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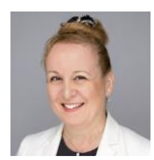

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AI and digital trust – A practical approach

[Research-in-Progress]

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Abstract

Artificial intelligence (AI) use cases are rapidly widening across use cases, business functions and industry sectors. At the same time, the level of criticality and risk represented by AI use is increasing. However, evidence from the field shows that human actors show decreasing levels of trust in their interactions with AI actors. The paper presents a summary of trust factors, including the dependency between relative trust and business or financial success of an AI case. It further suggests a practical approach towards development of an extended trust framework for conceptualizing and successfully realizing AI implementation.

Keywords: AI, digital trust, trust factors, human factors.

Introduction

The use of artificial intelligence (AI) in practice is a rapidly growing field, giving rise to a number of – mostly speculative – predictions about its role in business. From a business perspective, AI has become a central piece of the overarching organizational and business strategy. At the same time, increasing business criticality has led to a more comprehensive view on AI risks, weaknesses and threats. This raises the issue of digital trust in AI across a number of phases in the life cycle. Even at the early conceptual stage, AI use cases must be evaluated – and frequently questioned – in respect of their trustworthiness and their robustness vis-à-vis weaknesses that might impair the level of trust attributed to them. Once deployed, the AI use case must continuously prove its level of trustworthiness (and actual trust) throughout its lifespan. During and after decommissioning, the trust question arises once more, mainly with regard to “leftovers” of personal data.

Practical research must therefore develop robust frameworks that describe, measure and show levels of digital trust in AI. The concepts, underlying parameters and subsequent measurements should be generally agreed and accepted. Likewise, the concept of digital trust in AI should be applicable to both human-AI relationships (does the human trust the AI?) and AI-AI relationships (do AI instances trust each other and to what extent?).

This paper outlines the ISACA Digital Trust Ecosystem Framework (DTEF) as a “tried and tested” tool for ensuring digital trust across organizations and their supply chains. It describes the steps taken to date as work in progress and provides a perspective on future steps to be taken to fully apply the framework to AI use cases.

Problem Statement

Existing trust frameworks were not designed for autonomous, probabilistic, non-deterministic systems. In contrast, they were geared towards use by human actors, often designed to support legal or regulatory provisions. In some cases, the notion of "trust" was subject to divergent interpretations, for instance where a trust framework would address aspects of key management or identity and access management (IAM). It is, however, open whether the DTEF, built for systemic digital trust, can be extended to address AI-specific trust dynamics, and identify the domains requiring adaptation.

A further dimension of digital trust in AI — largely absent from current literature — concerns trust between AI actors themselves. As organizations move toward agentic architectures, multi-agent systems, and protocol-mediated AI-to-AI interactions (for example, through emerging standards such as the Model Context Protocol), the trust question expands beyond the human-AI dyad. AI instances must increasingly evaluate the trustworthiness of other AI instances, the integrity of their outputs, the provenance of their data, and the legitimacy of their delegated authority. This raises novel questions: how does one AI "trust" another's reasoning chain, its alignment, or its adherence to shared policy? Traditional trust models, anchored in human cognition and social contract, offer limited guidance here. A robust digital trust framework must therefore accommodate both relational dimensions — human-to-AI and AI-to-AI — and recognize that weaknesses in either can cascade through interconnected ecosystems. This paper takes the position that the DTEF's systemic, ecosystem-oriented design is well suited to address both dimensions, though the AI-to-AI dimension warrants targeted extension in future work.

State of Research

Background and Theory

Digital trust as an artefact has been discussed from a variety of perspectives, including the political and regulatory one (Bullock et al., 2025), the organization (Vuori et al., 2025), the interactive one (Walter, 2025) and design (Glassberg et al., 2025) as well as the overarching responsibility (Jäger et al., 2025) to name but a few. For the purposes of an industry-centric view, these theoretical contributions provide a foundation, but not necessarily a solution to the practical problem of obtaining, maintaining and defending digital trust. Earlier theories equating digital trust with notions of "security", "risk", "governance" point out trust factors but do not address them in a holistic manner. In other words, theoretical evidence defining and describing "trust" towards AI is scarce and, at best, anecdotal. It remains for the interested observer to resort to classical models of trust as have existed for "analog" trust for decades.

Empirical View

In the field, the perspective on digital trust in AI is somewhat pessimistic. A recent survey in the United States (Clifton, 2025) indicates that up to 25% of participants characterized their level of trust as "much lower" or "a little lower", while broader studies (Gillespie et al., 2025) indicate a significant shift of trust across geographies, with Europe being the group of most skeptical nations. Trust also varies by sector, as indicated by an interesting survey carried out in a smaller country (Orbán & Stefkovics, 2025). Another recent survey highlighting the insurance sector confirms a preference for human interaction rather than "trusting" AI actors (Miller, 2025). While more comprehensive empirical research is needed, even these anecdotal results indicate a more deep-rooted problem. This leads to an interesting working hypothesis for practice: in contrast to earlier thinking that attributed the lack of trust in AI to unfamiliarity, resistance to change and preferred cultural behaviour patterns, it appears to be the increasingly pervasive nature of AI in day-to-day life that causes discomfort and discourages trust. Much of this discomfort further appears to be caused by uncertainty with regard to the use of personal data (Miller, 2025) and autonomous decision making. However, more empirical data is needed to confirm or refute this hypothesis. In industry and practice, however, even early indicators of what might be called "AI mistrust" or even "AI fatigue" give rise to very real business problems. On the one hand, substantial investments are required to implement and operate AI on a day-to-day basis. On the other hand, the return on these investments will obviously depend on AI acceptance and increasing, rather than decreasing trust.

Digital Trust Factors in the DTEF Model

Following earlier work (ISACA, 2010; Kiely & Benzel, 2006; von Roessing, 2009), digital trust was first formalized in a comprehensive model by adapting the concept of systemic security to the wider aspect of trust (ISACA, 2022). The resulting Digital Trust Ecosystem Framework aims at

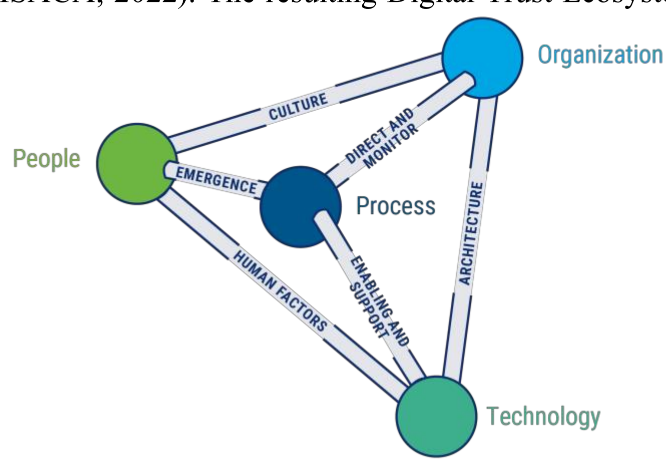

Figure 1. Digital Trust Ecosystem Framework (DTEF)
Source: Digital Trust Ecosystem Framework, ISACA ©2022.
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formalizing trust through a dynamic model that connects a number of nodes by means of dynamic interconnections (Figure 1) called domains. Each domain hierarchically breaks down into trust factors, underlying practices and detailed activities (Figure 2).

Activities are linked to outcomes and a number of other artefacts, such as risk indicators, performance indicators and controls. This reflects the so-called "lenses", or professional viewpoints on the model. For example, a "risk" lens takes a different perspective from a "security" or "quality" lens. In its published format, this provides a comprehensive universe of digital trust that encourages objective and precise measurement in a systemic way. It is worth noting that in the traditional triad of people, process and technology, both the human factors and the emergence domains can and should be applied to AI.

Table 1. DTEF Domains and Trust Factors

Domain	Trust Factors
Culture	CU.01 Manage Culture
	CU.02 Create and Manage the Digital Trust Cultural Environment
	CU.03 Manage Skills and Competencies
Emergence	EM.01 Identify, Evaluate and Manage Potential Triggers
	EM.02 Detect and Manage Process and People Related Emergence
	EM.03 Support Process and People Related Emergence
	EM.04 Foster Emergence Practices
Enabling & Support	ES.01 Manage Digital Trust Ecosystem Objectives
	ES.02 Manage Process Services
	ES.03 Manage Technology Services
	ES.04 Manage Technology Development
	ES.05 Implement Services and Solutions
	ES.06 Operate Services and Solutions
	ES.07 Monitor Services and Solutions
Human Factors	HF.01 Manage Human Factor Interaction with Technology
	HF.02 Optimize Use of Digital Trust IT
	HF.03 Manage User Experience
	HF.04 Manage User Centric Product Development
Direct & Monitor	DM.01 Create, Measure and Manage the Digital Trust Ecosystem
	DM.02 Create and Maintain the Digital Trust Governance System
	DM.03 Manage Risk

	DM.04 Manage Organization
	DM.05 Communicate Digital Trust
	DM.06 Administer Digital Trust
	DM.07 Manage Data and Information Ownership
	DM.08 Optimize Processes to the Organization
	DM.09 Manage Sustainability and Resilience
	DM.10 Manage Compliance
	DM.11 Manage Assurance
	DM.12 Evolve the Organization
Architecture	AR.01 Create Enterprise Trust Architecture
	AR.02 Manage Information and Technology Architecture
	AR.03 Manage Digital Trust Resources
	AR.04 Align Digital Trust Technology with Organizational Needs

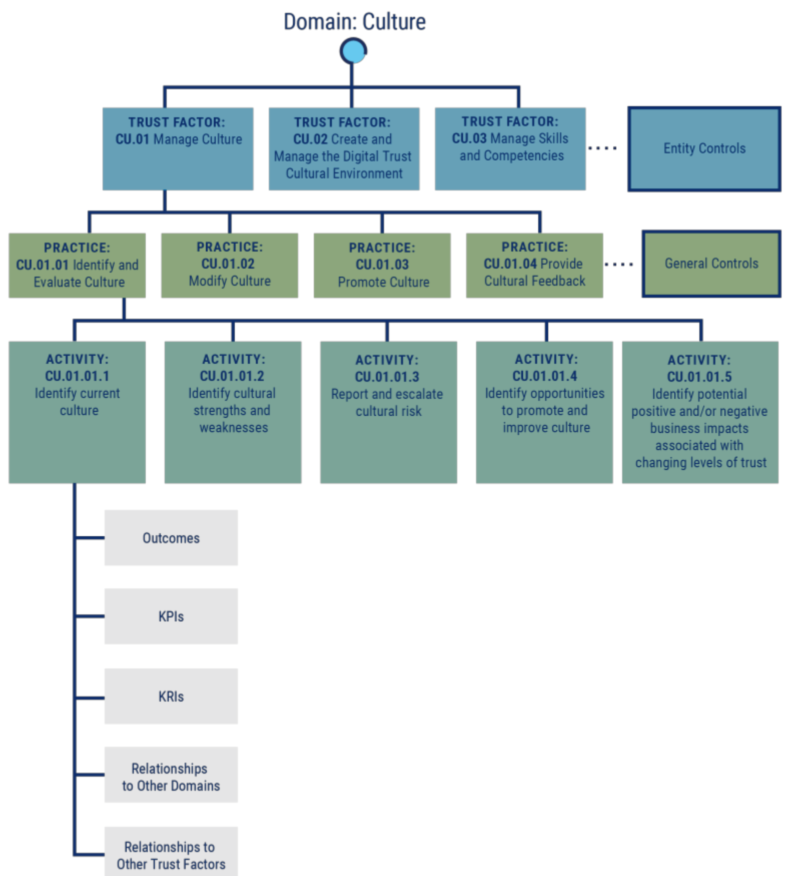

Figure 2. DTEF Domain Hierarchy Example
Source: Digital Trust Ecosystem Framework, ISACA ©2022.

Applying the DTEF to AI

For most DTEF domains, the application of the DTEF is straightforward. As an example, “Architecture” easily translates into the architectural artefacts underlying the AI use case, for instance LLMs, IT infrastructure and data sources. Likewise, “Enabling & Support” follows the pattern of other technology and process interactions. For the Human Factors and Emergence domains, a different approach is needed to fully capture the specifics of AI interactions in terms of human users, technology and processes.

The next step towards adapting the DTEF to AI is the creation of a full set of activities and outcomes that are specific to applying trust factors and practices to the organizational and supply chain use of AI. This is followed by defining appropriate key performance indicators (KPI) and key risk indicators (KRI) following the systematic applied for other lenses.

Applying Human Factors and Emergence Analysis

Further work needs to be done in analyzing human factors, specifically the dynamics of humans using technology and AI. At this juncture, traditional human factors analysis is often focused on convenience, simplicity, user experience and ease of use. However, the work program envisaged for DTEF in AI takes a wider approach in that it considers ethical risk, responsible AI and safe / secure AI implementations. As the simple question "can you trust an AI?" has multiple dimensions, more work is envisaged to improve the human factors domain. In a similar way, emergence, as occurs between human users and processes, requires additional work to achieve a best fit of the DTEF to AI use. Emergent patterns of AI use are well known in practice, ranging from utilizing AI to facilitate office tasks to creating deep fakes. Standard measures for ensuring digital trust are therefore not strong enough to enable reliable measurements of trust through the DTEF. As a result, an extension of the framework may be needed to accommodate the wider perspective. Four human factor dynamics warrant particular attention in the AI context, each of which extends the DTEF Human Factors domain beyond its traditional scope.

First, automation bias. The tendency for human users to over-rely on automated outputs even when those outputs are demonstrably wrong is a long-standing concern in any environment where humans supervise machine decisions. With generative AI, this bias is amplified by the fluency and apparent confidence of model outputs, which can mask hallucination, fabrication, or subtle reasoning errors. The polished surface of an AI response often outpaces its underlying reliability. Trust frameworks must therefore distinguish between *felt* trust (what the user experiences in the moment) and *warranted* trust (which reflects what the system actually merits given its design, training, and operational context).

Second, the problem of trust calibration becomes acute with AI systems whose competence varies significantly across tasks, domains, and contexts. A user who correctly trusts an AI assistant for code completion may incorrectly extend that trust to legal reasoning, medical triage, or financial advice. Unlike traditional IT systems, where capability is relatively bounded and predictable, AI systems present a moving target: confident in some areas, unreliable in others, and rarely transparent about which is which. The DTEF Human Factors domain must therefore address not only whether users trust AI, but also whether their trust is appropriately calibrated to the system's actual reliability envelope.

Third, anthropomorphization introduces a trust dynamic largely absent from prior digital systems. Conversational AI, by design, mimics human linguistic and social cues (turn-taking, empathy markers, conversational repair) which in turn triggers human social responses. Users disclose information they would never type into a search bar, attribute intent and understanding where none exists, and form parasocial relationships with systems that have no awareness of them. This raises governance questions about consent, transparency, and the ethical design of AI interfaces — questions that fall squarely within DTEF's Culture and Human Factors domains.

Fourth, skill atrophy and cognitive offloading represent a longer-term human factors concern that few organizations are tracking. As analytical, creative, and decision-making tasks are increasingly delegated to AI, the corresponding human capabilities tend to erode — slowly, quietly, and often unnoticed until they are needed. For trust frameworks, this introduces a temporal dimension that is easy to miss: an organization's trust posture today may rest on human oversight capabilities that are gradually being hollowed out by the very systems being overseen. The DTEF should accommodate this dynamic explicitly, particularly within the Manage Skills and Competencies (CU.03) and Manage Human Factor Interaction with Technology (HF.01) trust factors.

Taken together, these four dynamics suggest that the Human Factors domain — far from being a soft or peripheral element of the framework — represents one of the most consequential areas of extension for AI use cases.

Practical Approach – Current State of Research

Extending the DTEF

As outlined above, the research work program covers extensions to the DTEF to reflect the specifics of trust in AI use. The scope and extent of these additions will be developed based on theory input as well as empirical data observed in industry. Areas identified to date include all domains to ensure that aspects of practical use are adequately covered. Likewise, the changing legislative and regulatory landscape must be taken into account. As a final point, standardization and the emergence of new frameworks are to be considered to ensure that the DTEF remains up to date over time.

Table 2. Projected DTEF Extensions

Domain / Work Area	Planned Steps
Emergence	Extended set of practices, activities, outcomes and related parameters
Human Factors	Extended set of practices, activities, outcomes and related parameters
Culture	Adaptation of existing trust factors and artefacts to specific AI needs and requirements
Direct & Monitor	Inclusion of advancing legislative and regulatory background (AI-GRC) as well as other AI-related standards and frameworks
Enabling & Support	Adaptation of existing trust factors and artefacts to specifics of AI-related models, infrastructures etc.
Architecture	Adaptation of existing trust factors and artefacts to specifics of AI-related architectures

Integrating Legal and Regulatory Provisions

AI-related legislation and regulation is being passed rapidly and on a global scale. For Europe, the EU Artificial Intelligence Act is the first formal regulation with direct impact, opening the field for further Delegated Acts. Other world regions follow different strategies towards AI-related policy making, ranging from a guidance approach to intricate state or local laws. In practice, it has been observed that much of this activity can be cross-mapped to reduce the effort of integrating new provisions. For the purpose of creating a first proof of concept, a mapping of the provisions of the EU Artificial Intelligence Act (Regulation 2024/1689/EU) has been prepared using a Claude / Opus 4.7 setup in cowork mode. The result shows a sustainable mapping of EU-AIA provisions against the DTEF artifacts. The mapping was performed using a large language model under direct human authorship and review, with each mapped item independently verified against the source provisions; the authors acknowledge the methodological tension of using AI to support the development of an AI trust framework, and treat the current output as a proof of concept requiring further expert validation. While this step demonstrates how mapping tasks can be achieved quickly by means of AI support, the validity of interpretation and legal construction remains to be confirmed. The next steps in extending the DTEF for AI therefore include the development of a robust process for integrating new legal and regulatory provisions, giving due consideration to similarities as well as potentially contradictory elements. As legislation and regulation is likely to reach a higher level of maturity on a five year timeline, it is expected that DTEF changes and extensions will gradually become less. The work plan therefore includes lateral European legislation such as EU-GDPR (Regulation 2016/679/EU) for privacy-related matters as well as sector-specific legislation including EU-NIS2 (Directive 2022/2555/EU) and EU-DORA (Regulation 2022/2554/EU & Delegated Acts). Subsequent steps will cover other world regions using the above-mentioned process.

Integrating AI-related Standards

AI standardization through international and national standards organizations has been growing since 2020, culminating in the recent publication of ISO/IEC 42001:2024 as a management systems standard. In terms of the DTEF work plan, it is however expected that detailed standardization will follow a pattern previously seen in other large management system standards. This in turn will require the incremental application of the integration process. As above, for the purposes of creating a proof of concept, a mapping of ISO 42001 and related standards has been prepared using the same AI support. The result shows an adequate but probably incomplete mapping which requires further human oversight. Further work is needed to achieve complete coverage of standards currently in publication by the responsible ISO committee (SC 42).

Integrating AI-related Frameworks

As with standards, open frameworks exist and are being published on various aspects of AI use. These range from comprehensive efforts such as the NIST AI Risk Management Framework (NIST, 2023; 2024) to more specific toolsets like the AI Controls Matrix (Cloud Security Alliance, 2025). The DTEF for AI work plan envisages a gradual mapping of these frameworks, leveraging the cross-mappings that already exist between them. As with standards, an incremental application of the integration process is envisaged to ensure currency and accuracy of the DTEF. As frameworks evolve over time, the above-mentioned robust process for model maintenance and onboarding of changes will be applied. In contrast to legislative and regulatory changes, it is expected that updating frameworks will likely be a more extensive and continuous task.

Interim Results and Outlook

At this stage in the development process for the DTEF and its application to AI, several conclusions have been identified. From a theory point of view, the model and framework appear robust enough to be applicable to AI without fundamental gaps. Some areas of extension and adaptation have been identified for further research work and framework changes. As regards mappings, the effort to date has not yielded any "orphaned" items in laws, regulations, standards or frameworks that could not be attributed to one or more activities and outcomes of the DTEF. However, this does not prove that the DTEF scope is complete, and additional work may be needed to integrate new external materials.

In the field, the DTEF as a model has been met with caution, as its applicability to defined use cases has not been asserted. To date, the perception of "YAF" (yet another framework) often prevents partial or full adoption. Exploratory field interviews nevertheless indicate that digital trust in AI may be an easily understood case for DTEF use.

In its experimental form, the model does not lend itself to practical use, as it is primarily spreadsheet-based to provide a proof of concept. While the formal result is correct, further steps are needed to transform it into a "manageable" format, for instance by creating a proper database foundation and editability features. Furthermore, accessibility and ease of use – for example by adding an AI-based chatbot – are considered essential for day-to-day use.

In continuing the research, future steps will consider a focusing exercise that will provide a prioritization and weighting model for the somewhat extensive "universe" of DTEF outcomes, activities and related attributes.

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Rolf von Roessing, CISA, CISSP, CISM, CGEIT, CDPSE, FBCI, CABCF, AAIA, AAISM, FMRA. Rolf von Roessing is a partner and CEO at FORFA Consulting AG, an international consultancy firm specialising in GRC, security and related disciplines. He has also been teaching as a senior lecturer in M. Sc. courses at the University for Further Education in Krems (formerly Donau-Universität Krems) since 2005 and is a member of the Academic Council for M. Sc. Management and IT, M. Sc. Information Security Management, and M. Sc. Cybersecurity. Since 2024, he has been co-developing regulatory mentoring programmes with the Cyber Security Centre at Aston University (Birmingham UK). From 2021 to 2024, Rolf was lead developer within the core team developing the ISACA Digital Trust Ecosystem and Framework (DTEF), including the focus areas and the audit and assurance guide document.

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Greg Witte, CISSP, ISSEP, CISM, COBIT Foundation. Greg is President of Palydin Security Services and supports international commercial and public-sector constituents with establishing and maintaining governance and risk management models. He currently serves as a trusted advisor to the U.S. Department of Homeland Security and is an Associate Researcher at the U.S. National Institute of Standards and Technology (NIST). Greg provides instruction for international companies and helps enterprises apply technical and workforce frameworks. Greg joined Rolf and Mark as part of the core team developing the ISACA Digital Trust Ecosystem and Framework (DTEF), building on more than twenty years developing ISACA/CMMI business, maturity and risk management frameworks. In his work at NIST, Greg co-authored the Cybersecurity Framework, NIST's AI Risk Management Framework and Cybersecurity Workforce Framework.

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Operationalizing AI governance in higher education: Translating the SPARKE framework into practical institutional tools

[Complete Research]

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Abstract

Artificial intelligence (AI) is reshaping teaching, learning, and administration in higher education while introducing risks related to privacy, academic integrity, bias, cybersecurity, and accountability. Many institutions adopt AI faster than they develop coherent governance structures, leading to fragmented practices and weak knowledge-management processes. This paper operationalizes the SPARKE Framework, a knowledge-management–informed model for responsible AI integration, built on six pillars: Safeguards, Policy, Accountability, Risk Management, Knowledge Development, and Education. SPARKE is translated into two applied tools: a faculty checklist and a student guide. These tools transform governance principles into actionable academic practice, supporting ethical decision-making, institutional alignment, and sustainable AI governance.

Keywords: Artificial intelligence, higher education, governance, knowledge management, academic integrity, responsible AI, institutional policy, risk management, SPARKE framework.

Introduction

Artificial intelligence (AI) has evolved from an emerging innovation to an embedded feature of contemporary higher education, functioning as a powerful asset across instructional, administrative, and research domains. Institutions increasingly deploy AI in assessment systems, academic advising, and operational decision-making, while students rely on it for productivity, content creation, and learning support, and faculty integrate it into pedagogical design and instructional delivery (Ghnemat et al., 2022). Prior studies highlight the expanding academic, administrative, ethical, and regulatory implications of AI adoption (Alqahtani et al., 2023; Campus Technology, 2024). In this context, AI is no longer optional but integral to modern academic practice. At the same time, AI introduces significant ethical, technical, and organizational risks. These include concerns related to data privacy, academic integrity, algorithmic bias, cybersecurity vulnerabilities, and misinformation, as well as legal and institutional challenges associated with AI-enabled assessment and surveillance technologies (Boateng & Boateng, 2025; Cheatham et al., 2019; Mita, 2022; Wired, 2023). As a result, AI practices often vary across departments, producing inconsistency, inequity, and ambiguity in institutional application (Mysechko et al., 2024). Although many institutions have begun developing governance policies, these efforts are frequently fragmented, outdated, or insufficiently integrated into practice. Moreover, the absence of robust knowledge-management mechanisms limits institutions' ability to communicate, internalize, and sustain governance practices effectively (ISO/IEC, 2023; NIST, 2023; OECD, 2019). Consequently, AI adoption often outpaces governance maturity, resulting in reactive rather than strategic institutional responses. Previous research has extensively examined the ethical, regulatory, and institutional implications of AI adoption in higher education, including concerns related to transparency, accountability, bias, privacy, and academic integrity (Barus et al., 2025, Bittle & El-Gayar, 2025, Pikhart & Al-Obaydi, 2025). Existing studies have also emphasized ethical governance frameworks, institutional policy development, and responsible AI adoption strategies within higher education environments (Dotan et al., 2024; Nguyen et al., 2023). However, much of this literature remains focused on conceptual principles and governance recommendations rather than the operational mechanisms required to embed AI governance into everyday institutional practice. Consequently, institutions often face challenges translating governance policies into sustainable, role-specific implementation processes across academic and administrative environments.

To address this gap, higher education requires governance approaches that extend beyond abstract principles and provide structured, actionable, and sustainable mechanisms for managing AI use. Building on prior work introducing the SPARKE Framework (Malomo et al., 2025), this study advances SPARKE from conceptual formulation to an operationalization framework for institutional AI governance in higher education. This operational layer addresses a critical gap in AI governance research, where frameworks often remain policy-oriented and insufficiently embedded in day-to-day institutional workflows. By bridging conceptual governance and applied implementation, this study contributes a practical mechanism for aligning institutional policy, faculty practice, and student behavior. Drawing on knowledge management theory and contemporary AI governance standards (Alavi & Leidner, 2001; Argote, 2013; OECD, 2019; UNESCO, 2021), the paper translates SPARKE into role-specific governance tools that embed policy, accountability, and organizational learning into institutional practice. This study is positioned as an applied extension of the SPARKE Framework, focusing on implementation rather than conceptual development. By translating governance principles into faculty checklists, student-use guidelines, and workflow-oriented decision-support tools, the study frames AI governance as an ongoing knowledge-management process rather than a static policy artifact. This paper makes three primary contributions to AI governance research and practice in higher education. First, it advances the SPARKE Framework from a conceptual governance model to an operationalization framework designed to support institutional AI governance in higher education. Second, it demonstrates how AI governance principles can be translated into role-specific governance mechanisms that support responsible AI use among faculty and students while strengthening policy alignment, accountability, and organizational learning. Third, it contributes a knowledge-management perspective on AI governance by framing operationalization as a process of institutional learning, knowledge transfer, and governance sustainability rather than as policy development alone.

Research Questions

This study is guided by the following research questions, which focus on the operationalization of AI governance in higher education rather than empirical measurement:

1. How can a conceptual AI governance framework be operationalized into practical, role-specific tools for higher education institutions?
2. In what ways can the SPARKE Framework be translated into actionable guidance for institutional leaders, faculty, and students to support responsible AI use?
3. How does operationalizing AI governance through structured checklists and guides contribute to knowledge management, organizational learning, and governance consistency in higher education?

Related Work

The rapid adoption of AI in higher education has generated growing scholarship on ethical governance, institutional accountability, and responsible AI integration. Existing studies have examined issues including transparency, bias, academic integrity, privacy, and regulatory compliance, while international frameworks such as those developed by UNESCO, OECD, and NIST emphasize principles for trustworthy and responsible AI governance (NIST, 2023; OECD, 2019; UNESCO, 2021). Recent higher education research has also explored institutional AI policy development, faculty perspectives, and responsible adoption strategies within academic environments (Barus et al., 2025; Dotan et al., 2024; Nguyen et al., 2023).

Despite these contributions, much of the existing literature remains concentrated on conceptual governance principles and policy guidance rather than implementation-oriented governance mechanisms (Kim et al., 2024; Ribeiro et al., 2025). Limited research has examined how governance frameworks can be operationalized into role-specific institutional practices that support faculty decision-making, student accountability, and sustainable organizational learning (Neumann et al., 2026; Wu et al., 2024). From a knowledge-management perspective, this limitation reflects broader challenges related to institutional learning, governance consistency, and cross-role knowledge transfer. Building on prior conceptual work on the SPARKE Framework (Malomo et al., 2025), this study addresses this implementation gap by translating governance principles into practical mechanisms designed for integration within everyday academic workflows.

Methodology

This study employs a conceptual development methodology appropriate for emerging and rapidly evolving technological domains (Snyder, 2019; Tranfield et al., 2003; Webster & Watson, 2002). The study draws on a targeted review of institutional AI policies, international governance standards, and peer-reviewed literature related to AI governance in higher education. Sources were selected based on their relevance to governance challenges including policy fragmentation, accountability, academic integrity, risk management, and knowledge transfer. Building on prior conceptual work on the SPARKE Framework (Malomo et al., 2025), the study operationalizes the framework by mapping recurring governance challenges identified in the literature to the six SPARKE pillars. This process informed the development of role-specific governance mechanisms for faculty and students designed to support institutional implementation, responsible AI use, and organizational learning across higher education environments. Although the study does not include empirical validation, it provides a structured foundation for future pilot testing, institutional evaluation, and quantitative assessment of AI governance maturity.

Overview of the SPARKE Framework

The SPARKE Framework was developed to support higher education institutions in managing the dual-use nature of AI, both as an asset and a liability. AI offers innovation, productivity, and learning enrichment; yet, without structured governance, it also introduces ethical uncertainty, institutional risk, and operational exposure. SPARKE provides an organized system for universities to integrate AI responsibly, transparently, and sustainably. SPARKE is anchored on six foundational pillars:

- Safeguards emphasize institutional protections that reduce misuse, bias, privacy violations, and unintended consequences. Safeguards ensure that AI implementation aligns with institutional values and legal expectations.
- Policy establishes clarity regarding acceptable AI use, disclosure expectations, authorship rules, and institutional responsibilities. Policy harmonizes practice across departments and prevents fragmented interpretation.

- Accountability ensures that ownership for AI decisions is defined. Clear roles determine who approves tools, who monitors performance, and who is responsible for failures when they happen.
- Risk Management focuses on systematic identification, evaluation, and mitigation of AI-related threats, including cybersecurity exposure, data misuse, and operational vulnerabilities.
- Knowledge Development strengthens institutional learning through documentation, communication, and continuous updating of AI practices. It ensures that guidance is not static, but evolves with technology.
- Education equips faculty, students, and administrators with literacy, training, and ethical awareness to engage AI responsibly in teaching, learning, research, and administration.

While previous scholarship positioned SPARKE conceptually, this paper advances its operational dimension. The unique contribution here is translating SPARKE into concrete academic tools — ensuring that professors and students have structured, practical guides that transform policy expectations into everyday behavior (ISO/IEC, 2023; NIST, 2023; OECD, 2019; UNESCO, 2021).

Operationalizing SPARKE in Practice

SPARKE is operationalized through two role-specific implementation tools designed to support responsible AI use in everyday academic practice:

1. The SPARKE for Professors Practical AI Integration Checklist, which supports faculty decision-making related to instructional AI use, policy alignment, transparency, and academic integrity.
2. The SPARKE Responsible AI Use Guide for Students, which provides guidance for ethical, transparent, and academically responsible engagement with AI technologies.

Together, these tools translate institutional AI governance into actionable faculty and student practices. The SPARKE governance architecture and its operationalization are illustrated in Appendix A (Figure 1), Appendix B (Figure 2), and Appendix C (Figure 3), presenting the institutional-level framework and its translation into role-specific guidance for faculty and students.

SPARKE For Professors: Practical AI Integration Checklist

The SPARKE for Professors checklist provides practical guidance for responsible instructional AI use aligned with institutional policy and academic integrity expectations. Figure 2 illustrates SPARKE implementation in instructional practice (See Appendix B for the SPARKE for Professors Operationalization Diagram).

Safeguards: Ensure AI use aligns with institutional ethics, privacy protections, academic integrity requirements, and approved technology standards.

Policies: Align instructional AI practices with institutional governance policies, disclosure expectations, and approved pedagogical guidelines.

Apply Controls: Use secure, institutionally approved AI tools while protecting sensitive data and verifying AI-generated outputs.

Raise Literacy: Promote responsible AI literacy by helping students understand appropriate, transparent, and ethical AI use in academic work.

Keep Monitoring: Continuously evaluate AI use within courses to identify misuse, assess learning impact, and maintain governance compliance.

Ensure Compliance: Document and maintain alignment with institutional regulations, accessibility standards, and academic integrity policies.

The SPARKE Professor Checklist supports responsible innovation while maintaining instructional integrity and transparency. By transforming institutional policy into everyday classroom practice, SPARKE strengthens teaching integrity while supporting innovation.

SPARKE Responsible AI Use Guide for Students

The SPARKE Student Guide provides practical guidance for ethical, transparent, and academically responsible AI use in student learning activities. Figure 3 provides a structured model to help students navigate ethical responsibility, disclosure, safe usage, bias awareness, and accountability when engaging with AI tools (See Appendix C for the SPARKE for Students Operationalization Diagram).

Safeguards: Use AI tools responsibly while protecting privacy, academic integrity, and sensitive information.

Policies: Follow institutional guidelines regarding acceptable AI use, disclosure requirements, and academic honesty expectations.

Apply Controls: Verify AI-generated information, avoid unauthorized AI use, and use approved platforms when completing coursework.

Raise Literacy: Develop critical understanding of AI capabilities, limitations, bias, and ethical implications.

Keep Monitoring: Reflect on personal AI use habits and evaluate whether AI supports meaningful learning and skill development.

Ensure Compliance: Maintain compliance with course policies, institutional regulations, and responsible AI usage expectations.

Together, the faculty and student tools operationalize SPARKE by embedding responsible AI practices into everyday academic workflows. The revised diagrams emphasize usability and implementation rather than institutional architecture.

Implementation and Knowledge Management Implications

The operationalization of SPARKE has several implications for AI governance and knowledge management in higher education. By translating governance principles into structured, role-specific governance mechanisms, SPARKE supports institutional learning through the development of shared practices, consistent policy interpretation, and documented guidance for responsible AI use. The framework enables institutions to convert informal or fragmented governance knowledge into accessible operational processes that can be reviewed, refined, and adapted over time. SPARKE also strengthens knowledge transfer across institutional roles by establishing a common governance language for administrators, faculty, and students. Through role-specific implementation mechanisms, the framework aligns institutional expectations with instructional practice and student behavior while supporting accountability, communication, and governance consistency across academic environments. This shared structure reduces ambiguity and supports coordinated institutional responses to evolving AI technologies and governance challenges. Finally, SPARKE contributes to governance sustainability by embedding AI governance into routine academic processes rather than relying solely on static policy documents. Its modular and implementation-oriented structure supports phased institutional adoption, continuous monitoring, and long-term governance adaptation as AI technologies evolve. Although the present study is conceptual in nature, the framework provides a foundation for future empirical assessment of governance maturity, institutional effectiveness, and responsible AI integration in higher education.

Discussion

This study contributes to AI governance research in higher education by advancing SPARKE from a conceptual governance model to an operational implementation framework. The study demonstrates how governance principles can be translated into role-specific governance mechanisms that support institutional consistency, responsible AI integration, and organizational learning across academic environments. The contribution of this study lies not in proposing new governance principles, but in operationalizing existing governance concepts into structured institutional implementation mechanisms. By incorporating a knowledge-management perspective, SPARKE positions AI governance as an ongoing institutional process involving communication, adaptation, and shared responsibility rather than policy development alone. At the same time, operationalizing AI governance within higher education presents significant institutional challenges. Universities often face policy incoherence across departments, inconsistent interpretations of acceptable AI use, and uneven governance implementation across academic units (Wu et al., 2024; Xiao et al., 2023). In addition, digital inequalities may affect both students and faculty, as access to AI tools, technical infrastructure, and AI literacy varies considerably across institutional and socioeconomic contexts (Beckman et al., 2025; Hodøl et al., 2025). Faculty workload also represents an important challenge, as responsible AI governance requires continuous monitoring, assessment redesign, policy communication, and ongoing adaptation to rapidly evolving technologies (Dotan et al., 2024). These realities highlight that effective AI governance depends not only on governance frameworks themselves, but also on institutional capacity, coordination, training, and long-term organizational support. Several limitations should be acknowledged. The present study is conceptual and does not include empirical validation of the proposed governance mechanisms within institutional settings. Future research should evaluate the effectiveness of SPARKE through pilot implementations, governance maturity assessments, and longitudinal studies examining faculty adoption, student engagement, and institutional outcomes related to responsible AI governance in higher education.

Future Research and Empirical Validation

This study operationalizes SPARKE into applied governance tools; however, empirical validation remains essential. Future research will develop and validate a multi-stakeholder survey instrument to assess SPARKE implementation across faculty, students, and administrators. This work will examine the reliability of SPARKE constructs, the relationship between implementation and governance maturity, and the impact of maturity on outcomes such as policy clarity, responsible AI use, and organizational learning. A hierarchical model may be tested in which SPARKE pillars predict AI governance maturity, which in turn influences institutional outcomes. Structural equation modeling can support this analysis and the development of a SPARKE Governance Maturity Index for benchmarking. Such validation would strengthen the framework's predictive capability and enable cross-institutional comparison.

Conclusion

Artificial intelligence is reshaping higher education, increasing the need for governance approaches that move beyond policy development toward practical institutional implementation. This study advances the SPARKE Framework as an operationalization framework for institutional AI governance by translating governance principles into role-specific mechanisms for faculty and students. The resulting implementation tools support institutional consistency, responsible AI use, academic integrity, and organizational learning across higher education environments. By embedding governance expectations into everyday academic practice, SPARKE provides institutions with a practical foundation for sustainable and adaptable AI governance. Future research will evaluate the framework's effectiveness, governance maturity outcomes, and applicability across diverse institutional contexts.

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Ayse N. Balas, Ph.D., is an Associate Professor of Management and Marketing at the Reginald F. Lewis College of Business, Virginia State University. With over two decades of experience, her work focuses on international business and the integration of emerging technologies, including artificial intelligence, in business practice. She has actively participated in international research initiatives and contributes to advancing global engagement and innovation in business education.

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Moses Garuba, Ph.D., is a faculty member in Electrical and Computer Engineering at the School of Engineering, Architecture, and Aviation, Hampton University. He previously served as Associate Dean for Academic Affairs at Howard University’s College of Engineering and Architecture. His research focuses on artificial intelligence, data governance, and intelligent systems, emphasizing ethical and practical applications of emerging technologies. He is an active researcher and mentor, contributing to scholarly publications and the development of future engineers.

Appendix A: SPARKE Framework Overview

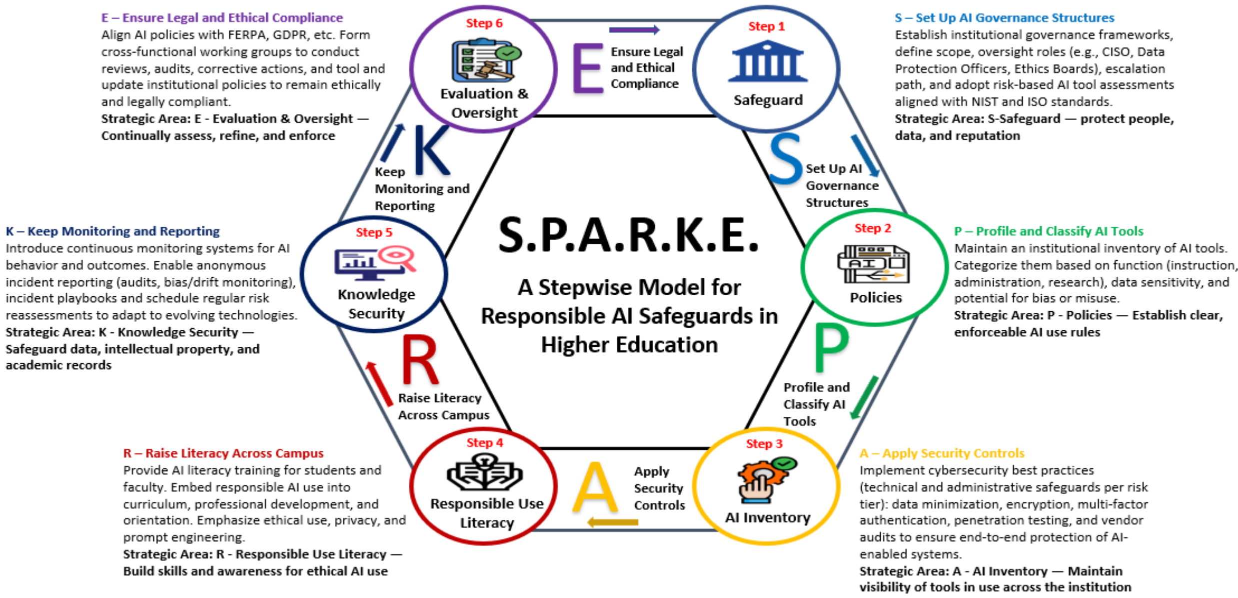

Figure 1. Institutional-Level SPARKE Governance Architecture (Malomo et al., 2025)

Appendix B: SPARKE for Professors – Operationalization Diagram

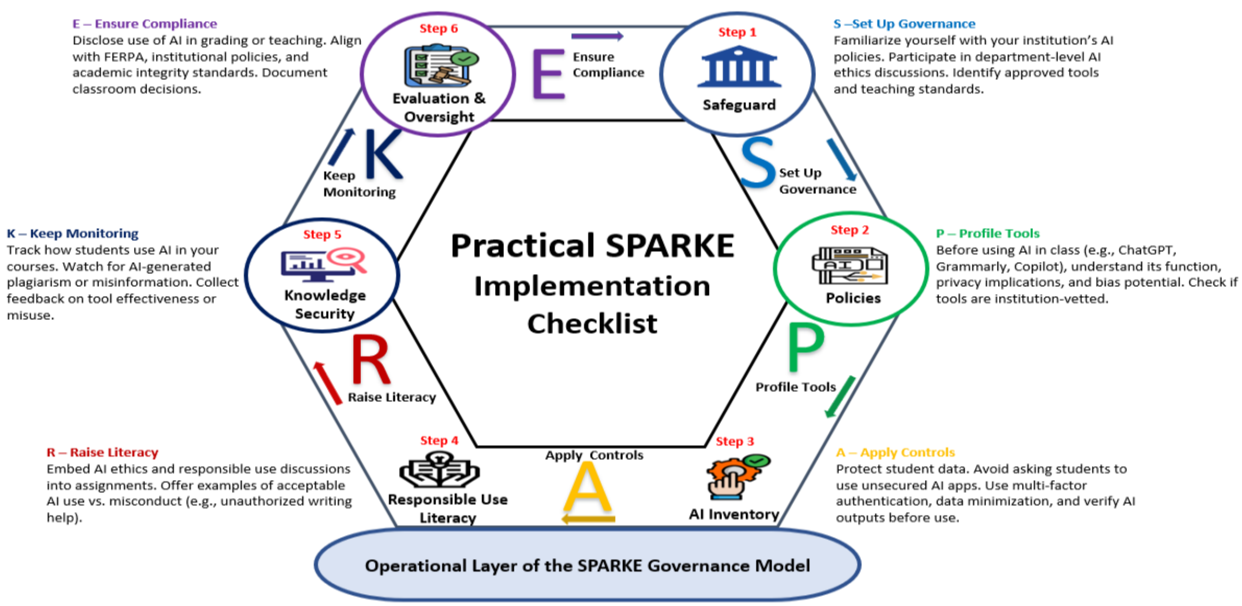

Figure 2. Operationalized SPARKE Framework for Faculty Implementation: Role-Specific Governance Translation for Instructional Practice.

Appendix C: SPARKE for Students – Operationalization Diagram

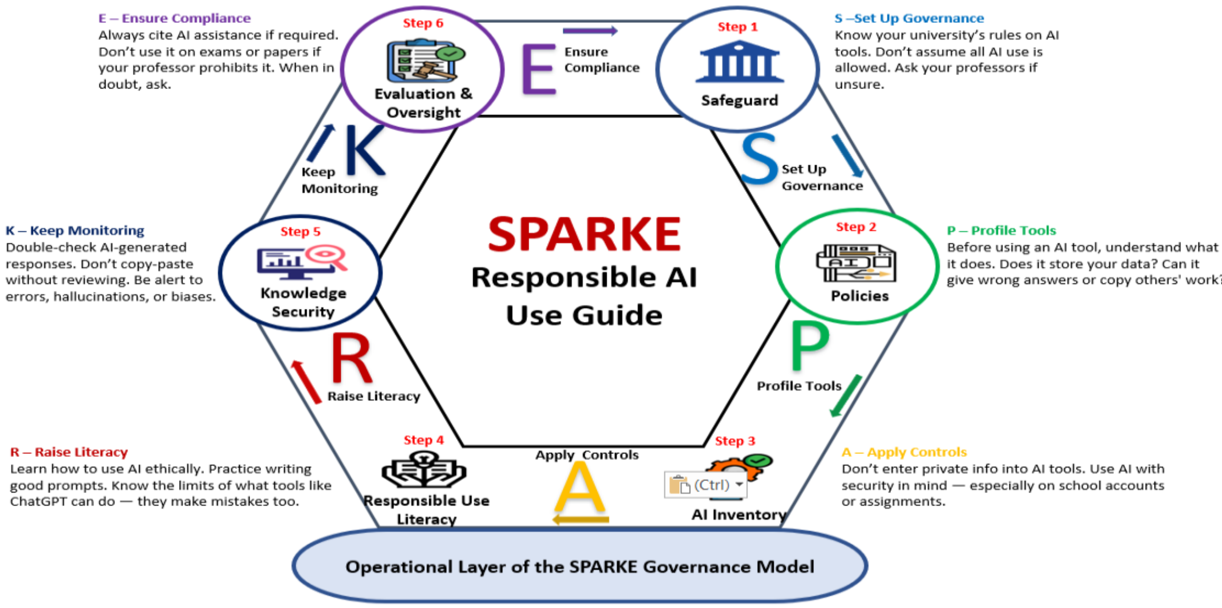

Figure 3. Operationalized SPARKE Framework for Students: Responsible AI Engagement Model Aligned with Institutional Governance

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An integrated knowledge management, resource-based view, and task-technology fit framework for AI readiness and organizational performance

[Research-in-Progress]

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Abstract

This paper examines how organizations develop Artificial Intelligence (AI) readiness to improve organizational performance. Despite growing adoption, many organizations fail to move beyond pilot implementations due to insufficient organizational capabilities and alignment between AI technologies and operational tasks. Drawing on Knowledge Management (KM), the Resource-Based View (RBV), and Task-Technology Fit (TTF) theory, this exploratory study proposes an integrated conceptual framework explaining how knowledge assets and capabilities enable AI readiness maturity. KM provides the processes through which organizations develop and apply knowledge, RBV explains how these knowledge assets function as strategic resources, and TTF describes how alignment between AI capabilities and task requirements determines effective utilization. AI readiness is conceptualized as a maturity continuum reflecting the organization's ability to integrate AI into workflows and decision-making. The proposed framework links knowledge resources, technology alignment, and AI readiness to organizational performance and competitive advantage, providing a foundation for future empirical research on AI capability development. The implications of this framework suggest that AI readiness should be understood as an organizational capability emerging from the interaction of knowledge resources and task-technology alignment rather than from technology adoption alone.

Keywords: Artificial Intelligence readiness, knowledge management, resource-based view, task-technology fit, organizational performance, learning organizations.

Introduction

Artificial Intelligence (AI) has emerged as one of the most transformative technologies shaping organizational strategy, operations, and competitive dynamics. Global estimates suggest AI may contribute more than $15 trillion to the world economy by 2030, underscoring its strategic importance for organizations seeking operational efficiency, innovation, and market differentiation (Chui & Francisco, 2017). Organizations face unprecedented pressure to adopt AI amid digital transformation, yet many struggle with AI readiness, leading to suboptimal capabilities and performance. Learning Organizations (LOs) adopt AI to improve operational efficiency and enhance decision-making. However, despite significant investment in AI technologies, many organizations struggle to move beyond pilot implementations and experimental deployments. This variation suggests that AI readiness depends on technological acquisition as well as the organizational capabilities required to support, integrate, and apply AI successfully.

Existing research provides several theoretical lenses relevant to this challenge. Knowledge Management (KM) research highlights that knowledge creation, sharing, and application enable organizations to develop and leverage strategic capabilities (Alavi & Leidner, 2001). LOs are defined as organizations that continually expand their capacity to create competitive advantage through the creation, integration, and application of knowledge (Kumar et al., 2021). Resource-Based View (RBV) emphasizes that sustainable competitive advantage emerges from valuable, rare, inimitable, and non-substitutable organizational resources and capabilities (Barney, 2001). Task-Technology Fit (TTF) theory explains that technology improves performance only when its capabilities align with the tasks users perform (Goodhue & Thompson, 1995). These perspectives suggest that AI readiness depends on organizational knowledge resources and the extent to which AI technologies align with operational tasks. Despite their relevance, these theories have rarely been integrated to explain AI readiness, defined as the organizational maturity and capability required to successfully deploy and utilize AI (Uren & Edwards, 2023). AI represents a uniquely knowledge-intensive technology that depends on organizational data, expertise, governance, and workflow integration. Without sufficient knowledge resources or alignment between technology and operational tasks, AI adoption may fail to produce meaningful organizational outcomes.

This paper addresses this gap by proposing an integrated conceptual framework positioning KM concepts within RBV by linking knowledge resources to TTF to determine AI readiness maturity and organizational performance. The central research question guiding this work is how do organizational knowledge resources and capabilities enable TTF and AI readiness, leading to improved organizational performance? The purpose of this study is to synthesize existing literature and propose a conceptual model that can guide future empirical research. Furthermore, this paper contributes to information systems and organizational learning literature in three ways. First, it conceptualizes AI readiness as a knowledge-dependent capability emerging from RBV resources rather than a purely technological or operational construct. Second, it integrates TTF to explain how knowledge resources translate into AI readiness. Third, it positions KM as the conceptual foundation enabling learning organizations to develop and sustain AI capabilities. Together, this framework provides a structured foundation for future empirical investigation of AI adoption and organizational performance outcomes.

Background and Related Work

Recent research in information systems and KM extends the RBV by treating knowledge assets and capabilities as key drivers of performance in digital strategies (Mele et al., 2024). KM capability mediates the effect of technical resources on performance whereas AI capability has been conceptualized as a dynamic capability shaped by data quality, infrastructure, and governance (Neiroukh et al., 2025). TTF remains validated for emerging technologies including analytics and AI (Kankanhalli, 2024). Together, these frameworks support a model in which knowledge resources are embedded within organizational processes, aligned with TTF, and manifest as AI readiness to drive organizational performance.

Knowledge Management and Learning Organizations

KM refers to the systematic processes by which organizations create, store, share, and apply knowledge to achieve strategic objectives (Costa & Monteiro, 2016). Knowledge exists in both explicit forms, such as documented procedures and structured data, and tacit forms, including employee expertise, experience, and organizational routines (Bhardwaj & Monin, 2006). Effective KM enables organizations to transform individual knowledge into collective organizational capability. LOs are characterized by their ability to continuously acquire and apply knowledge to adapt to changing environments (Appelbaum & Goransson, 1997). These processes are critical in AI contexts, where successful implementation depends on integrating technical expertise, domain knowledge, and organizational processes. AI systems rely on organizational knowledge assets. Data must be interpreted within organizational contexts, models must reflect domain realities, and users must understand how to apply AI tools effectively (Olan et al., 2022). Without effective KM processes, organizations may possess technological tools but lack the infrastructure required for effective implementation. Thus, KM provides the foundational processes through which knowledge assets are developed, enabling organizations to build capabilities necessary for AI readiness. KM provides an overarching theoretical foundation for understanding how organizations develop and apply AI capabilities.

Learning organization theory posits that organizations achieve sustained performance improvement through the continuous acquisition, integration, and application of knowledge (Shin et al., 2017). Unlike physical assets, knowledge accumulates over time and becomes embedded in organizational processes, making it difficult for competitors to replicate (Kumar et al., 2021). This perspective emphasizes knowledge as the most critical resource underpinning competitive advantage. AI represents an advanced form of knowledge management infrastructure because it enables organizations to analyze large volumes of data, generate predictive insights, and embed knowledge directly into operational workflows (Jarrahi et al., 2023). As organizations progress in their ability to manage and operationalize knowledge through AI, they increasingly exhibit characteristics of LOs, including improved adaptability, continuous improvement, and enhanced performance. Thus, AI readiness maturity can be understood as a manifestation of an organization’s knowledge management capability.

Resource-Based View as Strategic Resources

The RBV provides a theoretical foundation for understanding how organizational resources contribute to sustained capability development and competitive advantage. According to RBV, resources that are valuable, rare, inimitable, and non-substitutable (VRIN) enable organizations to outperform competitors (Dzreke, 2025). These resources include both tangible assets, such as technological infrastructure, and intangible assets, such as knowledge, skills, and organizational processes. These resources form the foundation necessary to support the progression of AI readiness maturity. Organizations gain sustained competitive advantage through VRIN resources which collectively make up knowledge assets and capabilities.

These resources determine whether organizations can successfully develop, deploy, and sustain AI capabilities (Papagiannidis, 2021). High-quality data enables accurate AI outputs when integrated technological infrastructure allows systems to function effectively across organizational workflows. Human expertise ensures that AI systems are properly implemented and utilized, whereas governance structures ensure reliability, compliance, and strategic alignment. Financial investments provide the capital to acquire technological infrastructure, development of the workforce, and support the ongoing development, deployment, and maintenance of AI systems (Adenuga et al., 2024). RBV emphasizes that resources alone do not create value unless they are effectively deployed and aligned with organizational activities (Dzreke, 2025). Thus, RBV provides the theoretical framework to explain how knowledge assets and capabilities form the foundation for AI readiness.

Task-Technology Fit

TTF theory explains how technology contributes to performance by examining the degree to which technological capabilities align with task requirements. TTF is the degree to which a technology assists an individual in performing their tasks (Goodhue & Thompson, 1995). TTF proposes that technology improves individual and organizational performance only when its functionality appropriately supports the tasks that users must perform. TTF serves as the mechanism through which organizational knowledge resources are operationalized. Andersone et al. (2021) stated that according to TTF theory, "a higher fit between technology, task requirements, and individual abilities will contribute to better performance, and lead to more efficient task accomplishment." Even when organizations possess substantial technological infrastructure and data resources, AI systems will not produce meaningful outcomes unless they align with user needs and operational tasks. Studies integrating TTF with AI demonstrate that the alignment between AI capabilities and organizational task requirements is a critical determinant of effective AI utilization and resulting performance outcomes (Ann & Ahn, 2024). When AI technologies appropriately support task demands, organizations are better able to extract meaningful insights from large and complex data environments, thereby improving decision quality and operational effectiveness (Sonntag et al., 2025).

Organizations that demonstrate higher levels of TTF indicate that AI systems are better aligned with operational tasks and integration into workflows which reflect greater AI readiness maturity (Passmore et al., 2025). When TTF is high, AI systems align with task requirements in ways that enhance productivity, improve decision quality, and increase user adoption. Conversely, low levels of fit reflect experimental or fragmented AI implementation, characteristic of early readiness stages. TTF provides a theoretical mechanism through which organizational resources and knowledge capabilities translate into measurable AI readiness. Przegalinska et al. (2025) examined this relationship through the combined lenses of RBV and TTF. They found that the availability of AI resources alone is insufficient and performance improvements depend on the degree to which those resources are embedded in workflows that complement their strengths. The alignment between AI capabilities and task fit represents a critical mechanism through which organizations translate AI investments into competitive advantage (Przegalinska et al., 2025). Poor alignment limits organization performance regardless of resource availability. Thus, TTF represents a critical capability linking organizational knowledge resources to AI readiness maturity across all levels.

AI Readiness and Maturity

AI readiness refers to the extent to which an organization possesses the technological, human, and organizational capabilities necessary to successfully deploy AI systems (Holmström, 2022). AI readiness reflects a maturity continuum, ranging from no AI capability to fully integrated, enterprise-wide AI systems embedded within operational and strategic processes. This maturity progression reflects an organization's ability to transform knowledge resources into operational capabilities. AI readiness encompasses infrastructure, data availability, governance, workforce skills, and organizational processes that enable effective AI implementation (Uren & Edwards, 2023). The concept of readiness as a progression through maturity levels is supported by prior frameworks describing how organizations evolve from minimal or no AI integration to advanced, enterprise-wide deployment. For example, Fornasiero et al. (2024) proposed a maturity model examining AI and big data implementation across multiple organizational dimensions, while Lichtenthaler (2020) outlined stages of AI management capability reflecting increasing integration of artificial and human intelligence. Building on these AI maturity perspectives, the conceptual framework adopts a five-level AI readiness progression: nascent, emerging, developing, expanding, and mature.

At the nascent level, organizations demonstrate minimal knowledge of AI and little or no practical application. At this stage, organizations may lack awareness of AI's strategic potential or have not yet invested in the infrastructure, governance, or expertise required to support implementation. As organizations move toward the emerging level, they begin experimenting with pilot initiatives and limited AI applications. These early efforts are typically exploratory and focused on assessing technical feasibility and potential business value rather than achieving large-scale operational impact (Fornasiero et al., 2024; Lichtenthaler, 2020). The developing level reflects a more advanced stage in which organizations implement AI solutions that meaningfully influence operational processes. At this stage, organizations pursue multiple AI initiatives and begin aligning them with organizational goals, although capability development may remain uneven across technological, organizational, and human dimensions (Fornasiero et al., 2024). Research suggests that many organizations reach this intermediate stage, where AI is used primarily to optimize existing processes rather than fundamentally transform organizational strategy or innovation (Lichtenthaler, 2020).
Organizations at the expanding level demonstrate broader integration of AI across functions and workflows. AI applications become interconnected, allowing outputs from one system or process

to inform others, and organizations increasingly coordinate AI initiatives to achieve strategic alignment and operational synergy. At this stage, AI adoption moves beyond isolated projects toward systematic integration that supports organizational growth and innovation (Fornasiero et al., 2024; Lichtenthaler, 2020). The mature level represents the highest level of readiness, characterized by fully integrated AI capabilities embedded across organizational processes and decision-making structures. At this stage, organizations effectively combine human expertise and AI systems to continuously improve performance and generate new capabilities. However, prior research notes that relatively few organizations have achieved this level, and even leading firms often retain unrealized potential for deeper integration and sustained competitive advantage (Fornasiero et al., 2024; Lichtenthaler, 2020). Together, these maturity levels conceptualize AI readiness as a progressive capability-building process, reflecting the degree to which organizations develop the resources, knowledge, and integration necessary to fully realize the value of AI. Each stage emphasizes that progression through readiness levels requires multi-dimensional development rather than through technology adoption alone. AI readiness represents the organization's ability to process, apply, and generate knowledge through technological systems. These maturity stages reflect increasing levels of organizational capability.

AI readiness therefore represents an outcome of organizational knowledge resources and technology alignment processes. Organizations with strong knowledge resources are better positioned to achieve higher levels of TTF because these resources enable AI systems to align with operational workflows and decision-making requirements. Organizations lacking knowledge resources or task alignment remain at lower AI maturity levels whereas those with stronger knowledge assets and alignment achieve higher readiness and performance outcomes (Olan et al., 2022). Organizations with higher readiness levels demonstrate stronger data governance, system integration, workforce capability, and workflow alignment. TTF directly influences this progression by ensuring that AI systems effectively support operational tasks. Without sufficient alignment, organizations remain at early stages of AI maturity despite possessing technological resources.

Task-Technology Fit Levels and Their Relationship to AI Readiness

As shown in the AI Readiness and Task-Technology Fit Progression graph in Figure 1 (see the Appendix), TTF increases progressively across AI readiness maturity levels. Organizations at lower readiness levels lack the infrastructure, data quality, and workflow integration necessary to support AI-enabled tasks (Uren & Edwards, 2023). As readiness improves, technology becomes increasingly aligned with task requirements, resulting in improved performance, efficiency, and decision-making (Pumplun et al., 2019). At mature readiness levels, AI technologies are fully embedded within workflows and dynamically enhance organizational capabilities.

- **No Fit (Nascent AI Readiness):** AI capabilities are absent. Tasks remain manual or fragmented, and AI does not contribute to task execution or decision-making. Organizational resources have not yet translated into functional AI capability and AI readiness remains at the nascent stage.

- **Low Fit (Emerging AI Readiness):** AI tools exist but may be limited to pilot experiments or isolated functions with incomplete data access, poor interoperability, or limited user experience resulting in experimental rather than operational use.
- **Moderate Fit (Developing AI Readiness):** AI capabilities support targeted AI solutions. Workflows are increasingly digitized, and data quality and system integration are improving. AI contributes to measurable efficiency or decision-making improvements in targeted areas, but integration is not yet enterprise wide.
- **High Fit (Expanding AI Readiness):** AI is strongly integrated within multiple applications. and analytical tasks across departments. Systems are interoperable, workflows are standardized, and users routinely rely on AI-generated outputs. At this level, AI meaningfully enhances productivity, consistency, and decision accuracy, reflecting substantial organizational capability and maturity.
- **Optimal Fit (Mature AI Readiness):** AI capabilities are fully integrated within organizational workflows. Systems continuously learn from organizational data and adapt to evolving task requirements. AI enables new forms of analysis, prediction, and automation, reflecting the highest level of organizational AI readiness and strategic capability.

This progression reflects increasing AI readiness maturity. As AI readiness improves, organizations experience measurable performance gains such as improved efficiency, faster decision-making, stronger predictive capabilities, and greater innovation capacity. Thus, organizational knowledge resources serve as the foundational drivers that enable TTF which in turn determines AI readiness and influences organizational performance.

Learning Organization Performance and Competitive Advantage

Both KM and RBV theory identify effective knowledge utilization as a primary driver of organizational performance and competitive advantage (Osobajo & Bjeirmi, 2021). AI enhances organizational learning by enabling faster analysis, improved decision-making, and predictive capabilities (King & Ko, 2001). Studies show that as AI readiness increases, LOs gain the ability to automate routine processes, identify patterns, and generate insights that improve operational efficiency and strategic planning (Benbya et al., 2020). Organizations that successfully align knowledge resources with task requirements and achieve higher levels of AI readiness are more likely to realize performance improvements, including increased efficiency, improved decision quality, and innovation capability. These outcomes reflect the digital transformation of knowledge resources into organizational capabilities that support sustained competitive advantage (Mele et al., 2024). When mediated by TTF and AI readiness, organizational performance and competitive advantage outcomes include improved efficiency, better decision quality, predictive capabilities, innovation capacity, sustained competitive advantage.

Conceptual Framework and Model Development

This study proposes a conceptual framework linking KM, RBV, TTF, and AI readiness to Organizational Performance. RBV provides the foundational explanation for AI capability by emphasizing the role of strategic organizational resources, including data, infrastructure, and human expertise. TTF serves as the operational mechanism through which resources are translated into functional capability. As fit improves, organizations progress through increasing levels of AI readiness, from nascent to mature. Organizations with strong strategic resources and high TTF achieve greater operational performance and sustained competitive advantage.

The AI-Driven Organizational Performance Model depicted in Figure 2 (see the Appendix) illustrates how Resource-Based View (Knowledge Assets and Capabilities) enables Task-Technology Fit (alignment of AI with organizational tasks), which determines AI Readiness Level (maturity of AI implementation) and influences Organizational Performance and Competitive Advantage.

Knowledge Management as Foundational Context Layer: KM provides the processes through which organizations develop knowledge assets and capabilities. Through knowledge creation, sharing, and application, organizations build the necessary RBV structures necessary for AI readiness maturity.

Resource-Based View as Foundational Capability Layer: RBV explains how knowledge assets and capabilities serve as strategic VRIN resources. These resources form the capability foundation required for AI readiness maturity.

Task-Technology Fit as Alignment Mechanism Layer: TTF explains how organizations translate resources into effective technology deployment. RVB capabilities enable organizations to configure AI systems to align with workflows, improving usability, reliability, and adoption.

AI Readiness as Capability Outcome Layer: AI readiness reflects the organizational capability to deploy AI effectively. It represents the cumulative outcome of knowledge resources and task-technology alignment. When AI technologies align with organizational tasks, utilization increases and organizations progress toward higher AI readiness stages.

Organizational Performance as Strategic Outcome Layer: AI readiness maturity enables improved organizational performance and competitive advantage. Competitive advantage occurs when resources enable improved organizational performance.

This integrated conceptual framework addresses the research question by explaining how knowledge assets create the foundation for AI capability development. Through the RBV, these resources become strategic knowledge assets that enable organizations to align AI with organizational tasks. TTF serves as the mechanism through which these resources are translated into functional alignment between AI systems and organizational workflows. Higher levels of fit accelerate progression through AI readiness maturity stages leading to improved organizational performance and sustained competitive advantage. Therefore, organizational performance outcomes are driven by the organization's ability to develop, align, and apply knowledge resources effectively.

Research Implications and Future Direction

This exploratory study provides several opportunities for future empirical research. Future studies can examine the proposed constructs using survey instruments, maturity models, or case study methodologies. Researchers may measure organizational knowledge resources using indicators such as data quality, infrastructure integration, workforce expertise, and governance maturity. TTF can be measured through perceived usefulness, workflow compatibility, and system integration. AI readiness can be assessed using maturity models reflecting stages of implementation and integration. Organizational performance can be measured through operational efficiency, decision quality, and innovation outcomes.

Limitations

This research is limited by its conceptual nature and lack of empirical validation. While it integrates strong theoretical foundations from KM, RBV, and TTF, the relationships among constructs remain theoretical assumptions rather than validated causal relationships. Additionally, the framework may not fully generalize across industries where AI readiness is shaped by specific regulations, data environments, and operational demands (Holmström, 2022). The model assumes a universal progression of AI readiness maturity, but organizational progression may vary through readiness stages due to these differences.

Future Research

Future empirical research should test the proposed relationships within this conceptual framework. Longitudinal studies may examine how organizations progress through AI readiness maturity stages over time. Such research can provide insight into how knowledge resources and task alignment evolve during digital transformation (Dey & Ghose, 2025). Case study research may provide insight into how organizations develop knowledge capabilities and integrate AI into workflows (Olan et al., 2022). Empirical testing of this framework can contribute to both information systems and KM literature by explaining how knowledge capabilities enable AI readiness and performance outcomes.

To address the central research question regarding how organizational knowledge resources and capabilities enable TTF and AI readiness leading to improved organizational performance, the following hypotheses are proposed for future empirical testing of the constructs within the conceptual framework:

H1: Organizational knowledge resources positively influence TTF in AI implementation.

H2: Higher levels of TTF positively influence AI readiness maturity.

H3: The relationship between AI readiness and organizational performance varies across industries due to environmental and regulatory factors.

Conclusion

AI adoption represents both a technological and organizational transformation requiring knowledge resources, alignment, and capability development. Existing theories provide partial explanations but lack integration. This exploratory paper proposes a conceptual framework positioning Knowledge Management within the Resource-Based View, linking knowledge-based capabilities to Task-Technology Fit, AI readiness, and organizational performance. By synthesizing these perspectives, this conceptual framework explains how organizations develop AI capabilities and provides a foundation for future empirical research examining AI readiness and performance outcomes.

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Authors Biographies

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Tyler Price is a graduate from Southern New Hampshire University where he obtained a MS in Information Technology. While pursuing his Master's degree, he was a graduate Research Assistant in the Management Science and Information Systems Department. He will be attending the college of Northeastern University in the Fall of 2026 to pursue a Master's in Computer Science.

Appendix

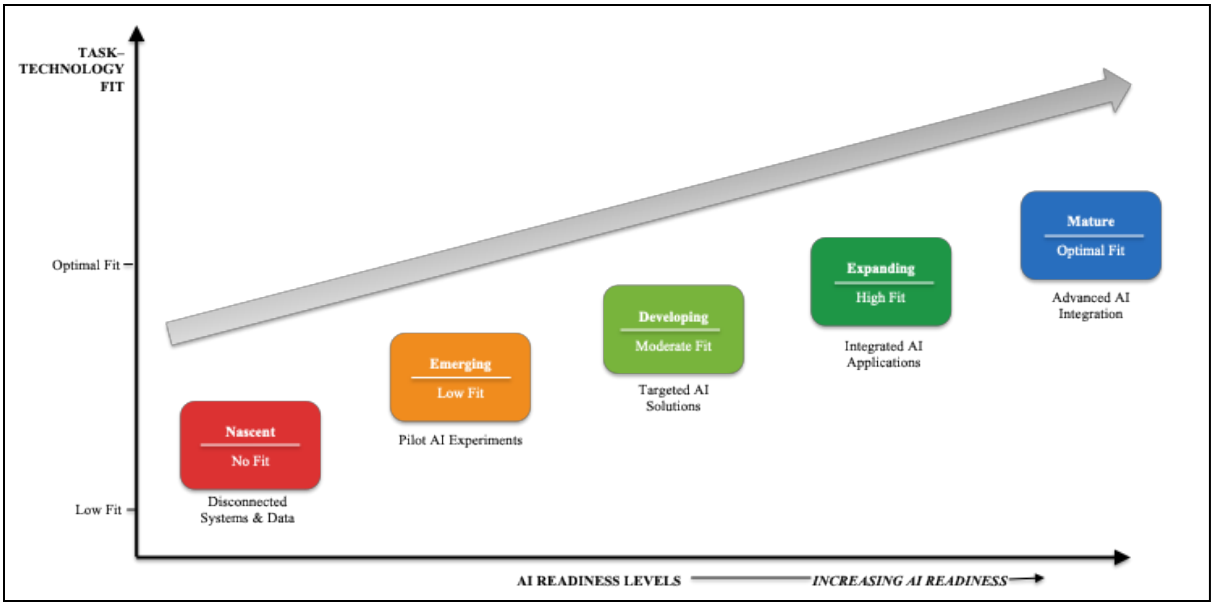

Figure 1. AI Readiness and Task-Technology Fit Progression

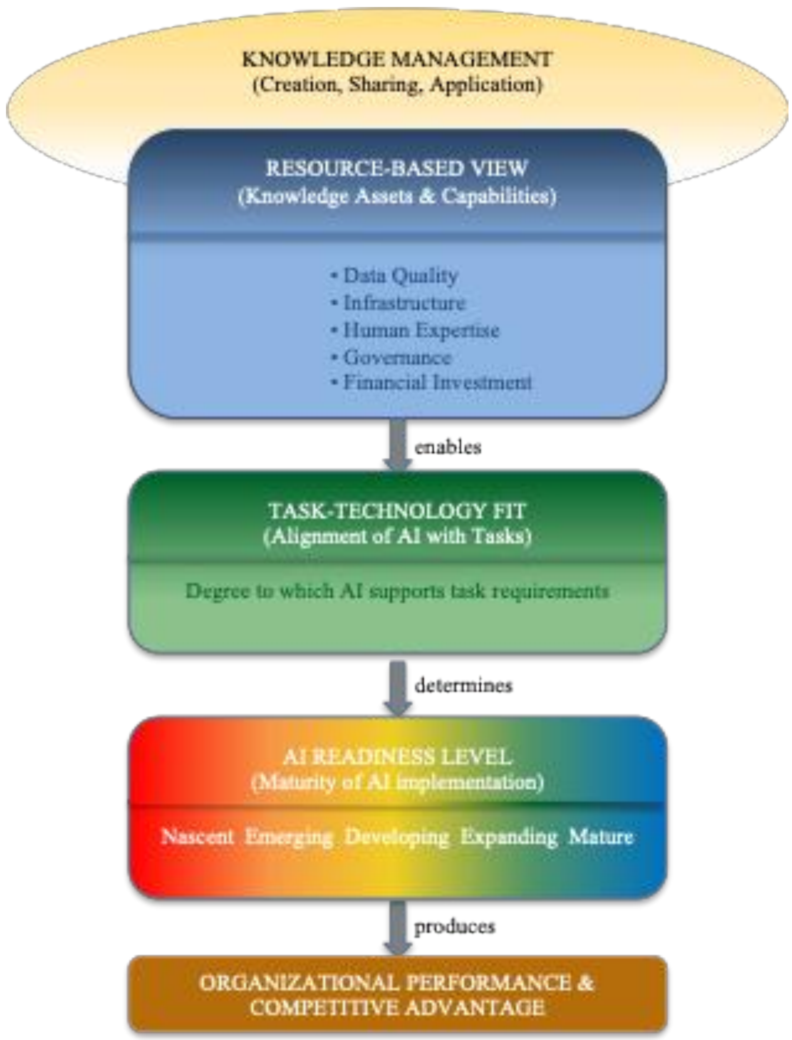

Figure 2. AI-Driven Organizational Performance Model

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Applied use cases for knowledge graphs in public administration – A multiple case study from Germany

[Complete Research]

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Abstract

Public administration organizations face persistent knowledge management challenges arising from fragmented information systems, heterogeneous data semantics, and limited interoperability across organizational boundaries. Although digitalization initiatives have increased the availability of administrative data, they often fall short of enabling systematic knowledge integration and reuse. Knowledge graphs (KG) have recently gained attention as a promising approach to addressing these challenges by representing knowledge as semantically linked entities and relationships. This paper investigates the role of KGs as an enabling infrastructure component for knowledge management (KM) in public administration. The study follows an exploratory qualitative multi-case design and analyzes seven real-world initiatives from the German public administration that apply KGs in different administrative contexts. These include semantic integration of heterogeneous information sources, improved knowledge retrieval and semantic search, support for knowledge sharing and reuse across organizational units, structured representation of administrative knowledge, and support for advanced analytical and automation tasks. The findings contribute to KM by providing empirically grounded insights into how KGs support core KM processes in public administration. The study highlights the role of KGs as a semantic infrastructure component that connects fragmented knowledge sources and enables more integrated KM practices in complex administrative environments.

Keywords: Knowledge graph, knowledge management, public administration, semantic interoperability, information integration.

Introduction

Driven by the ongoing digital transformation, public administration (PA) organizations are increasingly confronted with the challenge of managing growing volumes of information and data while simultaneously ensuring transparency, interoperability, and effective service delivery (Wieczorkowski & Pawełoszek, 2025). Although digital transformation initiatives have substantially expanded the availability of administrative data, this has not automatically resulted in improved organizational knowledge. Instead, knowledge in PAs often remains fragmented across organizational units, information systems, and administrative levels, which limits its reuse, integration, and contribution to organizational learning (Zeginis & Tarabanis, 2024). From a knowledge management (KM) perspective, these challenges are closely linked to the predominance of document-centric and system-specific approaches to information processing. Knowledge relevant to administrative processes, services, and decision-making is frequently embedded in heterogeneous data structures, legal texts, and procedural documents. As a result, public organizations struggle to establish a shared understanding of concepts, relationships, and responsibilities across institutional boundaries, which represents a major obstacle to effective knowledge integration (Rajabi et al., 2023).

Knowledge graphs (KG) have already demonstrated their ability to address these challenges in other domains like enterprise or research information management (Auer et al., 2021; Galkin et al., 2016). KGs represent knowledge as interconnected entities and relationships with explicit semantics, enabling the integration of heterogeneous information sources and context-aware access to organizational knowledge (Zeginis & Tarabanis, 2024). While KGs have been widely discussed in the context of search engines, data integration, and artificial intelligence, their role as an enabling infrastructure component for KM in the public sector remains underexplored. Existing research on KGs in government contexts has largely focused on technical architecture, interoperability standards, or isolated application scenarios. Empirical studies that systematically examine KGs from a KM perspective and across multiple organizational settings in the PA domain are still limited. Against this backdrop, this study examines the following research questions: *RQ1) What potential do knowledge graphs and other linked data technologies offer for the organization and utilization of the growing volume of data in digital public administration? RQ2) Which specific use cases have already been addressed in real-world projects, and what insights can be gained from them regarding the use of knowledge graphs?*

To answer these questions, we conducted an exploratory qualitative multi-case study in the German public sector. Germany provides a particularly relevant empirical context due to its federal administrative structure, high degree of organizational fragmentation, and ongoing digitalization initiatives. The study analyzes seven knowledge graph–related initiatives across different administrative domains and levels of government. By synthesizing insights across these cases, the paper identifies recurring knowledge-oriented use cases and discusses their implications for administrative KM.

Research Background

Despite extensive digitalization efforts, public authorities often struggle to bridge the gap between information availability and actionable organizational knowledge due to fragmented IT-systems and semantic inconsistencies (Ahmed & Twinomurinzi, 2025). The concept of a knowledge graph (KG) represents an increasingly prominent approach to semantic knowledge representation (Peng et al., 2023). Hogan et al. (2021, p. 71:3) define a KG as “a graph of data intended to accumulate and convey knowledge of the real world, whose nodes represent entities of interest and whose edges represent potentially different relations between these entities”. A graph based data model together with a graph query model offers significant advantages compared to relational or NoSQL models, among others more flexibility for dynamic data evolution, more powerful data navigation, and enhanced semantics through ontologies and rules (Hogan et al., 2021). By modeling knowledge as a network of entities and relationships enriched with explicit semantics, KGs enable flexible integration of heterogeneous knowledge sources and support evolving knowledge structures (Zeginis & Tarabanis, 2024). KGs have already been applied in domains such as enterprise information management, healthcare, finance, and Industry 4.0 (Galkin et al., 2016; Cheng et al., 2022; Yahya et al., 2021; Peng et al., 2023).

The growing relevance of KGs is also reflected in recent advances in artificial intelligence (AI). Rather than competing with modern AI approaches such as large language models, KGs provide a structured and factual backbone that can improve semantic relevance, explainability, and factual consistency in AI applications (Yu, 2023). At the same time, AI methods can support the development of KGs by extracting structured knowledge from unstructured data (Liao et al., 2023). This increasingly symbiotic relationship highlights the value of KGs as a foundation for more reliable and transparent AI systems.

Although PA has not been identified as a prominent application area in the aforementioned studies, the knowledge work character of administrative processes implies a high potential for improvement through the use of KGs. KM in PA is shaped by institutional complexity, legal constraints, and multi-level governance structures. Knowledge relevant to administrative action is distributed across legal frameworks, organizational procedures, information systems, and individual expertise, often resulting in fragmented and context-dependent knowledge bases (Rajabi et al., 2023). A recurring challenge highlighted in the literature is the dominance of document-centric practices in PAs (Zeginis & Tarabanis, 2024). Legal texts, policy documents, forms, and reports act as primary carriers of knowledge, yet they are typically stored in isolated systems and lack explicit semantic structure. This limits systematic knowledge reuse, shared interpretation, and cross-organizational learning (Zeginis & Tarabanis, 2024). In addition, demographic change and staff turnover increase the risk of losing institutional knowledge, reinforcing the need for approaches that support knowledge preservation.

Consequently, several studies have investigated the potential of KGs for PA and proposed system designs and architectures. Loutas et al. (2010) describe the architecture of a semantic e-government portal based on their development of domain-specific ontologies for PA and present a working prototype. Promikyridis & Tambouris (2022) take a similar approach by developing a KG for public services based on the Core Public Service Vocabulary (CPSV) developed by the European Union. They aim to investigate the benefits of using the CPSV data model for implementing KGs for public services. Zeginis & Tarabanis (2024) focus on the event-centric character of KGs to overcome the weaknesses of the current document-centric perspective in PA. Several studies explicitly refer to single cases in the sense of a larger application scenario that provides requirements for designing conceptual KG solutions and demonstrating their feasibility through research prototypes. The use of KGs as knowledge base for chatbots in e-government is evaluated by Patsoulis et al. (2021). They constructed a new KG schema for “the case of getting a passport” service, devise a technical architecture, and demonstrated technically feasible and potential benefits through a prototype. Extensive research has been conducted by Soylu et al. (2022) to develop the KG-based platform TheyBuyForYou for public procurement including schemas, tools, APIs and services. Rajabi et al. (2023) constructed a KG for "the case of Nova Scotia disease datasets", open data provided through a Canadian government portal. They advocate for a linked data strategy to connect similar open statistical datasets across a country. Serderidis et al. (2024) refer to the Greek Diavgeia case and propose an integrated ontology for government decisions and acts based on standard EU ontologies, core and controlled vocabularies to implement a KG for exploitation of publicly available data.

From a KM perspective, KGs can be understood as a semantic infrastructure that supports core KM processes. In line with the SECI model (Nonaka & Takeuchi, 1995), they support the externalization and combination of knowledge by structuring heterogeneous knowledge into explicit and machine-interpretable representations (Karagiannis et al., 2017). In addition, KGs facilitate knowledge retrieval, reuse, and contextualization across organizational boundaries and may contribute to organizational memory by preserving relationships between concepts, processes, and decisions over time. While prior research has demonstrated the technical feasibility of KGs in PA, comparative empirical insights across multiple organizational settings remain limited.

Methodology

This study follows a qualitative, exploratory research design based on a multi-case study approach. Case study research is particularly suitable for investigating contemporary phenomena in real-world contexts, especially when the boundaries between the phenomenon and its context are not clearly defined (Yin, 2018). Given the emerging nature of KGs in administrative KM and the limited availability of systematic empirical evidence, a qualitative approach allows for an in-depth understanding of implementation practices, organizational conditions, and contextual factors. A multi-case design was chosen to enable analytical comparison across different organizational settings and application domains. Studying multiple cases supports the identification of recurring patterns, similarities, and differences and increases the robustness of findings through replication logic (Baxter & Jack, 2008). Rather than aiming for statistical generalization, the study seeks analytical generalization by relating empirical observations to KM concepts (Yin, 2018).

Cases were selected using purposive sampling to identify initiatives that explicitly apply KG in PA contexts. Selection focused on initiatives addressing knowledge-related challenges such as information integration, semantic interoperability, or knowledge reuse. Relevant cases were identified through web-based research, professional networks, and expert recommendations from PA, research, and industry. To capture different implementation experiences, initiatives at varying stages of maturity (from conceptual projects to operational solutions) were included. Data collection combined document analysis and semi-structured expert interviews. Project documentation, publicly available materials, and relevant technical or organizational descriptions were analyzed to gain an initial understanding of each case. The core data source consisted of interviews with project representatives. Interviewees were selected based on their direct involvement in or expertise related to KG initiatives in the public sector. The sample covers a range of roles, including strategic, managerial, and technical perspectives. This ensures that both operational insights and higher-level organizational considerations were captured. Further interviews were conducted with subject-matter experts from the public domain who were not directly related to the cases but responded to our public call for interviewees. The interview guide combined confirmatory elements, such as clarification of project scope and terminology, with exploratory questions focusing on project objectives, organizational context, the role of KGs, and perceived benefits and challenges. This structure enabled both comparability across interviews and openness to case-specific insights. Between November 2024 and April 2025, 16 interviews were conducted online via video conferencing and recorded with participants' consent. Interviews lasted between 30 and 90 minutes and were transcribed for analysis.

Following data collection, the relevance and analytical richness of each case were reassessed, resulting in the selection of seven cases for detailed analysis. Table A1 in the appendix lists the selected cases, their project phase reflecting the implementation progress, owner organizations, interview number with interviewee's role, and available references.

The collected data were analyzed using an iterative cross-case qualitative comparison of interview transcripts, project documentation, and supplementary materials. The analysis focused on identifying recurring themes related to the role of KGs in administrative KM, including semantic integration, interoperability, knowledge retrieval, and reuse. Case descriptions were first developed individually and then compared across cases to identify common patterns, differences, and recurring use cases. Emerging interpretations were continuously discussed among the authors and contrasted with publicly available project materials to improve consistency and contextual understanding.

Results

Resulting from the comparative analysis of interviews and project materials across the seven cases, five recurring use cases (UC) were identified. Table A2 in the appendix gives a brief overview of the seven cases (C1-7) selected for this study. Each case is described by its underlying problem, the planned solution and the role of the KG for the solution. The UCs illustrate the role of KGs as a flexible infrastructure component in support of multiple KM processes in public sector organizations:

UC1: Semantic integration and interoperability. Harmonizing heterogeneous data structures, terminologies, and legal concepts across organizational and system boundaries. As one expert explained, "the same district was represented in different systems using abbreviations, vehicle registration codes, or plain text names" (I11, all quotations from the interviews are translated from German and redacted). This role is particularly visible in C2, C5 and C7, where KGs are used to model relationships between environmental data, administrative evidence requirements or legal norms. In fragmented administrative environments, characterized by sector-specific registers and legacy IT systems, they function as a semantic integration layer. By making relationships machine-interpretable, KGs support the integration of heterogeneous information sources and facilitate interoperable data exchange across administrative systems.

UC2: Knowledge retrieval and semantic search. The cases show that KGs are used to improve information retrieval within administrative organizations. Instead of relying solely on document-based or keyword-driven search, KGs enable context-aware retrieval by linking entities, roles, processes, and legal concepts. For example, one interviewee noted that employees frequently "search PDFs of organizational charts to identify responsible contacts in other administrations," describing the process as "highly inefficient" (I6). Both interviewees from C1 emphasized that linked organizational data improved the identification of responsible contacts across departments, while C4 and C6 highlighted improved contextualization and discoverability of open and tourism-related information. This improves internal access to organizational knowledge (e.g., responsibilities, procedures, service definitions) and enhances external service navigation. Semantic linking reduces search effort and increases transparency.

UC3: Knowledge sharing and reuse. Several cases demonstrate the potential of KGs to modularize and formalize service definitions, data models, and process components in a reusable way. For instance, one participant emphasized that many publicly funded innovation projects resulted in "data silos that could neither scale nor continue after the funding ended" (I14). C7 shows how a standardized process and data models can be reused when transforming legal texts into digital services. Once modeled semantically, these elements can be reused or adapted across administrative units or levels. This facilitates the reuse of structured knowledge resources and reduces redundancy in the development of digital services and data models.

UC4: Structured representation of organizational knowledge. The case analysis also shows that KGs can support the structured representation of administrative knowledge. C1 and C5 illustrate how organizational structures, administrative data fields, and evidence requirements can be modeled explicitly. By modeling relationships between entities such as organizations, processes, data fields, and legal concepts, KGs make implicit domain knowledge explicit and machine understandable. Compared to traditional document repositories, graph-based representations enable the contextual linking of information and allow knowledge to be queried and explored across domains.

UC5: Advanced analysis and automation. Finally, KGs support more advanced analytical and automation tasks. C3 demonstrates a matching between citizen profiles and eligibility criteria for public benefits. By formally representing rules, criteria, and relationships, KGs enable automated matching and structured evaluation of information. This use case illustrates how graph-based knowledge representations can support the transition from knowledge documentation toward more automated administrative processes.

Across interviews and project materials, recurring patterns emerged regarding the role of KGs in addressing fragmented administrative knowledge structures. Despite differences in organizational context and maturity, the cases show substantial convergence regarding objectives, use cases, and implementation conditions. Across all cases, KGs were primarily introduced in response to fragmented information landscapes and semantic inconsistencies between administrative systems and organizational units. Rather than replacing existing systems, they were implemented as a semantic integration layer that connects heterogeneous knowledge sources. The maturity of initiatives ranged from conceptual models to operational solutions; however, even advanced cases emphasized incremental development and reuse over large-scale transformation.

Organizational factors emerged as a key differentiator. Initiatives with clear governance structures, defined responsibilities for knowledge modeling, and institutional anchoring demonstrated higher sustainability and reuse potential. Conversely, technically mature solutions without long-term organizational ownership faced scalability limitations.

Discussion

The findings suggest that KGs may function less as isolated technologies and more as enabling infrastructure components for integrated KM in PA contexts. The identified use cases indicate potential links to core KM processes such as knowledge integration, sharing, retrieval, and preservation, thereby extending existing conceptual discussions on semantic knowledge representation with empirical evidence from public sector practice. For practitioners, our study provides real-world examples of how the theoretical benefits of KGs can be integrated into digital solutions that provide value added services. From a PA perspective, the results underline that semantic integration alone is insufficient to realize KM benefits. Organizational anchoring, governance structures, and sustained ownership of knowledge models are critical conditions for success. KG initiatives that remained primarily technology-driven showed limited scalability, whereas initiatives aligned with organizational knowledge objectives exhibited greater long-term potential. The multi-case analysis also highlights the relevance of KGs for managing institutional knowledge in complex administrative environments. By explicitly modeling relationships between concepts, processes, and responsibilities, KGs support shared understanding and reduce dependency on individual expertise, an aspect of particular importance in PAs facing demographic change.

Although we could identify seven cases for this study, the results of our search for practical cases and the response rate to our public calls were lower than expected. Considering the well-documented use of KGs in various domains of the private sector and the close connection of the KG concept to the Open Government paradigm (e.g., Serderidis et al., 2024), our a priori expectations of the diffusion of KGs in the public sector were higher. In addition, all identified cases were in early conceptualization or implementation phases. Data from the case interviews indicate that the reasons for this situation include a lack of domain-specific standards, vocabularies, and ontologies. This interpretation is supported by efforts to develop these missing components as part of the investigated cases (e.g., GerPS in C7). On the other hand, the need for software development work illustrates the component characteristic of KGs in KM infrastructures. Today, KGs are not available as ready-to-use standard software products for PA.

The study is subject to limitations. Interviews focused primarily on experts involved in practical KG implementation projects. Therefore, no light could be shed on the perspective of non-technical staff and decision makers in PA regarding their knowledge and assessment of KG potentials. In addition, the cases are restricted to one national context and differ in maturity level. While this enables rich exploratory insights, future research could extend the analysis through longitudinal or cross-country studies and further investigate organizational barriers and AI-supported applications of KGs in PA. Given the exploratory character of the study and the inclusion of several early-stage initiatives, the findings should be interpreted as indicative rather than representative of public administration practice more broadly.

Conclusion

This paper examined the role of KGs as an enabling infrastructure component for KM in PA. Based on an exploratory multi-case study from Germany, the findings indicate that KGs have the potential to support a range of knowledge-oriented use cases, including semantic integration, knowledge sharing, retrieval, and preservation. The study suggests that the value of KGs may lie not primarily in their technical capabilities but in their contribution to addressing persistent KM challenges in PAs. Organizational and governance conditions emerged as potentially important factors for sustainable implementation. For KM research, the paper provides empirical insights that link semantic technologies with core KM processes in PA contexts. For practice, the results highlight the importance of aligning KG initiatives with organizational knowledge objectives rather than treating them as standalone IT projects. Future research may build on these findings by examining reasons for slow KG adoption, long-term impacts, cross-national comparisons, and the integration of KGs with emerging AI-based KM approaches.

AI usage disclosure: During the preparation of this work the authors used ChatGPT 5.2 in order to assist with literature search as well as to translate and copyedit text. After using this tool, the authors reviewed and edited the content as needed and take full responsibility for the content of the published article.

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Appendix A

Table A1. Selected Cases and Interviews

Case	Phase	Body[1]	Interviews/roles	References
C1: Linked open data in the state senate department a) budget data online b) organization charts tool	Working prototype	Senate department of federal city state	I1: open data officer I6: project manager	(Stubert et al., 2025)
C2: Envir Data – intelligent data management for environmental data	Stable release	Environmental agency of city 1 (600,000)	I3: project lead I10: CEO of software vendor	(Rudolf et al., 2025)
C3: FörderFunke – Finding social benefits	Stable web app	FörderFunke UG (social impact startup)	I5: CEO	https://github.com/Citizen-Knowledge-Graph
C4: DataStories – making complex data tangible	Working prototype	Administration lab of FHVD Altenholz	I4: open data officer I8: project lead	https://www.datastories-sh.de/
C5: RegCheck – transmission of evidence in the reporting system	Feasibility study	State Ministry of Finance	I11: project manager	https://github.com/RegCheck2024/RegCheck
C6: Social Knowledge Graph (SKG) for tourist information of municipalities, cities and districts	Working prototype	Joint project SKG	I13: project lead	https://www.knowledgegraph.de/
C7: "Production line" for digital public services: digitalization of unconditional basic income	Working prototype	Joint project of small town (100,000) and university	I14: project lead	(Bachinger et al., 2025; Brunzel et al., 2025)
Non case related	n/a	Federal state chancellery Wikimedia Germany Federal Employment Agency City 2 (600,000) City 2 (600,000)	I2: register modernization officer I7: policy & public sector officer I9: head of Automation Center of Excellence I15: head of innovation lab I16: domain architect data	n/a

1) Round brackets contain the population size.

Table A2. Characteristics of the Cases

Id	Case characteristics
C1	**Problem:** a) existing open budget data lacked semantics and meaningful relationships, b) organizational charts not available as linked open data, although citizens and staff rely on this information to identify responsible contacts. **Solution:** a) providing information on the budget as linked open data via the open data portal, b) open-source tool enabling departments to create and maintain organizational charts as linked open data. **KG role:** technical implementation of self-developed ontologies, vocabularies, and rules as a searchable knowledge base using open standards such as OWL, RDF and SPARQL.
C2	**Problem:** environmental data fragmented across heterogeneous systems and datasets. Lack of semantic integration makes it difficult to combine, analyze, and reuse environmental information across administrative units. **Solution:** intranet portal for semantical data management that integrates heterogeneous environmental datasets and enables improved data analysis and reuse. **KG role:** enabling integrated analysis and interoperability across different environmental information systems by modeling entities and relationships semantically.
C3	**Problem:** citizens do not apply for public benefits even though they are eligible, often due to limited knowledge about available programs and complex eligibility requirements. **Solution:** online platform allowing users to store relevant personal information and automatically identify suitable public benefits by matching personal profiles with eligibility requirements of funding programs. **KG role:** semantic model of funding programs, eligibility criteria, and target groups, enabling automated matching between user profiles and funding conditions.
C4	**Problem:** open government datasets are often difficult to interpret due to missing context and semantic structure. Many datasets are available only in formats such as Excel or PDF, limiting their analytical and communicative value. **Solution:** transformation of selected open datasets into semantically structured data cubes and development of automated visualization approaches to make complex data more accessible and understandable. **KG role:** to provide the semantic structure for linking datasets and contextual information, enabling automated visualization, improved interpretation, and reuse of open data.
C5	**Problem:** administrative data requirements for register modernization are fragmented and difficult to interpret across authorities. Lack of standardized semantic representations limits interoperability and automated verification of required evidence. **Solution:** concept for representing administrative evidence requirements and data fields using semantic technologies to support standardized and interoperable data exchange. **KG role:** modeling data fields, evidence requirements, and their relationships using shared vocabularies, enabling structured representation, and potential automation of data verification and exchange processes.
C6	**Problem:** tourism information is distributed across multiple organizations and information systems. Lack of semantic linking reduces discoverability and integration of tourism services and data. **Solution:** social knowledge graph for linking tourism information from different sources in order to improve discoverability and integration of tourism services. **KG role:** core of the solution.

C7	**Problem:** translating legal texts and administrative regulations into digital public services is complex and largely manual. In particular, the lack of machine-understandable representations of processes and data fields limits automation and interoperability in service digitalization. **Solution:** automated "production pipeline" that translates legal texts into digital administrative services based on standardized process and data models (open standards), demonstrated through the end-to-end digitalization of the citizen allowance approval process. **KG role:** semantic representation of legal concepts, processes, and data fields through dedicated ontologies (e.g., GerPS), creating a machine-interpretable knowledge base that links legal norms with administrative processes and enables automated service generation.