

Conceptualizing an AI Module for HISinOne RES: Pilot Planning at FernUniversität in Hagen

Otmane Azeroual^{1*} and Christina Kummert¹

¹FernUniversität in Hagen (FeU), Universitätsstraße 47, 58097 Hagen, Germany
Otmane.azeroual@fernuni-hagen.de, christina.kummert@fernuni-hagen.de

Abstract

Current Research Information Systems (CRIS) have become indispensable infrastructures for documenting publications, projects, funding, patents, and collaborations. Yet many institutional CRIS implementations remain primarily retrospective, offering descriptive views of past activity rather than anticipatory intelligence for future-oriented decision-making. This paper conceptualizes a modular Artificial Intelligence (AI) component for HISinOne RES and positions FernUniversität in Hagen (FeU) as the pilot setting for its design and subsequent implementation. The proposed module combines semantic enrichment, predictive analytics, collaboration recommendation, and explainable decision support within the existing CRIS environment. Rather than replacing the system, the concept introduces an integrative AI layer that preserves governance, data stewardship, and established workflows. Methodologically, the paper develops a design-oriented framework that brings together natural language processing, machine learning, network analytics, explainable AI, and participatory co-design. We discuss the functional architecture, the underlying governance requirements, and a roadmap from conceptualization to pilot deployment. The paper argues that AI-enhanced CRIS can evolve from passive repositories into dynamic, intelligence-driven infrastructures for university research management, provided that transparency, privacy, and user trust are embedded from the outset.

1 Introduction

Research-performing organisations increasingly depend on robust digital infrastructures to collect, curate, and interpret heterogeneous information about research activities and outputs. CRIS support this task by integrating information on publications, projects, funding, patents, organisational units, and collaborations into structured institutional environments. Such systems provide essential evidence

* Corresponding Author

for reporting, visibility, benchmarking, and strategic management (Rybinski et al., 2017; Biesenbender et al., 2019; Fabre et al., 2021). At the same time, the growing scale and heterogeneity of research information create analytical demands that exceed the capabilities of traditional descriptive reporting.

A central limitation of many CRIS implementations lies in their retrospective orientation. Even when data quality is high and workflows are well established, the system logic often remains focused on documenting what has already happened rather than assisting users in anticipating what may happen next. This limits the capacity of researchers and research managers to identify emerging fields, detect promising collaboration constellations, or assess strategic fit in funding contexts. In the broader context of research evaluation and responsible research management, institutions need infrastructures that can convert accumulated metadata into timely, transparent, and actionable intelligence (Sivertsen, 2019; Schöpfel & Azeroual, 2024).

This paper addresses that gap by presenting a conceptual framework for an AI module designed for integration into HISinOne RES. The concept has been developed with FernUniversität in Hagen (FeU) in mind as a pilot site. The institution offers a particularly relevant environment because of its distributed research landscape, digital administrative culture, and heterogeneous disciplinary profile. The paper therefore pursues three objectives: first, to position AI integration in CRIS as a response to current limitations in research information management; second, to describe a modular architecture that can extend HISinOne RES with predictive and semantic capabilities; and third, to outline a responsible implementation pathway grounded in explainability, privacy, and participatory design.

1.1 Research Contribution

This paper makes three main contributions to the field of research information management and CRIS development.

First, it conceptualizes a modular AI architecture that is specifically designed for integration into an existing CRIS environment (HISinOne RES), rather than as an external analytics tool. This contributes to the ongoing discussion on how AI can be operationalized within institutional infrastructures.

Second, the paper proposes a structured combination of semantic enrichment, predictive analytics, and network intelligence tailored to research management use cases, including collaboration discovery and funding support.

Third, it introduces a governance-aware design that integrates explainability, transparency, and participatory development as core architectural elements. This responds to current challenges in trustworthy AI and responsible research assessment within CRIS environments.

Together, these contributions provide a transferable conceptual framework for AI-enhanced CRIS systems in European research institutions.

2 Related Work and Conceptual Background

The development of CRIS has been closely linked to the institutional need for reliable, interoperable, and reusable research metadata. Prior work has shown that CRIS environments support institutional visibility, research assessment, and interoperability across repositories and administrative infrastructures (Rybinski et al., 2017; Biesenbender et al., 2019; Zendulková et al., 2025). Increasingly, CRIS are understood not merely as administrative back-office systems but as strategic infrastructures mediating between research production, evaluation, and communication (Asserson & Jeffery, 2010; Pinto et al., 2014; De Castro et al., 2014).

At the same time, persistent challenges remain, particularly in integrating heterogeneous data models, ensuring metadata quality, and translating raw information into actionable intelligence (Fabre

et al., 2021; Sivertsen, 2019). These challenges are amplified by the growing complexity of research ecosystems and the need for evidence-based institutional decision-making.

In parallel, the field of the “science of science” has demonstrated how large-scale scholarly data can be analysed to identify patterns, trends, and structural dynamics in research systems (Fortunato et al., 2018). AI and machine learning are increasingly used to support such analyses, including topic modelling, citation analysis, and research trend prediction (Van Noorden & Perkel, 2023).

Semantic technologies and knowledge graphs have been identified as key enablers for structuring heterogeneous research information and enabling advanced analytics (Nickel et al., 2015; Hogan et al., 2021). Similarly, network science provides powerful tools for analysing collaboration structures and identifying influential actors and emerging communities (Barabási, 2016; Newman, 2018).

However, the integration of AI into institutional infrastructures such as CRIS raises significant challenges. Issues of transparency, explainability, bias, and governance are central concerns in the deployment of AI systems in organisational decision-making contexts (Doshi-Velez & Kim, 2017; Arrieta et al., 2020; Cannarsa, 2021). These concerns are particularly relevant in research management, where decisions may affect funding, careers, and institutional strategy.

Recent work by Azeroual and colleagues points toward AI-enabled CRIS as a next step in the evolution of research information systems, including adaptive explainability, knowledge-centric architectures, and CRIS-based innovation ecosystems (Azeroual, 2025a; 2025b; 2025c; Azeroual et al., 2025).

Nevertheless, there remains a gap between technical AI capabilities and their integration into real-world CRIS environments. This paper addresses this gap by proposing a modular, governance-aware AI architecture that is embedded directly within HISinOne RES.

3 Research Problem and Objectives

The core research problem addressed here is how a university CRIS can be extended beyond retrospective documentation toward proactive and trustworthy decision support. In operational terms, this means asking how HISinOne RES can be complemented by AI functions that help users anticipate trends, discover relevant expertise and collaboration opportunities, and interpret institutional research dynamics without undermining data governance or user confidence.

Based on this problem framing, the paper formulates the following research objectives: (1) to specify the architectural requirements of an AI module that can be integrated into HISinOne RES; (2) to define the main analytical functions of that module across semantic enrichment, predictive modelling, and network intelligence; (3) to articulate the governance, privacy, and explainability requirements that must accompany such an integration; and (4) to derive a pilot-oriented implementation roadmap for FernUniversität in Hagen (FeU). Because the work is conceptual at this stage, the emphasis lies on design rationale, functional scope, and implementation feasibility rather than on empirical validation of model performance.

4 Methodological Approach

The paper adopts a design-oriented and socio-technical perspective. Rather than reporting results from an implemented prototype, it develops a conceptual architecture that is intended to guide pilot planning and later deployment. This methodological stance is appropriate because the research challenge is not only algorithmic but also organisational: meaningful AI support in CRIS requires the alignment of data structures, workflows, governance rules, and user expectations.

Methodologically, the concept combines several complementary strands. First, it draws on the CRIS and research information management literature to identify institutional requirements and persistent system limitations. Second, it incorporates AI methods that are relevant for heterogeneous metadata environments, notably natural language processing (NLP), supervised and unsupervised machine learning, graph and network analytics, and explainable AI. Third, it embeds participatory design principles through the planned involvement of researchers, research managers, administrative units, and institutional leadership in iterative requirement elicitation and feedback cycles. This combination supports a user-centred architecture in which the technical design is continuously informed by practical decision contexts.

The resulting framework therefore treats the proposed AI module as both a technical and organisational intervention. Its success depends not only on model quality but also on the interpretability of outputs, the legitimacy of data use, and the degree to which recommendations can be integrated into everyday institutional routines. In that sense, the approach resonates with current scholarship on responsible and trustworthy AI in software and information systems (Balasubramaniam et al., 2023).

The methodological approach is closely aligned with design science research principles, where artefact design, relevance to practice, and iterative refinement are central elements (Hevner et al., 2004). The proposed AI module can therefore be understood as a conceptual artefact that addresses a real-world problem in research information management.

5 Pilot Context: FernUniversität in Hagen (FeU)

FeU provides a particularly suitable pilot environment for the conceptual development of an AI-enhanced CRIS. As Germany's largest distance-learning university, it operates in a highly digital setting and coordinates research activities across distributed organisational arrangements. This context creates both opportunities and demands for advanced research information management. The university needs reliable ways to connect dispersed expertise, to interpret multidisciplinary research activity, and to support evidence-based decision-making across a digitally mediated institutional landscape.

The pilot setting is especially relevant because heterogeneous data and user groups are already part of the everyday operational reality. Researchers, administrative staff, and leadership require different levels of aggregation, explanation, and actionability. An AI module that is viable in this environment must therefore support differentiated user interfaces and role-sensitive outputs while relying on a common metadata foundation within HISinOne RES. The pilot also enables co-design processes in which concrete user needs can shape dashboard logic, explanation formats, and governance safeguards from an early stage.

6 Conceptual Architecture of the AI Module

The proposed AI module is conceived as an integrative layer embedded within HISinOne RES rather than as a detached external service. This architectural approach ensures compatibility with existing workflows and institutional governance structures aligns with organisational policies and governance requirements. The overall system architecture is illustrated in Figure 1.

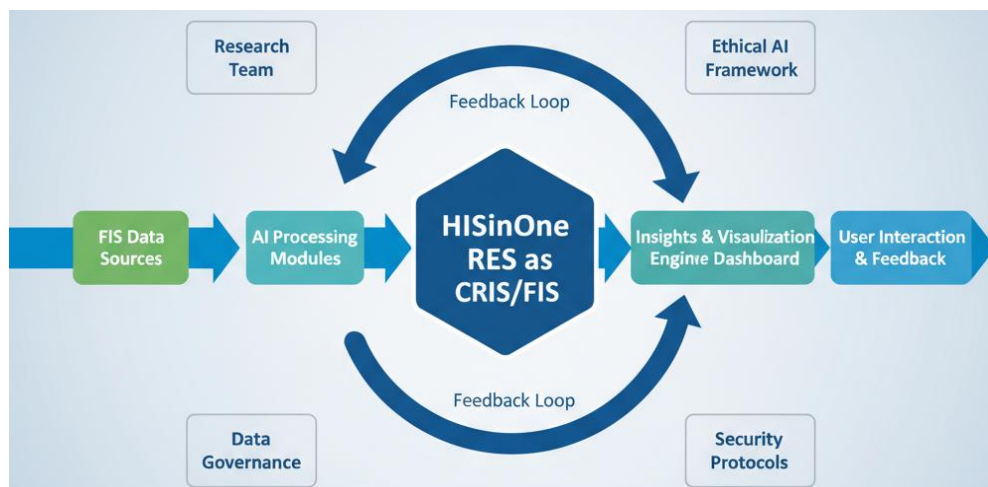


Figure 1: Conceptual architecture of the AI-enhanced HISinOne RES system at FernUniversität in Hagen (FeU).

Figure 1 illustrates the integration of internal CRIS data and external data sources within the CRIS/FIS[†] infrastructure, processed through AI modules to generate decision-support insights. Research data from heterogeneous FIS sources, complemented by relevant external data sources such as funding calls, Open Access monitoring, regulatory documents, and collaboration databases, are processed through AI-driven modules, generating insights that are delivered via interactive dashboards. Feedback loops enable continuous system improvement, while governance layers—including data governance, ethical AI frameworks, and security protocols—ensure compliance, transparency, and trust.

As shown in Figure 1, the architecture follows a modular pipeline approach in which research data are progressively transformed into actionable insights through successive analytical layers. This design choice is central because it preserves existing workflows, aligns with institutional governance structures, and reduces adoption barriers. Functionally, the module starts from the research metadata already managed in the CRIS environment, including publications, projects, funding records, organisational affiliations, cooperation links, and related descriptive fields. These data are first harmonised and transformed into features suitable for downstream analytics. In addition to internal CRIS data, the architecture incorporates external information sources that provide contextual signals about funding priorities, scientific developments, and regulatory environments.

Building on this data foundation, the module integrates three core analytical layers. The first is a semantic intelligence layer that uses NLP to enrich metadata by extracting thematic information from textual sources such as abstracts, project descriptions, and policy documents. This includes identifying key topics, normalizing terminology, and generating semantic representations (e.g., embeddings), which enable similarity analysis and clustering of research outputs. The second is a predictive analytics layer that estimates developments such as emerging research areas or the likely strategic fit and potential success of funding applications. These predictions are based on the combined analysis of internal CRIS data and external signals, including funding calls, publication trends, and collaboration networks, enabling more context-aware and robust forecasting. The third is a network intelligence layer that examines collaboration structures and identifies promising internal and

[†] CRIS (*Current Research Information System*) and FIS (*Forschungsinformationssystem*) refer to institutional information systems that collect, manage, and provide access to structured research-related data such as publications, projects, funding, affiliations, and collaborations. In this text, CRIS/FIS is used as a combined term to indicate both the English and German designations for such systems.

external partnerships by combining institutional collaboration data with external network information and bibliometric datasets. Across all three layers, explainability functions provide reasons, evidence traces, or feature-level rationales so that users can understand why the system generated a specific signal or recommendation.

A governance and trust layer encapsulates the analytical core. This includes privacy-aware data handling, access rules, auditability, human oversight, and ethical evaluation criteria. In operational use, outputs are channelled into dashboards and decision-support views tailored to different user groups. Researchers may receive topic and collaboration suggestions; research managers may access portfolio-level trends and risk indicators; and leadership may view aggregated, policy-relevant strategic signals. The modular architecture is designed for scalability and transferability so that other universities or CRIS environments can adapt the approach with limited structural changes.

The main functional layers of the proposed architecture are summarised in Table 1.

Layer	Main functions	Primary methods	Expected value
Data foundation	Metadata harmonization, cleaning, feature engineering	Schema mapping, entity resolution, controlled vocabularies	Improved consistency and analytic readiness
Semantic intelligence	Topic detection, similarity analysis, clustering of publications and projects	NLP, embeddings, semantic search, unsupervised learning	Richer knowledge discovery across heterogeneous records
Predictive analytics	Trend forecasting and estimation of proposal success potential	Supervised and unsupervised machine learning using internal CRIS data and external data sources (e.g., funding calls, publication trends)	Forward-looking decision support for researchers and managers
Network intelligence	Identification of internal and external collaboration opportunities	Graph analytics, centrality measures, link prediction	Stronger collaboration strategies and partner discovery
Trust and governance	Explanations, audit trails, privacy and ethical oversight	XAI, human-in-the-loop review, governance rules	Transparent and responsible institutional adoption

Table 1: Functional layers of the AI module for HISinOne RES.

As outlined in Table 1, the architecture integrates data preparation, semantic analysis, predictive modelling, and network-based intelligence into a unified framework supported by governance and explainability mechanisms.

The architecture can be interpreted as a data-to-decision pipeline, where both internal CRIS data and relevant external information sources are progressively integrated and transformed into higher-level insights and decision-support signals. This layered transformation is essential for bridging the gap between data availability and actionable intelligence, ensuring that decision-support outputs remain aligned with evolving research environments, funding landscapes, and policy contexts, thereby enabling more informed, transparent, and proactive research management.

This architecture provides a robust foundation for implementing AI-driven decision support within CRIS environments while maintaining alignment with institutional governance and ethical requirements.

7 Analytical Functions and AI Methods

Semantic enrichment is a foundational function of the proposed module. Research information systems typically contain large amounts of textual and semi-structured metadata whose analytical value is underused when interpretation relies only on manually assigned categories. NLP can help detect thematic patterns across publications, projects, abstracts, and keywords, thereby enabling topic discovery, semantic similarity analysis, and clustering. These functions can improve search, contextual classification, and the identification of intersections between otherwise disconnected records.

Predictive analytics constitutes the second major function. Here, supervised and unsupervised machine learning can be used to identify early signals of emerging research areas, infer trajectories from historical project and publication portfolios, and estimate the likelihood of specific outcomes under defined assumptions. In the context of research management, such forecasts are not deterministic decisions; they are probabilistic signals intended to support, not replace, expert judgement. Their value depends on careful feature engineering, data quality control, and clear communication of uncertainty.

A third function concerns collaboration intelligence. Universities increasingly need to understand how expertise is distributed and how internal and external networks can be mobilised strategically. Graph-based methods can analyse co-authorship, project participation, funding relations, and organisational affiliations to identify central actors, structural gaps, and plausible partner constellations. In a pilot setting such as FernUniversität in Hagen (FeU), these methods may be particularly useful for connecting distributed expertise and strengthening interdisciplinary or cross-institutional collaboration opportunities.

Across all these functions, explainable AI is essential. Black-box outputs would be difficult to legitimise in institutional management processes, especially where recommendations may influence resource allocation, strategic priority setting, or proposal preparation. The conceptual design therefore includes feature-level explanations, confidence indications, provenance traces, and human-in-the-loop review options. Such measures are necessary to maintain trust, facilitate contestability, and enable informed interpretation of machine-generated results (Balasubramaniam et al., 2023; Azeroual, 2025b).

8 Governance, Privacy, and Responsible AI

The integration of AI into CRIS raises governance questions that are at least as important as algorithmic design choices. Research information often includes personal, organisational, and evaluative dimensions that require careful handling. For this reason, the proposed module is grounded in privacy-aware and ethically informed design principles. Data minimisation, role-based access, transparency of processing logic, and documentation of model assumptions are not secondary compliance measures; they are constitutive elements of the architecture.

Responsible deployment further requires that model outputs remain advisory and interpretable. In contexts such as funding support or collaboration recommendation, users need to know what the system considered, what it did not consider, and where uncertainty remains. Human oversight is therefore built into the conceptual design, particularly for high-stakes interpretations. Similarly, governance arrangements should define who can access which analytics, how biases are monitored, how feedback is incorporated, and how model performance is reviewed over time. These requirements are consistent with broader debates on trustworthy AI and responsible research assessment within research information management (Alzubaidi et al., 2023; Schöpfel & Azeroual, 2024).

9 Implementation Roadmap and Pilot Workstreams

Although the module has not yet been implemented, the concept implies a clear sequence of pilot workstreams. The first workstream concerns data preparation: inventorying relevant metadata sources within HISinOne RES, assessing data quality, harmonising schemas, and engineering features for semantic, predictive, and network analyses. The second workstream focuses on model development and selection, including topic modelling or embedding-based semantic methods, forecasting or classification pipelines, graph analytics, and explanation techniques. The third workstream addresses technical integration into HISinOne RES, including interfaces, dashboards, access rights, and workflow embedding.

A fourth workstream centres on participatory validation and user acceptance. Workshops, focus groups, and iterative testing cycles should be used to evaluate relevance, comprehensibility, and usability from the perspective of distinct user groups. This is especially important because the value of AI support in CRIS depends on whether users consider outputs actionable within their real work contexts. A fifth workstream addresses governance and ethics, including policy alignment, documentation, auditing routines, and guidance for responsible use. Together, these workstreams create a structured path from conceptual architecture to pilot deployment and later institutional scaling.

The pilot is also expected to generate implementation knowledge beyond the local case. Documenting barriers such as heterogeneous data quality, conflicting expectations, or explanation needs will be critical for transferability. In this sense, the pilot should not only produce a technical prototype but also a set of guidelines and best-practice recommendations for wider adoption across universities and CRIS environments (Azeroual et al., 2025).

10 Discussion

The conceptual design presented here suggests that AI can expand the role of CRIS from documentation infrastructure to strategic intelligence infrastructure. This shift is significant for at least three reasons. First, it reframes institutional metadata as a source of anticipatory insight rather than merely as a compliance or reporting resource. Second, it strengthens the ability of universities to coordinate complex research landscapes through semantically and analytically enriched views. Third, it creates new expectations regarding accountability and interpretability because algorithmic outputs enter domains that are institutionally consequential.

At the same time, the concept should not be interpreted as technological determinism. Predictive indicators and recommendations cannot replace expert judgement, contextual knowledge, or deliberative governance. Their value lies in augmenting human interpretation, surfacing patterns that would otherwise remain hidden, and supporting more informed institutional conversations. In this respect, the proposed AI module should be understood as a socio-technical decision-support system rather than an automated management engine.

The pilot at FernUniversität in Hagen (FeU) is important precisely because it allows these issues to be explored in a real operational setting. A key scientific contribution of the project is therefore methodological: it provides a testbed for understanding how AI, governance, and user-centred design can be aligned in CRIS environments. This is highly relevant to the euroCRIS community, where questions of interoperability, standards, responsible metrics, and AI-enabled research information management are increasingly interconnected.

11 Conclusion

This paper has developed a conceptual framework for integrating a modular AI component into HISinOne RES, using FernUniversität in Hagen (FeU) as a pilot context. The framework responds to a clear limitation of conventional CRIS implementations: their tendency to remain retrospective and descriptive despite growing institutional demand for proactive, contextualised, and trustworthy decision support. By combining semantic enrichment, predictive analytics, collaboration intelligence, and explainability within an existing CRIS environment, the proposed design outlines how research information systems can evolve into more dynamic and strategic infrastructures.

The contribution is intentionally conceptual, but it is not speculative. It defines concrete analytical functions, governance requirements, and implementation workstreams that can guide a future pilot. It also foregrounds responsible AI principles, participatory design, and transparency as prerequisites for institutional legitimacy. As such, the paper offers both a local planning framework for FernUniversität in Hagen (FeU) and a transferable model for other universities seeking to integrate AI into research information management responsibly and effectively.

Future work will need to focus on implementation, empirical evaluation, and comparative transfer across institutional contexts. Nevertheless, the conceptual blueprint already demonstrates that AI-enhanced CRIS can be designed in a way that is operationally useful, ethically grounded, and aligned with the evolving role of research information systems in Europe.

References

- Alzubaidi, L., Al-Sabaawi, A., Bai, J., Dukhan, A., Alkenani, A. H., Al-Asadi, A., ... & Gu, Y. (2023). Towards risk-free trustworthy artificial intelligence: Significance and requirements. *International Journal of Intelligent Systems*, 2023(1), 4459198. <https://doi.org/10.1155/2023/4459198>
- Arrieta, A. B., Díaz-Rodríguez, N., Del Ser, J., Bennetot, A., Tabik, S., Barbado, A., ... & Herrera, F. (2020). Explainable Artificial Intelligence (XAI): Concepts, taxonomies, opportunities and challenges. *Information Fusion*, 58, 82–115. <https://doi.org/10.1016/j.inffus.2019.12.012>
- Asserson, A., & Jeffery, K. (2010). CRIS and institutional repositories. *Data Science Journal*, 9, CRIS14-CRIS23. <https://doi.org/10.2481/dsj.CRIS3>
- Azeroual, O., Storl, U., Rothfritz, L., Schöpfel, J., Herb, U., & Borges, G. (2025). Datenmanagement 4.0: Künstliche Intelligenz als Treiber für innovative Forschungsinformationssysteme. *Information-Wissenschaft & Praxis*, 76(1), 32-42. <https://doi.org/10.1515/iwp-2024-2048>
- Azeroual, O. (2025a). AI4Knowledge: Shaping the Future of Research Data Systems. In 2025 International Conference on Artificial Intelligence, Computer, Data Sciences and Applications (ACDSA) (pp. 1-7). IEEE. <https://doi.org/10.1109/ACDSA65407.2025.11166485>
- Azeroual, O. (2025b). Beyond Black Boxes: Adaptive XAI for Dynamic Data Pipelines. In Proceedings of the 17th International Joint Conference on Knowledge Discovery, Knowledge Engineering and Knowledge Management (Vol. 2, pp. 428-437). <https://doi.org/10.5220/0013736100004000>
- Azeroual, O. (2025c). AI-CRIS Knowledge Hub: Driving Innovation in Research Information. Strategic Membership Meeting 2025 - Autumn (Izmir). <http://hdl.handle.net/11366/2794>
- Balasubramaniam, N., Kauppinen, M., Rannisto, A., Hiekkanen, K., & Kujala, S. (2023). Transparency and explainability of AI systems: From ethical guidelines to requirements. *Information and Software Technology*, 159, 107197. <https://doi.org/10.1016/j.infsof.2023.107197>
- Barabási, A. L. (2016). *Network science*. Cambridge University Press, Cambridge.

Biesenbender, S., Petersohn, S., & Thiedig, C. (2019). Using Current Research Information Systems (CRIS) to showcase national and institutional research (potential): research information systems in the context of Open Science. *Procedia Computer Science*, 146, 142-155. <https://doi.org/10.1016/j.procs.2019.01.089>

Cannarsa, M. (2021). Ethics guidelines for trustworthy AI. *The Cambridge handbook of lawyering in the digital age*, 30, 97-283. <https://doi.org/10.1017/9781108936040.022>

De Castro, P., Shearer, K., & Summann, F. (2014). The gradual merging of repository and CRIS solutions to meet institutional research information management requirements. *Procedia Computer Science*, 33, 39-46. <https://doi.org/10.1016/j.procs.2014.06.007>

Doshi-Velez, F., & Kim, B. (2017). Towards a rigorous science of interpretable machine learning. *arXiv preprint arXiv:1702.08608*. <https://doi.org/10.48550/arXiv.1702.08608>

Fabre, R., Egret, D., Schöpfel, J., & Azeroual, O. (2021). Evaluating the scientific impact of research infrastructures: The role of current research information systems. *Quantitative Science Studies*, 2(1), 42-64. https://doi.org/10.1162/qss_a_00111

Fortunato, S., Bergstrom, C. T., Börner, K., Evans, J. A., Helbing, D., Milojević, S., ... & Barabási, A. L. (2018). Science of science. *Science*, 359(6379), eaao0185. <https://doi.org/10.1126/science.aao0185>

Hevner, A. R., March, S. T., Park, J., & Ram, S. (2004). Design science in information systems research. *MIS quarterly*, 28(1), 75-106.

Hogan, A., Blomqvist, E., Cochez, M., d'Amato, C., Melo, G. D., Gutierrez, C., ... & Zimmermann, A. (2021). Knowledge graphs. *ACM Computing Surveys (Csur)*, 54(4), 1-37. <https://doi.org/10.1145/3447772>

Newman, M. (2018). *Networks*. Oxford University Press.

Nickel, M., Murphy, K., Tresp, V., & Gabrilovich, E. (2015). A review of relational machine learning for knowledge graphs. *Proceedings of the IEEE*, 104(1), 11-33. <https://doi.org/10.1109/JPROC.2015.2483592>

Rybinski, H., Skonieczny, L., Koperwas, J., Struk, W., Stepniak, J., & Kubrak, W. (2017). Integrating IR with CRIS - a novel researcher-centric approach. *Program*, 51(3), 298-321. <https://doi.org/10.1108/PROG-04-2017-0026>

Schöpfel, J., & Azeroual, O. (2024). Responsible research assessment and research information management systems. *Encyclopedia*, 4(2), 915-922. <https://doi.org/10.3390/encyclopedia4020059>

Sivertsen, G. (2019). Developing Current Research Information Systems (CRIS) as data sources for studies of research. In *Springer handbook of science and technology indicators* (pp. 667-683). Springer. https://doi.org/10.1007/978-3-030-02511-3_25

Van Noorden, R., & Perkel, J. M. (2023). AI and science: what 1,600 researchers think. *Nature*, 621(7980), 672-675. <https://doi.org/10.1038/d41586-023-02980-0>

Zendulková, D., Azeroual, O., & Krivjanská, A. (2025). From Data Silos to FAIR Research: Interoperability and Integration in European CRIS. In *Digitalization and Management Innovation IV* (pp. 228-240). IOS Press. <https://doi.org/10.3233/FAIA250723>