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From realism and socio-cognitivism to AI constructs: enhancing domain analysis through artificial intelligence?

Martin Thellefsen and Alon Friedman

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Abstract

Introduction. This study explores the integration of artificial intelligence (AI) within the framework of domain analysis (DA), traditionally grounded in socio-cognitive and realist perspectives. The aim is to assess AI's potential to enhance DA's focus on contextual and disciplinary knowledge, while examining possible epistemological challenges.

Method. Building on established concepts from Hjørland's socio-cognitive DA framework, this paper employs a theoretical review to examine AI's capacity to augment DA by improving classification, retrieval and interdisciplinary mapping within knowledge organisation.

Analysis. The study critically analyses how AI may either enhance or disrupt DA's philosophical foundations by potentially reducing domain specificity. Particular attention is given to AI's tendency toward generalisation, which could dilute DA's contextual sensitivity.

Results. The findings suggest that while AI has transformative potentials for DA, there is a risk of oversimplifying epistemic structures. AI could reorient DA towards machine-centric interpretations, limiting DA's capacity to accommodate complex, domain-specific nuances.

Conclusion(s). The paper concludes that AI can benefit DA if carefully integrated, respecting its epistemological depth. Future research should focus on developing AI approaches that enhance DA without undermining its socio-cognitive foundations.

Introduction

Domain Analysis or DA was originally formulated by Birger Hjørland and Hanne Albrechtsen (Hjørland and Albrechtsen, 1995), as a socio-cognitive framework developed as an alternative to the user-centred cognitive view proposed by Nicolas Belkin (Belkin, 1990). While the cognitive view focused on how cognitive structures influence individual information behaviour and interactions with information systems, DA shifted the focus to a broader socio-cognitive perspective, and emphasised how social factors, such as culture, language, knowledge interests and context shape the conduct of individuals within information environments. In this view, understanding information behaviour necessitates examining not only individual mental states but also the broader social context that influences them. Therefore, DA stands as a critical response to the individualist epistemology inherent in the cognitive view.

Today, the advent of AI represents a significant disruptive force in both public and professional information environments. AI research is not only changing the theoretical landscape but also the methodologies by which we are searching for new knowledge. This technological shift calls for a recalibration of foundational theories within Library and Information Science (LIS) and knowledge organisation (KO). The emphasis on human cognition, socially motivated behaviour, intentionality and meaning-making, principles already central to DA, has become even more pertinent in the context of AI (Cox, 2023), raising questions about how or in what respect AI can simulate human cognition, social behaviour and interpretive processes. The underlying assumption of this paper is that AI, as a forceful transformative technology, has already reshaped tasks and functions within LIS and knowledge-producing communities. Given that AI impacts both individuals and communities, this paper examines how AI influences the information environment from a LIS standpoint.

The scope of the paper

While DA was introduced as a reorientation or a new horizon in information science (Hjørland and Albrechtsen, 1995), it was later developed methodologically by Hjørland (2002) and in an even more applied sense by Smiraglia (2015), both suggesting eleven non-exclusive methodological approaches to knowledge organisation (KO). Methodologically DA has also been discussed by Tennis (2003) seeking to encapsulate the breadth and depth of domains, in order to delineate what is being studied and what is excluded in a DA, a view that was incorporated in Smiraglia's methodological work.

Thus, the focus of this paper is aimed at whether AI technologies can improve DA and is guided by two primary questions:

1. In what ways can artificial intelligence integrate with and augment traditional domain analytical methodologies to facilitate the development of more adaptive and dynamic knowledge organization systems?

2. In what ways can artificial intelligence enrich DA by mitigating human-centred biases and improve the elucidation of knowledge structures, while safeguarding a sensitivity to the social and epistemological dimensions as articulated in DA?

This paper utilises artificial intelligence (AI) as both a conceptual and a methodological lens to explore its integration into domain analysis (DA). Since its conception in the mid-1950s, when John McCarthy envisioned simulating learning and intelligence in machines (McCarthy et al., 2007), AI has evolved into sophisticated models for data processing and decision-making, including subfields like Natural Language Processing (NLP) and, more recently, Large Language Models (LLMs) (Dwivedi et al., 2021; Goel, 2017). While LLMs such as ChatGPT analyse global linguistic resources, their effectiveness in handling domain-specific terminology can vary depending on context and training data (Ashcroft and Whitaker, 2024; Matarazzo and Torlone, 2025). To address this, researchers are exploring DA's socio-cognitive framework to develop nuanced, domain-sensitive models that can advance AI's capacity to meet specialised knowledge organisation needs (Ge et al., 2024). This study examines how these AI developments could augment or challenge DA's focus on contextual and disciplinary knowledge.

Theoretical assumptions of DA

DA is primarily concerned with uncovering and understanding the structures and dynamics of knowledge domains. It focuses on how knowledge is produced, organised and used within specific communities. Theoretically the framework adopts a realist stance, leaning towards scientific or pragmatic realism (Hjørland, 2004). Hjørland's realist perspective, influenced by Thomas Kuhn's ideas on paradigms, argues that while theories shape our ontologies, reality resists arbitrary conceptual structures through anomalies which highlight the misalignments between concepts and the world.

In a similar vein, critical realism, as articulated by Roy Bhaskar (Bhaskar, 1978), provides a framework for understanding how reality encompasses both events and perceptions of those events. Perceptions fuel theories and assumptions, which are shaped by diverse epistemological views. Social constructivism, for instance, explains how conceptual knowledge is grounded in social processes, norms and ideals, while also recognising that reality imposes constraints on socially constructed views (see also Thellefsen, 2023). Concepts like democracy or human rights are socially motivated, evolving over time, but they encounter resistance from the more stable elements of reality.

This dialectical relationship between the real and the socially constructed is a fundamental foundation of DA, that emphasises the interplay between social processes and knowledge production within specific domains. Central to this analysis are communities of practice, or discourse communities, as domains are defined by shared goals, language, norms and tools. However, DA also recognises that the meaning and relevance of information are context-dependent and shaped by the situations in which they are used. However, even though DA does acknowledge the social conduct and context dependence of users' information behaviour, DA should avoid being based on arbitrary user needs or preferences, as this would tend to favour subjectivity over the pursuit of general domain knowledge (Hjørland, 2009).

Furthermore, DA is also sensitive to the often interdisciplinary nature of knowledge production, thus examining the interactions between different fields and how they influence each other. It explores the concept of epistemic cultures, which refers to the specific ways in which knowledge is produced and validated within a domain, echoing Thomas Kuhn's paradigm theory (Kuhn, 1962). However, interdisciplinarity also poses a significant challenge for DA, because each domain often has its own unique taxonomy, terminology and conceptual frameworks, which can be incommensurable with those of other domains. This means that the categories and concepts in one domain may not have direct equivalents in another, which makes it difficult to integrate or compare knowledge across domains.

The existence of interdisciplinarity in a scholarly community may be conflicting at an ontological level, but can intersect epistemologically and teleologically. For instance, a social scientist and a biologist might have different views on what constitutes an individual or a group, leading to ontological disagreements; however, both may use statistical analysis to interpret data, share methods of enquiry and pursue common goals.

As a result, interdisciplinarity can lead to the emergence of new domains. When scholars combine methods and insights from multiple disciplines to tackle complex problems, they often develop new frameworks and taxonomies. This process can be seen as the initial step in the formation of a new domain that encompasses aspects of the contributing fields.

It would seem that AI offers significant potentials to enhance DA both theoretically and methodologically. By automating and refining the time-consuming processes required in relation to developing specialised classification systems, conducting systematic information retrieval, performing user studies, bibliometrics and critical inquiry, AI may contribute to a cost effective and deeper understanding of how knowledge is structured, accessed and used across various domains. AI has the remarkable ability to perform a wide range of tasks, from gathering and processing vast and diverse datasets to analysing patterns and trends. It can then distil complex results into human-readable language, making it accessible. Those capabilities allow AI to excel in data-intensive applications, where it can efficiently gather, filter and interpret information far beyond human capacity. By automating these processes, AI not only enhances productivity, but also provides us with the ability to improve DA theoretically and methodologically.

This technological advancement may mitigate some of the challenges posed by interdisciplinarity and the incommensurability of domain-based taxonomies, as AI can identify and map connections between disparate fields. Moreover, by minimising reliance on arbitrary user needs or preferences, AI reduces subjectivity, aligning with the pursuit of general knowledge. This interplay between AI and DA not only enriches LIS research but also prompts a reassessment of how we conceptualise knowledge in an increasingly AI-driven world.

However, we will raise some critical questions in the discussion section regarding how AI fundamentally differs from human intelligible behavior in terms of reasoning, purpose and transparency.

LIS and epistemology of knowledge discovery

Throughout the history of LIS, epistemology has played a vital role, guiding researchers in exploring how knowledge is created, validated and shared. In LIS, epistemology influences the design of information systems, the organisation of knowledge and user interactions with information.

In the field of AI, Luger (2021) argues that AI systems embody an epistemic stance where knowledge is actively constructed, tested and revised through interactions with their environment. This approach aligns closely with pragmatic realism, which holds that truth is not absolute but emerges through practical success and adaptability. AI systems, much like humans, engage in a process of model-building that attempts to represent aspects of the world. The goal here is not to arrive at an objective truth, but to create models that function effectively in specific contexts, where their success is measured by utility and adaptability rather than by absolute accuracy.

Luger also suggests that AI systems reflect a constructivist epistemology, where knowledge is not passively received but actively built and continuously adjusted based on new data and experiences. This dynamic, iterative process highlights AI's role as a constantly evolving construct, much like human understanding.

Furthermore, Luger incorporates neopragmatic ideas from philosophers such as Kuhn and Rorty to emphasise that AI's pursuit of knowledge is grounded in specific applications and goals. Thus, AI is a tool which value is proven through practical use and relevance, contrasting it with traditional epistemological views that seek objective truths. As a result, AI embodies a form of pragmatic realism, where its validity is inherently contextual and action oriented.

Integrating AI with DA

In the domain of knowledge organisation (KO), Hjørland's analyses (Hjørland, 2013) delve into the progressive integration of user-centred and cognitive frameworks that began to prominently evolve during the 1970s and 1980s. He critically assesses instances where these frameworks have been claimed to focus on user preferences and cognitive strategies, such as in the Book House system (Mark Pejtersen, 1989) and in the application of the word association method for thesaurus construction (Lykke Nielsen, 2002). Hjørland challenges these claims, arguing that they often mask a superficial integration of actual user needs, overshadowed by a combination of empirical research and the broad application of cognitive theories that may not truly reflect actual user data. Instead, Hjørland advocates for a more holistic and socially grounded understanding of users' information behaviour that is sensitive to domain-specific knowledge and the social nature of meaning-making processes.

Inspired by Hjørland's critical investigation of the cognitive view and user-centred approaches in KO, we identified six empirical research perspectives that are relevant for our discussion: *critical evaluation of user-centred designs*, *role of empirical data*, *cultural and disciplinary contexts*, *beyond one-size-fits-all approaches*, *interdisciplinary insights* and *future directions in context-sensitive cognition*.

Critical evaluation of user-centred designs: Hjørland (2002b, 2013) is critical of the assumptions underlying cognitive and user-centred approaches, particularly those that suggest a universal model of cognitive functions. He contends that such approaches overlook the deeply embedded, context-dependent nature of knowledge practices, which are shaped by social, cultural and disciplinary factors. Instead of relying on general models that presume a uniformity in user behavior, Hjørland insists that (KO) must be grounded in the specific realities of various domains. This means attending to how knowledge is constructed, shared and utilised within particular communities rather than seeing users as isolated from these broader social and epistemological structures.

In this respect, Torkamaan et al. (2024) propose a framework for designing systems that considers various dimensions, such as technology, user needs and broader human and societal concerns. While this approach acknowledges some of the factors that Hjørland emphasises, he would advocate for an even deeper integration of domain-specific perspectives. For Hjørland, the key lies in understanding that knowledge is not merely a product of user preferences but is embedded within the norms, values and practices of specific fields. Thus, systems should be informed by the nature of the knowledge itself, not just by user interactions.

This perspective is also relevant to the work of Förster et al. (2023) and Dodeja et al. (2023), who emphasise the importance of creating systems that users find intuitive and relevant. They focus on making systems more transparent and understandable, which is important for fostering trust and engagement. However, Hjørland would argue that systems must do more than respond to what users find immediately useful or satisfying: they must be developed with a sensitivity to the deeper structures of knowledge within specific disciplines. User-centred design should not be an end in itself, but rather a means to engage with the richness of the domain in which users are situated.

The approaches taken by Lombardi et al. (2017) and Lai et al. (2021), which emphasise the role of empirical data in refining and adapting systems, resonate with aspects of Hjørland's thought. They recognise the value of grounding systems in evidence from real-world interactions, which moves beyond purely theoretical constructs. Yet, for Hjørland, the true value of empirical data lies not just in its ability to reflect user behaviour but in its capacity to reveal how knowledge functions within different contexts. In this sense, the iterative refinement of systems should be guided by a deeper understanding of the principles that govern knowledge production and organisation within specific domains.

Rather than simply adapting to user feedback, Hjørland's view calls for a more holistic approach, one that integrates empirical observations with an appreciation for the socio-cultural and epistemological underpinnings of knowledge domains. Such an approach ensures that systems are not only responsive to immediate needs but are also aligned with the deeper currents that shape how knowledge is formed and communicated within particular communities. In doing so, the design of knowledge systems can move beyond surface-level adjustments and instead engage more fully with the complexity of the knowledge landscapes they aim to serve.

Role of empirical data: For Hjørland, the value of empirical data lies in its ability to ground knowledge organisation theories in the realities of specific domains (Hjørland, 2013). He argues that data must not merely support abstract cognitive theories but should be used to reveal the dynamics of knowledge as it is practised within particular social and disciplinary contexts. Empirical data, in this view, is not just a means of refining models but a way to understand how knowledge structures operate within different fields, providing insights into how information is accessed, interpreted and utilised by communities.

This focus on empirical grounding finds some resonance in the work of Lai et al. (2021), who emphasise the importance of empirical frameworks for understanding decision-making processes. Their approach, which calls for using data to develop a foundational understanding of interactions, aligns in part with Hjørland's insistence on evidence-based inquiry. Yet, where Lai et al. focus on creating generalisable insights into human-AI interactions, Hjørland would emphasise that such generalisations must always be situated within the specific conditions of each knowledge domain. For him, the empirical inquiry should not aim for universality but rather for a deeper understanding of how knowledge functions within particular social and epistemological frameworks.

Similarly, Lombardi et al. (2017) highlight the role of empirical data in refining decision models through an iterative process. This approach, which seeks to adapt models continuously based on real-world interactions, aligns with Hjørland's critique of theories that rely too heavily on untested assumptions. Lombardi et al. recognise that empirical evidence can provide the necessary feedback to refine models, ensuring their relevance to practical contexts. However, Hjørland would argue that the iterative use of data must also be guided by an awareness of how knowledge is organised and validated within the domains themselves, so that empirical findings do not merely reflect user behaviours but are interpreted through the lens of domain-specific knowledge practices.

For Hjørland, then, the true strength of empirical data is not in its capacity to validate generic cognitive models but in its role as a tool for revealing the complexities of knowledge production in varied contexts. By focusing on how data can illuminate the ways in which knowledge is shaped by disciplinary norms and social structures, he encourages a more context-sensitive approach to knowledge organisation; one that respects the specificity of each domain rather than seeking to flatten knowledge into generalisable patterns. This approach ensures that empirical data is used not merely to refine systems but to deepen our understanding of the intricate relationships between knowledge and the communities that produce and use it.

Cultural and disciplinary contexts: Hjørland (2008, 2010) highlights the fundamental role that cultural and disciplinary contexts play in shaping information-seeking behaviours and the organisation of knowledge. He argues that understanding knowledge requires an appreciation of the specific social, cultural and disciplinary environments in which it is produced and utilised. This perspective challenges approaches that seek universal cognitive explanations, emphasising instead that knowledge is inherently situated within particular traditions, practices and values.

This understanding resonates with the observations of Jaillant and Caputo (2022), who address the complexities of bias and ethical considerations in AI applications within cultural heritage institutions. They argue that AI systems, if not carefully designed, risk overlooking the unique cultural dimensions that shape how information is preserved and accessed. Similarly, Ferrer et al. (2021) explore the layers of bias within AI systems, emphasising that bias can arise during modelling, training and implementation stages. They propose methods for assessing and addressing these biases, noting that effective mitigation requires attention to the interplay between technical, social, legal and ethical considerations.

In contrast to purely technical solutions, Ferrer et al. (2021) underscore the necessity of an interdisciplinary approach, one that aligns closely with Hjørland's insistence on considering the broader contexts in which knowledge systems operate. This means that addressing bias in AI cannot be isolated from the social realities and cultural frameworks that inform how information is processed and understood.

Dai et al. (2024) add to this conversation by focusing on the challenges and opportunities presented by generative AI in fields like professional communication training. They emphasise the importance of cultural sensitivity, emotional intelligence and cross-disciplinary collaboration, acknowledging that effective AI tools must be attuned to the diverse cultural contexts in which they are applied. This emphasis on cultural representation echoes Hjørland's critique of universal cognitive models, emphasising that systems must be aware of the specific environments in which they function.

Together, these studies reinforce the need for a nuanced and context-sensitive approach to designing and deploying information systems. While they tackle issues like bias and ethical challenges in AI, their broader message aligns with Hjørland's view: that knowledge cannot be understood in isolation from the contexts that shape it. Rather than seeking to impose uniform standards, effective systems must respect the rich variety of disciplinary and cultural perspectives that influence how information is created and accessed. By integrating these insights, we gain a deeper understanding of the complex interplay between technology, culture and human knowledge, moving beyond the limits of generic models to embrace the diversity inherent in knowledge practices.

Beyond one-size-fits-all approaches: Hjørland (2004b, 2013) argues against the use of universal cognitive models in knowledge organisation (KO), stressing the importance of creating systems that are flexible and adaptable to the specific needs of different user communities. He maintains that knowledge is not a monolithic entity but is shaped by the particularities of the social, cultural and disciplinary environments in which it is situated. Therefore, effective knowledge systems must be sensitive to these nuances, rather than relying on a uniform approach that assumes all users share the same cognitive frameworks.

This perspective finds resonance in the work of Kirk et al. (2024), who address the challenges of aligning large language models (LLMs) with the diverse values and needs of human users. Both Hjørland and Kirk et al. emphasise that one-size-fits-all solutions are inherently limited, as they fail to account for the varied and evolving nature of human values and knowledge practices. Instead, these authors advocate for systems that are aware of their context and can adapt to different user groups and their specific needs.

Meskó and Topol (2023) further highlight the need for regulatory oversight when it comes to the deployment of LLMs. They argue that given the complexity, flexibility and societal influence of these models, it is essential to develop regulatory frameworks that can evolve alongside technological advancements and respond to diverse applications. This call for adaptable governance echoes Hjørland's own insistence on the necessity of systems that can accommodate the unique conditions of each domain. Rather than imposing standardised models, effective regulation and design must consider the specific contexts in which knowledge and technology are applied.

Hjørland's critique thus extends beyond mere adaptability: it involves a deeper commitment to understanding how knowledge is produced and organised differently across fields. It calls for systems that are not only responsive to change but are grounded in the specific knowledge practices of the communities they serve. In this way, the discussion around LLMs and their societal impact parallels Hjørland's vision for KO; one that respects the diversity and complexity of human knowledge rather than attempting to reduce it to a uniform framework.

Interdisciplinary insights: Hjørland (2002a, 2008, 2015) emphasises that the enrichment of KO is best achieved by integrating insights from various fields such as psychology, anthropology and sociology. He argues that interdisciplinary approaches should delve deeply into the specific epistemological contexts of each discipline rather than merely blending knowledge from different fields. For Hjørland, true interdisciplinarity respects the unique ways in which different domains conceptualise and engage with knowledge, thus ensuring that each domain's contribution is valued on its own terms. This perspective aligns with the approach taken by Boyko et al. (2023), who explore how LLMs can enhance scientific enquiry by supporting human capabilities across different research stages. Their work illustrates how AI can act as a bridge between disciplines, fostering collaboration and facilitating new forms of enquiry. However, consistent with Hjørland's critique, the use of AI should remain sensitive to the specificities of each domain, ensuring that the integration of machine learning tools respects the situated nature of disciplinary knowledge rather than imposing a universal framework. Similarly, Kusters et al. (2020) highlight both the opportunities and the challenges inherent in interdisciplinary AI research. They stress the need for methodological rigor, collaboration and ethical awareness when working across disciplinary boundaries. This aligns with Hjørland's emphasis on grounding KO in a deep understanding of how different domains structure and interpret knowledge. Rather than seeking a simple synthesis, interdisciplinary approaches should aim to map out the relationships between fields, allowing for both the distinctiveness and the shared concerns of each domain to come into focus.

This reflects Hjørland's view that KO must be context-sensitive, recognising the particularities of knowledge practices within different fields. For Hjørland, interdisciplinary engagement should be guided by a respect for the traditions and values that shape each domain, ensuring that collaborative efforts do not dilute the richness of specialised knowledge. Together, these perspectives underline the value of an approach to interdisciplinarity that is consistent with Hjørland's critique of cognitive models. Rather than relying on a one-size-fits-all approach, they advocate for a practice that respects the diversity of knowledge while facilitating meaningful exchanges between disciplines. This view ensures that the integration of insights remain grounded in the specific contexts of each domain, ultimately enriching both the theory and practice of knowledge organisation. By doing so, it becomes possible to address complex challenges while recognising the depth and complexity of the knowledge systems that shape our understanding of the world.

Future directions in context-sensitive cognition: Although Hjørland does not directly address AI, his discussion of socio-cognitive epistemology (Hjørland, 2002b) indicates that cognition is deeply influenced by both immediate interactions and the broader historical and cultural contexts in which it occurs. These ideas present valuable opportunities for enhancing AI systems within KO, offering a framework that recognises the complex, context-sensitive nature of human thought and behaviour. Such a perspective aligns well with contemporary developments in AI, as seen in the work of Gill et al. (2024), who explore the intersection of AI and next-generation computing paradigms. Their focus on autonomic computing systems that can adapt to changing conditions mirrors the dynamic, adaptable nature of cognition that Hjørland describes. Zhao et al. (2022) provide a practical example of cognitive integration in AI, emphasising aspects like engagement, regulation, decision-making and discovery. Their approach to cognitive AI resonates with Hjørland's focus on situated and enculturated cognition, showing how these concepts can inform the design of AI systems that are more attuned to human contexts. They suggest future research directions that align with Hjørland's views, including:

Embodied AI: Developing systems that interact with the physical world in a manner similar to human experience.

Contextual understanding: Creating AI that adapts to a variety of cultural and social contexts.

Human-AI collaboration: Designing systems that work seamlessly with humans to solve complex problems.

Ethical AI: Ensuring that AI is developed and applied responsibly, with attention to societal values.

By pursuing these directions, it becomes possible to develop AI systems that go beyond efficient information processing to better understand and respond to human needs in a nuanced, context-sensitive way. While this discussion does not cover all potential intersections between Hjørland's DA and AI research, it highlights significant overlaps and possibilities for synergy.

The implications of AI in DA, let's discuss

The introduction of AI into DA represents a fundamental shift from traditional epistemological frameworks, challenging long-established concepts within LIS. While classical DA, as defined by Hjørland, is rooted in pragmatic realism (Hjørland, 2004a), linking knowledge to human and socially constructed contexts, AI disrupts these foundations by introducing a machine-driven, data-centred approach, shifting the focus from human interpretation to algorithmic processing and pattern recognition. AI thus challenges the concept of knowledge as a purely human-mediated process and consequently aligns more closely with a (data) constructivist epistemology, where knowledge is created rather than discovered, as argued by scholars like Floridi (2011). Floridi argues that AI-driven knowledge systems may emphasise functional utility over truth and prioritise patterns and correlations within data as valuable regardless of their ontological grounding.

The philosophical study of AI was pioneered by Alan Turing, who posed the question: '*Can machines think*?' (Turing, 1950/2009, p. 23). In his attempt to address this, he introduced the Turing Test, a method designed to evaluate whether a machine's responses could be indistinguishable from those of a human. Turing's work laid the foundation for AI epistemology, framing intelligence as an emergent property of computational processes rather than an exclusively human trait. The shift towards machine epistemology, where AI autonomously constructs knowledge, directly challenges traditional human-centred epistemological assumptions. Floridi (2014) describes this as the '*fourth revolution*,', which redefines epistemology by positioning machines as active participants in knowledge creation. Within LIS, this shift raises critical questions: Do AI-generated knowledge structures represent *real* knowledge, or are they merely functional constructs optimised for transient informational needs? The absence of explicit discussions of AI in DA suggests an opportunity to critically examine how AI-driven classification and knowledge representation align with, or diverge from, traditional human-centred methodologies.

In traditional LIS, knowledge organisation systems are often stable, human-created classifications that evolve slowly over time. AI, conversely, enables dynamic, data-driven knowledge structures that can adapt in real time to new information. AI-driven systems, such as those using LLMs, can continuously refine classifications based on emergent data patterns, rendering the knowledge structure highly flexible and responsive. This ability for AI to rapidly update and reorganise knowledge reflects a move away from static taxonomies towards a more fluid and evolving knowledge system. As a result, LIS practitioners and theorists must reconsider whether AI-driven structures can still fit within the classical view of domain knowledge or whether they signal a fundamentally different way of organising knowledge.

A major theme in DA is the challenge of interdisciplinarity, where knowledge across distinct domains is often incompatible because of their unique terminologies and epistemic frameworks. Kuhn (1962) addresses this as the issue of incommensurability. AI offers potential pathways for bridging these disciplinary divides by integrating disparate data sources and providing holistic models of knowledge. However, the integration facilitated by AI may not equate to true epistemic unification. Instead, it risks merely amalgamating data in ways that do not fully capture, or even obscure, the nuanced, context-rich frameworks within each discipline (see e.g., Edwards, 2010;

Leonelli, 2016; Weinberger, 2011). AI's role in facilitating interdisciplinary knowledge raises questions about the authenticity of such integration. Does AI's ability to connect data across domains represent genuine epistemic synthesis, or is it a superficial blend that sacrifices depth for breadth? The answer depends on whether AI can respect the distinct epistemological bases of each field or if it will create entirely new domains of knowledge that transcend traditional disciplinary boundaries. AI-driven data integration may thus ultimately reshape the boundaries between fields, and lead to the development of hybrid domains that challenge conventional LIS taxonomies.

The ethical dimensions of AI in DA are substantial, particularly in terms of knowledge gatekeeping, transparency and accountability. Traditionally, expert communities within LIS have acted as gatekeepers, curating and validating information to maintain accuracy and credibility. AI democratises knowledge production by automating classification and generation processes, raising questions about who controls the resulting information. Floridi (2013) emphasises the responsibility to maintain ethical standards in automated systems, as AI can produce content without the same oversight as human-driven processes.

André de Tienne's concept of *semioethics* (De Tienne, 2024) is also relevant here, stressing the need for ethical scrutiny in how knowledge is communicated and verified. In AI-driven knowledge systems, the absence of human editorial oversight can result in issues of accuracy, bias and accountability. Without human intervention, there is a risk that AI may propagate unverified or biased information, undermining the reliability of domain-specific knowledge. Thus, there is a growing need for frameworks that address the ethical implications of AI-driven knowledge construction, including who holds accountability for AI-generated content and how such knowledge can be transparently validated.

The incorporation of AI into DA calls for a re-evaluation of the theoretical foundations of LIS, particularly regarding realism, interdisciplinarity and knowledge ethics. As AI continues to reshape the information landscape, LIS scholars and practitioners face open questions: How can human epistemological frameworks be reconciled with machine-driven knowledge systems? Can AI-driven knowledge still be considered real, or does it represent a separate class of practical constructs? Furthermore, as AI challenges the boundaries between disciplines, should new, machine-defined domains be acknowledged in LIS taxonomies?

Future research in LIS must address these questions by developing theories that integrate AI's capabilities while recognising its limitations. This involves creating frameworks that can accommodate AI's adaptive knowledge structures, interdisciplinary potential and ethical considerations, ensuring that DA remains relevant and responsive to the transformative power of AI.

Conclusion

This study demonstrates that KO and AI intersect in their efforts to structure and comprehend information within specific domains. Drawing on Hjørland's definition of DA, we highlight the significance of the human aspect in knowledge organisation, as noted by Roberts et al. (2024). Hjørland's approach stresses the importance of considering the perspectives, practices and epistemologies of human actors within certain fields, ensuring that knowledge systems remain pertinent and accessible. Although our study sheds light on the connections between KO and AI, it also indicates a need for further research to fully explore the potential synergies between DA and AI technologies. Preliminary findings suggest that incorporating the human-centred principles of DA into AI development presents a promising area for future research. By leveraging the strengths of both disciplines, researchers can aid in developing AI systems that are not only technologically sophisticated but also socially responsible and human-focused. This interdisciplinary approach can result in AI applications that better understand and address the nuanced needs of specific knowledge domains, and improve both the efficacy of AI systems and the quality of knowledge organisation. Aligning AI development with the human element reflects the increasing focus on ethical considerations and societal impacts in technology, fostering AI solutions that resonate more closely with human values and the contexts of specific domains.

About the authors

Martin Thellefsen is Associate Professor at the Department of Communication, University of Copenhagen, Denmark. He holds a PhD in Library and Information Science. His research is interdisciplinary and centres on knowledge organisation, information studies and the semiotics of information. He can be contacted at martin.thellefsen@hum.ku.dk

Alon Friedman is Associate Professor at the School of Information, University of South Florida, USA. He holds a PhD in Information Science. He is an interdisciplinary researcher with a particular focus on visualisation theory and the visualisation of data. He can be contacted at alonfriedman@usf.edu

References

Ashcroft, C., & Whitaker, K. (2024). Evaluation of domain-specific prompt engineering attacks on large language models. *ESS Open Archive eprints*, 362, 36267312.

Belkin, N. J. (1990). The cognitive viewpoint in information-science. *Journal of Information Science*, 16(1), 11-15. https://doi.org/10.1177/016555159001600104

Bhaskar, R. (1978). A *realist theory of science*. Harvester Press.

Boyko, J., Cohen, J., Fox, N., Veiga, M. H., Li, J. I., Liu, J., ... & Xie, X. (2023). An interdisciplinary outlook on large language models for scientific research. *arXiv preprint* arXiv:2311.04929. https://doi.org/10.48550/arXiv.2311.04929

Çelikok, M. M., Peltola, T., Daee, P., & Kaski, S. (2019). Interactive AI with a theory of mind. *arXiv preprint* arXiv:1912.05284 https://doi.org/10.48550/arXiv.1912.05284

Clarke, R. (2019). Why the world wants controls over Artificial Intelligence. *Computer Law & Security Review*, 35(4), 423-433. https://doi.org/10.1016/j.clsr.2019.04.006

Cox, A. (2023). How artificial intelligence might change academic library work: applying the competencies literature and the theory of the professions. *Journal of the Association for Information Science and Technology*, 74(3), 367-380. https://doi.org/10.1002/asi.24635

Dai, D. W., Suzuki, S., & Chen, G. (2024). Generative AI for professional communication training in intercultural contexts: where are we now and where are we heading? *Applied Linguistics Review*, AOP. https://doi.org/10.1515/applirev-2024-0184

De Tienne, A. (2024). Pausing the send command: a semioethical methodology to arm the hinge between information and communication. *Informatio (Montevideo.)*, 29(1). https://doi.org/10.35643/Info.29.1.6

Dodeja, L., Tambwekar, P., Hedlund-Botti, E., & Gombolay, M. (2024). Towards the design of user-centric strategy recommendation systems for collaborative human–AI tasks. *International*

Journal of Human-Computer Studies, 184, Article 103216. https://doi.org/10.1016/j.ijhcs.2023.103216

Dwivedi, Y. K., Hughes, L., Ismagilova, E., Aarts, G., Coombs, C., Crick, T., ... & Williams, M. D. (2021). Artificial Intelligence (AI): multidisciplinary perspectives on emerging challenges, opportunities, and agenda for research, practice and policy. *International Journal of Information Management*, 57, 101994. https://doi.org/10.1016/j.ijinfomgt.2019.08.002

Edwards, P. N. (2010). *A vast machine: computer models, climate data, and the politics of global warming*. MIT Press.

Felin, T., & Holweg, M. (2024). Theory is all you need: AI, human cognition, and causal reasoning. *Human Cognition, and Decision Making*. https://dx.doi.org/10.2139/ssrn.4737265

Ferrer, X., Van Nuenen, T., Such, J. M., Coté, M., & Criado, N. (2021). Bias and discrimination in AI: a cross-disciplinary perspective. *IEEE Technology and Society Magazine*, 40(2), 72-80. https://doi.org/10.1109/MTS.2021.3056293

Floridi, L. (2011). *Philosophy of information*: Oxford University Press.

Floridi, L. (2013). *The ethics of Information*. Oxford: Oxford University Press.

Floridi, L. (2014). *The fourth revolution: how the infosphere is reshaping human reality*. Oxford University Press.

Förster, M., Hühn, P., Klier, M., & Kluge, K. (2023). User-centric explainable AI: design and evaluation of an approach to generate coherent counterfactual explanations for structured data. *Journal of Decision Systems*, 32(4), 700-731. https://doi.org/10.1080/12460125.2022.2119707

Ge, Y., Hua, W., Mei, K., Tan, J., Xu, S., Li, Z., & Zhang, Y. (2024). Openagi: when LLM meets domain experts. *Advances in Neural Information Processing Systems*, 3
https://doi.org/10.48550/arXiv.2304.04370

Gill, S. S., Xu, M., Ottaviani, C., Patros, P., Bahsoon, R., Shaghaghi, A., ... & Uhlig, S. (2022). AI for next generation computing: emerging trends and future directions. *Internet of Things*, 19, 10051. https://doi.org/10.1016/j.iot.2022.100514

Goel, B. (2017). Developments in the field of natural language processing. *International Journal of Advanced Research in Computer Science*, 8(3). https://doi.org/10.26483/ijarcs.v8i3.2944

McCarthy, J. (2007). From here to human-level AI. *Artificial Intelligence*, 171(18), 1174-1182. https://doi.org/10.1016/j.artint.2007.10.009

Hjørland, B. (2002a). Domain analysis in information science: eleven approaches - traditional as well as innovative. *Journal of Documentation*, 58(4), 422-462. http://dx.doi.org/10.1108/00220410210431136

Hjørland, B. (2002b). Epistemology and the socio-cognitive perspective in information science. *Journal of the American Society for Information Science and Technology*, 53(4), 257-270. https://doi.org/10.1002/asi.10042

Hjørland, B. (2004a). Arguments for philosophical realism in library and information science. *Library Trends*, 52(3), 488-506.

Hjørland, B. (2004b). Domain analysis: a socio-cognitive orientation for information science research. *ASIS&T Bulletin*, 30(3). http://www.asis.org/Bulletin/Feb-04/hjorland.html

Hjørland, B. (2008). What is knowledge organization? *Knowledge Organization*, 35(2/3), 86-101. http://dx.doi.org/10.5771/0943-7444-2008-2-3-86

Hjørland, B. (2010). The foundation of the concept of relevance. *Journal of the American Society for Information Science and Technology*, 61(2), 217-237. https://doi.org/10.1002/asi.21261

Hjørland, B. (2013). User-based and cognitive approaches to knowledge organization: a theoretical analysis of the research literature. *Knowledge Organization*, 40(1), 11-27. http://dx.doi.org/10.5771/0943-7444-2013-1-11

Hjørland, B. (2015). Theories are knowledge organization systems (KOS). *Knowledge Organization*, 42(2), 113-128. http://dx.doi.org/10.5771/0943-7444-2015-2-113

Hjørland, B., & Albrechtsen, H. (1995). Toward a new horizon in information science: domain-analysis. *Journal of the American Society for Information Science*, 46(6), 400-425. https://doi.org/10.1002/(SICI)1097-4571(199507)46:6%3C400::AID-ASI2%3E3.0.CO;2-Y

Kuhn, T. S. (1962). *The structure of scientific revolutions*. The University of Chicago Press.

Jaillant, L., & Caputo, A. (2022). Unlocking digital archives: cross-disciplinary perspectives on AI and born-digital data. *AI & Society*, 37(3), 823-835. https://doi.org/10.1007/s00146-021-01367-x

Kirk, H. R., Vidgen, B., Röttger, P., & Hale, S. A. (2024). The benefits, risks and bounds of personalizing the alignment of large language models to individuals. *Nature Machine Intelligence*, 6, 383-392. http://dx.doi.org/10.1038/s42256-024-00820-y

Kirsh, D. (1991). Foundations of AI: the big issues. *Artificial Intelligence*, 47(1-3), 3-30. https://doi.org/10.1016/0004-3702(91)90048-O

Kozinets, R. V., & Nocker, M. (2018). Netnography: engaging with the challenges. In *Unconventional methodology in organization and management research* (pp. 127–146). Oxford University Press.

Kusters, R., Misevic, D., Berry, H., Cully, A., Le Cunff, Y., Dandoy, L., ... & Wehbi, F. (2020). Interdisciplinary research in artificial intelligence: challenges and opportunities. *Frontiers in Big Data*, 3, 577974. https://doi.org/10.3389/fdata.2020.577974
Kuhn, T. S. (1962). *The structure of scientific revolutions*. The University of Chicago Press.
Lai, V., Chen, C., Liao, Q. V., Smith-Renner, A., & Tan, C. (2021). Towards a science of human-AI decision making: a survey of empirical studies. *arXiv preprint* arXiv:2112.11471. https://doi.org/10.48550/arXiv.2112.11471

Leonelli, S. (2016). *Data-centric biology: a philosophical study*. University of Chicago Press.

Lombardi, M., Milano, M., & Bartolini, A. (2017). Empirical decision model learning. *Artificial Intelligence*, 244, 343-367. https://doi.org/10.1016/j.artint.2016.01.005

Luger, G. F. (2021). *Knowing our world: an artificial intelligence perspective*. Springer.

Meskó, B., & Topol, E. J. (2023). The imperative for regulatory oversight of large language models (or generative AI) in healthcare. *NPJ Digital Medicine*, 6(1), 120. http://dx.doi.org/10.1038/s41746-023-00873-0

Matarazzo, A., & Torlone, R. (2025). A Survey on large language models with some insights on their capabilities and limitations. *arXiv preprint* arXiv:2501.04040

Mökander, J., & Schroeder, R. (2022). AI and social theory. *AI & Society*, 37(4), 1337-1351. https://link.springer.com/article/10.1007/s00146-021-01222-z

Simon, H. A. (1995). Artificial intelligence: an empirical science. *Artificial Intelligence*, 77(1), 95-127. https://doi.org/10.1016/0004-3702(95)00039-H

Paolo, G., Gonzalez-Billandon, J., & Kégl, B. (2024). A call for embodied AI. *arXiv preprint* arXiv:2402.03824. https://doi.org/10.48550/arXiv.2402.03824

Smiraglia, R. P. (2015). *Domain analysis for knowledge organization*. Chandos.

Tennis, J. T. (2003). Two axes of domains for domain analysis. *Knowledge Organization*, 30(3-4), 191-195.

Torkamaan, H., Tahaei, M., Buijsman, S., Xiao, Z., Wilkinson, D., & Knijnenburg, B. P. (2024). The role of human-centered AI in user modeling, adaptation, and personalization: models, frameworks, and paradigms. In A *human-centered perspective of intelligent personalized environments and systems* (pp. 43-83). Springer Nature Switzerland

Thellefsen, M. M. (2023). Domain analytical information and knowledge organization: investigating the externalist and internalist conception of information. *Journal of Documentation*, 79(1), 21-35. https://doi.org/10.1108/JD-07-2021-0126

Turing, A. M. (2009). Computing machinery and intelligence. In R. Epstein, G. Roberts, & G. Beber (Eds.), *Parsing the Turing test: philosophical and methodological issues in the quest for the thinking computer* (pp. 23-65). Springer Netherlands.

Udeh, E. O., Amajuoyi, P., Adeusi, K. B., & Scott, A. O. (2024). AI-enhanced fintech communication: leveraging chatbots and NLP for efficient banking support. *International Journal of Management & Entrepreneurship Research*, 6(6), 1768-1786. https://doi.org/10.51594/ijmer.v6i6.1164

Wang, Y. (2009). On abstract intelligence: Toward a unifying theory of natural, artificial, machinable, and computational intelligence. *International Journal of Software Science and Computational Intelligence* (IJSSCI), 1(1), 1-17.

Weinberger, D. (2011). *Too big to know: rethinking knowledge now that the facts aren't the facts, experts are everywhere, and the smartest person in the room is the room*. Basic Books.

Zhao, J., Wu, M., Zhou, L., Wang, X., & Jia, J. (2022). Cognitive psychology-based artificial intelligence review. *Frontiers in Neuroscience*, 16, 1024316. https://doi.org/10.3389/fnins.2022.1024316