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# From Information Overload to Knowledge Integration: Generative AI as an AI-Enabled Information Management Capability in Science–Industry Innovation Ecosystems

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# Abstract

Science–industry collaboration increasingly depends on the ability of innovation ecosystem actors to identify, integrate, evaluate, and mobilise knowledge distributed across organisational and digital boundaries. Although generative artificial intelligence (GenAI) offers new capabilities for processing and synthesising heterogeneous information, its potential role in supporting ecosystem-level knowledge integration remains conceptually underdeveloped and empirically underexplored.

This study examines how innovation ecosystem stakeholders perceive the information management challenges constraining science–industry collaboration and which AI-enabled capabilities they consider important for supporting knowledge integration and collaborative decision-making. The study draws on 24 semi-structured interviews with researchers, industry representatives, and policymakers in Slovenia, analysed using reflexive thematic analysis.

The findings indicate that collaboration challenges arise less from information scarcity than from ecosystem fragmentation, information overload, limited visibility and evaluability of competencies, and uncertainty regarding potential partners. Stakeholders identified five complementary GenAI-enabled capability areas: partner and competency matching, funding opportunity analysis, competency and reference visibility, proposal development support, and decision support. Across these capabilities, transparency and explainability, traceability of AI-supported recommendations, data protection and security, and human oversight and accountability emerged as cross-cutting governance conditions.

The study develops an empirically grounded conceptualisation of GenAI as an AI-enabled information management capability for ecosystem knowledge integration. Rather than positioning GenAI as an autonomous innovation intermediary, the findings indicate that its potential value lies in augmenting information-intensive intermediary functions by making distributed ecosystem knowledge more accessible, connected, evaluable, and actionable while preserving human judgement and decision authority. By integrating perspectives from knowledge management, innovation intermediation, and AI-enabled information systems, the study provides a theoretical foundation for understanding and subsequently testing the role of GenAI in ecosystem knowledge integration and informs the design of human-governed AI-enabled collaboration infrastructures.


# 1. Introduction

Innovation ecosystems are increasingly characterised by the continuous creation, exchange, and recombination of scientific, technological, and organisational knowledge across universities, industry, government agencies, and innovation support organisations. While this expansion has substantially increased opportunities for collaboration and innovation, it has also created a growing challenge: organisations are no longer constrained primarily by limited access to knowledge but by their ability to identify, integrate, evaluate, and mobilise fragmented information distributed across multiple actors, institutions, and digital environments. Consequently, effective knowledge integration has emerged as a

critical capability for innovation ecosystems seeking to accelerate collaboration, innovation, and knowledge transfer (Adner, 2017; Granstrand & Holgersson, 2020; Alavi et al., 2024).

Science–industry collaboration constitutes a core mechanism of open innovation, enabling organisations to purposefully exchange and combine knowledge across organisational boundaries to accelerate innovation (Chesbrough, 2003; Chesbrough & Bogers, 2014). This collaboration represents one of the most knowledge-intensive forms of inter-organisational collaboration because it requires participants to combine heterogeneous knowledge bases, institutional logics, incentives, and expertise distributed across organisational boundaries. Successful collaboration therefore depends not only on generating new knowledge but also on organisations' ability to identify relevant expertise, integrate heterogeneous knowledge, and coordinate distributed information resources. Although such collaborations are widely recognised as fundamental drivers of innovation, technology transfer, and regional competitiveness, they remain difficult to establish and sustain. Systematic reviews consistently identify organisational differences, divergent incentives, administrative complexity, intellectual property concerns, and limited trust as persistent barriers to collaboration (Nsanzumuhire & Groot, 2020; Rossoni et al., 2024). However, these barriers increasingly reflect a broader information management problem: the fragmentation of expertise, funding opportunities, research infrastructures, and potential collaboration partners across complex innovation ecosystems. In the context of this study, information management refers to the organisational capabilities and processes involved in identifying, integrating, synthesising, evaluating, and mobilising distributed knowledge to strengthen collaboration and informed decision-making across organisational boundaries (Alavi & Leidner, 2001; Alavi et al., 2024).

To address these challenges, innovation ecosystems have increasingly relied on innovation intermediaries that facilitate knowledge exchange, partner search, network formation, and coordination among heterogeneous actors (Howells, 2006). More recent research suggests that innovation intermediaries have evolved beyond their traditional brokerage role by increasingly supporting ecosystem orchestration, integrating dispersed knowledge resources, and coordinating collaboration across organisational boundaries (Reischauer et al., 2021; Randhawa et al., 2022; Sultana & Turkina, 2023). At the same time, rapid advances in digital technologies and artificial intelligence are reshaping how these intermediation functions are performed. Rather than relying solely on human expertise, digital technologies increasingly augment intermediation through AI-enabled information management capabilities that facilitate knowledge integration, ecosystem coordination, and informed decision-making (Howells, 2024; Colovic et al., 2024; Alavi et al., 2024). This evolution suggests that digital technologies do not replace innovation intermediaries but augment their capacity to coordinate increasingly complex innovation ecosystems.

Conventional information systems have substantially improved access to information but remain primarily designed to store, retrieve, and organise existing knowledge. Compared with conventional information systems, GenAI offers capabilities for semantic information processing and retrieval, knowledge synthesis, contextual recommendation, and natural-language interaction across heterogeneous information sources. Rather than simply improving information retrieval, GenAI has the

potential to transform how organisations create, integrate, transfer, and apply knowledge within complex organisational environments. Recent research therefore increasingly conceptualises GenAI not merely as a productivity tool but as an organisational mechanism supporting knowledge management, decision-making, and innovation. However, the successful deployment of GenAI also depends on transparency, trust, and human oversight, particularly in contexts involving complex organisational decision-making and inter-organisational collaboration (Dwivedi et al., 2023; Fasano et al., 2025).

Although recent research has rapidly expanded our understanding of GenAI in organisational settings, existing studies have primarily examined its role in enhancing individual productivity, creativity, software development, and organisational innovation processes (Dwivedi et al., 2023; Feuerriegel et al., 2024; Mariani & Dwivedi, 2024). Considerably less attention has been devoted to understanding how GenAI can function as an AI-enabled information management capability that supports knowledge integration, ecosystem coordination, and decision-making across innovation ecosystems. Consequently, the theoretical understanding of GenAI as an AI-enabled information management capability for supporting knowledge mobilisation and ecosystem orchestration remains conceptually underdeveloped, limiting our ability to explain how AI-enabled collaboration platforms create value within innovation ecosystems.

Building on the literature on innovation intermediaries (Howells, 2006; 2024; Reischauer et al., 2021; Randhawa et al., 2022; Sultana & Turkina, 2023), knowledge management (Alavi et al., 2024), and AI-enabled information systems (Dwivedi et al., 2023; Feuerriegel et al., 2024; Mariani & Dwivedi, 2024), this study develops a conceptualisation of GenAI as an AI-enabled information management capability that supports knowledge integration, decision-making, and ecosystem coordination across organisational boundaries. Rather than viewing GenAI merely as a productivity-enhancing technology or a replacement for human innovation intermediaries, we argue that its primary value lies in augmenting organisations' ability to identify, integrate, synthesise, and mobilise fragmented ecosystem knowledge. This conceptualisation extends existing theoretical perspectives by integrating insights from the innovation intermediary, knowledge management, and AI-enabled information systems literature into an integrative conceptual explanation of how GenAI may create value within innovation ecosystems. Accordingly, this study addresses the following research question: How do innovation ecosystem stakeholders perceive the information management challenges constraining science–industry collaboration, and which AI-enabled capabilities do they consider essential for supporting knowledge integration, collaborative decision-making, and ecosystem coordination?

This study makes three contributions to the literature. First, it extends the emerging literature on AI-enabled innovation ecosystems by conceptualising GenAI as an AI-enabled information management capability that supports knowledge integration and ecosystem coordination rather than merely enhancing individual productivity or automating information retrieval. Second, it provides empirical evidence on stakeholders' perceptions of the information management challenges constraining science–industry collaboration and the AI-enabled capabilities required to address them. Third, it derives empirically grounded design principles for AI-enabled collaboration platforms by identifying the

functionalities required to reduce information fragmentation, improve partner discovery, and support knowledge exchange and cross-organisational decision-making.

## 2. Literature Review

# 2.1 Open Innovation, Innovation Ecosystems, and Knowledge Integration

Open innovation emphasises that organisations create value not only through internally generated knowledge but also through purposive knowledge inflows and outflows across organisational boundaries (Chesbrough, 2003; Chesbrough & Bogers, 2014). Within this perspective, science–industry collaboration represents one of the principal mechanisms through which universities, firms, governments, and other stakeholders jointly generate, exchange, and apply knowledge to accelerate innovation and address increasingly complex technological and societal challenges.

Contemporary innovation research conceptualises these collaborative processes within innovation ecosystems, where value creation emerges from interactions among interdependent actors, resources, institutions, and technologies rather than from individual organisations acting in isolation (Adner, 2017; Granstrand & Holgersson, 2020). As innovation ecosystems become increasingly knowledge intensive, their effectiveness depends not only on the generation of new knowledge but also on the ability of ecosystem participants to identify relevant expertise, integrate heterogeneous knowledge, and mobilise distributed information across organisational boundaries. Accordingly, the capacity to integrate and mobilise distributed knowledge is increasingly important for collaborative innovation and knowledge-based decision-making (Alavi & Leidner, 2001; Alavi et al., 2024).

This evolution reflects a broader transformation of innovation ecosystems. Rather than operating under conditions of information scarcity, organisations increasingly face information abundance, where scientific expertise, technological capabilities, funding opportunities, research infrastructures, and potential collaboration partners are widely available but highly fragmented. Under these conditions, the central challenge is no longer obtaining information but effectively managing, integrating, and applying dispersed knowledge distributed across heterogeneous organisational and digital environments.

# 2.2 Innovation Intermediaries as Mechanisms for Knowledge Integration

The growing complexity of innovation ecosystems has increased the importance of innovation intermediaries in facilitating collaboration among heterogeneous actors. Traditionally, innovation intermediaries have reduced information asymmetries by supporting partner identification, knowledge exchange, network formation, brokerage, and coordination across organisational boundaries (Howells, 2006). Their role therefore extends beyond facilitating individual collaborations to enabling the circulation and integration of knowledge among otherwise disconnected ecosystem actors.

More recent research indicates that innovation intermediation has evolved beyond traditional brokerage towards broader ecosystem-level coordination. Innovation intermediaries increasingly perform orchestration functions by coordinating relationships among stakeholders, aligning complementary capabilities, integrating dispersed knowledge resources, and facilitating collaborative value creation across complex innovation environments (Reischauer et al., 2021; Randhawa et al., 2022; Sultana & Turkina, 2023). This evolution is occurring alongside a broader digital transformation of innovation intermediation, in which emerging digital technologies increasingly augment the capacity of intermediaries to search, process, connect, and mobilise distributed knowledge at greater scale (Howells, 2024; Colovic et al., 2024). Innovation intermediation can therefore be understood as increasingly combining relational and organisational coordination with digitally enabled information management capabilities.

Nevertheless, systematic reviews continue to identify organisational differences, divergent incentives, administrative complexity, intellectual property concerns, communication barriers, and limited trust as persistent constraints on science–industry collaboration (Nsanzumuhire & Groot, 2020; Rossoni et al., 2024). Importantly, many of these challenges can also be understood as problems of fragmented and difficult-to-evaluate information rather than simply insufficient information. Stakeholders may have access to extensive information while still facing difficulties in identifying relevant expertise, locating appropriate partners, navigating funding opportunities, and evaluating collaboration potential. Under conditions of information abundance, effective innovation intermediation therefore increasingly depends not only on facilitating relationships among ecosystem actors but also on supporting the identification, integration, evaluation, and mobilisation of distributed knowledge.

## 2.3 Artificial Intelligence and AI-enabled Information Management

Rapid advances in artificial intelligence are transforming how organisations create, manage, and apply knowledge. Conventional information systems have substantially improved information storage, retrieval, and communication but remain primarily designed to organise existing information. By contrast, GenAI provides capabilities for semantic information processing and retrieval, knowledge synthesis, contextual recommendation, natural-language interaction, and intelligent decision support across heterogeneous information sources (Feuerriegel et al., 2024).

Recent research increasingly examines AI and GenAI as technologies that augment organisational knowledge management, learning, and decision-making processes rather than merely automating routine tasks (Alavi et al., 2024; Dwivedi et al., 2023; Mariani et al., 2023; Mariani & Dwivedi, 2024). These capabilities are particularly relevant in innovation ecosystems, where collaboration depends on identifying complementary expertise, integrating distributed knowledge, matching potential partners, synthesising large volumes of heterogeneous information, and supporting evidence-informed decisions across organisational boundaries.

At the same time, the successful deployment of AI requires transparency, explainability, trust, and meaningful human oversight. Human-centred AI emphasises that artificial intelligence should augment rather than replace human judgement, particularly in contexts involving uncertainty, multiple stakeholders, and complex organisational decision-making (Shneiderman, 2022; Amershi et al., 2019; Dwivedi et al., 2023; Fasano et al., 2025). Consequently, the value of AI within innovation ecosystems depends not only on algorithmic performance but also on its ability to support trustworthy, transparent, and collaborative knowledge management.

## 2.4 Towards an AI-enabled Information Management Capability

Although research on innovation intermediaries, knowledge management, and GenAI has expanded rapidly, these literature streams have largely evolved independently. Research on innovation intermediaries primarily explains how collaboration is facilitated through brokerage, knowledge exchange, coordination, and ecosystem orchestration (Howells, 2006, 2024; Reischauer et al., 2021; Randhawa et al., 2022). In contrast, research on GenAI has predominantly focused on its contribution to individual productivity, creativity, software development, organisational innovation, and decision support (Dwivedi et al., 2023; Feuerriegel et al., 2024; Mariani & Dwivedi, 2024). Comparatively little attention has been devoted to understanding how GenAI can augment the information management functions traditionally performed by innovation intermediaries within innovation ecosystems.

Building on these complementary streams of research, we develop a conceptualisation of GenAI as an AI-enabled information management capability that strengthens the information-intensive functions of innovation intermediaries. Specifically, we propose that the principal contribution of GenAI lies in augmenting organisations' ability to identify, integrate, synthesise, and mobilise fragmented ecosystem knowledge through capabilities such as partner discovery, knowledge synthesis, funding intelligence, contextual recommendation, and collaborative decision support. Rather than replacing human innovation intermediaries, GenAI is conceptualised as augmenting their information management capacity to support knowledge integration and ecosystem coordination, thereby contributing to broader orchestration processes across organisational boundaries.

This conceptualisation provides the theoretical foundation for examining how researchers, industry representatives, and policymakers perceive the information management challenges constraining science–industry collaboration and which AI-enabled capabilities they consider essential for supporting knowledge integration, decision-making, and ecosystem coordination within innovation ecosystems.

# 3. Methodology

## 3.1 Research Design

This study employed a qualitative exploratory design to investigate how innovation ecosystem stakeholders perceive the information management challenges constraining science–industry

collaboration and which AI-enabled capabilities they consider important for supporting knowledge integration, decision-making, and ecosystem coordination. A qualitative approach was appropriate because the potential role of Generative Artificial Intelligence (GenAI) in facilitating cross-organisational knowledge integration within innovation ecosystems remains theoretically and empirically underexplored. Rather than testing predefined relationships, the study sought to develop an in-depth understanding of stakeholders' experiences of collaboration, the information-related challenges they encounter, and their expectations regarding AI-enabled support.

The study was conducted within the Slovenian innovation ecosystem as part of the research project *Usability and effectiveness of a GenAI-supported tool for connecting science and industry* (L7-70279), funded by the Slovenian Research and Innovation Agency (ARIS). The project aims to develop and evaluate an AI-enabled platform designed to facilitate interaction between research organisations, businesses, innovation intermediaries, and other innovation ecosystem stakeholders. Slovenia therefore constituted the bounded empirical context of the study, while the phenomenon of interest was science–industry collaboration across organisational and institutional boundaries.

The empirical setting was particularly suitable for examining the research question because the study focused on actors occupying complementary positions in the same national innovation ecosystem rather than on members of a single organisation, scientific discipline, or collaboration programme. The common analytical basis across participants was their direct professional involvement in activities related to science–industry collaboration, including collaborative research and innovation projects, technology and knowledge transfer, funding and project development, innovation management, or innovation policy and support. This ecosystem-level sampling logic enabled the study to examine how information management challenges and expectations regarding AI-enabled support are experienced across institutional boundaries.

## 3.2 Participants and Sampling

A purposive, criterion-based sampling strategy was used to recruit information-rich participants with direct professional experience of science–industry collaboration and related innovation activities. Eligibility required current or previous involvement in at least one of the following: collaborative research or innovation projects involving science and industry; technology or knowledge transfer; preparation or evaluation of collaborative funding applications; innovation management or intermediary activities; or the development and implementation of innovation-related policies and support mechanisms.

The sampling strategy was designed to capture perspectives from three actor groups occupying complementary positions within the Slovenian innovation ecosystem. The final sample comprised 24 participants: researchers affiliated with universities and research institutions (n = 9), representatives of industry and business organisations (n = 11), and policymakers and innovation support stakeholders (n = 4). Rather than representing a single scientific discipline or collaborative programme, participants were united by their direct professional involvement in science–industry collaboration and related innovation activities within the Slovenian innovation ecosystem. This common experiential basis provided the

analytical rationale for examining their perspectives within a single study while enabling comparison across distinct institutional positions.

Table 1
Characteristics of the Study Participants

| Stakeholder group | n | Organisational context | Examples of participant roles |
|---|---|---|---|
| **Researchers** | 9 | Universities and research institutions | Researchers, professors, project leaders, research managers |
| **Industry representatives** | 11 | Private companies and business organisations | Company managers, entrepreneurs, innovation managers, development specialists |
| **Policymakers and innovation support stakeholders** | 4 | Public agencies, innovation intermediaries and policy organisations | Policy and innovation-support professionals |
| **Total** | **24** | | |

Sample adequacy was assessed using the concept of information power, whereby the required sample size depends on the specificity of the sample, the study aims, the quality of dialogue, and the analytical strategy (Malterud et al., 2016). Given the focused research question, participants' direct experience of science–industry collaboration, and the depth and recurrence of relevant patterns across stakeholder groups, the final sample was considered sufficiently information-rich for the analytical purpose of the study.

# 3.3 Data Collection

Data were collected between April and June 2026 through semi-structured individual interviews. Semi-structured interviews provided a consistent framework across the three stakeholder groups while allowing participants to elaborate on experiences and issues specific to their institutional roles.

The interview guide was structured around three domains aligned with the research objective: (1) experiences and information needs related to science–industry collaboration; (2) barriers encountered in identifying partners, developing collaborative projects, accessing funding opportunities, and exchanging knowledge; and (3) experiences with existing digital tools and expectations regarding AI-enabled functionalities for supporting collaboration and decision-making.

Participants were encouraged to provide concrete examples of successful and unsuccessful collaborations, describe how they currently identify expertise, partners, and funding opportunities, and discuss the limitations of existing information sources and digital platforms. They were subsequently invited to reflect on how GenAI-enabled functionalities might address these challenges. This sequencing was intended to ground discussions of AI-enabled capabilities in participants' actual collaboration experiences rather than in abstract evaluations of GenAI.

Interviews lasted between 30 and 75 minutes and were conducted face-to-face or online according to participant availability and preference. All interviews were conducted in Slovenian, audio-recorded with informed consent, and transcribed verbatim. The resulting dataset comprised approximately 150 pages of verbatim interview transcripts. Transcripts were anonymised prior to analysis and identifying references to individuals and organisations were removed or generalised.

## 3.4 Data Analysis

Data were analysed using reflexive thematic analysis (RTA), following Braun and Clarke (2019, 2021). RTA was selected because it enables the systematic development and interpretation of patterns of shared meaning while explicitly recognising the active role of researchers in analytical knowledge production. This approach was consistent with the exploratory and conceptually generative purpose of the study and with its aim of moving beyond descriptive accounts of collaboration barriers towards an interpretation of the information management capabilities that GenAI could provide within innovation ecosystems. The analysis followed the six recursive phases of RTA: familiarisation with the dataset; generation of initial codes; development of candidate themes; review and refinement of themes; definition and naming of themes; and production of analytical narrative. Coding was initially inductive and data-oriented, focusing on participants' experiences of collaboration, information-related challenges, current practices, and expectations regarding AI-enabled support. As the analysis progressed, interpretation became increasingly conceptually oriented, examining how identified patterns related to knowledge integration, innovation intermediation, decision-making, and ecosystem orchestration.

The analysis was led by the lead qualitative researcher, who coded the complete dataset and developed the initial thematic structure. The wider research team subsequently engaged in iterative discussions of the codes, candidate themes, thematic boundaries, and alternative interpretations. Themes were progressively refined through this recursive process of individual analysis and collaborative interpretative discussion. Consistent with reflexive thematic analysis, these discussions were not intended to establish inter-coder reliability or achieve coding consensus as an indicator of objective accuracy. Rather, they served to deepen interpretation, critically examine assumptions, consider alternative explanations, and strengthen the conceptual coherence of the analysis (Braun & Clarke, 2019, 2021).

Analytical development proceeded iteratively between individual transcripts, stakeholder groups, and the dataset. Comparisons across researchers, industry representatives, and policy/innovation-support stakeholders were used to examine convergence and divergence in experiences while retaining the ecosystem-level phenomenon as the primary analytical focus.

In a subsequent interpretative stage, the thematic findings were examined in relation to the theoretical domains developed in the literature review. This involved considering how the empirically identified challenges and expected GenAI functionalities related to information management, knowledge integration, innovation intermediation, and ecosystem orchestration. The purpose was not to impose an a priori coding framework on the data, but to develop an empirically grounded conceptual explanation of GenAI as an AI-enabled information management capability.

Representative quotations were selected to demonstrate the relationship between empirical material and analytical interpretations. Participants were identified using stakeholder-group codes and participant numbers (e.g., R4 = researcher, I7 = industry representative, P2 = policymaker/innovation-support stakeholder).

## 3.5 Researcher Reflexivity

The research team brought complementary disciplinary and professional perspectives spanning innovation studies, management, information systems, and social sciences. Team members also had professional experience of research projects and science–industry collaboration within the Slovenian innovation ecosystem. This contextual knowledge facilitated engagement with participants and interpretation of institutional and organisational practices, while also creating the possibility that prior assumptions could shape data generation and analysis.

Consistent with RTA, researcher subjectivity was treated as an analytical resource rather than as bias that could be eliminated (Braun & Clarke, 2019, 2021). Reflexive discussions were therefore incorporated throughout the analytical process. Researchers critically examined how their disciplinary backgrounds, professional experiences, expectations regarding science–industry collaboration, and assumptions about the potential of GenAI could influence interviewing, coding, theme development, and interpretation. Alternative explanations and interpretations were discussed within the research team throughout theme development.

## 3.6 Trustworthiness and Ethical Considerations

Several strategies were used to strengthen the methodological rigour and transparency of the study. First, the inclusion of three stakeholder groups enabled examination of the phenomenon from complementary positions within the innovation ecosystem and supported analysis of convergent and divergent perspectives. Second, analytical documentation was maintained throughout coding and theme development, including records of coding decisions, thematic revisions, and reflexive observations. Third, iterative discussions within the research team were used to critically examine interpretations, thematic boundaries, and alternative explanations. Fourth, representative verbatim quotations were retained in the reporting of findings to make the relationship between participants' accounts and analytical interpretations transparent. Trustworthiness was considered in relation to credibility, dependability, confirmability, and transferability (Lincoln & Guba, 1985; Nowell et al., 2017). Credibility was supported through information-rich sampling, engagement with multiple stakeholder perspectives, and transparent presentation of empirical evidence. Dependability was addressed through systematic documentation of the analytical process. Confirmability was supported through reflexive analytical discussions and documentation of interpretative decisions. Transferability was facilitated through explicit description of the Slovenian innovation ecosystem as the empirical context, participant characteristics, sampling logic, and analytical procedures, enabling readers to assess the relevance of the findings to other innovation ecosystems.

The study was conducted in accordance with established ethical principles for social science research. The study was approved by the University of Novo mesto Research Ethics Committee for Research Involving Human Participants (No. 12/2026). Participation was voluntary, and all participants provided informed consent prior to data collection. Participants received information about the purpose of the study, interview procedures, confidentiality and data-processing arrangements, the voluntary nature of participation, and their right to withdraw without adverse consequences. All identifying information was removed or pseudonymised during transcription and analysis. Audio recordings, transcripts, and analytical materials were stored in a secure institutional environment, with access restricted to authorised members of the research team. Data were processed and retained in accordance with applicable institutional requirements and data-protection legislation. Findings are reported using anonymised quotations and aggregated participant descriptions to minimise the possibility of identifying individuals or organisations.

# 4 Results

The thematic analysis revealed two interrelated analytical dimensions. The first concerned information management challenges constraining science–industry collaboration, encompassing ecosystem fragmentation, information overload and limited visibility of competencies, and the relational role of trust and credibility. The second concerned the AI-enabled capabilities stakeholders considered necessary to address these challenges, including intelligent partner matching, funding opportunity analysis, competency and reference visibility, proposal development support, and decision support. Across stakeholder groups, GenAI was consistently perceived as augmenting rather than replacing human judgement. Integration of these two analytical dimensions provided the empirical basis for conceptualising GenAI as an AI-enabled information management capability for ecosystem knowledge integration.

# 4.1 Information Management Challenges Constraining Science–Industry Collaboration

# 4.1.1 Ecosystem Fragmentation and Distributed Information Resources

Ecosystem fragmentation emerged as a pervasive barrier to science–industry collaboration. Participants did not primarily describe an absence of information, expertise, or collaboration opportunities; rather, they emphasised that these resources were dispersed across institutions, digital platforms, funding schemes, support mechanisms, and informal networks. This fragmentation increased the effort required to identify relevant information and potential partners and reinforced dependence on existing personal networks.

Although this challenge was shared across stakeholder groups, participants emphasised different aspects of fragmentation. Policymakers primarily framed it as a systemic coordination problem and highlighted the absence of integrated mechanisms for connecting ecosystem actors. As one policymaker noted, “We need more systematic approaches to networking and digital solutions that provide an overview of competencies, opportunities, and potential partners” (P1). Industry representatives focused more strongly on the practical burden of navigating disconnected information sources: “The biggest problem is not that information is unavailable but that it has to be searched for in ten different places” (I2). Researchers emphasised the resulting reliance on established networks, noting that “many collaborations happen simply because people already know each other” (R2).

Across the three groups, fragmentation therefore operated at both informational and relational levels. Information resources and support mechanisms were distributed across disconnected systems, while access to potential collaborators frequently depended on informal and pre-existing relationships. This limited opportunities to identify new partners outside established collaboration networks.

Table 2
Ecosystem fragmentation and distributed information resources

| Subtheme | Empirical indicators | Illustrative evidence | Analytical interpretation |
|---|---|---|---|
| Fragmented information resources | Dispersed information sources; disconnected portals; information opacity; absence of a single-entry point | “There is a lot of information about collaboration opportunities, but it is scattered.” (R4) | Relevant ecosystem knowledge exists but is distributed across disconnected sources. |
| Disconnected support mechanisms | Fragmented support services; disconnected tools; duplication of processes; lack of coordination | “The tools are functional, but they are often disconnected.” (P1) | Existing support mechanisms do not provide integrated access to collaboration resources. |
| Dependence on existing networks | Personal networks; closed collaboration circles; difficulties identifying new partners | “Without personal contacts, finding partners would take a very long time.” (R2) | Fragmentation increases dependence on established relationships and constrains discovery of new partners. |

## 4.1.2 Information Overload and Limited Visibility of Competencies

A second challenge concerned the volume and usability of available information. Participants repeatedly challenged the assumption that collaboration is constrained primarily by insufficient information. Instead, they described an environment characterised by information abundance combined with limited capacity to identify what is relevant, credible, and actionable. Information on funding opportunities, research activities, potential partners, and support programmes was widely available but distributed across multiple sources and costly to monitor.

A researcher described “a great deal of information about collaboration opportunities, sometimes even too much, but it is scattered and time-consuming to review” (R3). Similarly, an industry representative emphasised the absence of an integrated information environment: “We lack a centralised system where all relevant information would be available in one place” (I3). Policymakers particularly emphasised difficulties navigating funding mechanisms and called for greater transparency, coordination, and integrated support.

Information overload was closely connected to limited visibility of competencies. Participants reported difficulty determining who possessed relevant expertise, experience, infrastructure, or project references. An industry representative explained that “there is often no clear overview of who actually has specific expertise and who has relevant references” (I6), while a researcher similarly noted that “we often do not know who is working on similar topics or who could contribute specific expertise” (R9).

These findings indicate that stakeholders perceived value in mechanisms capable of filtering and evaluating information and connecting specific collaboration needs with relevant knowledge, expertise, and opportunities.

Table 3
Information overload and limited visibility of competencies

| Subtheme | Empirical indicators | Analytical interpretation |
|---|---|---|
| Information overload | Excessive volume; dispersed sources; information burden; difficulty identifying relevant information | The primary challenge is not information scarcity but the transformation of abundant information into relevant and actionable knowledge. |
| Limited competency visibility | Low visibility of experts and research groups; unclear expertise profiles; limited access to references | Existing expertise is difficult to identify and evaluate across organisational boundaries. |
| Funding information complexity | Fragmented calls; difficult monitoring; unclear requirements; administrative complexity | Identifying relevant funding opportunities requires substantial search, interpretation, and evaluation effort. |

## 4.1.3 Trust, Credibility, and Relational Knowledge

Trust emerged as a third dimension of science–industry collaboration. Participants consistently emphasised that access to information alone was insufficient for partner selection and collaborative decision-making; information about potential partners also needed to be credible, verifiable, and embedded in an understanding of previous experience and collaborative performance.

Researchers, industry representatives, and policymakers all described interpersonal relationships and previous collaborative experience as important mechanisms for reducing uncertainty. An industry representative captured this relational dimension by observing that “in the end, business is not only business-to-business, but people-to-people” (I9). A researcher similarly emphasised “effective

communication and mutual understanding between both sides” (R8), while policymakers highlighted early engagement among potential partners.

Trust was also associated with demonstrable competencies, references, and organisational reputation. Participants sought evidence not only of what potential partners claimed to know but also of what they had previously accomplished. Formal participation alone was therefore considered insufficient. As one researcher noted, “in collaborative projects, it is particularly important that partnerships are not only formal but also substantive” (R5).

Taken together, participants' accounts indicate that trust operated both as a relational mechanism and as an information requirement. Partner selection depends partly on tacit relational knowledge derived from previous interactions, but also on access to verifiable information regarding competencies, references, and collaboration histories. This distinction became particularly relevant when participants considered the potential role of AI-enabled support.

Table 4
Trust, credibility, and relational knowledge

| Subtheme | Empirical indicators | Analytical interpretation |
|---|---|---|
| Interpersonal relationships | Personal networks; mutual familiarity; communication; long-term relationships | Relational knowledge reduces uncertainty and facilitates collaboration. |
| Verifiable credibility | Previous experience; references; professional credibility; competencies; reputation | Partner evaluation requires credible and verifiable information, not simply visibility. |
| Substantive engagement | Shared goals; active participation; commitment; avoidance of symbolic partnerships | Formal connection alone does not generate effective collaboration. |

# 4.2 AI-Enabled Capabilities for Ecosystem Knowledge Integration and Decision Support

The second analytical dimension concerned the capabilities stakeholders expected from GenAI-enabled information systems. Across all three stakeholder groups, GenAI was conceptualised neither as a substitute for human innovation actors nor as an autonomous decision-maker. Rather, participants identified a set of complementary capabilities through which GenAI could reduce information complexity, connect distributed knowledge, increase the visibility and evaluability of expertise and opportunities, and support cross-organisational decision-making.

Five closely related capability areas emerged: partner and competency matching, funding opportunity analysis, competency and reference visibility, proposal development support, and decision support. These capabilities were underpinned by a cross-cutting requirement for transparency, traceability, data protection, and human oversight.

### 4.2.1 Partner and Competency Matching

The capability most consistently emphasised across stakeholder groups concerned the identification of appropriate collaboration partners. Participants envisaged GenAI as enabling search and matching based not simply on organisational names or predefined categories but on competencies, research interests, innovation needs, project experience, and complementary expertise.

Researchers highlighted the value of identifying qualified partners beyond existing personal networks, while industry representatives emphasised matching organisational needs with relevant research competencies. Policymakers similarly envisaged integrated access to information about partners, expertise, and collaboration opportunities. As one industry representative described it, the platform should provide “smart partner matching based on interests and competencies” (I5).

This capability directly addressed the fragmentation and competency-visibility challenges identified in the first analytical dimension by connecting distributed information about needs and expertise.

### 4.2.2 Funding Opportunity Analysis and Information Filtering

Participants also identified a need for AI-enabled support in navigating complex funding environments. Desired capabilities included monitoring and filtering funding calls, interpreting eligibility and application requirements, identifying opportunities relevant to organisations or competencies, and providing personalised recommendations.

An industry representative stated that “artificial intelligence could significantly help with analysing funding calls” (I7), while policymakers highlighted the value of centralised information combined with filtering and personalised notifications.

Rather than simply aggregating additional information, participants therefore envisaged GenAI as reducing information overload by prioritising, contextualising, and interpreting existing information.

### 4.2.3 Competency and Reference Visibility

A third capability concerned making ecosystem knowledge and expertise more visible and evaluable. Participants described the value of structured competency profiles, expertise mapping, project references, and evidence of previous collaboration experience.

This capability extended beyond simple directory functions. Participants emphasised that information about competencies should enable users to assess the relevance and credibility of potential partners. As one policymaker stated, “it is crucial that the platform provides a systematic overview of competencies” (P3).

Competency visibility therefore served two related purposes: improving discovery of relevant expertise and providing information required for informed partner evaluation.

### 4.2.4 Proposal Development and Administrative Support

Participants also identified potential value in GenAI-enabled support for project development. Relevant capabilities included interpretation of funding requirements, draft generation, compliance checking, document management, and assistance across different stages of proposal preparation.

Researchers and industry representatives particularly emphasised the administrative burden associated with collaborative projects. One industry participant noted that “if the tool could assist with applications and bureaucracy, it would be extremely useful” (I8), while a policymaker envisaged support extending “from idea development to proposal submission” (P2).

These capabilities were perceived as reducing administrative complexity rather than replacing substantive project development by collaboration partners.

### 4.2.5 Decision Support, Transparency, and Human Oversight

Across stakeholder groups, participants consistently rejected the notion of fully automated decision-making. GenAI was instead perceived as a mechanism for supporting users in evaluating potential partners, opportunities, and project alternatives. A policymaker articulated this distinction directly: “Artificial intelligence should support decision-making, not make decisions on behalf of users” (P4).

Trust in AI-supported recommendations was closely associated with transparency and traceability. Participants emphasised that users should be able to understand why particular recommendations were generated and what information informed them, while retaining responsibility for final decisions. Data protection and security were likewise regarded as prerequisites for adoption.

These findings indicate that human oversight is not an additional platform feature but a cross-cutting condition governing the use of AI-enabled capabilities. GenAI was therefore envisaged as augmenting human judgement by organising and interpreting distributed information while leaving evaluation and final decision authority with users.

Table 5
AI-enabled capabilities identified by stakeholders

| AI-enabled capability | Information management function | Intended contribution |
|---|---|---|
| Intelligent partner and competency matching | Connect needs, competencies, expertise, and project experience | Identify relevant collaboration partners beyond existing networks |
| Funding opportunity analysis | Filter, interpret, and contextualise funding information | Reduce information overload and improve opportunity identification |
| Competency and reference visibility | Integrate expertise profiles, references, and collaboration histories | Improve knowledge visibility and informed partner evaluation |
| Proposal development support | Synthesise requirements and support documentation | Reduce administrative burden and support project development |
| Decision support | Integrate and evaluate information relevant to alternatives | Support informed selection of partners and opportunities |

Cross-cutting governance conditions identified across all capability areas included data protection and security, transparency and explainability, traceability of AI-supported recommendations, and human oversight and accountability.

## 4.3 From Information Management Challenges to an AI-Enabled Information Management Capability

Integration of the two analytical dimensions revealed a systematic relationship between the information management challenges experienced by stakeholders and the AI-enabled capabilities they considered necessary to address them. Ecosystem fragmentation was associated with a perceived need for integrated access to distributed information and expertise; information overload with demand for intelligent filtering, synthesis, and contextual recommendation; limited competency visibility with demand for competency mapping and partner matching; and uncertainty regarding potential partners with the importance attributed to verifiable references, transparency, and traceability.

Participants did not attribute value to GenAI based on any single technological functionality. Rather, the potential value of GenAI emerged from the combination of complementary capabilities through which distributed ecosystem knowledge could be identified, integrated, evaluated, and mobilised for collaborative decision-making. Partner matching depended on access to structured competency information; funding recommendations required filtering and contextual interpretation; partner evaluation required verifiable references and collaboration histories; and all AI-supported recommendations depended on transparency and continued human judgement.

In this conceptualisation, GenAI does not constitute an autonomous innovation intermediary. Instead, it augments intermediation by supporting the integration and mobilisation of distributed ecosystem

knowledge while retaining human actors as the locus of relational engagement, judgement, and decision authority.

Table 6
From information management challenges to AI-enabled ecosystem knowledge integration

| Information management challenge | AI-enabled capability identified | Knowledge integration function | Design implication |
|---|---|---|---|
| Fragmented ecosystem information | Integrated information access and semantic synthesis | Connect distributed information resources | Single-entry ecosystem information architecture |
| Information overload | Intelligent filtering, synthesis, and contextual recommendation | Identify and prioritise relevant knowledge | Personalised information filtering and recommendation |
| Limited visibility of competencies | Competency mapping and intelligent partner matching | Connect collaboration needs with distributed expertise | Dynamic competency profiles and semantic matching |
| Complex funding environment | Funding-call analysis and opportunity matching | Connect organisational competencies with relevant opportunities | AI-supported funding navigation |
| Uncertainty regarding partner credibility | Reference and collaboration-history verification | Support evaluation of potential partners | Transparent and verifiable profiles |
| Decision complexity | Context-sensitive decision support | Mobilise integrated knowledge for collaborative decisions | Human-in-the-loop recommendation mechanisms |
| Trust in AI-enabled support | Explainability, traceability, data protection, and human oversight | Enable responsible use of AI-mediated knowledge | Transparent and accountable AI architecture |

Figure 1 integrates these findings into a conceptual model linking the information management challenges identified by participants with AI-enabled information management capabilities and their proposed contributions to ecosystem knowledge integration, under cross-cutting governance conditions, under cross-cutting governance conditions.

# 5. Discussion

This study examined how innovation ecosystem stakeholders perceive the information management challenges constraining science–industry collaboration and which AI-enabled capabilities they consider important for supporting knowledge integration, decision-making, and ecosystem coordination. The findings reveal a consistent pattern across researchers, industry representatives, and policymakers: collaboration difficulties were associated less with information scarcity than with the fragmentation,

volume, uneven visibility, and limited evaluability of information distributed across the innovation ecosystem. At the same time, stakeholders identified a complementary set of GenAI-enabled capabilities—partner and competency matching, funding opportunity analysis, competency and reference visibility, proposal development support, and decision support—that could help transform distributed information into knowledge usable for collaborative action. Taken together, these findings provide the empirical basis for conceptualising GenAI as an AI-enabled information management capability for ecosystem knowledge integration.

# 5.1 From Information Scarcity to Ecosystem Knowledge Integration

The first important finding concerns the nature of the information problem underlying science–industry collaboration. Previous research has identified partner search, coordination difficulties, divergent institutional practices, and access to relevant information among persistent barriers to university–industry collaboration (Nsanzumuhire & Groot, 2020; Rossoni et al., 2024). The present findings refine this understanding by showing that stakeholders did not primarily describe an absence of information. Rather, they experienced an environment in which relevant expertise, funding opportunities, research infrastructures, competencies, and potential partners were distributed across multiple organisations, platforms, databases, and informal networks.

This distinction between information availability and information usability is theoretically important. From a knowledge management perspective, organisational value does not arise simply from possessing or accessing information, but from processes through which knowledge is identified, integrated, interpreted, and applied (Alavi & Leidner, 2001; Alavi et al., 2024). The findings extend this logic beyond the organisational level. In science–industry collaboration, relevant knowledge is distributed not only within organisations but across heterogeneous ecosystem actors operating under different institutional logics and information environments. The findings therefore suggest that a central challenge is one of ecosystem knowledge integration: identifying relevant distributed knowledge, establishing connections among previously disconnected information resources, evaluating their relevance and credibility, and mobilising them for collaborative decision-making.

This perspective also helps explain why conventional digital repositories and information portals may provide only a partial response to collaboration barriers. Increasing the quantity of accessible information does not necessarily reduce information complexity and may intensify the cognitive burden associated with searching, comparing, and evaluating heterogeneous information. The stakeholder demand for filtering, semantic matching, synthesis, contextual recommendation, and integrated access therefore indicates a shift from information provision towards intelligent knowledge integration. This finding is consistent with emerging research suggesting that the organisational value of GenAI increasingly lies in its capacity to synthesise heterogeneous information and support knowledge-intensive activities rather than merely automate information retrieval or content generation (Dwivedi et al., 2023; Feuerriegel et al., 2024; Mariani & Dwivedi, 2024).

## 5.2 AI-Enabled Information Management Capability for Ecosystem Knowledge Integration

The principal theoretical contribution of this study is the development of an empirically grounded conceptualisation of GenAI as an AI-enabled information management capability for ecosystem knowledge integration. Existing research has predominantly examined GenAI in relation to individual productivity, content generation, creativity, knowledge work, and decision support (Dwivedi et al., 2023; Feuerriegel et al., 2024; Mariani & Dwivedi, 2024). The present findings suggest that its potential role in innovation ecosystems may be broader. Stakeholders attributed value to GenAI not because of any single technological function, but because of the potential combination of capabilities through which distributed ecosystem knowledge could be identified, integrated, evaluated, and mobilised.

This distinction is important because the proposed conceptualisation is not synonymous with GenAI technology itself. Rather, it refers to a configuration of AI-enabled information management capabilities through which technological functionalities can support knowledge integration across organisational boundaries. The empirical findings identify five interrelated capability areas: intelligent partner and competency matching, funding opportunity analysis, competency and reference visibility, proposal development support, and decision support. Their value lies in their complementarity. For example, effective partner matching depends on structured and credible competency information; funding recommendations require contextual interpretation of both opportunities and organisational capabilities; and decision support depends on the integration and evaluation of information from multiple sources. The capability therefore resides not in isolated AI functions but in their coordinated use to support ecosystem-level knowledge integration.

This conceptualisation extends knowledge management research in two respects. First, it shifts the analytical focus from AI as a discrete technological tool towards AI as an information management capability. Second, it extends knowledge integration beyond intra-organisational processes to distributed inter-organisational environments in which relevant knowledge is dispersed across multiple autonomous actors. In this sense, the findings suggest that GenAI may create value in innovation ecosystems by strengthening the connective capacity through which heterogeneous knowledge resources become visible, interpretable, and actionable across organisational boundaries.

## 5.3 Reconsidering AI-Enabled Intermediation: Augmentation Rather than Substitution

The findings also contribute to the literature on innovation intermediaries. Traditional innovation intermediaries facilitate collaboration by connecting actors, supporting knowledge exchange, reducing information asymmetries, enabling partner search, and coordinating innovation activities (Howells, 2006; Randhawa et al., 2022). More recent research has expanded this perspective towards ecosystem orchestration and digitally enabled forms of intermediation. The capabilities identified by participants

overlap substantially with these established intermediary functions, particularly partner identification, knowledge brokerage, opportunity recognition, and coordination.

However, the findings suggest that GenAI should not be conceptualised as an autonomous innovation intermediary. This distinction is central to the theoretical argument of the study. Innovation intermediation encompasses relational, institutional, interpretative, and legitimacy-building activities that cannot be reduced to information processing. Participants repeatedly emphasised the importance of interpersonal relationships, contextual understanding, previous collaboration experience, credibility, and human judgement. GenAI may therefore reproduce or augment selected information-intensive functions of intermediation without replacing the broader social and institutional role performed by human and organisational intermediaries.

The contribution of GenAI is consequently better understood as augmentation of intermediation capacity. AI-enabled information management can increase the scale, speed, and potentially the contextual relevance with which ecosystem information is processed and connected, while human actors retain responsibility for relationship formation, interpretation, negotiation, and strategic decision-making. This interpretation moves beyond a simple technological substitution perspective and points towards hybrid socio-technical arrangements in which AI-enabled information capabilities complement human and organisational intermediation.

Such a perspective also clarifies the relationship between information management capability and ecosystem orchestration. The present study does not suggest that GenAI independently orchestrates an innovation ecosystem. Rather, AI-enabled knowledge integration may provide an informational infrastructure that supports orchestration by making distributed competencies, opportunities, relationships, and resources more visible and actionable. Ecosystem orchestration therefore remains a socio-organisational process, while GenAI may strengthen the information management capabilities upon which effective coordination depends.

## 5.4 Trust as Both a Relational Mechanism and an AI Governance Requirement

Trust represents a further theoretical connection between science–industry collaboration and AI-enabled information management. Previous research has established trust as an important determinant of university–industry collaboration (Ankrah & Al-Tabbaa, 2015; Plewa et al., 2013). The present findings confirm its importance but reveal two analytically distinct dimensions.

First, trust between ecosystem actors remained fundamentally relational. Participants associated credible collaboration with personal relationships, previous experience, substantive engagement, demonstrated competencies, and organisational reputation. This indicates that greater access to digital information cannot substitute for the relational foundations of collaboration. However, AI-enabled systems may support informed trust by increasing the visibility and verifiability of competencies, references, previous project experience, and collaboration histories. In this sense, information

management can reduce uncertainty surrounding potential partners without replacing interpersonal trust itself.

Second, the introduction of AI creates a distinct problem of trust in AI-supported information and recommendations. Participants emphasised transparency, traceability, data protection, and continued human oversight as prerequisites for accepting AI-supported recommendations. This directly qualifies an exclusively positive interpretation of AI-enabled innovation. The ability to synthesise large volumes of information may generate substantial value, but opaque recommendation processes, unverifiable outputs, inappropriate use of sensitive information, or excessive delegation of judgement can introduce new forms of uncertainty and risk (Dwivedi et al., 2023; Fasano et al., 2025).

The conceptual model therefore treats transparency, explainability, traceability of AI-supported recommendations, data protection and security, and human oversight and accountability as cross-cutting governance conditions, rather than additional technological functionalities. This distinction is important because responsible AI use cannot be separated from the capabilities it enables. AI-supported partner matching or decision support is valuable only insofar as users can critically evaluate recommendations and retain authority over consequential decisions.

This finding is consistent with human-centred AI perspectives that emphasise augmentation rather than replacement of human capabilities (Shneiderman, 2022) and with human–AI interaction research highlighting transparency and user control (Amershi et al., 2019). In the context of innovation ecosystems, where decisions may involve strategic uncertainty, intellectual property, long-term partnerships, and institutional commitments, preservation of human agency appears particularly important.

## 5.5 Theoretical Implications

The study makes three related theoretical contributions. First, it extends knowledge management research by positioning ecosystem knowledge integration as a central information management problem in science–industry collaboration within increasingly information-rich environments. The findings indicate that information availability alone is insufficient when relevant knowledge remains fragmented, difficult to evaluate, or disconnected from specific collaboration needs. This shifts attention from information access towards the capability to identify, integrate, evaluate, and mobilise distributed knowledge across organisational boundaries. Second, the study develops an empirically grounded conceptualisation of AI-enabled information management capability for ecosystem knowledge integration. This conceptualisation provides a theoretically more precise explanation of GenAI's potential role than viewing it simply as a productivity technology, collaboration platform, or autonomous digital intermediary. It captures how complementary AI-enabled functionalities can collectively support the transformation of distributed ecosystem information into actionable knowledge for collaboration and decision-making. Third, the findings refine innovation intermediary theory by distinguishing AI-enabled information management from innovation intermediation itself. GenAI can augment information-intensive intermediary functions—including search, matching, synthesis, visibility, and decision support—

without reproducing the relational, institutional, and legitimacy-building functions of human intermediaries. The resulting theoretical perspective is therefore one of AI-augmented intermediation, in which technological and human capabilities are complementary rather than substitutive. Together, these contributions connect knowledge management, innovation intermediation, and AI-enabled information systems within a common conceptual framework. The proposed model suggests that GenAI contributes to ecosystem coordination not by independently orchestrating innovation actors, but by strengthening the information management capability through which distributed knowledge becomes accessible, connected, evaluable, and actionable.

From an information systems perspective, the study further shifts attention from isolated AI functionalities towards the configuration of complementary AI-enabled information management capabilities embedded in an inter-organisational information environment. The findings suggest that the value of GenAI-enabled information systems depends not only on technological functionality but on how matching, synthesis, recommendation, visibility, and decision-support capabilities are configured to connect distributed knowledge while preserving human agency. This provides a socio-technical basis for examining AI-enabled information systems beyond organisational boundaries.

## 5.6 Practical and Design Implications

The findings also have implications for the design and governance of AI-enabled collaboration infrastructures. First, platform development should move beyond the logic of centralised information repositories. Stakeholders did not primarily request more information; they required mechanisms capable of integrating, filtering, contextualising, and prioritising information according to specific collaboration needs. Semantic search, intelligent filtering, contextual recommendation, and cross-source synthesis should therefore constitute core design capabilities. Second, partner discovery should be based on dynamic competency and evidence profiles rather than organisational directories alone. Effective matching requires information on expertise, project experience, references, research interests, organisational needs, and previous collaborative activity. Importantly, such information should support both discovery and credibility assessment. Third, funding support should combine opportunity identification with contextual interpretation. AI-enabled systems could reduce the burden of monitoring fragmented funding environments by matching calls with competencies and organisational characteristics, summarising requirements, and supporting proposal development. However, final assessments of strategic relevance and partnership suitability should remain with users. Fourth, responsible implementation requires governance mechanisms to be embedded throughout the system architecture. Transparency and explainability, traceability of recommendations, appropriate data protection and security, and explicit human oversight should not be treated as supplementary features introduced after technological development. They are conditions for responsible adoption of AI-enabled information management capabilities.

For policymakers and innovation support organisations, the findings also suggest that investment in additional portals or databases may have limited value unless these infrastructures improve interoperability and knowledge integration across existing ecosystem resources. The policy challenge is

therefore not simply digitalisation, but the development of connected, trustworthy, and human-governed information infrastructures capable of supporting collaboration across institutional boundaries.

## 5.7 Limitations and Future Research

Several limitations should be considered when interpreting the findings. First, the study was conducted within the Slovenian innovation ecosystem and therefore reflects a specific institutional, economic, and policy context. Slovenia provides an analytically useful, bounded setting for examining interactions among researchers, industry representatives, policymakers, and innovation support actors, but the transferability of the findings to larger, more decentralised, or institutionally different innovation systems requires further investigation. Second, the study involved 24 purposively selected participants and adopted an exploratory qualitative design. The objective was analytical depth and conceptual development rather than statistical generalisation. Although the inclusion of three stakeholder groups enabled comparison across complementary ecosystem positions, future research should examine whether the identified information management challenges and AI-enabled capabilities are reproduced across different national, sectoral, and disciplinary contexts. Third, the study examines stakeholder perceptions and expectations rather than actual interaction with an operational GenAI-enabled system. Consequently, the proposed relationships between AI-enabled capabilities, ecosystem knowledge integration, and expected collaboration outcomes should be understood as empirically grounded conceptual propositions, not demonstrated causal effects. Future studies should therefore develop and evaluate operational prototypes and examine how the proposed capabilities affect information search, partner discovery, decision quality, user trust, collaboration formation, and project development in real-world settings. Fourth, future research should investigate the proposed conceptualisation of AI-enabled information management capability more systematically. Comparative case studies could examine how this capability develops across different innovation ecosystems, while quantitative research could operationalise its dimensions and test their relationships with knowledge integration, inter-organisational coordination, and collaboration outcomes. Longitudinal research would be particularly valuable for determining whether AI-enabled information management changes collaboration networks over time, reduces dependence on established personal networks, or enables participation by actors that are currently less visible within innovation ecosystems. Finally, future studies should examine the governance boundary between AI-supported information management and human judgement. Attention should be given to explainability, algorithmic bias, data quality, accountability, privacy, and the potential for AI-generated recommendations to reproduce existing visibility inequalities within innovation ecosystems. Such research would help establish the conditions under which AI-enabled information management can support ecosystem knowledge integration without undermining human agency, institutional trust, or responsible decision-making.

# 6. Conclusion

This study advances understanding of the role of GenAI in science–industry collaboration by reframing a central information management challenge from information scarcity to ecosystem knowledge

integration. The findings indicate that stakeholders experience collaboration difficulties primarily through fragmented information environments, information overload, limited visibility and evaluability of competencies, and uncertainty regarding potential partners. Addressing these challenges therefore requires more than improved access to information; it requires capabilities for identifying, integrating, evaluating, and mobilising distributed ecosystem knowledge.

Building on these findings, the study develops an empirically grounded conceptualisation of GenAI as an AI-enabled information management capability for ecosystem knowledge integration. This capability is conceptualised as comprising complementary functions—partner and competency matching, funding opportunity analysis, competency and reference visibility, proposal development support, and decision support—that collectively enable distributed information to become more accessible, connected, and actionable across organisational boundaries. Importantly, this conceptualisation distinguishes AI-enabled information management from innovation intermediation itself: GenAI may augment information-intensive intermediary functions, but relational engagement, contextual interpretation, and consequential decision-making remain fundamentally human and organisational responsibilities.

The value of GenAI in innovation ecosystems therefore lies not in replacing innovation intermediaries or automating ecosystem orchestration, but in augmenting the information management capacity that supports collaboration and coordination. Realising this potential depends on embedding AI-enabled systems within human-governed socio-technical arrangements characterised by transparency, explainability, traceability, data protection, and human oversight. By connecting knowledge management, innovation intermediation, and AI-enabled information systems, this study provides a conceptual foundation for understanding—and subsequently testing—how GenAI can support ecosystem knowledge integration while preserving human agency and accountability.

## Declarations

**Ethics approval:**

The study was approved by the Research Ethics Committee for Research Involving Human Participants at the University of Novo mesto (Approval No. 12/2026).

# Consent to participate:

Informed consent was obtained from all participants prior to participation.

# Competing interests:

The authors declare that they have no competing interests.

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# Author Contribution

K.E. conceived and designed the study, developed the research methodology, conducted interviews, supervised the research, performed the qualitative analysis, interpreted the findings, and wrote the first draft of the manuscript. S.K. conducted interviews, prepared the figures, and critically revised the manuscript. M.G. conducted interviews and critically revised the manuscript. T.B. critically revised the manuscript. S.N. contributed to the study design, conducted interviews, contributed to data interpretation, and critically revised the manuscript. All authors contributed to the development of the conceptual framework, reviewed and approved the final version of the manuscript, and agree to be accountable for all aspects of the work.


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# Data Availability

The qualitative dataset generated and analysed during the current study is publicly available in the ReVIS Open Science Repository. The dataset can be accessed via the persistent identifier (PID): http://hdl.handle.net/20.500.12556/ReVIS-14022.

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# Figures

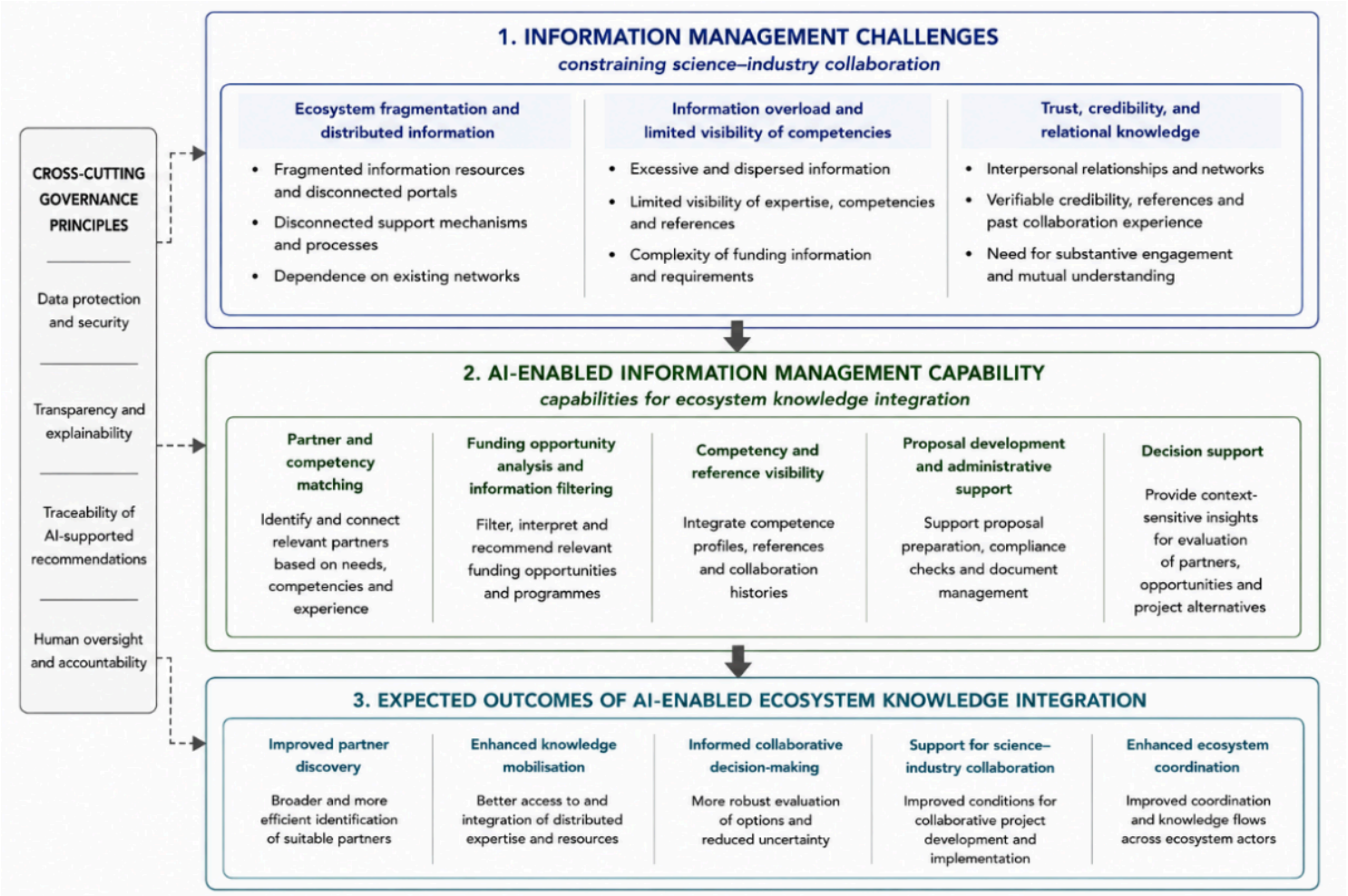



**Figure 1**

Conceptual model of AI-enabled information management capability for ecosystem knowledge integration