributed development of user-centred engineering configurators. *Procedia CIRP* 103, 134–139. doi: 10.1016/j.procir.2021.10.021

Schardt, C., Adams, M. B., Owens, T., Keitz, S., and Fontelo, P. (2007). Utilization of the PICO framework to improve searching PubMed for clinical questions. *BMC Med. Inform. Decis. Mak.* 7:16. doi: 10.1186/1472-6947-7-16

Shaqrah, A., and Alzighaibi, A. (2023). Linking knowledge management capabilities and the mediating role of the big data capabilities for enterprise value-adding processes. *Vine J. Inf. Knowl. Manag. Syst.* 53, 64–79. doi: 10.1108/VJIKMS-05-2020-0087

Shekhar, A., and Valeri, M. (2023). Trends in knowledge management in small businesses. *Eur. Bus. Rev.* 35, 573–599. doi: 10.1108/EBR-10-2022-0200

Skyrme, D. J., and Amidon, D. M. (1997). Creating the knowledge-based business. London, UK: Business Intelligence Limited.

Smuts, H., and Scholtz, I. I. (2020). A conceptual knowledge visualization framework for transfer of knowledge: An organizational context. Cham: Springer, 287–298.

Stohr, A., Ollig, P., Keller, R., and Rieger, A. (2024). Generative mechanisms of AI implementation: a critical realist perspective on predictive maintenance. *Inf. Organ.* 34:100503. doi: 10.1016/j.infoandorg.2024.100503

Stollberg, M., Zhdanova, A. V., and Fensel, D. (2004). H-techsight — a next generation knowledge management platform. *J. Inf. Knowl. Manag.* 3, 45–66. doi: 10.1142/S0219649204000651

Sumbal, M. S., Ali, M., Sahibzada, U. F., Mir, F. N., Tariq, A., and Munir, H. (2021). Big data based knowledge management vs. traditional knowledge management: a people, process and technology perspective. *J. Inf. Sci. Eng.* 37, 1053–1065. doi: 10.6688/JISE.202109_37(5).0005

Taherdoost, H., and Madanchian, M. (2023). Artificial intelligence and knowledge management: impacts, benefits, and implementation. *Computers* 12:72. doi: 10.3390/computers12040072

Teece, D. J. (2007). Explicating dynamic capabilities: the nature and microfoundations of (sustainable) enterprise performance. *Strateg. Manage. J.* 28, 1319–1350. doi: 10.1002/smj.640

Thomas, A., and Chopra, M. (2020). "On how big data revolutionizes knowledge management" in Digital transformation in business and society. eds. B. George and J. Paul (Cham, Switzerland: Palgrave Macmillan), 39–60. doi: 10.1007/978-3-030-08277-2_3

Torres-Dela Cruz, M., Ganapathy, S. A. P., and Yasin, N. Z. B. M. (2019). Knowledge management and predictive analytics in IT project risks. Int. J. Trend Scientific Res. Dev., Special Issue: International Conference on Advanced Engineering and Information Technology, 209–216. doi: 10.31142/ijtsrd19142

Tsai, H. H. (2013). Knowledge management vs. data mining: research trend, forecast and citation approach. *Expert Syst. Appl.* 40, 3160–3173. doi: 10.1016/j.eswa.2012.12.029

Viterouli, M., Belias, D., Koustelios, A., and Tsigilis, N. (2023). Linking adult learning to knowledge management in a multigenerational workforce Academic Conferences International Limited. *Eur. Conf. Knowledge Manag.* 24, 1410–1420. doi: 10.34190/eckm.24.2.1311

Vladova, G., Ullrich, A., Bahrs, J., and Bender, B. (2018). Digitalisation and enterprise knowledge (net)working. *Hilton Waikoloa Village Knowledge Economics*, Honolulu, Hawaii, USA: University of Hawaii at Mānoa. 4182–4191. doi: 10.24251/HICSS.2018.526

Webster, J., and Watson, R. T. (2002). Analyzing the past to prepare for the future: writing a literature review. *MIS Q.* 26, 13–23. Available at: https://www.jstor.org/stable/4132319 (Accessed September 12, 2025).

Weck, M., Gelashvili, T., Pappel, I., and Ferreira, F. (2022). Supporting collaboration and knowledge sharing in building SLEs for ageing well: using cognitive mapping in KMS design. *Knowl. Manag. Res. Pract.* 20, 865–877. doi: 10.1080/14778238.2022.2144513

Wielgórka, D. (2023). Technological tools, KM and innovation in SME enterprises. *Eur. Conf. Knowledge Manag.* 24, 1462–1470. doi: 10.34190/eckm.24.2.1306

Yadegari, M., and Mohammadi, S. (2024). A fuzzy cognitive map approach to selecting the best knowledge management strategy. *Vine J. Inf. Knowl. Manag. Syst.* doi: 10.1108/VJIKMS-07-2023-0186 [ahead-of-print].

Appendix 4

Publication IV

Gelashvili-Luik, T., Vihma, P., Pappel, I., & Ferreira, F. A. (in review). AI-augmented knowledge management in FinTech: Dynamic capabilities for strategic decision-making in complex and uncertain environments. *Journal of Modelling in Management.*

AI-AUGMENTED KNOWLEDGE MANAGEMENT IN FINTECH: DYNAMIC CAPABILITIES FOR STRATEGIC DECISION-MAKING IN COMPLEX AND UNCERTAIN ENVIRONMENTS

ABSTRACT

Purpose: This study investigates how artificial intelligence (AI) shapes knowledge management (KM) practices in FinTech and how these changes influence human judgment in strategic decision-making. It responds to the need for clearer understanding of how dynamic capabilities develop when AI is embedded in knowledge-intensive work.

Design/methodology/approach: The research draws on a qualitative case study of a global FinTech organisation. Data were gathered from ten semi-structured interviews with managers, KM specialists and operational staff, supported by internal documents. Thematic analysis was guided by the Dynamic Capabilities Framework (DCF).

Findings: The study shows that AI-enabled KM develops through recursive and overlapping capability cycles, rather than linear stages. Three mechanisms support this process: (1) knowledge trust and cross-functional alignment operate as ongoing preconditions for reliable AI use; (2) mediation roles, such as Business Intelligence teams, link technical outputs with operational interpretation; and (3) AI can ease cognitive load and improve efficiency but still requires active human judgment. These mechanisms highlight both the benefits of AI augmentation and the risks of over-reliance if knowledge or oversight structures lag behind.

Originality: The research extends the DCF by identifying how AI changes the microfoundations of sensing, seizing and transforming. It clarifies the role of alignment and mediation as enabling capabilities and demonstrates how KM evolves from maintaining static repositories to supporting continuous interpretation and organisational adaptability.

Research limitations/implications: As a single-case study, the findings reflect one organisational context and a specific moment in time. Future research should explore how these mechanisms operate across sectors and regulatory settings.

Keywords: Artificial Intelligence, Knowledge Management, Dynamic Capabilities, FinTech, Decision-making, Uncertain Environment.

1. INTRODUCTION

Artificial intelligence (AI) technologies including large language models, predictive analytics and machine-learning systems are increasingly embedded into organisational decision processes. These tools speed up analytical work by filtering large data sets, identifying pertinent information and reducing the manual effort required to process high-volume inputs (Al-Okaily and Al-Okaily, 2025; Khan *et al.*, 2025). In sectors such as financial technology (FinTech)[1], where operational, risk and compliance functions are closely interlinked, AI adoption takes place under conditions that demand high levels of accuracy, explainability and timely adaptation (Bank for International Settlements, 2024; World Economic Forum and Accenture, 2025).

Although AI systems can improve efficiency, they remain limited in contextual reasoning, ethical sensitivity and interpretive nuance (Kamila and Jasrotia, 2025; Matei *et al.*, 2025). Decisions such as customer verification, fraud assessment or exception handling often rely on information that requires human judgment, especially when cases do not fit standard patterns. Consequently, many organisations pursue AI-augmented decision-making approaches in which AI supports rather than replaces human expertise (Lui and Lamb, 2018; Wu and Chen, 2025). This model depends heavily on the quality, accessibility and interpretability of organisational knowledge.

These demands place renewed attention on knowledge management (KM). FinTech organisations need staff to work with knowledge that is both reliable and continually updated, yet traditional KM systems were designed for more stable organisational environments (Chierici *et al.*, 2019). For AI to enhance KM effectiveness, it must be embedded in organisational conditions such as consistent knowledge curation, clear governance roles and trust in underlying data and processes (Wanberg *et al.*, 2015; Kumar, 2025). Without these foundations, AI-enabled KM may generate faster outputs without improving decision quality.

Despite growing interest in AI-enabled decision support, existing research often underexamines the organisational capabilities required to integrate AI into knowledge-rich processes. Many studies focus on the technical properties of AI systems or treat organisational readiness as a secondary concern (Kerschbaum and Dachs, 2024; Bérubé *et al.*, 2021). Less attention has been given to how organisations coordinate across functions, refresh knowledge

[1] The Financial Stability Board (FSB) (2017) defines FinTech as *"technology-enabled innovation in financial services that could result in new business models, applications, processes or products with an associated material effect on financial markets and institutions and the provision of financial services"*.

as conditions evolve or ensure that human users can interpret AI-supported outputs in a defensible and consistent way. These questions are important in FinTech, where decision outcomes can carry regulatory, operational and customer consequences.

Dynamic capabilities (DC) offer a suitable framework for addressing these questions. DC theory explains how organisations sense change, mobilise resources and adjust routines in volatile environments (Kombo *et al.*, 2023; Paterson *et al.*, 2022). Although widely applied in digital transformation research, relatively little empirical work examines how dynamic capabilities develop in knowledge-intensive AI applications (Phan *et al.*, 2022; Oshodin *et al.*, 2019; Zakery and Saremi, 2025). This study addresses this gap by analysing how a multinational FinTech organisation builds and maintains the capabilities needed for AI-augmented KM.

This study makes three contributions. First, it reconceptualises dynamic capability development in AI-enabled KM as a recursive rather than sequential process, characterised by overlapping cycles and feedback loops. Second, it positions stakeholder alignment and trust in organisational knowledge as structural preconditions for AI integration, challenging accounts that treat alignment as a downstream outcome. Third, it identifies mediation structures that link data, knowledge and operational work as boundary-spanning microfoundations that stabilise interpretation and support coherent human–AI collaboration. These contributions refine assumptions in the DCF literature and extend its relevance to knowledge-intensive AI settings.

The research is guided by the following questions:

RQ1. How can organisations evaluate KM practices to support AI-augmented decision-making in complex environments?

RQ2. How do KM practices support human–AI collaboration in strategic decision-making?

RQ3. How might AI augmentation influence human judgment in strategic decision-making?

To investigate these questions, a qualitative case study was conducted using semi-structured interviews and organisational document analysis. This design enables close examination of the routines, knowledge flows and interpretive practices through which AI becomes embedded in decision work (Yin, 2018; Merriam and Tisdell, 2015).

The paper proceeds as follows. Section 2 reviews literature on AI in KM and dynamic capabilities. Section 3 outlines the research design. Section 4 presents the findings and Section 5 discusses their theoretical and practical implications. Section 6 concludes the study.

2. THEORETICAL LENS FOR AI-AUGMENTED KM IN FINTECH

2.1 Knowledge Management and the Need for Dynamic Capabilities

Knowledge management has evolved from a focus on codifying explicit knowledge toward recognising the value of tacit insight, social interaction and interpretive judgment (Nonaka and Takeuchi, 1995; Von Krogh *et al.*, 2000). In organisational settings shaped by ongoing digitalisation, KM is less concerned with storing information than with coordinating how knowledge is created, contextualised and applied under conditions of speed and uncertainty (Grant, 1996). AI technologies reinforce this shift by speeding up knowledge retrieval and pattern recognition, while at the same time heightening reliance on the quality and reliability of underlying organisational knowledge (Jarrahi *et al.,* 2022; Olan *et al.*, 2022).

However, AI also introduces significant ethical and social risks such as biased outputs, ambiguity in reasoning, data quality vulnerabilities and diffusion of accountability, all of which place additional pressure on KM systems. In financial environments, these risks are amplified by regulatory obligations, consumer protection requirements and the need for defensible, auditable decisions (Bank for International Settlements, 2024; Matei *et al.,* 2025). Ensuring knowledge integrity and traceability therefore becomes operational requirement also protecting against ethically or legally problematic AI-supported decisions.

These developments expose the limits of resource-based strategy models such as Resource-Based View (RBV), which explains competitive advantage in stable environments but give little guidance on how organisations continually renew and reconfigure their knowledge and processes (Barney, 1991). RBV stresses valuable, rare, inimitable and non-substitutable resources - "ordinary capabilities", as sources of sustained performance but these approaches underplay the dynamic processes through which firms renew resources to meet shifting markets (Teece, 2014; *Murcia et al., 2022;* Lacaze *et al.*, 2025).

The Dynamic Capabilities Framework addresses this gap (Teece *et al.*, 1997; Teece, 2007). It distinguishes between ordinary capabilities, which maintain efficiency in routine operations and dynamic capabilities, which involve sensing opportunities, seizing initiatives and transforming processes to maintain long-term agility (Teece, 2007). Dynamic capabilities are therefore typically firm-specific, embedded in routines and managerial cognition and thus difficult to imitate.

The DCF has also been criticised for conceptual abstraction and a lack of clarity regarding its microfoundations - the concrete practices and interaction patterns through which capabilities are enacted (Felin *et al.,* 2012; Teece, 2018).

AI-supported knowledge systems make this challenge more pronounced. They compress decision cycles, increase the pace at which sensing must occur, and introduce new interpretive and coordination demands that classical formulations of dynamic capabilities only partially address. This study therefore uses the DCF not as a complete explanatory model, but as a foundation requiring extension to capture the micro-level mechanisms involved in AI-augmented KM.

2.2 Dynamic Capabilities Framework in Financial Innovation

Financial services provide a rich context for examining dynamic capabilities due to rapid innovation cycles, stringent regulatory demands and high information intensity (Reyes-Mercado, 2021). *Figure 1* illustrates an adaptation of Warner and Wäger's (2019) model of dynamic capabilities for digital transformation, extended here to the context of AI-enabled knowledge management systems (AI-KMS). Following the contextual factors such as external triggers (acting as external influence), internal enablers (providing internal support) and barriers (representing friction/limitations), each stage is characterised by specific activities across the capability tiers.

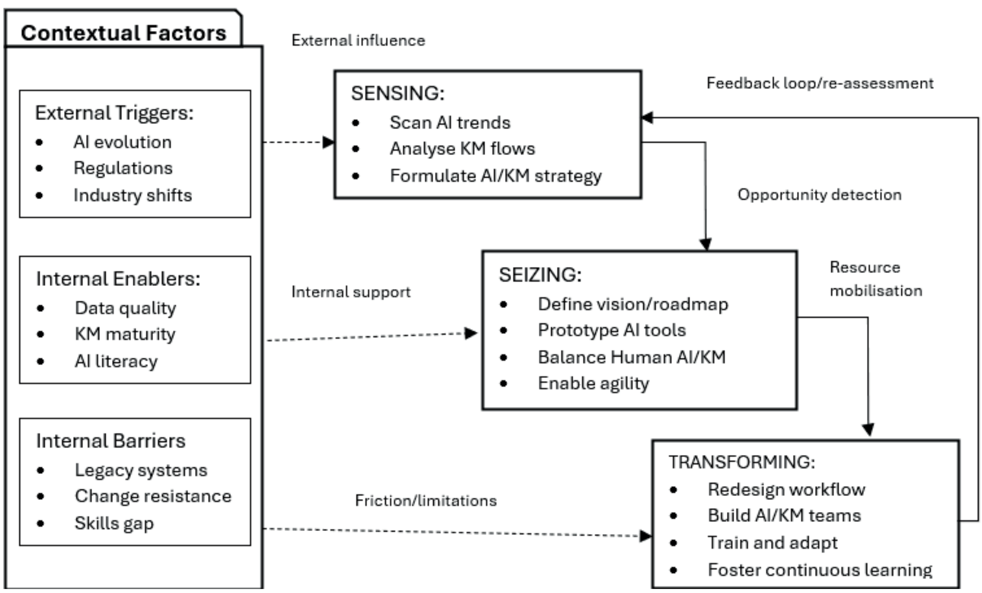

Figure 1. Adapted DCF for AI-Augmented Knowledge Management Systems (Source: Authors own work).

Prior research shows that sensing in rapidly changing environments requires deliberate monitoring of technological, regulatory and market developments, supported by digital infrastructures and organisational learning mechanisms (De Paula Pereira *et al.*, 2024). Seizing depends on coordinated resource mobilisation often via cross-functional collaboration and iterative development of AI tools (Abdurrahman, 2025; Zhang et *al.,* 2024). Transforming involves reconfiguring workflows, updating knowledge artefacts and adjusting roles as AI becomes embedded in decision processes (Hutter *et al.,* 2025).

Evidence across regions and industries reinforces that sensing, seizing and transforming require repeated alignment as technologies, regulations and organisational priorities shift (Warner and Wäger, 2019; Zhang *et al.,* 2024; Ismail and Rashidi, 2025; Tapia, 2025). In AI-enabled environments, this alignment must also encompass ethical oversight, bias monitoring and controls that ensure data accuracy and interpretability, particularly where model outputs directly influence risk, compliance or customer outcomes. Dynamic capabilities thus remain a relevant analytic frame, but they require closer attention to their microfoundations – namely, the concrete knowledge practices, coordination mechanisms and safeguards against ethical and model risks through which AI-enabled KM develops. These considerations inform the extended DCF for AI-augmented KM, which is elaborated in the Discussion and synthesised in *Figure 3*.

3. METHODOLOGY

3.1 Research Design and Case Context

This study adopts a qualitative single-case design (Yin, 2018), suitable for examining complex, context-dependent processes of capability development in real operational environments. The case organisation is a large financial services provider operating across multiple regions. It was selected as an information-rich case because strengthening knowledge management capabilities had become essential for managing rapid organisational scaling, evolving regulatory obligations and the complexity of digital service delivery. The company's name is anonymised for confidentiality. While a single case limits statistical generalisability, it supports analytical generalisation to other similar knowledge-intensive and fast-changing environments.

Primary data were collected through semi-structured interviews, combined with analysis of internal documents, knowledge base articles, project reports and strategic materials.

Triangulating interviews with documentary evidence allowed for a richer understanding of organisational context and reduced reliance on any one data source (Patton, 1999; Fusch *et al.,* 2018).

Knowledge management work in the organisation is structured through an internal framework reflecting principles from project lifecycle management (Kerzner, 2017; Turner, 2009) and knowledge-lifecycle models (Nonaka and Takeuchi, 1995). The framework follows four high-level activities of: (1) knowledge capture, (2) knowledge structuring, (3) knowledge dissemination and communication, and (4) ongoing review and refinement. These stages provide the operational foundation for ensuring that knowledge remains current, interpretable and aligned with organisational needs. Beyond repository maintenance, the KM function collaborates with cross-functional teams and evaluates opportunities for digital enhancement to support organisational learning and operational consistency. The framework therefore serves a dual role, supporting day-to-day work while enabling longer-term adaptation and knowledge renewal.

3.2 Data Collection and Analysis

Data collection combined semi-structured interviews with document review. Ten interviews were conducted in September–October 2024 via online platform (Zoom), each lasting between 40-60 minutes. Participants were selected through purposive sampling, initially via the head of knowledge management and subsequently expanded through snowball sampling as additional relevant roles emerged. Sampling aimed for functional representativeness and participants occupied strategic and operational roles linked to knowledge, data or decision-support activities (e.g. departments of knowledge management, analytics, operations). Selection criteria focused on seniority, subject-matter expertise and involvement in the KM team's evolution. This ensured coverage of both strategic oversight and operational execution.

The first author had prior professional familiarity with the organisational context, which facilitated access to participants. To minimise bias, all interviews followed a standardised protocol and were analysed independently of organisational involvement. The interview protocol was developed jointly with co-authors who had no prior connection to the organisation, which helped keep the questions aligned with the study's aims and prevented the introduction of organisational narratives. All interviews were conducted using a structured guide to limit the influence of pre-existing assumptions. Coding was carried out iteratively using Braun and Clarke's (2006) approach, with codes grounded strictly in the empirical material and not personal experience. Interpretations were continually compared against interview excerpts and documentary evidence to avoid privileging insider perspectives. As the participants represented a variety of strategic and operational roles, the findings were not dependent on any single viewpoint. These measures align with recommended practices for mitigating researcher bias in qualitative case research (Patton, 1999; Yin, 2018) and support the credibility of the analysis.

Prior to participation, respondents received an informed consent form outlining the study's purpose, their right to withdraw and assurances of confidentiality. Pseudonyms were used (ID1–ID10) and identifying details were removed during transcription. To complement interview data, internal company documents were reviewed. These included KM frameworks, stakeholder mappings, team structure reports, inter-departmental project reports and strategic agendas. Document analysis enriched contextual understanding, informed interview questions and allowed for triangulation with participant accounts. Interviews were audio-recorded with permission and transcribed. Analysis followed Braun and Clarke's (2006) thematic approach, combining deductive coding informed by the DCF with inductive coding to capture patterns not anticipated in the framework. *Atlas.ti* software was used to organise transcripts, manage codes and retrieve excerpts efficiently. The coding process was guided by the DCF's three dimensions: (1) *Sensing*: identifying opportunities, risks or emerging trends in AI-enabled KM; (2) *Seizing*: allocating resources, selecting tools and aligning initiatives with strategy; and (3) *Transforming*: Reconfiguring workflows, training staff and embedding cultural change. Codes were iteratively reviewed and refined across multiple rounds to ensure consistency, and triangulation with organisational documents strengthened analytical rigour.

4. FINDINGS

The analysis identified five themes and fourteen sub-themes for Sensing (RQ1), fourteen sub-themes for Seizing (RQ2) and seventeen sub-themes for Transforming (RQ3). These are summarised in Table 1 and discussed in the sections that follow.

Table 1. Thematic Distribution of Knowledge Management Capabilities Across Dynamic Capability Dimensions (Source: Authors own work).

Sensing | RQ1		Seizing | RQ2		Transforming | RQ3	
Themes	**Sub-categories**	**Themes**	**Sub-categories**	**Themes**	**Sub-categories**
Data and Knowledge Reliability	▪ Knowledge Quality & Trust ▪ Knowledge Structure and Access ▪ Domain-Specific and External Knowledge Sources	**Cross-functional Collaboration and Alignment**	▪ Cross-Team Collaboration and Knowledge Sharing ▪ Service and Strategy Alignment ▪ Customer and Internal Stakeholder Focus	**Need for Data in Knowledge Management**	▪ Data Access and Availability ▪ Data-Driven Decision Making and Insights ▪ Data Processing and Management
Stakeholder Communication and Alignment	▪ Stakeholder Communication and Engagement ▪ Cross-Departmental and Cross-Functional Alignment	**Communication and Change Management**	▪ Communication and Change Management ▪ Internal Team Focus	**AI Integration and Knowledge Automation**	▪ AI Integration for Knowledge Enhancement ▪ AI-Driven Knowledge Synthesis and Decision Support ▪ AI Integration for Personalised Decision-Making
Measuring KM Value and Impact	▪ Demonstrating KM Value ▪ Measurement Standards and Continuous Improvement ▪ Financial & Strategic Considerations ▪ Growth and Scalability	**Operational Efficiency and Tooling**	▪ Operational Efficiency and Time Reduction ▪ Data-Driven Process Optimisation ▪ Tooling, Access and Workflow Support	**Process Transformation and Adaptive KM**	▪ Tooling Investments for AI ▪ Process Improvement and Optimisation ▪ Operational Efficiency and Process Redesign ▪ Content and Knowledge Adaptation
Tooling Readiness	▪ Tooling and Integration ▪ Usability and Navigation Efficiency and Decision Support	**Data Quality, Impact and Learning**	▪ Data Quality, Reliability and Use ▪ Impact Demonstration and Resource Justification ▪ Continuous Improvement and Evaluation ▪ Best Practices and Team Learning	**Governance, Ethics and Stakeholder Alignment**	▪ Strategic Alignment and Governance ▪ Stakeholder Alignment and Accountability ▪ Data Privacy, Trust and Responsibility ▪ Costs and Operational Feasibility
KM Role, Leadership and Ownership	▪ Leadership and Ownership of KM ▪ Role Clarity and Strategic Positioning ▪ Timing and Process Standardisation	**Data and Process Mediation**	• Process and Decision-Making Evaluation • Support Function for Knowledge and Data Mediation	**Organisational Learning and Renewal**	▪ Organisational Enablement and Adaptive KM Frameworks ▪ Evolving Knowledge Integration and Automation Strategies ▪ Organisational Enablement and Adaptive KM Frameworks

4.1 Sensing: Evaluating KM Readiness for AI Integration

RQ1 asked how organisations can evaluate KM practices to support AI-augmented decision-making in complex environments. At the sensing stage, the case company assessed its readiness by focusing on several critical conditions: data and knowledge reliability, stakeholder alignment, scalability demands and tooling suitability. These factors shaped the extent to which AI could be meaningfully integrated into existing decision-making processes.

A recurring theme was the reliability of data and knowledge assets. Several participants noted that knowledge artefacts required frequent updating due to evolving regulations and product changes, with one respondent explaining that materials *"can become outdated quickly,"*. Participants also referenced the pace of organisational growth and the volume of regulatory and product updates that accompanied it. This environment required KM processes capable of absorbing rapid change: *"As the company grows rapidly, we constantly face new regulations, rules, features, and products…"* - illustrating the operational demands placed on knowledge maintenance in a fast-moving FinTech context. Thus, there was a need to ensure that the knowledge sources are up to date internally, but also reflect the domain specific, recent changes.

Equally important was stakeholder communication and alignment. Interviewees highlighted that AI adoption requires cross-department coordination, with one noting, *"KM must be synchronized with operations, product, learning and development, and Quality Assurance to prevent double work and maintain efficiency"*. This extends to another prominent theme which was role clarification of the KM team, their position in the ongoing transformation, responsibilities assigned to them and clarity of the scope (for maintaining cross-team efficiency mentioned by the respondent).

Finally, interviewees mentioned usability and workflow-integration readiness. The transition to the AI-enablement requires the restricting of the existing workflows which become operational with the appropriate tools in place. Thus, they saw AI as an opportunity to enhance accessibility and support decision-making, with one respondent suggesting that AI could *"provide accurate answers based on reliable sources…"* thereby improving speed and consistency. This was combined with the necessity of the tooling being intuitive and user-friendly.

The findings thus indicate that the sensing stage is less about simply "evaluating AI" and more about assessing the maturity of existing KM practices as a foundation for augmentation. Without reliable data, cross-functional alignment and scalable processes, AI initiatives might be implemented in ways that erode human judgment instead of enhancing them.

4.2 Seizing: Embedding KM Practices for Human–AI Collaboration

RQ2 question asked how KM practices support human–AI collaboration in strategic decision-making. At the seizing stage, the organisation strengthened structures that enable AI integration. A dedicated BI function played a *boundary-spanning role* mediating across functional divides linking data specialists, KM practitioners and operational teams and ensuring that knowledge, insights and requirements circulate coherently throughout the organisation. As one participant explained, the BI role *"sits between the users of the data and the data analysts and engineers,"* supporting KM with a variety of data requests. Their efforts improve how data is shared and interpreted, providing important foundation for AI tools to enhance decision-making.

Participants reported that clearer data flows, more consistent documentation, and refined tooling improved efficiency. One respondent emphasised reductions in *"search time and handle time,"* noting that these enhancements helped staff feel more confident in locating and applying relevant information. These improvements also ensured that AI systems would draw on stable and accurate knowledge sources.

A recurring practice was the use of phased implementation, beginning with "soft launches" to test and refine new tools before wider adoption. This approach managed uncertainty and reduced disruption while encouraging feedback from early users. However, participants also noted that coordination across teams is an area that continues to evolve, with one senior manager observing that information flows might not always be fully transparent *"However, being part of the service experience umbrella helps us work together to optimize communication and change procedures"*.

Participants stressed the importance of external orientation—*i.e.*, monitoring industry trends and best practices to remain agile. As one respondent put it, *"we are always making sure we keep our eyes open to the industry best practices, and we're trying to make sure that we are aligned"*. This suggests that seizing is not only about internal alignment but also about positioning the organisation within a broader and shifting FinTech ecosystem.

These findings indicate that effective seizing requires both structural adjustments (*e.g.*, BI integration and phased rollouts) and cultural ones (*e.g.*, collaboration and external awareness). These practices enable AI systems to support and not replace human judgment in decision-making.

4.3 Transforming: Strategic Impact of AI-Augmented KM on Human Judgment

RQ3 examined how AI augmentation influences human judgment in strategic decision-making. At the transforming stage, the company began embedding operational and cultural changes that reflect broader strategic shifts. Themes at this stage centred on AI integration, personalised decision support and organisational renewal, alongside ongoing concerns about costs and scalability.

A key finding was the integration of AI with existing knowledge systems. Participants stressed that manually reviewing extensive knowledge bases and datasets was both time-consuming and cognitively demanding. AI was seen as a way to accelerate information retrieval and improve decision transparency. As one participant noted, *"using AI to quickly retrieve answers related to company details from multiple resources instead of manually searching through them"* both improved efficiency and enhanced confidence in outcomes.

Another prominent theme was personalised decision support. Respondents described how AI systems could be adapted to users' needs, offering tailored recommendations while automating routine checks. One explained, *"I see AI playing an increasing role in automating repetitive tasks, improving accuracy, and supporting decision-making. With AI handling routine data checks and communications, human agents can focus more on strategic analysis and deeper insights"*. This shift reflects AI's role in supporting *cognitive offloading* where routine or information-heavy tasks are delegated to external systems thereby freeing human cognitive resources for higher-order judgment, interpretation and problem-solving.

Transformation also entailed organisational renewal. Interviewees described how KM processes were evolving toward real-time integration and greater automation, with knowledge increasingly embedded in service delivery. As one put it, *"KM is part of the servicing team, and the future strategy is to increase automation to provide instant services to customers"*. This redefined KM from a support function to a strategic enabler of agility and customer value. Yet participants also voiced concerns about funding, scalability and security, emphasizing that transformation is not a linear progression but an ongoing balancing act between innovation and feasibility. As one respondent concluded, *"I think it's just about cost, security, and finding a way to implement it into your daily processes."*

Overall, the findings show that AI augmentation influences human judgment less by replacing it than by reshaping its conditions. By reducing cognitive load, improving data reliability and embedding adaptive KM frameworks, AI creates the space for judgment to become more strategic, integrative and forward-looking. *Figure 2* illustrates this simplified process (*i.e.*, sensing identifies drivers, seizing mobilises resources and practices and transforming embeds changes that shape how human judgment operates in AI-augmented decision environments).

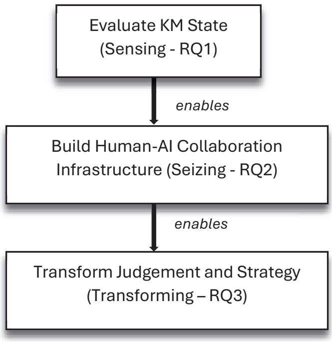

Figure 2. Summary Flow of Findings (Source: Authors own work).

5. DISCUSSION

This section introduces *Figure 3* which is an extended DCF framework of *Figure 1* and depicts the stages the case organisation underwent during its transformative trajectory with the key activities characterising each stage. The subsections that follow elaborate the foundational activities supporting capability development, draw similarities and distinctions across sectors, outline the major theoretical contributions of this research, and discuss its societal and practical implications.

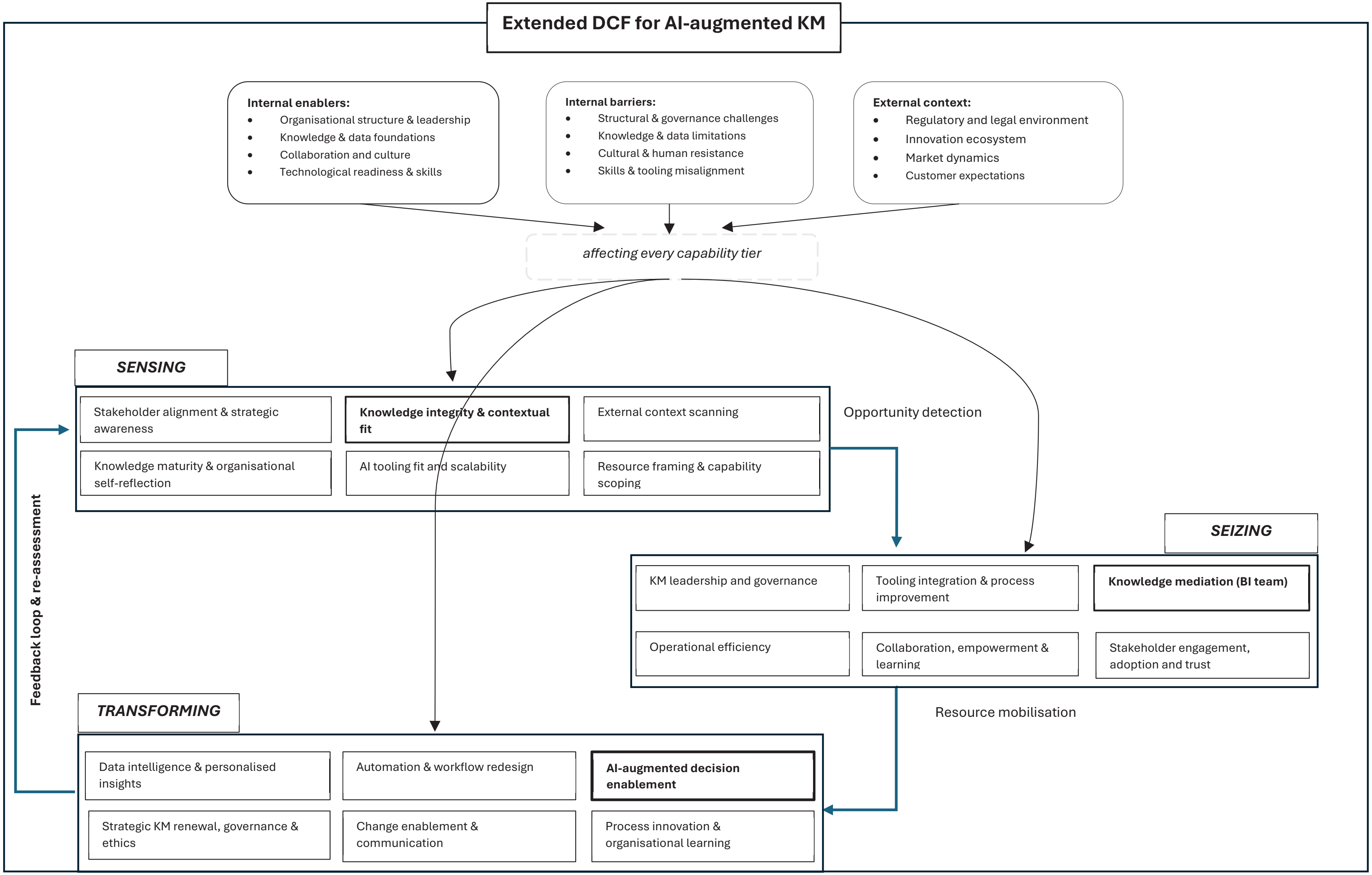

Figure 3. Framework of Knowledge Management Practices and Human–AI Collaboration in Strategic Decision-Making (Source: Authors own work).

5.1 Dynamic Capabilities in AI-Augmented Knowledge Environments

The extended framework (*Figure 3*) illustrates that dynamic capability formation in AI-augmented knowledge environments diverges from the linear or stage-based interpretations commonly associated with the Dynamic Capabilities Framework (Teece, 2007). The findings indicate that capability development unfolds through continuous and interdependent cycles in which sensing, seizing and transforming mutually reinforce one another. Sensing activities appear across all tiers, and capability cycles overlap as new technological developments reactivate or reshape existing routines. These dynamics introduce temporal unevenness, with certain routines evolving rapidly while others stabilise more slowly.

This pattern aligns with emerging research showing that dynamic capabilities in digitally intensive and rapidly changing contexts evolve recursively rather than sequentially, characterised by repeated reactivation, reconfiguration and feedback loops between capability elements and their antecedents, processes and outcomes (Warner and Wäger, 2019; de Aro and Perez, 2021; Abdurrahman, 2025). Such recursion requires continual recalibration between regulatory and market velocity, organisational knowledge infrastructures and operational routines. In AI-enabled knowledge environments where decision cycles shorten and knowledge assets change quickly, capability renewal becomes an iterative and cyclical process instead of progressing through discrete stages.

A second insight emphasizes the role of alignment as an enabling microfoundation and not merely an outcome of system design. It starts with shared understanding among the organisational structures. The analysis demonstrates that interpretive coherence across product, risk, compliance, operations and data functions is essential for ensuring that sensing signals are interpreted consistently and translated into coordinated action. Alignment does not emerge naturally as technical systems mature; it needs to be prioritised from an early implementation step throughout the organisational journey (Dulipovici and Robey, 2013). Such alignment is a central organising capability supporting trustworthy, explainable, domain-consistent and coordinated decision processes. It enables the orchestration of stakeholder expertise and ensures that AI-augmented knowledge practices remain coherent with organisational priorities, regulatory expectations and knowledge assets evolve.

Existing AI readiness and maturity models such as those proposed by PwC (2019), Gartner (2020) and Holmström (2021) primarily emphasise data maturity, infrastructure development and tool adoption as indicators of organisational preparedness for AI. While these models offer useful diagnostic guidance, they pay considerably less attention to the interpretive and coordinative work through which data, knowledge and operational judgement are connected in practice. This limitation emphasises the need to examine the microfoundations that sustain AI-enabled knowledge work, as technical readiness alone does not ensure consistent or reliable decision-making in knowledge-intensive environments.

A third insight concerns the function of mediation structures which enable capability coordination. It entails human and organisational infrastructures that integrate data, knowledge and operational expertise. These are not peripheral support, instead, they act as mediation structures performing boundary-spanning work that protects data reliability, secures interpretive consistency and coordinates knowledge flows across domains. Mediation structures therefore represent core microfoundations through which sensing, seizing and transforming become actionable within complex socio-technical environments (De Aro and Perez, 2021).

The mechanisms identified here connect to evidence across other knowledge-intensive sectors. In advanced manufacturing, curated knowledge infrastructures strengthen effective AI deployment (Leoni *et al.,* 2022); in healthcare, governance and alignment structures are essential for securing interpretive coherence (Lämmermann *et al.,* 2024); and in public-sector algorithmic systems, oversight bodies act as integrating governance mechanisms (Almeida and Santos Júnior, 2025). Small and medium-sized enterprises undergoing digitalisation similarly exhibit iterative cycles of capability refinement (Ceptureanu *et al.,* 2025). These parallels indicate that recursive capability development, alignment routines and mediation structures are not unique to FinTech but represent foundational microfoundations of AI-enabled organisational environments.

FinTech environments heighten these mechanisms because regulations shift rapidly, risk profiles evolve quickly and operational work is tightly connected to risk decisions. This places a stronger emphasis on keeping knowledge updated, maintaining alignment across functions and ensuring effective mediation. Although the intensity differs, these mechanisms themselves are not unique to FinTech. What varies across sectors is the pace of change and the types of institutional and operational pressures organisations face. This reinforces that the extended framework in *Figure 3* is applicable across diverse domains, even if its expression takes different forms depending on contextual conditions.

5.2 Ethical and Societal Implications in AI-Enabled Knowledge Management

The ethical and societal dimensions of AI-enabled knowledge management extend beyond internal organisational performance and directly shape how decisions are experienced by service users and the broader public. A recurring theme across the findings was the centrality of trust which is threefold - trust in data and knowledge artefacts, trust in system behaviour and trust in one's own ability to interpret AI-supported outputs. These layers are interconnected: if any element becomes unstable, confidence in the overall decision process can weaken. Studies in healthcare and public-sector AI deployments describe similar "multi-layer" trust dynamics, emphasising that technical reliability alone is insufficient without interpretive confidence and organisational transparency (Starke *et al.,* 2025; Mukherjee *et al.,* 2025). These trust layers relate closely to broader societal expectations. In digital finance and other customer-facing fields, individuals expect decisions to be explainable, contestable and grounded in up-to-date knowledge. Otherwise, the concerns about fairness and the risk of unintentionally excluding certain groups may arise.

Interpretation also carries ethical weight. Across interviews, AI was framed as an analytical amplifier rather than a decision-maker. The speed with which AI retrieves or synthesises information can create an impression of certainty, but the responsibility for determining relevance, sufficiency and proportionality remain with humans. This aligns with evidence from higher-risk settings such as legal services, healthcare and welfare systems, showing that accuracy alone does not resolve ambiguity and that critical judgment is required to contextualise outputs (Nosrati *et al.,* 2025; Khosravi *et al.* 2024; Vaccaro and Waldo, 2019). When interpretation falters, downstream effects can include inconsistent case handling, reduced procedural fairness or decisions that inadvertently disadvantage edge cases who do not fit model assumptions. This places interpretive capability at the core of responsible AI use: it is not simply a cognitive task but an ethical safeguard. Being "in the loop" is not enough; users must be able to interrogate outputs, recognise when a model's recommendation may not apply and justify their decisions when they diverge from system suggestions. These interpretive practices protect decision quality and also help maintain public trust in AI-enabled services.

Accountability forms the third dimension of these ethical implications. AI-supported decisions are shaped by layered inputs—data, models, workflows and human judgment—which can blur responsibility. Research in defence, healthcare and financial services highlights how unclear accountability can lead to what some authors describe as "responsibility gaps" or "diffusion of responsibility" (Zeiser, 2024; Conn and Bode, 2025; Pasupuleti, 2025). The findings support the growing consensus that accountability needs to be distributed across those who curate data, validate models, design workflows and make decisions, rather than attributed post hoc to a single actor. Clarity around who verifies inputs, who validates system behaviour and who retains interpretive authority reduces ambiguity and strengthens the defensibility of decisions (Conn and Bode, 2025; Papagiannidis *et al.,* 2025).

These ethical considerations also vary between regulatory and cultural contexts. In Europe, rights-based regimes such as the GDPR (European Union, 2016) and the EU AI Act (European Union, 2024) formalise expectations around explainability, traceability and human oversight, making many of the mechanisms identified here obligatory rather than optional. In North America, governance relies more on internal standards and organisational discretion e.g. National Institute of Standards and Technology (NIST) AI Risk Management Framework (National Institute of Standards and Technology, 2023) whereas in several Asian jurisdictions, state-led or technocratic approaches emphasise auditability, provenance and centralised oversight (China, 2023; Infocomm Media Development Authority, 2024). Cultural orientations shape practice further: for instance, high-uncertainty-avoidance contexts tend to institutionalise oversight mechanisms (Wilczek *et al.,* 2025), while higher power-distance settings may centralise interpretive authority at specific organisational levels (Cannavale *et al.,* 2025), These variations influence how trust, interpretation and accountability are enacted, but the underlying ethical concerns—fairness, transparency and responsible use—remain shared across contexts (Roberts *et al.*, 2022).

5.3 Practical implications

Building on the capability tiers and activities in the extended framework, several practical implications follow for organisations working with AI-supported knowledge management.

Knowledge integrity needs to be handled as an ongoing operational task rather than something that is addressed only during periodic updates. In practical terms, this means assigning clear responsibility for specific knowledge assets, keeping track of which decisions and AI components depend on which rules, and putting in place straightforward triggers so that regulatory or product changes lead to timely review.

The findings also point to the value of mediation structures that connect data work, knowledge maintenance and operational decision-making. Organisations can support this by creating small cross-functional groups or governance teams that monitor how changes in data, rules or product logic flow through service processes. When these teams have the mandate to question assumptions and coordinate updates, decision processes remain more stable even as risk patterns or regulatory expectations shift.

Alignment routines also need to be flexible but carried out with regularity. Brief cross-team check-ins, shared interpretation notes for regulatory updates and routine pre-deployment reviews help prevent small divergences in understanding from accumulating into inconsistent customer decisions. This becomes particularly important in settings where operational activity and risk management are closely linked.

Clarifying when human judgment is required is another essential element of responsible AI use. Setting out review points for borderline cases, documenting who is accountable for validating AI-supported outputs and specifying escalation paths for ambiguous situations help staff navigate uncertainty and maintain defensible decisions in regulated environments.

6. CONCLUSION

This study examined how organisations develop the capabilities required for AI-augmented knowledge management. Drawing on a single case, the analysis identified three core mechanisms that shape capability formation. Theoretically, it shows that capability development is recursive rather than sequential, and that alignment and mediation routines operate as capability-building mechanisms in their own right. Practically, the study offers a framework for designing knowledge processes that remain reliable and coherent when supported by AI. It points to ongoing knowledge stewardship, targeted mediation roles, and clear boundaries for human involvement as central to maintaining consistent decision practices. Societally, the findings highlight the importance of trust, interpretive clarity and accountable oversight for fairness and transparency within semi-automated decision systems.

While the analysis provides a detailed account of capability development within one organisation, it also has limits. The single-case design means that contextual factors specific to the organisation may have influenced how these mechanisms appeared, and the qualitative data reflect conditions at one point in time. Even so, the capability patterns observed align with evidence from other knowledge-intensive domains and offer a basis for wider comparison.

Future research could examine how these mechanisms operate in settings with different regulatory or organisational arrangements or follow how they develop over longer periods of AI use. Studies that observe AI-supported knowledge work as it unfolds in practice would further clarify how human judgment, organisational knowledge and automated systems interact.

REFERENCES

Abdurrahman, A. (2025), "Examining the impact of digital transformation on digital product innovation performance in banking industry through the integration of resource-based view and dynamic capabilities", *Journal of Strategy & Innovation*, Vol. 36 No. 1, Article 200540, available at: https://doi.org/10.1016/j.jsinno.2025.200540

Almeida, P.G.R. de and Santos Júnior, C.D. dos (2025), "Artificial intelligence governance: Understanding how public organizations implement it", *Government Information Quarterly*, Vol. 42 No. 1, Article 102003, available at: https://doi.org/10.1016/j.giq.2024.102003

Al-Okaily, M. and Al-Okaily, A. (2025), "Financial data modeling: An analysis of factors influencing big data analytics-driven financial decision quality", *Journal of Modelling in Management*, Vol. 20 No. 2, pp.301-321, available at: https://doi.org/10.1108/JM2-08-2023-0183

Bank for International Settlements (2024), "Regulating AI in the financial sector: recent developments and main challenges", *FSI Insights on Policy Implementation*, No. 63, Bank for International Settlements, Basel, available at: https://www.bis.org/fsi/publ/insights63.pdf (accessed 16 July 2025).

Barney, J. (1991), "Firm resources and sustained competitive advantage", *Journal of Management*, Vol. 17 No. 1, pp.99-120, available at: https://doi.org/10.1177/014920639101700108

Bérubé, M., Giannelia, T. and Vial, G. (2021), "Barriers to the implementation of AI in organizations: Findings from a Delphi study", *Proceedings of the 54th Hawaii International Conference on System Sciences*, pp.6702-6711, available at: https://hdl.handle.net/10125/71425

Braun, V. and Clarke, V. (2006), "Using thematic analysis in psychology", *Qualitative Research in Psychology*, Vol. 3 No. 2, pp. 77-101, available at: https://doi.org/10.1191/1478088706qp063oa

Cannavale, C., Claudio, L. and Koroleva, D. (2025), "Digitalisation and artificial intelligence development: A cross-country analysis", *European Journal of Innovation Management*, Vol. 28 No. 11, pp. 112–130, https://doi.org/10.1108/EJIM-07-2024-0828

Ceptureanu, S.I., Ceptureanu, E.G., Georgescu, B. and Iancu, L.A. (2025), "Sustainability, innovation and knowledge: a complex relationship based on an empirical study", *Soft Computing*, Vol. 29, pp. 3047–3062, available at: https://doi.org/10.1007/s00500-025-10574-3

Chierici, R., Mazzucchelli, A., Garcia-Perez, A. and Vrontis, D. (2019), "Transforming big data into knowledge: The role of knowledge management practice", *Management Decision*, Vol. 57 No. 8, pp.1902-1922, available at: https://doi.org/10.1108/MD-07-2018-0834

China (2023), "Interim Measures for the Management of Generative Artificial Intelligence Services", Cyberspace Administration of China, National Development and Reform Commission, Ministry of Education, Ministry of Science and Technology, Ministry of Industry and Information Technology, Ministry of Public Security and National Radio and Television Administration, translated by China Aerospace Studies Institute, available at: http://www.cac.gov.cn/2023-07/13/c_1690898327029107.htm (accessed 06 November 2025).

Conn, A. and Bode, I. (2025), "Establishing human responsibility and accountability at early stages of the lifecycle for AI-based defence systems", *Ethics and Information Technology*, Vol. 27, Article 51, available at: https://doi.org/10.1007/s10676-025-09862-1

de Aro, E.R. and Perez, G. (2021), "Identification of dynamic capabilities in open innovation", *Innovation & Management Review*, Vol. 18 No. 2, pp. 118–128, https://doi.org/10.1108/INMR-10-2019-0120

De Paula Pereira, G., Fleith de Medeiros, J., Kolling, C., Duarte Ribeiro, J., Morea, D. and Iazzolino, G. (2024), "Using dynamic capabilities to cope with digital transformation and boost innovation in traditional banks", *Business Horizons*, Vol. 67 No. 4, pp.317-330, available at: https://doi.org/10.1016/j.bushor.2024.03.006

Dulipovici, A. and Robey, D. (2013), "Strategic alignment and misalignment of knowledge management systems: A social representation perspective", *Journal of Management Information Systems*, Vol. 29 No. 4, pp.103-126, available at: https://doi.org/10.2753/MIS0742-1222290404

European Union (2016), "Regulation (EU) 2016/679 of the European Parliament and of the Council of 27 April 2016 on the protection of natural persons with regard to the processing of personal data and on the free movement of such data (General Data Protection Regulation)", available at: https://eur-lex.europa.eu/eli/reg/2016/679/oj (accessed 06 November 2025).

European Union (2024), "Regulation of the European Parliament and of the Council laying down harmonised rules on artificial intelligence (Artificial Intelligence Act)", available at: https://eur-lex.europa.eu/eli/reg/2024/1689/oj (accessed 06 November 2025)

Felin, T., Foss, N.J., Heimeriks, K.H. and Madsen, T.L. (2012), "Microfoundations of routines and capabilities: individuals, processes, and structure", *Journal of Management Studies*, Vol. 49 No. 8, pp. 1351–1374, available at: https://doi.org/10.1111/j.1467-6486.2012.01052.x

Financial Stability Board (2017), *Financial stability implications from FinTech: Supervisory and regulatory issues that merit authorities' attention*, Financial Stability Board, Basel, available at: https://www.fsb.org/wp-content/uploads/R270617.pdf (accessed 16 July 2025).

Fusch, P., Fusch, G. and Ness, L. (2018), "Denzin's paradigm shift: Revisiting triangulation in qualitative research", *Journal of Social Change*, Vol. 10 No. 1, pp.19-32, available at: https://doi.org/10.5590/JOSC.2018.10.1.02

Gartner (2020), AI Maturity Model: From awareness to transformation, Gartner Inc., Stamford, CT, available at: https://www.gartner.com/en/documents/3984965 (accessed 16 May 2025).

Grant, R. (1996), "Toward a knowledge-based theory of the firm", *Strategic Management Journal*, Vol. 17 No. S2, pp.109-122, available at: https://doi.org/10.1002/smj.4250171110

Hutter, K., Brendgens, F., Gauster, S. and Matzler, K. (2025), "Scaling organizational agility: Key insights from an incumbent firm's agile transformation", *Management Decision*, Vol. 63 No. 6, pp.1882-1913, available at: https://doi.org/10.1108/MD-05-2022-0650

Infocomm Media Development Authority (2024), "Model AI Governance Framework for Generative AI", AI Verify Foundation, Singapore, available at: https://aiverifyfoundation.sg/wp-content/uploads/2024/06/Model-AI-Governance-Framework-for-Generative-AI-19-June-2024.pdf (accessed 06 November 2025).

Ismail, I. and Rashidi, F. (2025), "Linking dynamic entrepreneurial capabilities and behavioral intentions to adopt FinTech in small and medium enterprises through digital financial innovation", *Cogent Business & Management*, Vol. 12 No. 1, Article 2470915, available at: https://doi.org/10.1080/23311975.2025.2470915

Jarrahi, M., Askay, D., Eshraghi, A. and Smith, P. (2022), "Artificial intelligence and knowledge management: A partnership between human and AI", *Business Horizons*, Vol. 65 No. 4, pp.549-559, available at: https://doi.org/10.1016/j.bushor.2022.03.002

Kamila, M. and Jasrotia, S. (2025), "Ethical issues in the development of artificial intelligence: Recognizing the risks", *International Journal of Ethics and Systems*, Vol. 41 No. 1, pp.45-63, available at: https://doi.org/10.1108/IJOES-05-2023-0107

Kerschbaum, C. and Dachs, R. (2024), "Challenges in AI implementation: Perspectives from practice and research", *Proceedings of the International Conference on AI Research (ICAIR 2024)*, Vol. 4 No. 1, available at: https://doi.org/10.34190/icair.5.1.3051

Kerzner, H. (2017), *Project management: A systems approach to planning, scheduling, and controlling*, John Wiley & Sons, Hoboken, NJ.

Khan, F., Bartáková, G., Almadhor, A., Qayyum, A., Abeer, K. and Durrani, A. (2025), "Evaluating the capacity and limitations of generative AI in financial decision making", *Computer Standards & Interfaces*, Vol. 93, Article 103965, available at: https://doi.org/10.1016/j.csi.2024.103965

Khosravi, M., Zare, Z., Mojtabaeian, S.M. and Izadi, R. (2024), "Artificial intelligence and decision-making in healthcare: a thematic analysis of a systematic review of reviews", *Health Services Research and Managerial Epidemiology*, Vol. 11, Article 23333928241234863, available at: https://doi.org/10.1177/23333928241234863

Kombo, V., Asbaş, C. and Tuzlukaya, Ş. (2023), "Artificial intelligence, dynamic capabilities, and business optimization: Impact on firm performance", in *Streamlining organizational processes through AI, IoT, blockchain, and virtual environments*, IGI Global, Hershey, PA, pp.1-20, available at: https://doi.org/10.4018/978-1-6684-8639-9.ch001

Kumar, P. (2025), "Artificial intelligence (AI)-augmented knowledge management capability and clinical performance: Implications for marketing strategies in health-care sector", *Journal of Knowledge Management*, Vol. 29 No. 2, pp.415-441, available at: https://doi.org/10.1108/JKM-01-2024-0111

Lacaze, A., Ferreira, F. and Santos, M. (2025), Adding value to the VRIO framework using DEMATEL, *Management Decision*, Vol. 63 No. 4, pp.1154-1175, available at: https://doi.org/10.1108/MD-10-2023-1935

Lämmermann, L., Hofmann, P. and Urbach, N. (2024), "Managing artificial intelligence applications in healthcare: Promoting information processing among stakeholders", *International Journal of Information Management*, Vol. 75, Article 102728, available at: https://doi.org/10.1016/j.ijinfomgt.2023.102728

Leoni, L., Ardolino, M., El Baz, J., Gueli, G. and Bacchetti, A. (2022), "The mediating role of knowledge management processes in the effective use of artificial intelligence in manufacturing firms", International Journal of Operations & Production Management, Vol. 42 No. 13, pp. 411–437, available at: https://doi.org/10.1108/IJOPM-05-2022-0282

Lui, A. and Lamb, G. (2018), "Artificial intelligence and augmented intelligence collaboration: Regaining trust and confidence in the financial sector", *Information & Communications Technology Law*, Vol. 27 No. 3, pp.267-283, available at: https://doi.org/10.1080/13600834.2018.1488659

Matei, S., Jackson, D. and Bertino, E. (2025), "Ethical reasoning in artificial intelligence: A cybersecurity perspective", *The Information Society*, Vol. 41 No. 2, pp.110-122, available at: https://doi.org/10.1080/01972243.2024.2429060

Merriam, S. and Tisdell, E. (2015), *Qualitative research: A guide to design and implementation*, Wiley, San Francisco, CA.

Murcia, N., Ferreira, F. and Ferreira, J. (2022). Enhancing strategic management using a "quantified VRIO": Adding value with the MCDA approach, *Technological Forecasting and Social Change*, Vol. 174, pp.1-9, available at: https://doi.org/10.1016/j.techfore.2021.121251

Mukherjee, S., Mukherjee, S., Ferraris, A. and Stehlikova, B. (2025), "Enhancing health-care service delivery through AI-integrated knowledge management systems", *Journal of Knowledge Management*, ahead-of-print, available at: https://doi.org/10.1108/JKM-01-2025-0119

National Institute of Standards and Technology (2023), Artificial Intelligence Risk Management Framework (AI RMF 1.0), NIST, Gaithersburg, MD, available at: https://nvlpubs.nist.gov/nistpubs/ai/NIST.AI.100-1.pdf (accessed 06 November 2025)

Nonaka, I. and Takeuchi, H. (1995), *The knowledge-creating company: How Japanese companies create the dynamics of innovation*, Oxford University Press, Oxford.

Nosrati, T., Nosrati, F. and Mashayekhi, M. (2025), "Human–AI collaboration in legal services: empirical insights on task–technology fit and generative AI adoption by legal professionals", *SAM Advanced Management Journal*, Vol. 90 No. 3, pp. 305-333, available at: https://doi.org/10.1108/SAMAMJ-07-2025-0041

Olan, F., Arakpogun, E.O., Suklan, J., Nakpodia, F., Damij, N. and Jayawickrama, U. (2022), "Artificial intelligence and knowledge sharing: Contributing factors to organizational performance", *Journal of Business Research*, Vol. 145, pp.605-615, available at: https://doi.org/10.1016/j.jbusres.2022.03.008

Oshodin, O., Molla, A., Karanasios, S. and Ong, C.E. (2019), "How do FinTech start-ups develop capabilities? Towards a FinTech capability model", in *PACIS 2019 Proceedings* (Paper 59), AIS Electronic Library (AISeL), available at: https://aisel.aisnet.org/pacis2019/59

Papagiannidis, E., Mikalef, P. and Conboy, K. (2025), "Responsible artificial intelligence governance: a review and research framework", *The Journal of Strategic Information Systems*, Vol. 34 No. 2, Article 101885, available at: https://doi.org/10.1016/j.jsis.2024.101885

Pasupuleti, M.K. (2025), "Human-in-the-loop AI: enhancing transparency and accountability", *International Journal of Academic and Industrial Research Innovations*, Vol. 5 No. 5, pp. 574-585, available at: https://doi.org/10.62311/nesx/rphcr18

Paterson, E., Pugalia, S. and Agarwal, R. (2022), "Innovation management as a dynamic capability for a volatile, uncertain, complex and ambiguous world", in *Innovation*, 1st ed., Routledge, London, pp.1-19, available at: https://doi.org/10.4324/9780429346033

Patton, M. Q. (1999), "Enhancing the quality and credibility of qualitative analysis", *Health Services Research*, Vol. 34 No. 5 Pt 2, pp.1189-1208.

Phan, X., Ngo, H., Nguyen, T., Pham, D., Truong, N., Pham, N. and Do, T. (2022), "The effects of dynamic employee capabilities, fintech and innovative work behavior on employee and supply chain performance: Evidence from Vietnamese financial industry", *Uncertain Supply Chain Management*, Vol. 10 No. 4, pp.1305-1314, available at: http://dx.doi.org/10.5267/j.uscm.2022.7.009

PwC (2019), AI Readiness Framework: Assessing your AI maturity, PwC, London, available at: https://www.pwc.com/gx/en/issues/analytics/assets/pwc-ai-analysis-sizing-the-prize-report.pdf (accessed 16 May 2025)

Reyes-Mercado, P. (2021), “Technology as a resource for FinTech”, in *FinTech strategy*, Palgrave Studies in Democracy, Innovation, and Entrepreneurship for Growth, Palgrave Macmillan, Cham, pp.15-32, available at: https://doi.org/10.1007/978-3-030-53945-0_2

Roberts, H., Cowls, J., Hine, E., Morley, J., Wang, V. and Taddeo, M. (2022), “Governing artificial intelligence in China and the European Union: Comparing aims and promoting ethical outcomes”, *The Information Society*, Vol. 39 No. 2, pp. 79–97, https://doi.org/10.1080/01972243.2022.2124565

Starke, G., Gille, F., Termine, A., Aquino, Y.S.J., Chavarriaga, R., Ferrario, A., Hastings, J., Jongsma, K., Kellmeyer, P., Kulynych, B., Postan, E., Racine, E., Sahin, D., Tomaszewska, P., Vold, K., Webb, J., Facchini, A. and Ienca, M. (2025), “Finding consensus on trust in AI in health care: recommendations from a panel of international experts”, *Journal of Medical Internet Research*, Vol. 27, Article e56306, available at: https://doi.org/10.2196/56306

Tapia, S. (2025), “Business model innovation in the big-data era from the perspective of knowledge-based dynamic capabilities: Case study of a FinTech”, in Zimmermann, R., Rodrigues, J.C., Simoes, A. and Dalmarco, G. (Eds), *Human-centred technology management for a sustainable future*, IAMOT 2024, Springer Proceedings in Business and Economics, Springer, Cham, pp.125-140, available at: https://doi.org/10.1007/978-3-031-72494-7_10

Teece, D. (2007), “Explicating dynamic capabilities: The nature and microfoundations of (sustainable) enterprise performance”, *Strategic Management Journal*, Vol. 28 No. 13, pp.1319-1350, available at: https://doi.org/10.1002/smj.640

Teece, D. (2014), “A dynamic capabilities-based entrepreneurial theory of the multinational enterprise”, *Journal of International Business Studies*, Vol. 45 No. 1, pp.8-37, available at: https://doi.org/10.1057/jibs.2013.54

Teece, D. (2018), “Business models and dynamic capabilities”, *Long Range Planning*, Vol. 51 No. 1, pp.40-49, available at: https://doi.org/10.1016/j.lrp.2017.06.007

Teece, D., Pisano, G. and Shuen, A. (1997), “Dynamic capabilities and strategic management”, *Strategic Management Journal*, Vol. 18 No. 7, pp.509-533, available at: https://www.jstor.org/stable/3088148

Turner, J. (2009), *The handbook of project-based management*, McGraw-Hill, New York, NY.

Vaccaro, M. and Waldo, J. (2019), “The effects of mixing machine learning and human judgment”, *Communications of the ACM*, Vol. 62 No. 11, pp. 104-110, available at: https://doi.org/10.1145/3359338

Von Krogh, G., Ichijo, K. and Nonaka, I. (2000), *Enabling knowledge creation: How to unlock the mystery of tacit knowledge and release the power of innovation*, Oxford University Press, Oxford, available at: https://doi.org/10.1093/acprof:oso/9780195126167.001.0001

Wilczek, B., Thäsler-Kordonouri, S. and Eder, M. (2025), “Government regulation or industry self-regulation of AI? Investigating the relationships between uncertainty avoidance, people’s AI risk perceptions, and their regulatory preferences in Europe”, *AI & Society*, Vol. 40 No. 5, pp. 3797–3811, available at: https://doi.org/10.1007/s00146-024-02138-0

Wanberg, J., Javernick-Will, A., Taylor, J. and Chinowsky, P. (2015), “The effects of organizational divisions on knowledge-sharing networks in multi-lateral communities of practice”, *The Engineering Project Organization Journal*, Vol. 5 Nos. 2-3, pp.118-132, available at: https://doi.org/10.1080/21573727.2015.1059823

Warner, K. and Wäger, M. (2019), "Building dynamic capabilities for digital transformation: An ongoing process of strategic renewal", *Long Range Planning*, Vol. 52 No. 3, pp.326-349, available at: https://doi.org/10.1016/j.lrp.2018.12.001

World Economic Forum and Accenture (2025), "Artificial intelligence in financial services", World Economic Forum, Geneva, available at: https://reports.weforum.org/docs/WEF_Artificial_Intelligence_in_Financial_Services_2025.pdf (accessed 16 July 2025).

Wu, F. and Chen, J. (2025), "Collaboration of generative AI and human: Paradigm shift for higher education", *Frontiers in Digital Education*, Vol. 2, p.24, available at: https://doi.org/10.1007/s44366-025-0061-z

Yin, R. (2018), *Case study research and applications: Design and methods*, 6th ed., Sage Publications, Thousand Oaks, CA.

Zakery, A. and Saremi, M. (2025), "The role of dynamic capabilities in internationalization performance of technology-based firms in Iran", *Journal of the Knowledge Economy*, Vol. 16 No. 1, pp.453-477, available at: https://doi.org/10.1007/s13132-024-01916-x

Zeiser, J. (2024), "Owning decisions: AI decision-support and the attributability-gap", *Science and Engineering Ethics*, Vol. 30 No. 4, Article 27, available at: https://doi.org/10.1007/s11948-024-00485-1

Zhang, F., Liu, Z., Feng, F. and Li, J. (2024), "Can FinTech promote enterprises' ambidextrous innovation capability? Organisational resilience perspective", *Finance Research Letters*, Vol. 68, Article 105994, available at: https://doi.org/10.1016/j.frl.2024.105994

Appendix 5

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ORIGINAL ARTICLE

Supporting collaboration and knowledge sharing in building SLEs for ageing well: Using cognitive mapping in KMS design

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ABSTRACT
This article seeks to contribute to the existing body of knowledge management systems (KMS) literature by using cognitive mapping and demonstrating its usefulness in terms of context analysis for identifying the knowledge needs of multiple stakeholders and the appropriate characteristics of a KMS technology solution. Empirical data were collected through two case studies conducted in Finland and Estonia that used knowledge panel meetings to bring together knowledgeable experts who represented quadruple helix (QH) regional innovation actors involved in building smart living environments for ageing well (SLEaws). Adopting a multi-criteria approach in both case studies, cognitive mapping as an important instrument of the strategic options development and analysis (SODA) methodology was used during the panel meetings of both cases to facilitate the decision making of the experts in developing an integrated framework or tool that can support KMS design.

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1. Introduction

Europe is going through a major societal challenge described as population ageing (United Nations, Department of Economic and Social Affairs, Population Division, 2015). If current societal changes continue, by 2060 one in three Europeans will be above the age of 60 (European Commission, 2019). Globally, this demographic transition has had a number of implications, and in many European countries, public budgets are already feeling pressured with regard to providing social welfare and health care services, along with the growing demands and expectations of senior citizens for equal and higher quality services (Schorr & Khalaila, 2018; United Nations, Department of Economic and Social Affairs, Population Division, 2015). The widespread deployment of information and communication technology (ICT) based products and services in supporting the healthy, active, and independent living and homecare of ageing populations has been recognised by the European Commission as having potential as a tool for tackling the aforementioned challenges, and numerous initiatives and programmes have begun to focus on the digital transformation of health and care (European Commission, 2019).

The provision of various ICT-based health and wellbeing assistive service solutions holds great promise in terms of allowing ageing people to manage their own health and live independently in their homes for longer (*e.g.*, Niehaves & Plattfaut, 2014; Czaja, 2015; Siegel & Dorner, 2017; Baraković et al., 2020). Moreover, a wide range of digital devices and service solutions are available on the market, and they are being actively used in providing different types of health care and social support services for senior citizens (*cf.*, Morris et al., 2013). However, it is also recognised that these service solutions have to be combined and integrated into a specific solution in the form of a hierarchical ICT-based infrastructure and located in a smart living environment (SLE) context (*e.g.*, Lynggaard & Skouby, 2016; Zheng & Pulli, 2007). In this respect, smart living environments for ageing well (SLEaws) represent physical spaces where services requested by senior citizens can be enabled through the Internet of things (IoT) and ICT solutions (Alliance for Internet of Things Innovation Alliance for Internet of Things Innovation, 2019.

Building SLEaws requires a commitment to knowledge collaboration among all stakeholders – business, academia, society, and government organisations – to make it possible to provide better products and services for improving the health and wellbeing of a community (*e.g.*,; Butt et al., 2021; Holopainen et al., 2018; Pappel et al., 2019), which is a common target of governments and businesses worldwide. The United Nations (UN) has proclaimed 2021–2030 the Decade of Healthy Ageing, with the aim of enabling people to live extended lives in supportive and safe living environments while staying active and independent members of society. The World Health

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Organisation (WHO) will act as the leader of international collaborative action during this period, bringing together various stakeholders, such as governments, civil society, international agencies, academia, the media, and the private sector, to improve the lives of older people, their families, and communities (World Health Organization, 2021). Particular emphasis will be placed on the participation of senior citizens, who will be fully engaged in this multi-stakeholder collaboration (*ibid.*). The engagement of senior citizens can affect them and their communities and is of increasing importance because it can offer a diversity of living experiences and valuable information regarding this group's health and care needs and expectations (Tuckett et al., 2018), which may also increase positive attitudes and acceptance and lead to the quicker uptake of technology solutions (Weck et al., 2020 and 2021).

The 2030 Agenda for Sustainable Development addresses the challenge of building SLEaws and was determined to ensure that every human being can fulfill his/her potential with dignity and equality and in a healthy environment. Additionally, the agenda calls for enhancing knowledge management (KM), and specifically knowledge sharing (KS), through multi-stakeholder and multi-sectoral collaboration (United Nations, Department of Economic and Social Affairs, Population Division, 2015). The practices of KM and KS have become pervasive and ubiquitous, enabling stakeholders to contribute to the successful application and creation of new knowledge that improves decision making, generates innovation, accelerates learning, increases productivity, and minimises the duplication of resources (*e.g.*, Wang & Noe, 2010; Wing & Chua, 2005).

Recognising the benefits that can result from effective KM, it is increasingly important to consider knowledge management systems (KMS) when building SLEaws, as many researchers and practitioners argue that KMS can be a vital tool in enabling and facilitating KM and KS (*e.g.*, Alavi & Leidner, 2001; Baloh, 2007; Zack, 1999). KMS have the potential to aid the work of multiple stakeholders (*e.g.*, by gathering and processing relevant information and knowledge from a variety of sources and circulating them among multiple stakeholders). This essentially informs the theoretical grounding of KMS design adopted in this study, which borrows a social constructivist view and sees knowledge as "socially constructed" (Kuhn, 1962).

Existing KM research has proposed valuable insights into KMS design in an organisational setting, but less support has been offered to KMS designers regarding the desired technology solutions supporting collaboration and enabling knowledge sharing in multi-stakeholder and multi-sectoral contexts. This article reports the integrated results of two case studies that sought to contribute to the existing body of KMS literature by using cognitive mapping and demonstrating its usefulness in terms of context analysis in order to recognise the knowledge needs of multiple stakeholders and relevant KMS technology characteristics, in contrast to most of the prior research. The role of senior citizens as stakeholders actively involved in building SLEaws was a specific focus of the analysis.

The two case studies were conducted within the frame of the Interreg BSR OSIRIS project, which aims to design a digital platform as a KMS solution that accumulates knowledge, enhances knowledge sharing between stakeholders from Baltic Sea regions, and enables multi-stakeholder and multi-sectoral collaboration. Two countries in the Baltic Sea region, Finland and Estonia, are targeting the building of SLEaws and ICT-based services for senior citizens and were each thus the focus of one of the case studies. The stakeholders in both cases are regional innovation actors, who are involved in building SLEaws and represent the "quadruple helix" (QH) innovation framework, implying broad collaboration in innovation between industry, academia, government, and civil society (Arnkil et al., 2010).

The structure of this article is as follows. The next section provides a brief overview of related literature about the role of KM systems and their design, as well as their supportive role in KM in a multi-stakeholder context. Following this, the third section presents the methodological background of the two case studies. Section four introduces the findings by reflecting on the methodology applied. The final section concludes with a discussion of the study's limitations, theoretical implications, and contributions to managerial practice, as well as the grounds for further research.

2. Related literature and the research gap

A plethora of KM definitions, concepts, and procedures have been developed by researchers (*e.g.*, Drew, 1999; Liao, 2003; Wiig, 1997) to help understand its methods, techniques, and functions. According to the broad definition of KM, it is a conceptual framework that includes activities and perspectives that determine and prioritise those knowledge areas that enable efficiency and sustainability (Wiig, 1997). Therefore, KM becomes an integral component in building sustainable SLEaws through enabling collaboration and supporting common visions across different stakeholders. Furthermore, KM can be a facilitator of such an innovation (Holsapple & Tsui, 2005; Johannessen et al., 1999).

Knowledge can be defined through the combination of two different approaches: first, its reference to the accumulated information (including facts, ideas, and concepts) processed and stored in individuals' minds and second, the knowledge existing beyond this – inside single or interconnected organisations. The complex nature of knowledge leads to challenges, such as how to systematise information and how to communicate and distribute knowledge among stakeholders to ensure its storable and shareable characteristics (Greco et al., 2013). Knowledge can be considered a driving force for organisations to be more competitive, and KM is a crucial factor, which has resulted in the inclusion of KM into ISO 9001:2015 and ISO 30401 standards for enterprise management systems (Kudryavtsev & Sadykova, 2019). Effective KM can strengthen organisational capabilities and enhance performance and value creation and competitiveness (Carlucci & Schiuma, 2007; Schiuma et al., 2012).

The creation, transfer, and application of knowledge are supported by a type of information systems (KMS), which, by drawing on various IT tools and flexible capabilities, can provide online forums for communication and discussion and create knowledge networks, bringing people together virtually to exchange and build their collective knowledge in each of the speciality areas (Alavi & Leidner, 2001; Massingham, 2014a and 2014b). As a widespread and effective business tool, KMS can also lead to different forms of KM support and extend *"beyond the traditional storage and retrieval of coded knowledge"* (Alavi & Leidner, 2001, p. 132).

The theoretical framework of KMS design in this study is grounded in a social constructivist approach, which views knowledge as *"socially constructed"* (Kuhn, 1962). This leads to KMS being associated with *"connectivity"*, with functions that support and enable collaboration among people (Baloh, 2007). In particular, the use of human-oriented design with underlying rationale to *"connect to people"* (McAdam & McGreedy, 1999) is well applicable when the aim is to support connectivity and collaboration between people, rather than storing the knowledge itself and enabling person-to-person or group knowledge sharing and the co-creation of innovative solutions (Baloh, 2007). *"Only individuals with a requisite level of shared knowledge can truly exchange knowledge"* (Alavi & Leidner, 2001, p. 112). KMS enables collaboration through supporting and initiating learning via knowledge transfer and reuse (Cooper, 2003; Zack, 1999). As highlighted by Alavi and Leidner (1999), it provides the possibility of locating and using shared knowledge. Therefore, a vital characteristic of KMS tools and systems in general is to *"support the dynamic need for multiple layers of information"* (Cooper, 2003, p. 128) coming from multiple stakeholders.

KMS design involves the rich business context analysis of working practices (*i.e.*, how and where knowledge gets created and utilised), knowledge needs characteristics (*i.e.*, the knowledge needs of those stakeholders who create and utilise knowledge), and the relevant KMS technology characteristics (Baloh, 2007). Identifying the most suitable KMS framework to support KM can be challenging. To avoid implementation impediments and system failures, a few key aspects should be taken into consideration during the KMS selection process, such as the primary context analysis of the setting, any established strategies, and a focus on what goals the KMS should serve (Greco et al., 2013), as well as the needs of the individual stakeholders involved. According to Cooper (2003), the underlying cause of KMS failures is the lack of suitability of KMS regarding existing needs. An accurate approach for achieving a positive influence over KM is the application of ICT capabilities in accordance with the implemented business processes of KM activities (Baloh, 2007). KMS should allow access to innovative ideas and the evaluation and in-depth analysis of these to facilitate innovation development within multi-stakeholder and multi-sectoral collaboration.

Fahey and Prusak (1998, p. 268) point out the *"mistake of not understanding that a fundamental intermediate purpose of managing knowledge is to create shared context"*, which can be perceived as another hindrance when applying particular KMS. What is meant beyond this concept is that the knowledge that exists among independent stakeholders should build a *"shared context"* to manage existing knowledge and make joint decisions. This shared context is dynamic and consists of various perspectives, beliefs, and assumptions of stakeholders. The mistake described above appears due to the *"stock"* view of knowledge, where information simply remains a pattern of the unconnected flow of data instead of an outcome of the experiences, reflections, and dialogue among them (Fahey & Prusak, 1998). Suitable KMS should mitigate such implications and serve the purpose of facilitating KM.

The perspective of knowledge sharing and collaboration leads to the concern of how to find the way to transform the very valuable, yet highly subjective, tacit knowledge possessed by each stakeholder into explicit knowledge so that it becomes transferable (Nonaka, 1991). The concept of the environment and conditions that facilitate knowledge transfer and creation has been defined using the notion of *"ba"* (a Japanese concept that is translated into English as a *"place for emerging relationships"* (Nonaka & Konno, 1998, p. 40), which represents a platform for advancing knowledge creation. One of the four modes of knowledge creation established by Nonaka and Konno (1998) is called *"Cyber Ba"* – virtual space – where knowledge is created through systematic interaction and collaboration. Cyber Ba can be represented via virtual collaborative environments (such as online platforms, networks, and databases) powered by ICTs, which further facilitate knowledge sharing among stakeholders.

Most of the literature to date has addressed the questions about KMS design in an organisational setting. However, there is a lack of empirical studies investigating KMS design that supports collaboration and knowledge sharing in multi-stakeholder and multi-sectoral contexts. The two case studies presented in this article aim to fill this gap in the existing body of KMS literature by providing a comprehensive view of the decision problems at hand by using cognitive mapping.

3. Methodological application

The purpose of this section is to present the research methods applied in the two case studies conducted within the frame of the Interreg BSR OSIRIS project. The first took place in Finland (Hämeenlinna, Häme region) at the end of 2019, and the second was carried out in Estonia (Tallinn) in the fall of 2020. In both case studies, a decision-making process related to highly complex multi-stakeholder and multi-sectoral context analysis was conducted during two knowledge panel meetings. The process engaged knowledgeable experts who represented QH regional innovation actors actively involved in building ICT-based services, which are integral parts of SLEaws. In the first case, SLEaws were the focus of the analysis, whereas in the second case, the focus of the analysis was deepened to include an examination of the ICT-based services context. To explore multidimensional research questions and to cope with the underlying complexity of the research context, the strategic options development and analysis (SODA) method (Eden & Ackermann, 2004) was applied to support collaborative decision making and enable all the decision makers to explore and structure the problem during the panel meetings. This method presumes that each participating expert has a clear understanding of the problem's context and overall structure (Belton & Stewart, 2002) and can make decisions based on their own opinions and views.

In both regions, the heterogeneity of the panel members in terms of professional expertise and gender was a key factor for gathering and collating informed judgements on research-specific issues. Heterogeneity in terms of professional expertise and hands-on knowledge related to the decision problem at hand were accomplished by applying the QH approach. However, it is worth noting that the representativeness or generalisation of the results was not the purpose of selecting the experts (Bell & Morse, 2013; Ormerod, 2020). The objective was to ensure that the panel members could collaborate effectively as a group of experts and contribute to a fruitful discussion on the topic (Belton & Stewart, 2002). As Bell and Morse (2013, p. 962) point out: *"there is less emphasis on the outputs per se and more focus on process: how the group members interact and what they learn about themselves from that interaction"*. Following the guideline of Ackermann and Eden (2001, p. 22), who suggest that *"the consultant* [*i.e.*, the researcher or facilitator] *will relate personally to a small number (say, three to ten persons)"*, the experts were recruited bearing in mind the important requirement of their commitment to participate in the whole decision-making process of the two knowledge panel meetings.

3.1. Finnish case with a focus on SLEs

Following Ackermann and Eden (2001), eight panel members participated in the two group meetings held in Finland, namely (1) two representatives from the local policymaker organisation; (2) two from the research institution; (3) two from business sectors – finance and urban architecture; (4) one from a senior citizen association; and (5) one from municipal social and health services for senior citizens. Both panel meetings were facilitated by one facilitator or instructor and two assistants and lasted four hours.

The first knowledge panel meeting focused on the issues related to the analysis of the SLEaws' multi-stakeholder and multi-sectoral context required for KMS design and KM among the QH regional innovation actors. The aim was to create a collective cognitive map that sought to represent experts' knowledge of the researched subject through cause-and-effect relationships among decision criteria, including not only causal loops but also the way decision criteria evolve individually or collectively over time (Ackermann & Eden, 2001). Belton and Stewart (2002, p. 48) corroborate this idea by arguing that *"a cognitive map aims to represent the problem/issue as a decision maker (participant) perceives it, in the form of a means-ends network-like structure"*. To this end, the following trigger question was introduced: *"Based on your values and personal experience, how would you describe the 'best' way to support KM?"*

In the collaborative decision-making process, the SODA method applied enabled the eight panel members to structure the problem during the panel meeting with the help of the *"post-its technique"* (Ackermann & Eden, 2001). They generated and wrote down 331 factors or determinants using one post-it note for each idea. Two assistants placed them on a whiteboard in front of the decision makers. The experts then had to identify determinants that had a negative impact on KM, to mark these determinates with a minus sign (–) on their post-it notes, and to organise the determinants by key areas of interest, thereby defining the central criteria clusters. This visual representation of ideas on the whiteboard was extremely helpful for the most important part of the decision-making process, which required the full engagement of decision makers in structuring a multiple criteria framework to support KM (Vaz de Almeida et al., 2019). Although *"simple"* visual representations of information and knowledge have been pointed out as an essential dimension of cognitive mapping-based approaches to supporting decision making (*cf.*, Eden & Ackermann, 2004), it should be noted that all the concepts comprising a cognitive map have a density/centrality index. As such, the decision makers involved in our study considered the areas of concern that, due to their density and centrality, are critical and play a fundamental role as catalysts for supporting collaboration and KS in building SLEaws.

In total, the panel members identified and labelled six clusters: (1) Involved Innovation Actors; (2) Motives and Benefits; (3) Barrier Issues and Limitations; (4) Improvement Actions and Initiatives; (5) General Skills, Capabilities, and Competences; and (6) Resources and Knowledge-based Activities. This was followed by creating a hierarchy of all the identified determinants within each cluster and organising the respective post-it notes by order of importance on the whiteboard from top to bottom (*i.e.*, from the most important to the least important). This procedure was carried out through discussions regarding the most fundamental characteristics of age-friendly SLEs. The final task of this first panel meeting was to discuss and characterise SLEaws. Three fundamental characteristics or strategic determinants were identified: (1) a *"Comfortable Life"*; (2) an *"Active Life"*; and (3) an *"Independent Life"*. Once the tasks of problem structuring were finalised and the first panel meeting was completed, the *Decision Explorer* software (www.banxia.com) was used to develop a collective cognitive map. The structure of the developed map comprises all the identified factors of the SLEaws' multi-stakeholder and multi-sectoral context and arrows that represent cause-and-effect relationships between them, thus providing a visual representation of the research phenomenon. The validated version of the cognitive map is displayed in Figure 1 (as size restrictions prevent the better visualisation of Figure 1, an editable version is available upon request).

The second panel meeting was conducted with the same group of experts who participated in the first meeting with the aim of validating the collective cognitive map developed through analysis, discussion, and revision. The map was presented to the experts, and they were encouraged to identify any necessary amendments to the content (*i.e.*, all determinants) and/or the shape of the map (in the in the Results Analysis and Discussion section, Table 1 shows an integrative framework of the clusters and context factors created in the two case studies).

The final task of the second panel meeting was dedicated to a focus group discussion and aimed to explore the potential contribution of senior citizens. The trigger question was as follows: *"Based on your values and personal experience, how can senior citizens contribute to KM among regional innovation actors?"* The nominal group technique (NGT) and multi-voting were chosen to promote the active participation of the experts in the decision-making process and to obtain a common ground from different perspectives. First, the experts were given a 15-minute period with no discussion in order to consider their answers to the trigger question without interruptions. Then, each expert was provided with an opportunity to present and defend his/her answers to this trigger question, which took another 15 minutes. As a result of these presentations, 21 initiatives and engagement actions were suggested. All the suggestions were written on a whiteboard, which was visible to everyone, for the discussion and validation. Finally, multi-voting was utilised to rank the scores assigned to the proposed senior citizens' engagement actions that can contribute to KM among QH regional innovation actors building SLEaws (see, Table 2 in the Results Analysis and Discussion section).

3.2. Estonian case with a focus on ICT-based services

The two expert panel meetings conducted in Estonia focused on ICT-based services as integral parts of SLEaws. The overall aim was to conduct rich business context analysis by identifying knowledge flows (*i.e.*, how and where knowledge is created and utilised among multiple stakeholders involved in providing ICT-based services for senior citizens). Due to the COVID-19 pandemic, both panel meetings were carried out online and involved seven representatives or QH innovation actors: (1) one representative of a governmental organisation; (2) one from a non-governmental organisation in social affairs; (3) one from a research institution; (4) three from the business sector – a service provider and a consultancy; and (5) one representing senior citizens. They were moderated by one facilitator and two assistants and lasted for two and a half hours each.

The following trigger question was asked during the first panel meeting: *"Based on your values and personal experience, how would you describe the 'best' way to manage ICT-based services for senior citizens?"* All the participants were asked to answer based on their own knowledge and experience in their field. With the aim of creating a group cognitive map, the NGT and multi-voting methodology were applied. After the initial procedures, the panel members identified and labelled the following five clusters: (1) Motives and Benefits; (2) Barriers and Limitations; (3) Actors Involved (in

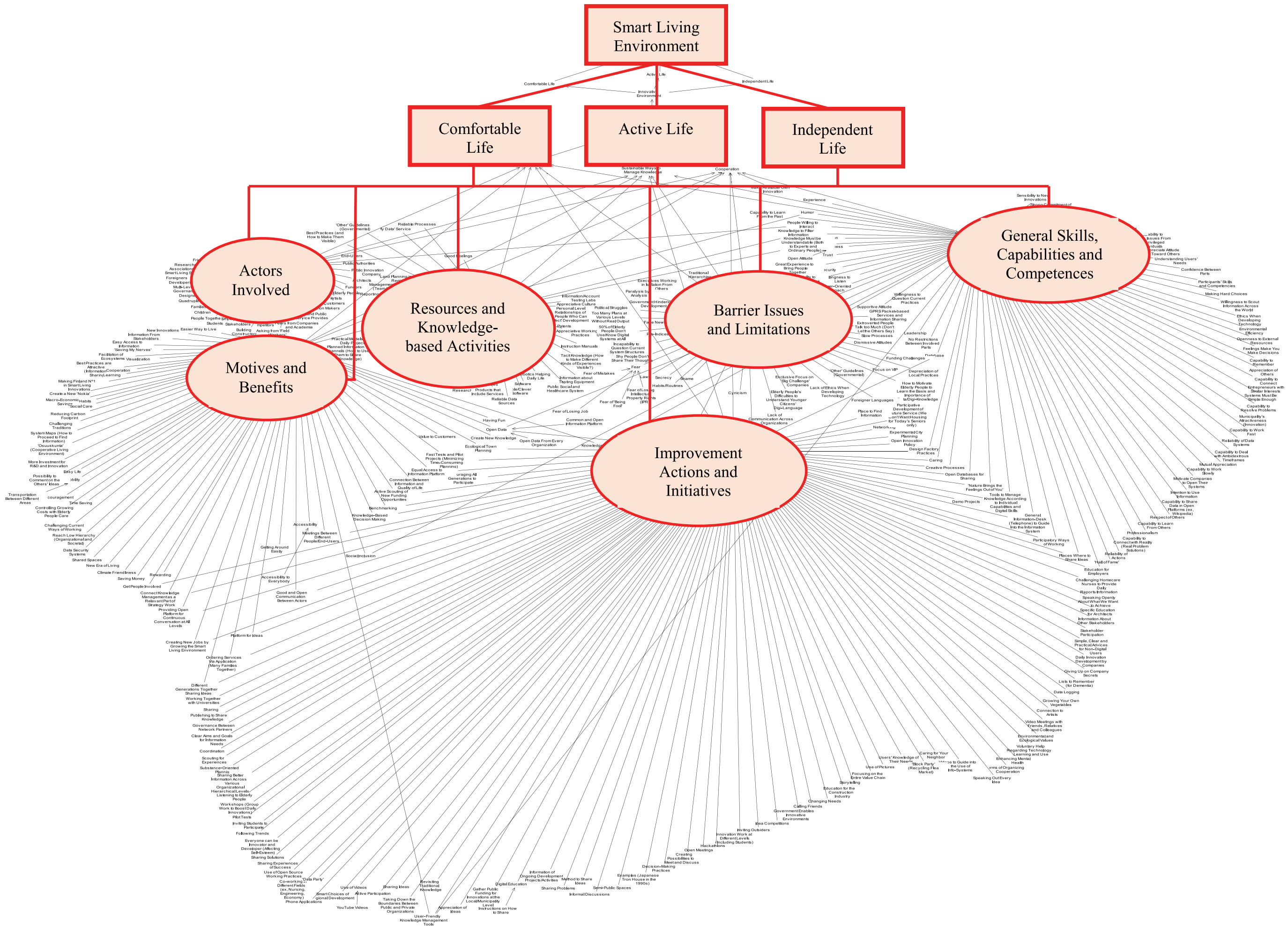

Figure 1. Finnish collective cognitive map [Source: Weck et al., 2021)].

Table 1. An integrated framework – The clusters and context factors defined in the two case studies.

Finnish case: SLEs for Ageing Well	Estonian case: ICT-Based Services for Senior Citizens	
Common clusters of context factors (*i.e.*, determinants)		Complementing cluster: Broad areas of possible intervention Sub-clusters of context factors
Involved innovation actors (31) • Public authorities • Private and public service providers • Building constructors; end users • Elderly people; researchers; designers; students; families • Third sector; etc.	**Actors involved (27)** • Contact persons of elderly people • Customers and users • Public sector (state-level and local-level + sub-institutions) • Service providers • Third sector (community services, support groups, volunteers, etc.)	**Housing (28)** • Community housing services (laundry, sauna, etc.) • Data from wearables and health- and location-tracking devices for dementia • Distance-controlled housing • Robots that help with house maintenance and cleaning • Smart home solutions that help to control and analyse data regarding electricity, water, and heating; etc.
Motives and benefits (59) • Good and open communication between actors; easy access to information • Controlling the growing costs of elderly care • New era of living; an easy life • Accessibility for everybody • Social care; shared spaces; etc.	**Motives and benefits (36)** • Access to information (using ICT tools helps it) • Encouraging cooperation between service users, service providers, and service developers • Keeping elderly minds active • Promoting lifelong learning • Providing flexible working conditions; etc.	**Social and health care, medicine, and caregiving (25)** • Access to service providers • Assistive technology (to provide independence) • Monitoring elderly people's health • Online training (keeping active with online training) • Status monitoring (home-based solutions, wearables, etc.)
General skills, capabilities, and competences (61) • Understanding users' needs • Appreciative attitude towards others; willingness to listen • Willingness to question current practices • Capability to address meaningful issues • Ability to filter information; reliability of actors; etc.	**Resources, skills, and competencies (28)** • Customers'/users' skills and awareness • Integration of various stand-alone systems between the government and citizens • Knowledge of user centres for service design • Market knowledge (what customers actually need) • Product owner; etc.	**Food and nutrition (24)** • Delivery services from shop to home (self-driving cars, outside cupboards, etc.) • Health monitoring data (sending information through smart devices) • Mealtime reminders (senior citizens living at home forgetting to eat) • Simple solutions for ordering food from grocery stores • Smart assistance tools for food preparation; etc.
Barriers and limitations (54) • 50% of elderly people do not use/know how to use any digital systems at all • Incapability to question current system structures • Political struggles; funding challenges • Fear of mistakes; prejudices; dismissive attitudes • Lack of communication across organisations; etc.	**Barriers and limitations (29)** • Biases/distrust towards digital technology use • Infrastructural issues (high-speed broadband access not available everywhere) • Lack of knowledge • Limited digital skills (of end users, service providers, and other crucial stakeholders) • No interest, no awareness of services; etc.	**Leisure and wellbeing (22)** • Bank services • Common events for the local community • Encouraging an active and healthy lifestyle (physical activity, mental activity, social activity, diet) • Involvement of senior citizens • Online communication tools to keep in contact with friends and family; etc.
		Educational, professional, and other activities (18) • Different events and training in the community • Easy platforms to keep the mind and brain active and in shape • Involvement of the elderly to share their knowledge • Promoting lifelong learning • Raising digital skills of senior citizens; etc.
		Mobility and transportation (16) • *"Bolt"* service for the elderly (transportation through a *"simple order")* • Self-driving vehicle solutions • Sharing economy in the community • Supporting home delivery of basic necessities (food, medicine, etc.) • Supporting MaaS (mobility-as-a-service); etc.
		Finance (14) • Developing financial literacy: knowledge and skills on personal budgeting • Free or AI-based legal support for seniors • Raising financial awareness (online training sessions on financial terms, legal topics, and work- and pension-related topics) • Safe payment solutions • Simple banking solutions; etc.

the everyday life of elderly people); (4) Knowledge-based Resources, Skills, and Competencies; and (5) Broad Areas of Possible Intervention. In addition, the following sub-clusters were recognised: (1) Social and Health Care; (2) Medicine and Caregiving, (3) Food and Nutrition, (4) Leisure and Wellbeing, (5) Finance, Mobility, and Transportation; (6) Housing; and (7) Educational, Professional, and Other Activities. With the help of the panel meeting facilitator and assistants, 267 different criteria were generated to create a collective cognitive map (Figure 2; an editable version is also available upon request).

Table 2. Senior citizens' engagement actions.

Finnish case: SLEs for Ageing Well				Estonian case: ICT-Based Services for Senior Citizens			
1	Taking part in city planning	12	Participating in digitalisation as an active learner	1	Explaining senior citizens' needs to service providers	12	Senior citizens taken onboard as mentors for development groups
2	Joining open discussion groups for end users	13	Improving digital skills	2	Describing problems that they face (providing input to the development team)	13	Seniors have life experience
3	Sharing ideas on open innovation platforms	14	Providing *"neighborly"* help	3	Giving feedback (through kids, services, etc.)	14	Volunteering capacity
4	Interpreting the needs of *"digi-passive"* senior citizens	15	Allowing access to senior citizens' personal data (medical data, etc.)	4	Keeping an open mind and using smart services	15	Developing critical thinking (protection against fraud and fake news)
5	Supporting the user-centred design of products/services for senior citizens	16	Supporting easy ways to get help for senior citizens	5	Testing products and services (together with mentors)	16	Informal knowledge and practical skills (life experience)
6	Supporting senior citizens to participate in pilots	17	Learning new methods of teaching and learning	6	Senior technology learning groups (with testing possibilities)	17	Early users with support of local government
7	Participating in innovation development activities	18	Accepting innovative home-based services	7	Descriptions of their (unmet) needs	18	Formal knowledge and skills in a specific field
8	Participating in decision making as an innovator	19	Joining discussion groups in senior associations	8	Awareness for youths who can help the elderly	19	Semi-formal organisations to implement innovative ideas
9	Gathering soon-to-be pensioners and students to co-create new solutions	20	Sharing own knowledge on social media	9	Community connections		
10	Introducing innovations to soon-to-be pensioners for their feedback	21	Providing peer-to-peer support when possible	10	Creating platforms for cooperation with different sectors, thematic areas, and generations		
11	Participating in idea exchange with the voluntary sector			11	Developing entrepreneurship opportunities in the community		

The aim of the second meeting was to (1) validate the cognitive map developed and (2) increase the understanding of the following trigger question: *"Based on your personal experience, in what ways can senior citizens enhance knowledge sharing between regional innovation actors?"* Using the same methodological approach (*i.e.*, the NGT and multi-voting), each expert was granted time to think about the question without interruption. Each expert was later given an opportunity to present their answers, and all of them were written down with the help of two assistants and discussed. After the meeting, all the answers were sent to the experts' emails for them to carry out multi-voting to establish the most important criteria in every category. The results are presented in Table 2 and discussed in the next section.

4. Results analysis and discussion

By adopting a multi-criteria approach in both case studies, cognitive mapping as the baseline tool of the SODA methodology was used to facilitate the decision making of experts in terms of analysing the multi-stakeholder and multi-sectoral context of SLEaws required for KMS design. As shown in both case studies, cognitive mapping simulates learning and allows the opinions of different experts to be formally projected, creating holistic frameworks within which decision criteria and their cause-and-effect relationships can be detected and understood. Additionally, due to its recursive nature, its application by managers and decision makers can provide (new) insights into key feedback loops in systems, which might otherwise go undetected by statistical approaches alone. This allows other important decision criteria to be *"uncovered"*, reducing the number of omitted decision criteria and fostering informed decision making.

As a result of this context analysis in the two case studies carried out in the Baltic Sea region countries of Finland and Estonia, two collective cognitive maps were generated. The first map represents the identified factors or determinates of the SLEaws' context, and the second of the ICT-based services for senior citizens. Integrating the results of both case studies allowed for the construction of a comprehensive understanding of the knowledge needs of multiple stakeholders involved in building SLEaws in both countries and the relevant technology characteristics needed to enable collaboration and knowledge sharing between them. Table 1 shows an integrative framework of the clusters and context factors with sizes (*i.e.*, numbers of determinants integrated in each cluster) created in the two case studies.

Specifically, Table 1 exemplifies the context factors identified in both cases. It is structured in a way that allows the observation of the level of similarity between the clusters of the Finnish and Estonian cases from strongest to weakest. As part of the analysis, the numbers of the context factors integrated into each cluster or the cluster size shows its significance and complexity. Given that four similar clusters were defined in both cases, the division of factors per cluster was not uniform. Three clusters stood out as having noticeable differences in terms of the numbers of

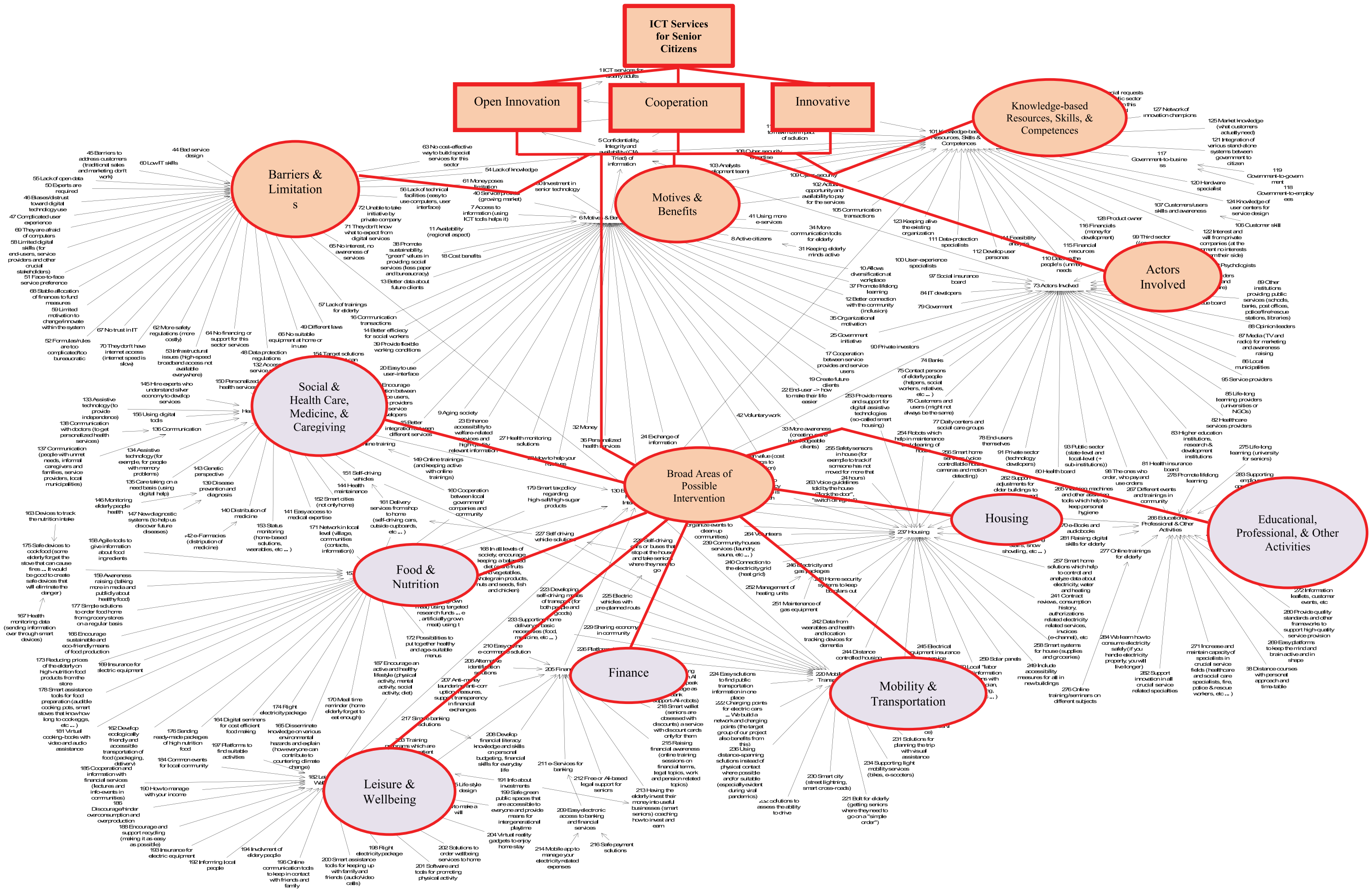

Figure 2. Estonian collective cognitive map.

context factors. Nevertheless, the comparison was not the main purpose of the integration of the analysis results, but it did provide evidence of how the factors identified in the two case studies complement one another and helped to describe more thoroughly the multi-stakeholder and multi-sectoral context of SLEaws needed for KMS design. Ranging from basic information about the actors or stakeholders involved and their motives to explicit recommendations for services, the context actors represent highly complex requirements for KMS characteristics.

The specific focus of the context analysis in both study cases was the engagement of senior citizens as QH regional stakeholders in the activities that contribute to KM and lead to better decisions in supporting the building of SLEaws. In both cases, the results showed that senior citizens are very motivated stakeholders who are willing and able to be actively engaged in decision making related to the creation of SLEaws. They also identified the key areas in which senior citizens can support collaboration and KS, the actions they can accomplish to enhance KM, and areas where their active participation can be increased. Thus, the role of senior citizens is evidently revealed by 21 well-focused engagement actions in the Finnish case and 19 actions in the Estonian case, through which senior citizens can contribute to collaboration and KS among QH regional stakeholders. Table 2 introduces the actions that were proposed and prioritised by the experts participating in the expert panel meetings.

Given that KMS have great potential in supporting the building of SLEaws, through enabling collaboration and KS among QH regional stakeholders in the design of KMS, special attention must be paid to the role of senior citizens representing active and motivated stakeholders. KMS characteristics should enable the senior citizens' engagement actions, support their knowledge needs, and help them tackle the problems that they face (see, Table 2).

In summary, by using expert opinions, the methodology proposed in both case studies assumes a different stance, and we were able to bring added realism into our maps, as the use of cognitive mapping brought new insights into the analysis processes based on the experts' know-how, which would not have been detected through the use of statistical methods alone. The issues of *"collaborative research"*, *"digital education"*, and/or *"getting people involved"*, for instance, can be easily overlooked, but are not without consequence. Furthermore, because our approach allows for the addition of new information over time, the proposed model is not only robust but also versatile. This means that the use of the methodology proposed in both case studies allowed for the construction of different but complementary models to those already existing and resulted in the design of transparent, simple, and well-informed systems, comprising both objective and subjective elements.

5. Conclusion

This article reports on the results of two case studies conducted in two Baltic Sea region countries, Finland and Estonia, focusing on SLEaws and ICT-based services for senior citizens, respectively. Grounded in a constructivist approach, these studies contribute to the understanding of multi-stakeholder and multi-sectoral contexts in order to recognise the knowledge needs of multiple stakeholders and the relevant characteristics of the proposed KMS technology solution in a concise and well-structured way. Given the increasingly high complexity of the studies' focus contexts, the task of designing an effective KMS for multiple stakeholders proves to be demanding and requires the comprehensive evaluation of a multiplicity of perspectives and ideas that form context factors.

Drawing on the SODA method, the collaborative decision-making process engaging HQ regional stakeholders of both countries gave substance to the context analysis and enabled the development of holistic conceptual frameworks in the form of two collective cognitive maps with a wide range of factors and cause-and-effect relationships between them. A comprehensive context analysis through integrating the results of both cases provided a solid basis for the design of a KMS solution characterised by capabilities for collaboration and knowledge sharing between QH innovation actors involved in building SLEaws. Thus, this study proposes an integrated framework or tool that can support decision makers in selecting the most appropriate KMS solution and its characteristics. Moreover, in terms of theoretical implications, it extends the KM empirical research body, offering new insights on KMS design in multi-stakeholder and multi-sectoral contexts.

Both case studies addressed the valuable role of senior citizens as QH regional stakeholders or innovation actors involved in building SLEaws. The analysis revealed the vast potential they have in terms of supporting collaboration and sharing knowledge as well as with regard to their possible engagement actions, which may contribute to better decisions when building SLEaws. These actions could be considered as practical recommendations for KMS designers making choices about KMS characteristics and functionalities that take into account the specific knowledge needs of senior citizens and facilitate their active engagement.

The SODA method combined with cognitive mapping was particularly useful in terms of analysing and structuring the highly complex decision problems of the two case studies. Creating cognitive maps implied transparent and collective decision making and demonstrated great potential for developing a holistic view of decision problems. The main reason for choosing mapping was the added value of eliciting and structuring decision criteria from various perspectives (*i.e.*, different kinds of expertise and experience), which allowed integrated results to enhance action plans (Simon, 1976) regarding KMS design. The usefulness of cognitive mapping has been addressed and has contributed to the existing body of KM literature, but empirical work on how to use cognitive maps successfully in context analysis facilitating KMS design is lacking.

However, the application of this methodology also imposed the following limitations. First, the structuring process had an intrinsically subjective nature. Therefore, cognitive maps with different content and shapes could be developed by other experts and over a longer period of time, although the decision making was very collaborative and thoroughly interactive in terms of knowledge and experience exchange during the expert panel meetings. Second, the idiosyncratic features of the proposed conceptual framework may not be universal or generalisable to different contexts, and the various specific needs of stakeholders could induce the necessity of customising the hierarchical structure and its determinants. However, these limitations can open avenues for further investigation, particularly with a focus on the role of senior citizens as active participants in the innovation process. While acknowledging the importance of context analysis in the process of KMS design, more empirical research is needed to address the usefulness and applicability of cognitive mapping in highly complex multidimensional contexts.

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References

Ackermann, F., & Eden, C. (2001). SODA – Journey making and mapping in practice. In J. Rosenhead & J. Mingers (Eds.), *Rational analysis for a problematic world revisited: Problem structuring methods for complexity* (pp. 135–190). John Wiley & Sons.

Alavi, M., & Leidner, D. (1999). Knowledge management systems: Issues, challenges, and benefits. *Communications of the AIS*, *1*(2), 1–37. https://doi.org/10.17705/1CAIS.00107

Alavi, M., & Leidner, D. (2001). Knowledge management and knowledge management systems: Conceptual foundations and research issues. *Management Information Systems Quarterly*, *25*(1), 107–136. https://doi.org/10.2307/3250961

Alliance for Internet of Things Innovation. (2019), *Alliance for the Internet of Things Innovation: Recommendations for Healthy Ageing Solutions*. Retrieved January 19, 2021, from https://aioti.eu/wp-content/uploads/2019/04/AIOTI-IoT-for-Smart-Living-Environments-Recommendations-for-healthy-ageing-solutions-April-2019.pdf

Arnkil, R., Järvensivu, A., Koski, P., & Piirainen, T. (2010). *Exploring the Quadruple Helix: Outlining User-Oriented Innovation Models*. Tampereen yliopisto. Retrieved January 10, 2021, from https://citeseerx.ist.psu.edu/viewdoc/download?doi=10.1.1.864.3864&rep=rep1&type=pdf

Baloh, P. (2007). The role of fit in knowledge management systems: Tentative propositions of the KMS design. *Journal of Organizational and End User Computing*, *19*(4), 22–41. https://doi.org/10.4018/joeuc.2007100102

Baraković, S., Husic, J., van Hoof, J., Krejcar, O., Maresova, P., Akhtar, Z., & Melero, J. (2020). Quality of life framework for personalized ageing: A systematic review of ICT solutions. *International Journal of Environmental Research and Public Health*, *17*(8), 1–20. doi:10.3390/ijerph17082940.

Bell, S., & Morse, S. (2013). Groups and facilitators within problem structuring processes. *Journal of the Operational Research Society*, *64*(7), 959–972. https://doi.org/10.1057/jors.2012.110

Belton, V., & Stewart, T. (2002). *Multiple criteria decision analysis: An integrated approach*. Kluwer Academic Publishers.

Butt, S., Elhadjamor, E., Pappel, I., Õunapuu, E., & Draheim, D. (2021). A knowledge map for ICT integration in the silver economy. *Procedia Computer Science*, *181*, 693–701. https://doi.org/10.1016/j.procs.2021.01.220

Carlucci, D., & Schiuma, G. (2007). Knowledge assets value creation map: Assessing knowledge assets value drivers using AHP. *Expert Systems with Applications*, *32*(3), 814–821. https://doi.org/10.1016/j.eswa.2006.01.046

Cooper, L. (2003). A research agenda to reduce risk in new product development through knowledge management: A practitioner perspective. *Journal of Engineering and Technology Management*, *20*(1/2), 117–140. https://doi.org/10.1016/S0923-4748(03)00007-9

Czaja, S. (2015). Can technology empower older adults to manage their health? *Generations*, *39*(1), 46–51. ISSN 0738-7806 (Print).

Drew, S. (1999). Building knowledge management into strategy: Making sense of a new perspective. *Long Range Planning*, *32*(1), 130–136. https://doi.org/10.1016/S0024-6301(98)00142-3

Eden, C., & Ackermann, F. (2004). Cognitive mapping expert views for policy analysis in the public sector. *European Journal of Operational Research*, *152*(3), 615–630. https://doi.org/10.1016/S0377-2217(03)00061-4

European Commission. (2019). The silver economy: An overview of the European commission's activities. *Proceedings of the first-ever global silver economy forum*, July 9–10, 2019, Finland. Retrieved January 11, 2021, from https://silvereconomyforum.eu/wp-content/uploads/2019/07/Silver-Economy-Brochure.pdf

Fahey, L., & Prusak, L. (1998). The eleven deadliest sins of knowledge management. *California Management Review*, *40*(3), 265–276. https://doi.org/10.2307/41165954

Greco, M., Grimaldi, M., & Hanandi, M. (2013). How to select knowledge management systems: A framework to support managers. *International Journal of Engineering Business Management*, *5*(5), 1–11. https://doi.org/10.5772/56003

Holopainen, A., Kämäräinen, P., Kaunisto, M., Kekäläinen, H., & Metsävainio, K. (2018). Living lab services promoting health in the community through participation. *Finnish Journal of Health and eWelfare*, *10*(4), 373–380. https://doi.org/10.23996/fjhw.74405

Holsapple, C., & Tsui, E. (2005). The inseparability of modern knowledge management and computer-based technology. *Journal of Knowledge Management*, *9*(1), 42–52. https://doi.org/10.1108/13673270510582956

Johannessen, J., Olsen, B., & Olaisen, J. (1999). Aspects of innovation theory based on knowledge-management. *International Journal of Information Management*, *19*(2), 121–139. https://doi.org/10.1016/S0268-4012(99)00004-3

Kudryavtsev, D., & Sadykova, D. (2019). Towards architecting a knowledge management system: Requirements for an ISO compliant framework. *Proceedings of IFIP working conference on the practice of enterprise Modeling*, Luxembourg. Springer, (pp.36–50). https://doi.org/10.1007/978-3-030-35151-9_3

Kuhn, T. S. (1962). *The Structure of Scientific Revolutions*. University of Chicago Press.

Liao, S. (2003). Knowledge management technologies and applications: A literature review from 1995 to 2002. *Expert Systems with Applications*, *25*(2), 155–164. https://doi.org/10.1016/S0957-4174(03)00043-5

Lynggaard, P., & Skouby, K. (2016). Complex IoT systems as enablers for smart homes in a smart city vision. *Sensors*, *16*(11), 18–40. https://doi.org/10.3390/s16111840

Massingham, P. (2014a). An evaluation of knowledge management tools: Part 2: Managing knowledge flows and enablers. *Journal of Knowledge Management*, *18*(6), 1101–1126. http://dx.doi.org/10.1108/JKM-03-2014-0084

Massingham, P. (2014b). An evaluation of knowledge management tools: Part 2 – Managing knowledge flows and enablers. *Journal of Knowledge Management*, *18*(6), 1101–1126. https://doi.org/10.1108/JKM-03-2014-0084

McAdam, R., & McGreedy, S. (1999). A critical review of knowledge management models. *The Learning Organization*, *6*(3), 91–100. https://doi.org/10.1108/09696479910270416

Morris, M., Adair, B., Miller, K., Ozanne, E., Hampson, R., Pearce, A., Santamaria, N., Viegas, L., & Long, M. (2013). Smart-home technologies to assist older people to live well at home. *Journal of Aging Science*, *1*(1), 1–9. https://doi.org/10.4172/2329-8847.1000101

Niehaves, B., & Plattfaut, R. (2014). Internet adoption by the ageing: Employing IS technology acceptance theories for understanding the age-related digital divide. *European Journal of Information Systems*, *23*(6), 708–726. https://doi.org/10.1057/ejis.2013.19

Nonaka, I. (1991). The knowledge-creating company. Retrieved February 5, 2021, from. *Harvard Business Review*, *69*(6), 96–104. https://memberfiles.freewebs.com/84/90/65819084/documents/The%20Knowledge-Creating%20Company.pdf

Nonaka, I., & Konno, N. (1998). The concept of "ba": Building a foundation for knowledge creation. *California Management Review*, *40*(3), 40–54. https://doi.org/10.2307/41165942

Ormerod, R. (2020). The pragmatic logic of OR consulting practice: Towards a foundational view. *Journal of the Operational Research Society*, *71*(11), 1691–1709. https://doi.org/10.1080/01605682.2019.1630331

Pappel, I., Tsap, V., & Draheim, D. (2019). The e-LocGov model for introducing e-governance into local governments: An Estonian case study. *IEEE Transactions on Emerging Topics in Computing*, *14*(8), 1–14. https://doi.org/10.1109/TETC.2019.2910199

Schiuma, G., Carlucci, D., Lerro, A., & Schiuma, G. (2012). Managing knowledge processes for value creation. *VINE: The Journal of Information and Knowledge Management Systems*, *42*(1), 4–14. https://doi.org/10.1108/03055721211207815

Schorr, A. V., & Khalaila, R. (2018). Aging in place and quality of life among the elderly in Europe: A moderated mediation model. *Archives of Gerontology and Geriatrics*, *77*, 196–204. https://doi.org/10.1016/j.archger.2018.04.009

Siegel, C., & Dorner, E. (2017). Information technologies for active and assisted living—Influences to the quality of life of an ageing society. *International Journal of Medical Informatics*, *100*, 32–45. https://doi.org/10.1016/j.ijmedinf.2017.01.012

Simon, H. (1976). From substantive to procedural rationality. In S. Latsis (Ed.), *Method and appraisal in economics* (pp. 65–86). Cambridge University Press.

Tuckett, A., Banchoff, A., Winter, S., & King, A. (2018). The built environment and older adults: A literature review and an applied approach to engaging older adults in built environment improvements for health. *International Journal of Older People Nursing*, *13*(1), 1–9. https://doi.org/10.1111/opn.12171

United Nations, Department of Economic and Social Affairs, Population Division. (2015). *World population* *ageing 2015*. Report ST/ESA/SER.A/390. Retrieved January 15, 2021, from https://www.un.org/en/development/desa/population/publications/pdf/ageing/WPA2015_Report.pdf

Vaz de Almeida, M., Ferreira, J., & Ferreira, F. (2019). Developing a multi-criteria decision support system for evaluating knowledge transfer by higher education institutions. *Knowledge Management Research and Practice*, *17*(4), 358–372. https://doi.org/10.1080/14778238.2018.1534533

Wang, S., & Noe, R. (2010). Knowledge sharing: A review and directions for future research. *Human Resource Management Review*, *20*(2), 115–131. https://doi.org/10.1016/j.hrmr.2009.10.001

Weck, M., Helander, N., & Meristö, T. (2020). Active DigiAge: Technology acceptance by ageing people. *International Journal of Telemedicine and Clinical Practices*, *3*(3), 223–242. https://doi.org/10.1504/IJTMCP.2020.104894

Weck, M., Humala, I., Tamminen, P., & Ferreira, F. (2021). Supporting sustainable development using multiple criteria decision aid: Towards an age-friendly smart living environment. In M. Doumpos, F. Ferreira, & C. Zopounidis (Eds.), *Multiple Criteria Decision Making for Sustainable Development: Pursuing Economic Growth, Environmental Protection and Social Cohesion* Springer. forthcoming. (pp. 151–173).

Wiig, M. (1997). *Knowledge management: The central management focus for intelligent-acting organizations*. Schema Press. Retrieved February 6, 2021, from https://www.researchgate.net/profile/Karl-Martin-Wiig/publication/31672278_Knowledge_Management_The_Central_Management_Focus_for_Intelligent-Acting_Organizations_KM_Wiig/links/568c05ba08ae71d5cd04a819/Knowledge-Management-The-Central-Management-Focus-for-Intelligent-Acting-Organizations-KM-Wiig.pdf

Wing, L., & Chua, A. (2005). Knowledge management project abandonment: An exploratory examination of root causes. *Communications of the Association for Information Systems*, *16*(16), 723–743. https://doi.org/10.17705/1CAIS.01635

World Health Organization. (2021). *UN Decade of Healthy Ageing (2021–2030)*. Retrieved January 8, 2021, from https://www.who.int/initiatives/decade-of-healthy-ageing

Zack, M. (1999). Managing codified knowledge. Retrieved February 3, 2021, from. *Sloan Management Review*, *40*(4), 45–58. http://web.nchu.edu.tw/pweb/users/arborfish/lesson/8948.pdf

Zheng, X., & Pulli, P. (2007). Towards high quality mobile services for senior citizens in smart living environments. *Proceedings of the international conference on multimedia and ubiquitous engineering (MUE'07)* April 26–28, (pp.164–170), Seoul, South Korea. IEEE. https://doi.org/10.1109/MUE.2007.208

Appendix 6

Additional peer-reviewed publication related to the doctoral project

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RESEARCH-ARTICLE

Bringing Innovation Towards Efficient Policy-making in ICT-enabled Service Provision for Senior Citizens

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Bringing Innovation Towards Efficient Policy-making in ICT-enabled Service Provision for Senior Citizens

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ABSTRACT

Societal challenges related to a recent phenomenon - population ageing, calls for national governments for new guidelines and understanding of how to help senior citizens through innovative solutions to enhance their everyday lives. Current research is the baseline study to analyse the existing context and circumstances and decide which direction Estonia should take with its policy-making when establishing the Welfare Strategy for 2023-2030. The empirical data was collected in Estonia through two knowledge panel meetings that brought together experts who represented Quadruple Helix (QH) regional innovation actors involved in providing ICT services. Adopting a multi-criteria approach, cognitive mapping as an important instrument was used during panel meetings to facilitate the decision making of the experts. Based on the study results, this paper discusses various innovative ICT solutions to bring together ageing population needs and market capacity. Various context factors and clusters were identified, supporting the strategy's planning and future related activities.

KEYWORDS

Service provision, Policy-making, ICT services, Senior citizens, innovation

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1 INTRODUCTION

Europe is going through a major societal challenge described as population ageing [1]. According to the United Nation's report [2], the number of people aged 60 or more is expected to grow by more than 50 per cent during 2015-2030. This transformation in population ageing will apply to most areas of the world [2] and affect numerous areas of the society, including socioeconomic, healthcare, labour market and transportation. In April 2018, the European Commission adopted a strategy [3], according to which there is an opportunity to utilise digital tools and services for helping older generations having functional and accessibility impairments allowing healthy and active ageing. This could also lead to maintaining senior citizens longer at their workplaces, support their inclusion in productivity and economic competitiveness while reducing pressure on national budgets. Thus, it is essential to consider how digital tools and solutions can be fully accessible to this group [3], [4].

The risk of national governments facing social policy issues when it comes to ensuring the adoption of advanced (and somewhat complex) technologies and ensuring the capability of citizens to use Information and Communication Technology (ICT)-enabled governmental services is high. Implications can be varied and encompass not only financial and technical but also human aspects, such as the readiness of the citizens to accept technology. To foster smart innovations for the ageing populations, an integrated response from different society actors represented in the Quadruple Helix (QH) model [5] is imperative. The QH model brings actors from public institutions (government and policymakers), the private sector (start-ups and SMEs, creating the products and services), academia (researchers, universities, research organisations) and end-users (in this case, senior citizens). This leads to the inclusion of representatives from each sector in innovation processes, knowledge sharing and collaboration.

This paper reports results of the empirical study conducted in the Estonian multi-stakeholder context, where the objective was to focus on ICT and its implications for social policy regarding senior citizens, particularly how ICT-enabled services can contribute to the wellbeing of senior citizens. Estonia already has a successful practice of applying ICT solutions in the public sector service provision and utilising e-Governance enablers, including data exchange framework - X-road [6] and digital signature, as the basis for the further development and advancement of ICT-enabled services [7], [8]. Existing digital tools provide a solid background for further development and encourage the Government of Estonia to provide limitless benefits to senior citizens. The results acquired through this study identified tools and solutions that will contribute to developing the new strategy (Estonian Welfare Development plan) for the years 2023-2030. The new welfare development plan will start setting up expert working groups in the summer of 2021, where the authors of this study will be participating.

The structure of this paper is organised as follows. The next section provides a theoretical background of the studied phenomenon: theories about adoption and readiness towards using ICT-enabled services, followed by the studies emphasising the importance of stakeholders' engagement to facilitate technology acceptance. The research methodology is described in the third section, followed

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by a presentation of findings (section four) and a discussion with future work (section five). The paper is ended with a section six - conclusion.

2 THEORETICAL FRAMEWORK

2.1 Important variables in technology acceptance and readiness among senior citizens

Advancements and innovations in ICT services have brought numerous advantages, nevertheless, achieved technological sophistication could hinder customers from using them, causing anxiety, technophobia, scepticism or resistance [9]. These possible pitfalls could be critical for senior citizens. To understand the determinants of using ICT-enabled services, researchers of the various field have come up with frameworks for comprehending the human perception of the technology [10]. The classical theoretical frameworks in technology acceptance literature are the Theory of Reasoned Action (TRA) [11], the Theory of Planned Behavior (TBP) [12], the Technology Acceptance Model (TAM) [13] and recently - Technology Readiness [14]. Within the context of this study, TAM and TR can be considered the most suitable as they are believed to be more technology-acceptance specific.

Nevertheless, as [15] Blut argues, TAM aims to understand the acceptance of new technology based on its usefulness and ease-of-use but is device-specific and not examining peoples' overall beliefs about technology. Researchers have utilised TR to understand people's beliefs towards technology better since it is individual-specific, determined to measure "people's propensity to embrace and use new technologies for accomplishing goals at home and at work" [14]. Consequently, recent studies conducted in the service industry [16], [17] address the nature of service, customers' experiences, and their relationships with service providers. The Technology Readiness Index (TRI), a 36-item scale to measure "technology readiness", encompasses four dimensions: (i) optimism, (ii) innovativeness, (iii) discomfort and (iv) insecurity [14]. While the first two dimensions are the catalyst to TR, meaning that a person's overall TRI score will be high, the latter two are "inhibitors", suppressing the TR and thus lowering the score [18]. To achieve the completion of the model and eradicate the possible shortcomings, scholars have attempted to integrate TR with other theories, such as TRAM - an integrated model proposed by Lin et al. [19], which adds personality traits related to technology (TR) into the system-specific constructs of the TAM.

Another example is TR integration with the expectation-confirmation model (ECM) [20]. An important variable described by Lansend and Tor [21] from Self-Service Technology (SST) studies employing TR is that for people to use the technology, the hindrance is not its capability or sophistication, but rather reliability and availability so that they will favour them instead of the interpersonal alternative. As they highlight, SSTs should be designed with a customer focus and based on relevant technology for the task [21]. Examination of the advantages and drawbacks of new technology-based systems and their implications for fostering acceptance have displayed that technology acceptance and readiness among senior citizens is a complex phenomenon, depended on various significant variables such as usefulness, usability, comfort (or discomfort), optimism (or insecurity), personal believes and experiences, overall IT literacy and perceived relevance of the proposed technology or technology-enabled service.

Another important variable that has not been discussed yet is the inclusion and engagement of the senior citizens in designing respective innovative solutions (or services). This will be further elaborated in the following sub-section.

2.2 The importance of stakeholder and senior citizen inclusion

Stakeholders' collective social participation transpires through individuals sharing their resources with others and becomes a central topic in the research concerning ageing [22]. Cooper et al. [23] highlight the phenomenon of renewed vivid interest in civic engagement at various levels, including citizens, the public, policymakers, and public administrators. According to the Organization for Economic Community and Development (OECD) report, wide acceptance of open and inclusive policy-making among OECD countries [24] is crucial, including citizens and other stakeholders in policy-making.

The share and role of senior citizens in civic engagement need further attention as it is closely related to their future engagement with innovative processes concerning them. According to Walker [25], the increased number of senior citizens across the globe has led to their enhanced involvement in those political processes affecting them. Such involvement stimulates their wellbeing, improves policies' quality and effectiveness, and even encourages innovative solutions [26]. After a thorough analysis of studies concerning senior participation, Falanga et al. [27] state that participation can be developed in individual and collective settings and that outputs generally determine the better quality of life and wellbeing. The study further reports the positive effect of such involvement on physical, mental and cognitive functions while reducing loneliness. According to Cooper et al. [23], citizen participation can be developed in either stage of the policy cycle; however, Falanga et al. [31] emphasise the importance of inclusion of senior citizens not only in the final stage of the implementation but rather initial policy design stage.

The socio-psychological theory from gerontology – the activity theory considers a strong relationship between higher levels of social involvement and satisfaction with life among the senior citizens [28]. According to this theory, a person is most likely to succeed in old age if they continue to be active and take on productive roles in society.

The theories discussed in sub-section 2.1 that address important variables of technology acceptance and readiness have clearly identified the significance of personal beliefs and expectations. Furthermore, the scholars represented in the studies of sub-section 2.2 have argued on the importance of stakeholders' inclusion in policy-making and the positive influence senior citizens' engagement and active life has over their attitudes and overall wellbeing. The results acquired through the review of the theories and literature supports this study to be conducted in the multi-stakeholder context, which enabled not only gaining thorough multi-sectoral insight but also outlined the prospects of the future research focusing on senior citizens' inclusion in designing innovative digital solutions.

3 METHODOLOGY

Research for this paper had various phases, during which different methodologies were discussed. The market overview with stakeholders and trigger question selection was conducted in February 2020. However, due to the spread of the COVID-19 pandemic, physical panel meetings planned initially had to be postponed. Strategic Options Development and Analysis (SODA) approach [29], which is a powerful problem-structuring method, requires face-to-face meetings with a panel of experts. In September 2020, it was still impossible for the postponed face-to-face meetings to take place; thus, online sessions were instead decided. The SODA approach baseline aspects are all the data for the model-building to be directly provided by the expert panel members after intense collective discussion and negotiation, group dynamics, and an experienced facilitator's physical presence. Therefore, the requirement of physical interaction with and among the participants prevented the SODA methodology to be applied online. To keep the integrity of the research, the work was further divided into two panel meetings (each lasted for two hours) which included nominal group techniques, multi-criteria selection and validation of the findings. 7 (seven) experts represented different views of the innovation ecosystem to support the QH approach [5]. The selection of stakeholders was based on their connection to the ICT development and ageing society to obtain the best understanding of the barriers. The participants were from the government (to support policymaker view), ICT organisations (cybersecurity and smart home solutions to support business side), researchers (to support academia) and Non-Governmental Institutions who are working closely with the people in senior citizen associations and social welfare. Additionally, an expert in financing was represented to help understand the market and funding needs/limitations.

Nominal group work was used to create the collective cognitive map. Cognitive mapping is a method to collect data from participants whom the researchers have met and interviewed and whose ideas, beliefs, values and attitudes, and links between them need to be modelled [30]. As well as it is widely used to identify one person's ideas, the approach allows creating a mind map of the whole group dynamics to understand how different or similar the interpretation might be. Collective cognitive maps have been widely used in various domains but not so much in policy-making [31]. In political science, cognitive mapping has been used but under the domain, for politicians to understand how they make decisions and whether their opinions come from tacit knowledge, not explicit [32].

The knowledge panel meetings took place at the end of September 2020 and focused on how ICT services can be best managed for senior citizens. What are the barriers and enablers to developing innovative ICT services and products for senior citizens to enhance their safety and wellbeing. As the mentioned topic is extensive, the research was divided into 11 different categories to have the possibility to gather ideas from diverse areas. The categories are as follows: (i) motives and benefits; (ii) issues and limitations; (iii) actors involved (in senior citizens everyday life); (iv) knowledge-based resources, skills and competencies; (v) social and healthcare, medicine and caregiving; (vi) food and nutrition; (vii) leisure and wellbeing; (viii) finance; (ix) mobility and transportation; (x) housing; (xi) educational, professional, and other activities. Previously stated trigger question was repeatedly asked together with baseline questions and all answers, hereon after data, was used to create a collective cognitive map which consisted of 267 different criteria.

After the workshop, a questionnaire was sent out to perform multi-voting criteria to determine which five elements of each group the experts thought were the most important to focus on in the future.

4 RESULTS

Figure 1 shows the collective cognitive map based on the initial 267 criteria. Due to the space constraints in this article, the map only depicts the collective cognitive framework (a larger version is available upon request). The arrows in the structure reflect cause-and-effect relationships between criteria and categories, making it easier to visualise and understand the initial research result. Table 1 will demonstrate key findings from each category in more detail. After the workshop, a questionnaire was sent out to perform multi-voting criteria to determine which five elements of each group the experts thought were the most important to focus on in the future.

Actorsinvolved. Experts pointed out that key players/actors who play a role in developing innovative solutions are government and government agencies (social insurance board, health insurance board etc.), customers and users and service providers. Experts also mentioned the importance of the third sector's engagement, since community services, interest and support groups and volunteers, are the ones who usually introduce the solutions to senior citizens together with contact people (helpers, social workers, senior citizens relatives etc.)

Motives and benefits. When asking about experts' opinions on what they see as motives and benefits of ICT services for senior citizens, they first mentioned the accessibility of information and how various (ICT) tools enhance gathering/reaching it. Lifelong learning promotion and keeping the senior minds active were also important criteria as innovative solutions might give a valuable learning experience. From a development perspective, the experts mentioned the cooperation encouragement between service end-users, providers and developers as this way more valuable products/services are possible.

Resources, skills and competencies. Panel members said that organisations need various resources, skills and competencies to develop services for senior citizens. The most crucial aspect mentioned was a customer or end-user own skills and awareness and what the customer needs. From the organisational side, the importance of integration between various stand-alone government systems and citizens was mentioned. It reflects that citizens and senior citizens need simple, integrated systems, not separately built solutions for the same government.

Barriers and limitations. Participants opinions towards barriers and limitations of what hinders organisations from developing and sharing services for senior citizens were quite contradictory. Some experts mentioned more infrastructure limitations and how high-speed broadband access is not available everywhere. Others mentioned senior citizens own distrust towards using digital technology. Some experts agreed that the lack of knowledge (and limited

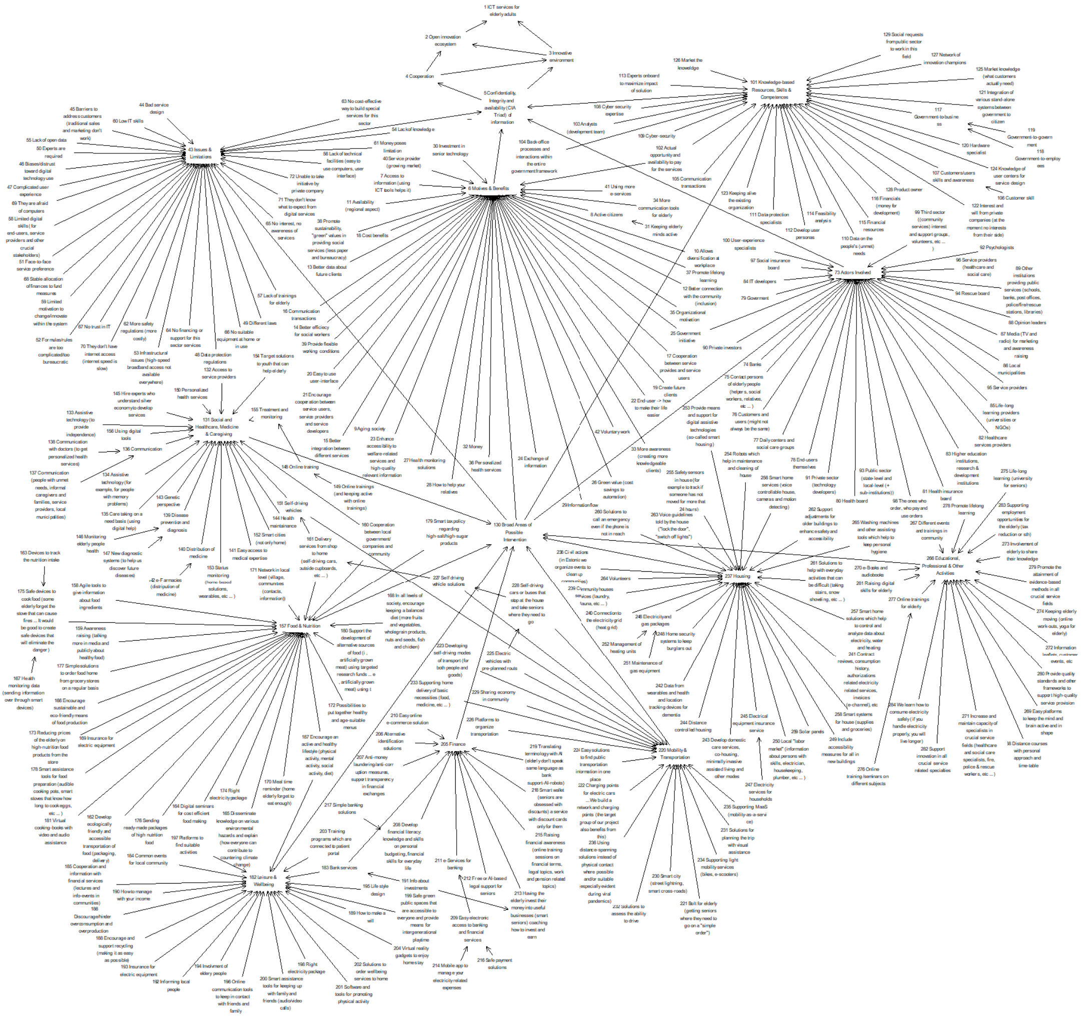

Figure 1: Collective cognitive map

digital skills) is a limitation for senior citizens and a constraint for service providers and other crucial stakeholders.

Educational, professional and other activities. When asking about how education and professionals could help develop ICT-based services, the responses focused on the seniors themselves and how their existing knowledge could be involved. Moving further from existing tacit knowledge to more explicit knowledge the different events and training could help to raise the digital literacy of seniors and promote lifelong learning. In experts' minds, the last aspect could be reached when educational development focus could be on easy platforms that enable seniors to keep their minds and brains active and in shape by virtually solving different daily tasks.

Mobility and transport. The experts pointed out interesting assistive technology ideas to support senior citizens' social inclusion when considering different mobility and transportation solutions. A key aspect had a straightforward sharing economy solution, "Bolt for seniors", to make quick and easy orders for a taxi. In recent years, there has been an increase in the development of self-driving vehicles which could help to meet the demand for transportation between rural areas where public and private companies still struggle

Table 1: Key findings from collective cognitive map categories

Context factors (i.e. determinants) and clusters identified in ICT-based services for senior citizens			
Actors Involved (27)	**Motives and benefits (36)**	**Barriers and Limitations (29)**	**Finance (14)**
Contact persons of senior citizens	Access to information (using ICT tools helps it)	Biases/distrust towards using digital technology	Develop financial literacy: knowledge and skills on personal budgeting
Customers and users	Encourage cooperation between service users, service providers and service developers	Infrastructural issues (high-speed broadband access not available everywhere)	Free or AI-based legal support for seniors
Public sector (state-level and local-level + sub-institutions)	Keeping senior citizens' minds active	Lack of knowledge	Raising financial awareness (online training sessions on financial, legal, & pension)
Service Providers	Promote lifelong learning	Limited digital skills	Safe payment solutions
Third sector (community services, support groups, volunteers, etc.)	Provide flexible working conditions	No interest or awareness of services	Simple banking solutions
Mobility & Transport (16)	**Educational, professional & other activities (18)**	**Housing (28)**	**Social and healthcare, medicine and caregiving (25)**
Bolt for senior citizens (getting seniors where they need to go on a "simple order")	Different events and training in the community	Community houses services (laundry, sauna, etc.)	Access to service providers
Self-driving vehicle solutions	Accessible platforms to keep the mind and brain active and in shape	Data from wearables and health and location tracking devices for dementia	Assistive technology (to provide independence)
Sharing economy in the community	Involvement of senior citizens to share their knowledge	Distance controlled housing	Monitoring senior citizens health
Supporting home delivery of necessities	Promote lifelong learning	Robots helping maintenance and cleaning of the house	Online training (and keeping active with online training)
Supporting MaaS (mobility-as-a-service)	Raising digital skills of senior citizens	Smart home solutions	Status monitoring (home-based solutions, wearables, etc.)
Food and Nutrition (24)	**Resources, skills and competencies (28)**	**Leisure and wellbeing (22)**	
Delivery services from shop to home	Customers/users skills and awareness	Bank Services	
Health monitoring data	Integration of various stand-alone systems between government to citizen	Common events for the local community	
Mealtime reminder	Knowledge of user centres for service design	Encourage an active and healthy lifestyle	
Simple solutions to order food home	Market knowledge (what customers need)	Involvement of senior citizens	
Smart assistance tools for food preparation; etc	Product owner; etc.	Online communication tools to keep in contact with friends and family etc.	

to offer a service (lack of human or physical resource of transportation means (bus, car etc.)).

Finance. When asking about important aspects to keep in mind with financing different solutions for seniors and what kind of solutions could experts point out, the panel member had various ideas. The discussion emphasised the development of financial literacy, meaning there is a need for more knowledge and skills related to personal budgeting. Related to the previous answer, the experts confirmed through multi-criteria voting that raising overall financial awareness is also one of the key aspects. This could be possible via online training sessions on financial terms, legal, work and pension-related terms.

Housing. How ICT-enabled services could help senior citizens in their housing was an essential question to enable independent living for seniors who might need some assistance at home. One of them was smart home solutions that help control and analyse data about electricity, water, and heating usage to ensure that the person living there is using all of these to have a better quality of life. Close connection to a smart house, distance-controlled housing is essential. Vital is the data from wearables and health and location tracking devices for senior citizens battling with dementia so that their relatives or caretaker has an overview of how they are doing and whether they are lost somewhere due to memory loss. Using robots that help in the maintenance and cleaning of a house could be helpful for seniors who have difficulties moving to keep their housing under control.

Social and healthcare, medicine and caregiving. Experts pointed out that seniors need to have easier access to service providers through their family physician, local municipality, or other channels to reach relevant information without quickly visiting multiple pages. To provide senior citizens independence, assistive technology must be organised so that anyone who wants or needs gets help and all needed support. Health monitoring and status monitoring (home-based solutions, wearables etc.) give ICT more opportunities to develop innovative solutions and senior citizens relatives or contact people to overview how senior manages their everyday life. Together with assistive technology, the monitoring could allow relatives peace of mind and senior citizens to manage their daily lives independently.

Food and nutrition. As food and nutrition are closely connected to healthcare, the experts pointed out that health-monitoring data is also a key aspect in this category. Tracking the physical activity of senior citizens indicates how much food they should eat to avoid obesity and keep the quality of their health. For senior citizens, mealtime reminders are crucial as seniors living alone who suffer from dementia might easily forget whether they ate or have already eaten. The development of various digital reminders could help them manage that aspect and other vital tasks, reminders and smart assistance tools for food preparation were mentioned, and there is a lack of simple solutions to order food home from a grocery store.

Leisure and wellbeing. Under the leisure and wellbeing category, participants had a very different understanding. Some of them pointed out the social involvement part, meaning that seniors should be included in the organised activities and be the target group. Others mentioned the importance of encouraging and promoting an active and healthy lifestyle (physical activity, mental activity, social activity). To further support the last two criteria, the recurring event organisation in local communities was mentioned.

5 DISCUSSION AND FUTURE WORK

This research takes the initial step towards ideation, discovering and validating the main problem areas towards the ICT-based solution development for senior citizens. Findings indicate that the senior citizens' resistance towards new technology is closely connected to the motivation and benefit and the development of infrastructure and competencies. If the ecosystem cannot provide an efficient and affordable environment (high-speed internet access needed for ICT-enabled services), then neither the private sector nor end-users would benefit from the services (service-provision). The important finding was also the fact that lack of knowledge or skills towards using information technology is not only senior citizens limitation but acts as a constraint for service providers too. It is vital to see different perspectives and how the seniors could contribute more to the improvement of the existing system. Unfortunately, the new innovative solutions are often brought to life without socially including the end-user target group in the ideation process.

The authors have identified the following limitations: the number of the panel session expert group members, which was limited due to the narrow specialisation from each sector required to cover each dimension; thematic mind map creation and validation needs nominal group work and including more participants would have affected the personal approach dynamic; as highlighted in the methodology section, the initial plan was to use SODA methodology, which was not possible to carry out due to Covid-19 pandemic; taking into consideration also the hybrid solution of panel meetings (half of the participants online and others on the spot) created complexity which had to be tackled by the facilitator.

Further discussion and analysis are required to identify which components of the results acquired from this study will contribute to developing the new strategy (Estonian Welfare Development plan) for the years 2023-2030. The working group for the strategy development will be set up in the summer of 2021, in which the authors of this paper will be included. Based on the outcome of this study, the development of future activities will be defined within the strategy's context.

6 CONCLUSION

The study reported in this paper presented the outcome of the two intensive expert panel meetings on how better policy-making, in terms of ICT-enabled service provision, could enhance possibilities for senior citizens welfare and wellbeing. Findings indicate that the development of innovation in the public sector that benefits senior citizens' lives is not up to only one actor but consists of multi-stakeholder cooperation together with various competencies, skills, and expertise. This study's results support the theory that stakeholders' collective social participation in policy creation is vital for success.

Furthermore, the findings of this study revealed that the criteria of lifelong learning among senior citizens is crucial, which might be the key to socially include the ageing population to address and solve the most important issues. The active and engaged groups of the population, who seek to be healthy, active, and curious to learn, will adapt to the complex circumstances and digital solutions delivered through advanced technologies.

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REFERENCES

[1] P. D. Department of Economic and Social Affairs, "World Population Ageing 2015," United Nations, New York, 2015.

[2] P. D. Department of Economic and Social Affairs, "World Population Prospects The 2015 Revision," United Nations , New York, 2015.

[3] European Commission, "The Silver Economy: An Overview of European Commission's Activities, The First-Ever Global Silver Economy Forum Finland, 9-10 July, 2019," European Commission, 2019.

[4] J. Holgersson, E. Söderström and J. Rose, "Digital Inclusion for Elderly Citizens for a Sustainable Society," in Proceedings of the 27th European Conference on Information Systems (ECIS), 2019.

[5] E. G. Carayannis and D. F. Campbell, "'Mode 3' and 'Quadruple Helix': toward a 21st century," Int. J. Technology Management, vol. 46, 2009.

[6] J. Tepandi, M. Lauk, J. Linros, P. Raspel, G. Piho, I. Pappel and D. Draheim, "The data quality framework for the Estonian public sector and its evaluation: establishing a systematic process-oriented viewpoint on cross-organizational data quality," in Transactions on Large-Scale Data- and Knowledge-Centered Systems XXXV, Berlin, Springer, 2017, pp. 1-26.

[7] I. Pappel, V. Tsap and D. Draheim, "The e-LocGov Model for Introducing e-Governance into Local Governments: an Estonian Case Study," IEEE Transactions on Emerging Topics in Computing, vol. 14, no. 8, pp. 1-14, 2021.

[8] I. Pappel, I. Pappel, T. Tampere, D. Draheim, "Implementation of e-invoicing principles in Estonian local governments". Proceedings of the 17th European Conference on Digital Government (ECDG): Military Academy, Lisbon, Portugal, 12-13 June 2017.

[9] J. Rojas-Méndez, A. Parasuraman and N. Papadopoulos, "Demographics, attitudes, and technology readiness: A cross-cultural analysis and model validation," Marketing Intelligence & Planning, vol. 35, no. 1, pp. 18-39, 2017.

[10] L. Leunga and C. Chen, "E-health/m-health adoption and lifestyle improvements: Exploring the roles of technology readiness, the expectation-confirmation model, and health-related information activities," Telecommunications Policy, vol. 43, no. 6, pp. 563-575, 2019.

[11] I. Ajzen and M. Fishbein, Understanding attitudes and predicting social behavior, New Jersey: Prentice-Hall, 1980.

[12] I. Ajzen and T. Madden, "Prediction of goal-directed behavior: Attitudes, intentions, and perceived behavioral control," Journal of Experimental Social Psychology, vol. 22, no. 5, pp. 453-474, 1986.

[13] F. D. Davis, "Perceived Usefulness, Perceived Ease of Use, and User Acceptance of Information Technology," MIS Quarterly, vol. 13, no. 3, pp. 319-340, 1989.

[14] A. Parasuraman, "Technology Readiness Index (Tri): A Multiple-Item Scale to Measure Readiness to Embrace New Technologies," Journal of Service Research, vol. 2, no. 4, pp. 307-320, 2000.

[15] M. Blut and C. Wang, "Technology readiness: a meta-analysis of conceptualizations of the construct and its impact on technology usage," Journal of the Academy of Marketing Science, no. 48, p. 649–669, 2020.

[16] J. M. Barrutia and A. Gilsanz, "Electronic Service Quality and Value: Do Consumer Knowledge-Related Resources Matter?," Journal of Service Research, vol. 16, no. 2, pp. 231-246, 2012.

[17] J. Doorn, M. Mende, S. M. Noble, J. Hulland, A. Ostrom, D. Grewal and A. J. Petersen, "Domo Arigato Mr. Roboto: Emergence of Automated Social Presence in Organizational Frontlines and Customers' Service Experiences," ournal of Service Research, vol. 20, no. 1, pp. 43-58, 2017.

[18] W. Chiu, "The role of technology readiness in individuals' intention to use health and fitness applications: a comparison between users and non-users," Asia Pacific Journal of Marketing and Logistics, vol. 33, no. 3, pp. 807-825, 2021.

[19] C. Lin, H. Shih and P. Sher, "Integrating technology readiness into technology acceptance: The TRAM model," Psychology and Marketing, vol. 24, no. 7, pp. 641-657, 2007.

[20] C. Lin and A. Bhattacherjee, "Extending technology usage models to interactive hedonic technologies: a theoretical model and empirical test," Information Systems Journal, no. 20, p. 163–181, 2007.

[21] E. Lanseng and T. Andreassen, "Electronic healthcare: a study of people's readiness and attitude toward performing self-diagnosis," International Journal of Service Industry Management, vol. 18, no. 4, pp. 394-417, 2007.

[22] A. Bukov and I. L. T. Maas, "Social participation in very old age: cross-sectional and longitudinal findings from BASE. Berlin Aging Study," Journal of Gerontology: PSYCHOLOGICAL SCIENCES, vol. 57, no. 6, p. 510–517, 2002.

[23] T. L. Cooper, T. A. Bryer and J. W. Meek, "Citizen-Centered Collaborative Public Management," Public Administration Review, vol. 66, no. Special Issue, pp. 76-88, 2006.

[24] OECD, Focus on Citizens: Public Engagement for Better Policy and Services, OECD Studies on Public Engagement, 2009.

[25] A. Walker, "Aging and politics: An international perspective," in Aging and the Social Sciences, vol. 38, San Diego, Elsevier Academic Press, 2006, p. 339–359.

[26] A. Terzi, T. Petrangolini and G. Savarese, Active Ageing in Practice! Experiences of Civic Engagement in Health Policies;, Belgium, 2012.

[27] R. Falanga, A. Cebulla, A. Principi and M. Socci, "The Participation of Senior Citizens in Policy-Making: Patterning Initiatives in Europe," International Journal of Environmental Research and Public Health, vol. 34, no. 18, pp. 1-21, 2020.

[28] J. M. Pinto and L. A. Neri, "Trajectories of social participation in old age: a systematic literature review," Revista Brasileira de Geriatria e Gerontologia, vol. 20, no. 2, pp. 259-272, 2017.

[29] C. Eden and F. Ackermann, "SODA- The Principles," in Rational Analysis for a Problematic World Revisited: Problem Structuring Methods for Complexity, London, John Wiley & Sons, 2001, pp. 21-42.

[30] N. Garoui and A. Jarboui, "Cognitive governance, cognitive mapping and cognitive conflicts: Structural analysis with the MICMAC method," Cogent Economics & Finance, vol. 2, no. 1, pp. 1-13, 2014.

[31] C. Eden and F. Ackermann, "Cognitive mapping expert views for policy analysis in the public sector," European Journal of Operational Research, vol. 152, no. 3, pp. 615-630, 2004.

[32] R. Axelrod, Structure of Decision: The Cognitive Maps of Political Elites, New Jersey: Princeton University Press, 1976.

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2. Olalekan Obasanjo Ojelade, Master’s Degree, 2022, (sup) Ingrid Pappel; Teona Gelashvili, Evaluating the Adoption of Mobile Governance: Case of Nigeria, Tallinn University of Technology.
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4. Marisa Susana Cardenas Silva, Master’s Degree, 2021, (sup) Teona Gelashvili; Ingrid Pappel, Smart Home Systems as a Way to Improve Senior Citizen’s Public Care, Tallinn University of Technology.

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1. Gelashvili, T., & Pappel, I. (2021). Challenges of transition to paperless management: Readiness of incorporating AI in decision-making processes. In L. Terán, J. Pincay, & E. Portmann (Eds.), *Proceedings of the 2021 Eighth International Conference on eDemocracy & eGovernment (ICEDEG)* (pp. 41–46). IEEE.
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