AI Use Cases in Knowledge and Technology Transfer: Evidence from Expert Interviews

Completed Research Paper

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Abstract

Knowledge and technology transfer units in German public non-university research institutions increasingly experiment with AI, especially large language models, yet adoption remains fragmented and rarely aligned with transfer workstreams. This paper presents a comparative AI use case matrix based on 12 semi-structured expert interviews across major German public research institutions. Using an inductive approach, we distinguish AI use cases already in use, including pilots, from those framed as desired or high-potential, and structure them along a modular KTT reference model from research to spin-off management. The results show a small set of broadly adopted entry-level applications for language-centric knowledge work and content preparation, alongside a larger portfolio of aspirational applications targeting process support, information discovery and triage, evidence synthesis, and decision-oriented workflow automation. We consolidate these findings in a comparative matrix and derive implications for KTT practice, AI-enabled process augmentation, and future evaluation.

Keywords: Artificial Intelligence, Knowledge and Technology Transfer, Large Language Model, AI Use Case, Non-University Research Institution, Inductive Reference Modeling

Introduction

Knowledge and technology transfer (KTT) describes the intentional movement of scientific knowledge and technological developments from research-performing organizations to actors that can apply and value them in economic and societal contexts (Piller et al., 2021). Through these transfer activities, KTT contributes to innovation and entrepreneurship, thereby supporting sustainable development and knowledge-based economies (Bengoa et al., 2020; Cunningham et al., 2019). In the European context, KTT is addressed as a policy-relevant activity of the public research base more broadly, reflecting efforts to strengthen links between publicly funded research and industry within regional, national, and supranational innovation systems (Siegel et al., 2007). Within this landscape, German public non-university research institutions (NURIs) constitute a major group of research organizations alongside universities. These institutions operate under distinct organizational mandates and funding structures, enabling stable research environments and sustained interaction with external partners. As a result, KTT is institutionally embedded in their research activities, making NURIs a particularly relevant context for examining contemporary KTT practices (Etzkorn et al., 2025a).

Prior research shows that KTT is realized through a broad set of distinct channels that extend beyond commercialization activities. These channels include both formally organized mechanisms, such as contracts and intellectual property arrangements, and informally organized modes of interaction, such as collaborative research, consulting, and personal exchanges between researchers and external partners (Bradley et al., 2013; Schaeffer et al., 2018). Studies further indicate that these channels are not used in isolation but coexist within KTT practices, often unfolding in parallel rather than in a predefined sequence (Bradley et al., 2013; Hayter et al., 2020). Empirical evidence suggests that formal and informal transfer activities are interrelated and may complement one another over time, contributing to cumulative and evolving transfer trajectories (Hayter et al., 2020; Schaeffer et al., 2018). As a consequence, KTT cannot be adequately represented as a linear process with clearly separable stages. Instead, it involves heterogeneous activities, multiple actors, and interdependent pathways that develop dynamically across organizational boundaries (Bradley et al., 2013; Hayter et al., 2020). This structural diversity and interactional complexity create a need for mechanisms that can connect information, activities, and actors, and support analytical overview as well as coordination across KTT processes.

Against this background, recent advances in AI suggest potential to support the connection, structuring, and analysis of large volumes of heterogeneous and unstructured data, thereby enabling automation (Coombs et al., 2020), pattern recognition (Kao, 2025), and analytical support for coordinating complex, knowledge-intensive activities (Basole et al., 2024). Conceptually, we understand AI in this study not merely as a set of isolated digital tools, but as an augmentation mechanism for knowledge-intensive KTT work. More specifically, AI can support KTT by improving information retrieval, structuring heterogeneous knowledge, synthesizing evidence for assessment and decision-making, and augmenting recurring communication and documentation tasks. This framing helps explain how AI may contribute to KTT processes across different modules rather than only describing individual applications. This potential has motivated growing scholarly interest in the application of AI to KTT-related activities. Within this domain, prior research has examined AI from two main perspectives: as a technology that itself is transferred to external actors and as a digital tool that supports and augments KTT processes (Etzkorn et al., 2025b). The latter stream has investigated the potential of AI applications across transfer activities, including knowledge representation and inferencing (Bowen & Kumar, 2002), knowledge exchange and collaboration (Arya et al., 2025), and the analysis of intellectual property and commercialization data (Novoselova & Grin, 2020). Empirical studies in this area have predominantly focused on narrowly defined KTT tasks, most notably patent valuation (Kim et al., 2021), transaction prediction (Kim & Geum, 2020), and domain-specific transfer platforms (Loiotile et al., 2024).

Despite the growing body of research on AI applications in KTT, existing studies remain largely fragmented and activity-specific, offering limited insight into how AI use cases are distributed across the broader KTT process within specific organizational settings. In particular, prior work lacks a systematic and comparative mapping of AI use cases along a KTT reference model that captures both formal and informal transfer activities in public research organizations. As a result, it remains unclear which AI-supported practices are already implemented in KTT organizations, particularly in NURIs with institutionalized transfer mandates, and which applications are perceived as desirable or promising for future use. To address this gap, this study asks the following research questions:

RQ: *Which AI use cases are currently employed in KTT activities within public non-university research organizations, and which AI use cases are desired or perceived as high-potential?*

To answer these questions, the objective of our study is to develop an empirically grounded AI use-case matrix that contrasts current usage with perceived future potential across KTT activities in NURIs. To achieve this objective, the study draws on expert interviews with professionals from German public NURIs, enabling a comparative, multi-case analysis of AI use cases across organizational contexts within this institutional setting. The remainder of the paper is structured as follows. The next section reviews the research background and related work. This is followed by a description of the research methodology, including data collection and analysis. The subsequent section presents the empirical results of the study. The paper then discusses the findings and outlines implications for research and practice. The final section concludes the paper and highlights directions for future research.

Research Background and Related Work

NURIs are key actors in national innovation systems, translating scientific knowledge into societal and economic value through dedicated KTT units (Etzkowitz & Leydesdorff, 2000; Siegel et al., 2007). In Germany, NURIs rely on KTT units to manage activities such as IP (Intellectual Property) protection, licensing, industry collaboration, and spin-off support. Prior research characterizes KTT work as knowledge-intensive, process-diverse, and strongly dependent on professional judgment and coordination across organizational boundaries (Perkmann et al., 2013; Wright et al., 2007).

While digital tools have become common in KTT, their use has largely remained fragmented and weakly aligned with end-to-end transfer processes (Audretsch et al., 2012). In parallel, IS (Information Systems) research highlights AI as a general-purpose technology with the potential to augment knowledge work, decision-making, and organizational processes (Rai et al., 2019). Recent studies further emphasize the role of generative AI in augmenting information practices in knowledge-intensive work, including knowledge generation, evaluation, explanation, and communication. In the KTT-related domain, emerging work also points to AI-supported knowledge exchange and collaboration between research organizations and external partners. Empirical studies show that early AI adoption typically focuses on low-risk, language-centric tasks such as text drafting, summarization, and information retrieval, whereas more advanced, process-integrated applications remain aspirational (Jarrahi et al., 2025).

LLMs (Large Language Models) are increasingly discussed as a flexible augmentation layer for knowledge-intensive work because they support core information practices such as producing, evaluating, and communicating text-based knowledge artifacts (Jarrahi et al., 2025). Evidence from controlled experiments suggests that generative AI can measurably improve performance in professional writing tasks, aligning with early organizational use in drafting and revision (Noy & Zhang, 2023). To move beyond isolated text work toward reliable knowledge support, Retrieval-Augmented Generation (RAG) has emerged as a dominant design that grounds model outputs in retrieved sources and improves factuality for knowledge-intensive tasks (Lewis et al., 2020). However, scaling such applications from tool-level pilots to process-integrated deployments remains difficult in practice, with persistent challenges around governance, integration, and heterogeneous impacts across workers and tasks (Brynjolfsson et al., 2023).

Knowledge and Technology Transfer in Non-University Research Institutions

A recent and empirically grounded presentation of the status quo of KTT is provided by Etzkorn et al. (2025a). The present study builds on the “Reference Model of Knowledge and Technology Transfer in Non-University Research Institutions” introduced in that prior work. The model comprises 10 modules that systematically structure the transfer process. In the reference model, a module is defined as a functionally delimited building block (represented as a separate box in the model) that captures a specific task area and corresponding subprocess within the overall KTT process. Taken together, the modules provide a structured decomposition of KTT activities along the transfer process. **Research (M1)** represents the core mission of the research institution. It encompasses the generation of scientific knowledge, technologies, and methodological advancements through research activities. **Technology and Method Identification (M2)** marks the first point at which the Technology Transfer Office (TTO) formally intervenes in the process. In this module, the TTO identifies technologies, methods, or other forms of knowledge with transfer potential. These may originate from internal research activities or emerge through external inputs and interactions with stakeholders from science, industry, politics, or society. **Transfer Case Processing (M3)** initiates the pathway of non-economic exploitation. This module focuses on the organization and management of non-commercial transfer channels, particularly teaching, cooperative research, participatory research like citizen science, and committee work. The objective is to facilitate the dissemination and application of knowledge beyond purely commercial contexts. **Invention Processing (M4)** addresses the handling of invention disclosures. Within this module, reported inventions are systematically examined and prepared for potential economic exploitation. This constitutes the transition from general knowledge generation to structured commercialization processes. Subsequently, **Patent Research and Processing (M5)** involves assessing whether the developed technology fulfills the legal and substantive requirements for patent protection. This includes conducting prior art researches to determine novelty and non-obviousness, evaluating potential conflicts with existing patents, and, where appropriate, formally filing a patent application. In parallel with these activities and as part of the economic exploitation pathway, **Market Research (M6)** is conducted to evaluate the commercial potential of the technology under consideration. **Contact Management (M7)** concerns the identification and coordination of the individuals required for processing a specific transfer case. Under the responsibility of the TTO, relevant internal and external stakeholders are identified, approached, and integrated into the transfer process to ensure its effective implementation. **Knowledge Management (M8)** constitutes a distinct and cross-cutting strand within the model. Its primary objective is to enable systematic access to knowledge available within the organization and to ensure that knowledge generated during transfer activities is stored in a structured manner. By doing so, the institution facilitates the reuse of knowledge in future transfer cases and supports organizational learning. **Contract Management (Licensing) (M9)** represents one of the principal transfer channels within the economically oriented transfer pathway. This module focuses on the formal transfer of intellectual property rights to existing companies or to start-ups established in connection with module ten. It includes the negotiation, drafting, and administration of licensing agreements and other contractual arrangements governing the commercialization of protected knowledge and technologies. Finally, **Spin-Off Management (M10)** addresses the creation and

development of new ventures based on the institution's intellectual property, transfer concepts, patents, or invention disclosures. This module encompasses the structured support of spin-off projects, from early-stage planning and validation to the formal establishment and further development. The described reference model, comprising its 10 modules M1 to M10, can be viewed and traced in the following figure 1, as outlined above.

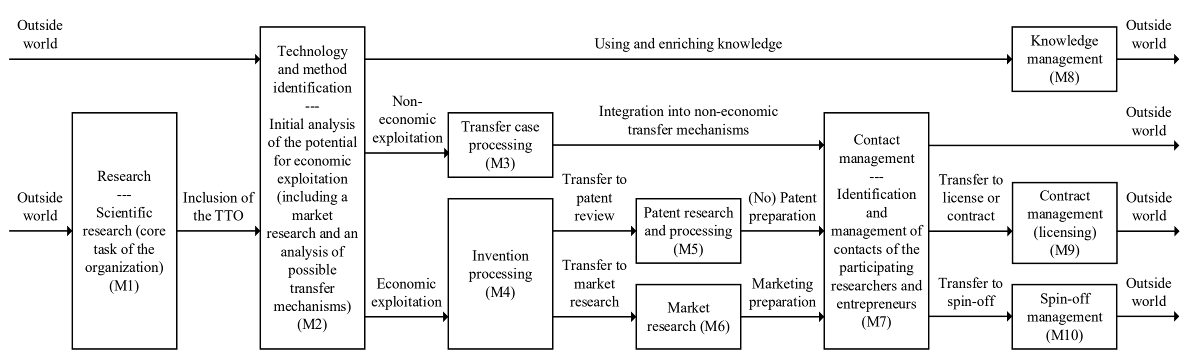

Figure 1: KTT Reference Model (Etzkorn et al., 2025a)

Methodology

To capture practice-based, context-specific insights into how KTT is currently organized and where AI-related needs and opportunities emerge, we chose a qualitative interview approach.

In the period from May to July 2025 we interviewed 12 KTT experts from German NURIs. The sample consists of two interviews with experts from each of the large German NURIs (Fraunhofer Society, Helmholtz Association, Leibniz Association, Max Planck Society), two from the medium-sized German Research Center for Artificial Intelligence (DFKI) and two from smaller NURIs (Max Weber Foundation, Hasso Plattner Institute (HPI)). The sample was selected purposively to capture variation across large, medium-sized, and smaller German NURIs and to include experts with direct responsibility for KTT activities. The interviewees therefore covered different KTT-related responsibility profiles, including transfer leadership, technology transfer, innovation management, and institution- or institute-level transfer coordination. Accordingly, the aim of the sampling strategy was analytical depth and cross-case comparison within this institutional context rather than statistical generalization. The prerequisite for interview partners was that they hold a position of responsibility for the transfer of the entire institution or an assigned institute (e.g., Head of Transfer, Technology Transfer Officer, or Innovation Manager).

Data was collected through semi-structured interviews. Semi-structured interviews allow for a conversational flow that enables interviewers to probe deeper into participants' experiences, opinions, and emotions, which can yield rich, contextualized data (Potter, 2018). This method fosters rapport and trust between the interviewer and interviewee, leading to more genuine and detailed insights, especially when addressing complex or sensitive topics (Adams, 2010). The interview guide was developed in accordance with the guidelines proposed by Sreejesh et al. (2014) and aimed to assess the current state and future development of KTT within the interviewees' organizations. The study seeks to identify the digital tools and systems currently used in KTT activities within NURIs, and to map the relevant data inputs, outputs, and flows. To structure this analysis, the reference model proposed by Etzkorn et al. (2025a) is adopted as an analytical framework. The study further analyzes key structural and procedural challenges and examines where artificial intelligence could enhance efficiency or address existing gaps. Overall, the study evaluates current practices and identifies opportunities for digital and AI-driven improvement in KTT. To structure the discussion, the interviewer presented a framework of KTT in NURIs, which was based on the work of Etzkorn et al. (2025a). The interviews were operated online via MS Teams. The length of the interviews conducted ranged from 40 to 62 minutes. The average length of an interview was 50 minutes.

In the subsequent data analysis, the interview transcripts and the notes taken during the interviews were examined. The analysis followed the principles of Qualitative Content Analysis as proposed by Mayring (2014) and Kuckartz (2014). Given the exploratory character of the study, the analysis did not follow a formal multi-coder procedure and therefore does not report inter-coder reliability. Instead, the analysis focused on the inductive identification and structured consolidation of recurring AI use cases across interviews. To increase transparency, the coding proceeded in three steps: first, passages referring to concrete, piloted, or envisioned AI applications were identified; second, similar applications were grouped into preliminary use-case categories; and third, these categories were refined, labelled, and assigned to either current/pilot use or desired/high-potential use based on the interview material. In the first stage of the data analysis, passages referring to concrete, piloted, or envisioned AI applications in KTT practice were identified and compared across interviews. Similar applications were iteratively grouped and refined into recurring AI use-case patterns. When at least two separate mentions of a similar case occurred, whether as already in active use/pilot phase or as an expressed need, wish, or perceived potential, the AI use case was consolidated into a defined AI use case. This threshold was used as a pragmatic consolidation rule for identifying recurring patterns, not as a statistical criterion for representativeness. In a small number of exceptional instances, single in-active-use AI use cases were retained where they represented already implemented instances of broader themes that otherwise recurred as desired or high-potential categories across interviews. Their retention was therefore based on their connection to broader recurring demand themes rather than on frequency alone. To avoid overstating their generality, these single-occurrence categories are treated as illustrative implementation examples rather than as broadly recurring current-practice patterns. The first stage of the data analysis resulted in the identification of 15 AI use cases. Among the 15 identified AI use cases, six were classified as already in active use or in pilot phase and were numbered UC1 to UC6. In the cross-interview matrix, these were marked accordingly with "X" (in active use) or "P" (in pilot phase) whenever the respective AI use case was reported in a given interview. Nine AI use cases were described as desired capabilities or potential needs; these were numbered D1 to D9 (D = Desired AI Use Case) and were likewise marked with an "X" whenever an interview indicated demand, a wish, or perceived potential for the respective AI use case within the organization. In the second stage of the data analysis, the AI use cases were assigned to the modules of the reference model according to Etzkorn et al. (2025a). This mapping was developed as an interpretive, inductive, and argumentatively grounded analytical step based on the interview material and the previously consolidated AI use cases. Accordingly, the narrative discussion of Matrix 3 and Matrix 4 does not aim to reproduce interview evidence module by module through additional quotations, but to provide a process-oriented interpretation of where the identified AI use cases are currently located or expected to become relevant along the KTT process. This is intended to illustrate the process steps and areas in which the defined AI use cases can be applied. The results of the analysis are presented in the following chapter.

Results

This section reports the empirical findings from the 12 expert interviews and synthesizes them into a comparative AI use-case landscape for KTT in German public NURIs. The purpose of presenting the results is twofold: first, to make transparent which AI applications are already being used in practice or piloted, and second, to contrast these with applications described as desired or as particularly high-potential for future support of transfer work.

To this end, the AI use cases mentioned in the interviews were inductively consolidated into recurring categories and subsequently mapped onto the KTT reference model (10 modules).

For analysis, all AI use case mentions were structured along two dimensions: status (in active use, in pilot phase, expressed as need/potential) and the AI use cases themselves as defined types (consolidated categories recurring across interviews). This coding yields two complementary result artifacts.

First, a comparative matrix "Use Cases × Interviews" shows which categories were mentioned in which organizations/roles (including implementation status). Second, a process-oriented matrix "Use Cases × KTT Modules" assigns the identified categories to the task areas of the reference model, thereby indicating where AI currently supports discrete points in the transfer process and where a stronger leverage effect is expected in the future.

To structure the presentation of the results, we distinguish between two status groups: AI use cases reported as already in active use or pilot phase and AI use cases expressed as desired or high-potential capabilities. In the remainder of this section, we condense the AI use-case landscape into defined AI use cases by status (in active use or pilot phase vs. desired/potential) and then present it systematically in two sets of tables: Matrix 1 and 2 (Use Cases × Interviews) to enable cross-organizational comparison and Matrix 3 and 4 (Use Cases × KTT Modules) to provide process-oriented positioning along the KTT reference model.

Overview: AI Use-Case Landscape

Based on the 12 interviews, a two-part AI use-case landscape emerges: first, applications already deployed or piloted, which predominantly provide low-threshold, language- and knowledge-centric support functions, and second, desired or high-potential applications that more strongly target end-to-end support, process integration, and decision-oriented automation. This points to a typical maturity dynamic: organizations start with safe, well-bounded text and research tasks, followed by expectations around agentic workflows, integrated data use, and scaling across larger information bases.

Core AI Use Cases in Active Use or Pilot Phase

Current AI use cases cluster around a small number of recurring categories that integrate well into day-to-day work and entail comparatively low organizational risk.

The most widespread category is **UC1**: LLM-supported text processing (translation, simplification, drafting) (n=11/12; 10× in active use, 1× in pilot phase). It functions as a broadly applicable entry point into language-based knowledge work and is typically realized through tools such as DeepL/DeepL Pro and ad-hoc ChatGPT use. Reported tasks include text translation, text simplification, first-pass overviews, as well as drafting/rewriting for contracts and project documents, marketing copy, and proposal/application materials (incl. slide text). A second recurring category is **UC2**: semantic search/clustering of internal content (internal knowledge search/project reports/taxonomy/RAG) (n=3/12; 2× in active use, 1× in pilot phase), implemented to improve the discoverability of project documents, reports, and reusable assets. Reported implementations range from early-stage scouting and clustering setups under development to established internal semantic search and demo-level implementations following the RAG principle (e.g., taxonomy- or knowledge-base-oriented prototypes). In more technically oriented settings, **UC3**: AI coding assistance/code generation (n=2/12; 1× in active use, 1× in pilot phase) is used as a productivity lever for development and prototyping, including PoC-level "coding assistant" implementations as well as trialed/"tested" usage in exploratory contexts. Two additional categories were mentioned only once but are included because they represent already deployed implementation instances of themes that otherwise appear primarily as desired capabilities in the demand landscape. **UC4**: AI-supported market & competitive analysis (n=1/12; 1× in active use) is used as ad-hoc support and partly as a transition toward more systematic "automated research," for example via LLM-based tools such as Perplexity to produce quick market and competitor overviews. In our overall results logic, this topic is closely aligned with D2 (automated research: market, patent, trend, and funding scans) in demand matrix 3, which captures the broader, repeatedly articulated need for continuous and structured scanning; UC4 is therefore reported here as a concrete "in active use" instance despite being mentioned only once. A similar pattern applies to **UC5**: chatbot intake/case bots (e.g., prototype/individual case) (n=1/12; 1× in active use). This refers to a chatbot-like solution used to structure incoming requests and support early case handling, for example by guiding an initial intake, collecting key information in a standardized way, or providing case-specific information to requesters. Functionally, UC5 aligns with D6 (technology/market triage across the data corpus), which captures the broader, repeatedly expressed need for AI-supported screening, prioritization, and routing of heterogeneous inputs before they become formal transfer cases; UC5 is included here because one interview described this triage/intake logic as an already deployed solution. Finally, **UC6**: data-protection-compliant LLM environment (on-premises/cloud/Germany-hosted services/regulated) (n=6/12; 2× in active use, 4× in pilot phase) emerges as a cross-cutting prerequisite that enables, or constrains, broader adoption in practice. Reported variants span, first, in-house build-ups explicitly framed around data protection; second, ad-hoc use of open-source LLMs on an organization's own cloud; third, pilots with Germany-hosted services; and fourth, established institutional AI service and infrastructure options (e.g., central data processing/AI services), as well as infrastructure-bound internal instances (e.g., federated IT/information infrastructures, Federated Information Systems), including organization-internal generative AI instances (e.g., "BlaBlaDor").

Overall, the dominant AI use cases in active use enhance language production and internal information retrieval without deeply intervening in core processes.

Core AI Use Cases Expressed as Need/Potential

Desired AI use cases substantially extend this picture. They address needs for scaling, systematic information processing, and cross-process coordination along the KTT modules. The most frequently mentioned categories are those that promise strong time leverage or safeguard quality/compliance requirements.

D1 (Privacy-compliant LLM infrastructure & governance; n=9/12) refers to a strategic framework (rules, roles, approvals, monitoring) that enables sustainable scaling and is often discussed in concrete terms such as regulated (non-ad-hoc) usage modes, guidance documents and operating models (including references to institutional service providers for data processing and AI), platform-related considerations (e.g., M365 Copilot), and infrastructure anchors within specific (federated) IT ecosystems. **D2** (Automated research: market, patent, trend, and funding scans; n=9/12) is envisioned as a continuous, structured monitoring function rather than one-off inquiries, including recurring trend and competition checks, market-fit screening, and agent-like "output" setups that combine patent and market signals; in more advanced descriptions, this extends to market/technology aggregation plus funding scans with explanation/scoring, multi-agent role concepts (e.g., observer/idea/matcher for market and patent), and systematic company screening based on fixed sources and defined cycles, sometimes framed as both internal potential identification and external commercialization/marketing support. **D3** (Contact/lead matching & outreach: target customers, contact persons, email drafting; n=6/12) aims to support partner identification and outreach, including notions of "output agents" that compile firms, relevant contacts, and email drafts; lead extraction from an overall market picture (including identifying the right contact persons); matching logic that assigns recipients plus estimated potential; and templated outputs such as draft matching reports, up to "one-stop(-shop)" visions connecting offerings with investors or co-founders. **D4** (Workflow & documentation agents: meeting transcripts, summarization, to-dos, automated documentation, compliance; n=3/12) is primarily motivated by the goal of reducing recurring coordination and documentation load, ranging from end-to-end meeting agents to "one-click" minutes (transcript → to-dos), as well as broader support for documenting ongoing activities and ensuring conformance and compliance documentation. **D5** (LLM-based summarization of large document collections / corpus QA; n=4/12) is framed as a response to increasing volumes of documents and communication, including pilots that started from tested simplification and evolved toward summarization potential, and concrete needs such as summarizing large hit lists (e.g., 200-500 results) to enable corpus-level Q&A and faster synthesis. **D6** (Technology/market triage across the entire data corpus: input agent, internal triage; n=3/12) focuses on prioritizing, assessing, and routing heterogeneous inputs across organizational units and is described in terms of automated screening and prioritization, input agents for specific artifacts (e.g., invention disclosures), and organization-internal "potential ID" functions to steer follow-up actions. **D7** (Business model/business case generation for spin-offs; n=2/12) is mentioned particularly with a view to venture creation and value argumentation, including business-case sketches, positioning against technology readiness levels, and structured comparisons to support decision-making for spin-off pathways. **D8** (Internal knowledge & asset search and expert finder: on-premises LLM/RAG; n=2/12) is conceived in a more organization-wide manner, often tied to on-prem/RAG requirements, and described in concrete terms such as building cross-references between people, assets, and prior cases to surface internal expertise and reusable components. Finally, **D9** (Automated content generation: reports, slides, social media, matching reports, courses; n=6/12) targets faster and more consistent internal and external communication, including course-pipeline visions (scripts/slides/quiz/text-to-speech), editorial acceleration, automated generation of slides and reports from existing databases, matching-report drafts, and smaller communications micro-automations (e.g., Save-the-Date messages).

In this "desired" AI use-case landscape, the emphasis is less on individual tools and more on integrated bundles of capabilities that connect task chains along the transfer process. This is a particularly noteworthy finding because it suggests that AI support in KTT can be conceptualized as process augmentation rather than merely as isolated tool adoption. The identified use cases point to recurring augmentation mechanisms, namely information retrieval and monitoring, knowledge structuring, evidence synthesis, decision support, and workflow/communication support. This interpretation provides a theoretical lens for understanding how AI may strengthen KTT capabilities across modules, particularly sensing, evaluation, matching, coordination, and organizational learning. In turn, the results point to a maturing AI perspective in KTT practice, one that frames AI not merely as a set of ad-hoc applications, but as a potential enabler of more systematic, scalable, and strategically aligned transfer work.

AI Use Cases in Active Use or Pilot Phase: Matrix 1

Table 1: Matrix 1 – AI Use Cases in Active Use or Pilot Phase

Use Case × Interview	I1	I2	I3	I4	I5	I6	I7	I8	I9	I10	I11	I12
UC1: LLM-supported text processing (translation, simplification, drafting)	X	X	P		X	X	X	X	X	X	X	X
UC2: Semantic search/ clustering of internal content (internal knowledge search/ project reports/taxonomy/RAG)	P	X					X					
UC3: AI coding assistance/code generation		X		P								
UC4: AI-supported market & competitive analysis (assigned to demand matrix 3 under D2)	X											
UC5: Chatbot intake/case bots (e.g., prototype/individual case) (assigned to demand matrix 3 under D6)		X										
UC6: Data-protection-compliant LLM environment (on-premises/ cloud/DE-hosted services/ regulated)	P				P	P	P	X				X

X = AI use case in active use; P = AI use case in pilot phase; I1-I12 = 12 numbered interviews

Matrix 1 summarizes the AI use cases that are already implemented (X) or in pilot phase (P) across all 12 expert interviews. Rows represent the defined AI use cases (UC1-UC6), while columns correspond to the individual interviews (I1-I12). A cell entry indicates that the respective AI use case was reported in that interview as in active use or pilot phase; empty cells indicate that the AI use case was not mentioned in that interview. The matrix thus provides a cross-case, comparative view of the current implementation status. Across cases, the reported use of AI, often still in pilot phase, is concentrated in a small number of recurring AI use cases. LLM-supported text preparation (UC1) is the dominant entry-level application and is mentioned in 11 of 12 interviews (including 10× in active use and 1× in pilot phase). Interviewees described UC1 as particularly relevant in multilingual and communication-heavy transfer settings: one interviewee stressed the practical need for translation when operating across languages: "We don't have native speakers for all languages we operate in, so translation matters" (I3, translated). The same interviewee also highlighted how LLMs help adapt specialist language to broader audiences, noting that "It's hard to turn technical jargon into understandable language; running it through a language model works very well" (I3, translated). Beyond translation and simplification, UC1 also includes routine drafting tasks in outreach and event communication; as one interviewee put it, "If I plan a networking event and want to send a save-the-date, I say: draft a save-the-date with target-group wording" (I12, translated). Finally, early experimentation extends into more formalized text genres, including patent-related drafting, where "Patent colleagues are experimenting a lot with AI, actually writing patent applications and so on" (I11, translated).

The second most frequently reported theme is the privacy-compliant LLM environment (UC6) as an enablement category (6/12), yet it is predominantly described as in pilot phase (4× in pilot phase, 2× in active use). This pattern suggests that while experimentation is widespread, broadly established infrastructure that is both governance- and privacy-compliant is often still being built. Some interviewees reported first concrete implementations in the form of organization-specific, controlled assistants, one interviewee described this as "our own AI… called Blablador, our own generative AI" (I12, translated). At the same time, UC6 was also framed as a response to persistent security concerns around mainstream tools: despite the availability of "certain security settings," one interviewee noted that "skepticism remains that things could end up in the wrong hands" (I12, translated). In other cases, interviewees pointed to technical workarounds that reduce exposure by limiting deployment scope and model size, for instance by running models locally: "It works on local laptops with smaller language models" (I7, translated).

In contrast, more function-specific and process-integrated applications are reported far less frequently. Semantic search and clustering of internal content (UC2) is mentioned in only 3 of 12 interviews (including 2× in active use and 1× in pilot phase), indicating that systematic, AI-supported access to internal knowledge bases is still comparatively rare. Where it is implemented, it is described as a way to unlock unstructured repositories for reuse: one interviewee reported that "we use a semantic model, semantic search over unstructured project data, to make it searchable and to cluster preparatory work" (I2, translated). Coding assistance (UC3) appears in only 2 of 12 interviews (with 1× in active use and 1× in pilot phase), suggesting that developer-facing AI tools are present but not yet a broadly shared staple across cases. Interviewees framed UC3 primarily as a speed and feasibility lever in early-stage development, for example when "AI-assisted programming helps us implement a proof of concept quickly and check feasibility" (I2, translated). Another interviewee emphasized that the productivity effect depends on how the tool is embedded into review practices, noting that "for pure coding, developers mainly just review the code, [and] productivity increases" (I4, translated).

Single instances such as AI-supported market and competitive analysis (UC4) and chatbot implementations (UC5) appear only sporadically (1 of 12 each). Accordingly, they are treated in the overall results logic less as established "current practice" patterns and more as transitional applications that later reappear, conceptually expanded, within broader desired or high-potential categories (e.g., automated research and screening/triage or agent-based support). For UC4, one interviewee described ongoing work that uses AI to structure external intelligence, stating: "We're currently working on AI-supported market and competitive analysis, what competitors do and what industry needs are" (I1, translated). UC5 was likewise reported as a concrete but isolated implementation example, where "a chatbot was implemented using an open-source framework together with the company" (I2, translated), pointing to early, project-specific deployments rather than a standardized cross-case capability.

Overall, Matrix 1 shows that current usage primarily centers on low-threshold, low-risk language applications and foundational enablement, whereas more deeply integrated AI use cases remain largely isolated or experimental at this stage. The reported examples therefore indicate that current implementations are mostly deployed as institutional services, controlled pilots, local prototypes, or task-specific tools rather than as fully integrated end-to-end KTT systems.

AI Use Cases Expressed as Need/Potential: Matrix 2

Table 2: Matrix 2 – AI Use Cases as Desired Capabilities

Use Case × Interview	I1	I2	I3	I4	I5	I6	I7	I8	I9	I10	I11	I12
D1: Privacy-compliant LLM infrastructure & governance	X	X	X		X	X	X	X	X			X
D2: Automated research (market, patent, trend, funding scans)	X	X		X	X	X			X	X	X	X
D3: Contact/lead matching & outreach (target customers, contact persons, email drafting)					X	X			X	X	X	X
D4: Workflow & documentation agents (meeting transcripts, summarization, to-dos, automated documentation, compliance)	X	X					X					
D5: LLM-based summarization of large document collections (corpus QA)			X	X				X	X			
D6: Technology/market triage across the entire data corpus (input agent, internal triage)					X	X						X
D7: Business model/business case generation (spin-offs)					X				X			
D8: Internal knowledge & asset search and expert finder (on-premises LLM/RAG)									X		X	
D9: Automated content generation (reports, slides, social media, matching reports, courses)					X		X	X	X		X	X

X = AI use case expressed as a need or potential; I1-I12 = 12 numbered interviews

Matrix 2 consolidates the AI use cases that were described across the 12 interviews as desired or particularly high-potential. Analogous to Matrix 1, the rows represent the consolidated AI use cases (D1-D9), and the columns represent the individual interviews (I1-I12). A cell entry indicates that the respective AI use case was explicitly discussed in the interview as a target state, a future need, or a high-leverage application for transfer. The matrix thus makes the breadth and prioritization of desired applications visible in a comparative way and helps identify recurring patterns of the next maturity stage. Overall, the desired AI use-case landscape is substantially broader, and less concentrated on a small number of types, than the landscape of AI use cases already in active use or pilot phase. Two topics stand out as near "quasi-standard" themes: privacy-compliant LLM infrastructure and governance (D1) and automated research/scanning (D2), each mentioned in 9 of 12 interviews. This emphasis indicates that many institutions conceptualize scaling and professionalizing AI not primarily as a tool-choice issue, but as a combination of enablement (compliant infrastructure, roles, approvals, monitoring) and systematic monitoring (market, patent, trend, and funding scans). For D1, interviewees repeatedly framed compliance as the key prerequisite for broader adoption, for instance, one interviewee stated that "data protection is a huge issue; we need the resources to do it in-house, so we don't have to send data outside" (I1, translated), while another described an explicit localization strategy: "We process data only in Germany, on servers located in Germany" (I7, translated). For D2, the desired future state was characterized by higher-throughput external intelligence work, ranging from competitive monitoring: "we are currently working AI-supported to do a kind of market and competitive analysis" (I1, translated), to improved novelty searches, where "there are providers on the market, but there is still room for improvement" (I11, translated), and to routine scanning of opportunity spaces such as funding and procurement, as one interviewee summarized: "We deal a lot with tender portals" (I1, translated).

A second group of frequently mentioned categories focuses on external impact and communication throughput. Contact/lead matching and outreach (D3) and automated content production (D9) are each mentioned in 6 of 12 interviews. In these areas, interviewees anticipate value primarily through faster partner identification, more targeted outreach, and more consistent preparation of transfer-relevant outputs (e.g., matching reports, outreach drafts, slides, and recurring reporting formats). For D3, interviewees often described a "go from insight to action" logic in which AI helps narrow down the most relevant targets and immediately supports engagement, one interviewee captured this pragmatically: "Here you already have the contact persons, why shouldn't that work? You have five big companies that have a real problem; call them" (I5, translated). Another framed the same need as a systematic capability, stating: "I'd like a matcher/networker that picks the right recipient for everything I do and maybe derives market potential" (I10, translated). For D9, the desired end state is less about creative writing per se and more about reducing repetitive communication workload and increasing consistency across deliverables. One interviewee expressed a clear automation wish for routine outputs: "Pull the data from our database and write those annoying reports; create presentations, then I have more time for what is actually my job" (I5, translated). Others pointed to emerging tool support for standardized communication artefacts, for instance, "things like PowerPoint Copilot are great: you can automatically format and generate communication materials" (I9, translated), and to first steps in institutional communication contexts, where "in public relations, we are starting to use various AI tools" (I8, translated).

Mid-frequency categories reflect needs to cope with growing information volumes and documentation burdens. Summarization of large document collections and corpus-style Q&A (D5) is mentioned in 4 of 12 interviews, typically framed as a way to reduce time spent on screening and sensemaking when evidence bases become too large for manual review. As one interviewee put it, "summaries from a large set of documents, if you have 200-500 results or more, AI helps you get an overview faster" (I4, translated).

Workflow and documentation agents (D4) and technology/market triage across the overall database (D6) are each mentioned in 3 of 12 interviews and mark a shift from stand-alone tools toward process-integrated, more "agentic" support (e.g., meeting-to-documentation pipelines, automatic task extraction, and structured intake/routing logic for new inputs and opportunities). A concrete example of this desired everyday support is captured in the request for "a running AI agent that documents daily work, like a meeting agent that summarizes meetings, just for everyday work" (I2, translated).

More selectively, but potentially with high impact, interviewees also mention business model or business case generation for spin-offs (D7) and internal knowledge/asset search and expert finding (D8), each appearing in 2 of 12 interviews. These themes tend to surface where decision support for venture creation and organization-wide reuse or expertise location are particularly salient. One interviewee summarized the ambition of D7 as follows: "You could ask the AI where there is demand and even think up a first business case from that" (I9, translated).

Patterns Emerging from Matrix 2

Three recurring patterns can be derived from the distribution of desired categories. First, an enablement-first scaling logic appears to emerge: the prominence of governance/infrastructure alongside automated scanning may indicate that many KTT units view the next adoption step less as "more prompting" and more as the establishment of reliable, compliant operating conditions combined with repeatable monitoring routines. Second, compared to Matrix 1, the focus appears to shift from isolated text tasks toward connected task chains (e.g., scanning → triage → outreach → documentation), which in turn suggests higher integration requirements, particularly with regard to data access, workflow tooling, and the clarification of roles and accountability. Third, the strong emphasis on outreach/matching and content production may indicate an expansion of expected AI value from internal productivity gains toward external impact, including improved partner engagement, communication quality, and transfer-facing outputs. Next, we map the AI use cases in active use/pilot phase onto the 10 modules of the KTT reference model and subsequently apply the same mapping to the desired AI use cases, to identify where along the transfer process AI support is currently concentrated and where the strongest future leverage is expected. The following module-based interpretation shifts the focus from interview-level evidence to process-oriented positioning along the KTT reference model; accordingly, the accompanying text synthesizes patterns across the material rather than documenting each module assignment through separate interview quotations.

AI Use Cases in Active Use/Pilot Phase Mapped to KTT Reference Model Modules: Matrix 3

Table 3: Matrix 3 – AI Use Cases in Active Use/Pilot Phase Mapped to KTT Reference Model Modules (Etzkorn et al., 2025a)

Use Case × KTT Module	M1	M2	M3	M4	M5	M6	M7	M8	M9	M10
UC1: LLM-supported text processing (translation, simplification, drafting)	X	X	X	X	X			X	X	
UC2: Semantic search/ clustering of internal content (internal knowledge search/ project reports/taxonomy/RAG)		X						X		
UC3: AI coding assistance/code generation	X									
UC4: AI-supported market & competitive analysis (assigned to demand matrix under D2)		X				X				
UC5: Chatbot intake/case bots (e.g., prototype/individual case) (assigned to demand matrix under D6)			X				X			
UC6: Data-protection-compliant LLM environment (on-premises/ cloud/DE-hosted services/ regulated)				X	X		X	X	X	X

X = AI use case is applied within the defined module.

M1: Research; **M2**: Technology and method identification; **M3**: Transfer case processing; **M4**: Invention processing; **M5**: Patent research and processing; **M6**: Market research; **M7**: Contact management; **M8**: Knowledge management; **M9**: Contract management (licensing); **M10**: Spin-off management

This matrix maps the AI use cases currently reported as in active use or in pilot phase to the 10 modules of the KTT reference model. Rows represent the consolidated and defined AI Use Cases (UC1-UC6), and columns represent the KTT modules (M1-M10). An "X" indicates that interviewees reported applying the respective AI use case within that specific task area/module. The matrix therefore provides a process-oriented view of where the transfer process AI support is already embedded, complementing the cross-case adoption perspective shown in Matrix 1. Overall, the mapping shows that current AI usage is concentrated first in broadly applicable language work that cuts across multiple modules and second in selected modules where compliance and documentation requirements are particularly salient. At the same time, more specialized or workflow-integrated applications appear only sporadically, suggesting that process-deep automation is still at an early stage. UC1 (LLM-supported text processing) is the most transversal category and spans a wide range of modules, from research and early scouting/intake (M1-M3) to invention-related work (M4-M5) and downstream activities such as knowledge management, licensing-related contract work, and spin-off support (M8-M10). This pattern underscores that the dominant "in active use" value proposition is improving text-heavy knowledge work (drafting, rephrasing, simplification, translation) wherever written artifacts are produced in KTT. By contrast, UC2 (semantic search/clustering of internal content) appears more targeted and is primarily anchored in early-stage opportunity work (M2) and organizational memory building (M8). This reflects a pattern focused on improving access to internal project documentation, reusable assets, and taxonomies, i.e., strengthening the information base that supports both early assessment and ongoing reuse. Two categories remain highly localized: UC3 (AI coding assistance/code generation) is reported mainly in research (M1), consistent with technical prototyping and development-related productivity support. UC4 (AI-supported market & competitive analysis) connects early identification/assessment (M2) with market research (M6), but occurs only as a narrow, punctual application (and is later consolidated under broader “automated research” ambitions in the desired AI use-case matrix). Finally, the mapping highlights early attempts to operationalize more process-integrated support: UC5 (chatbot intake/case bots) is linked to transfer-case processing (M3) and contact management (M7), indicating that structured intake and routing are recognized entry points for workflow support, even if still prototypical. UC6 (data-protection-compliant LLM environment) appears especially in modules with higher sensitivity and governance needs, invention disclosure and IP-related work (M4-M5) as well as downstream modules that often involve external interaction and formalization (M7-M10). This suggests that, in practice, establishing compliant environments is not merely a technical prerequisite but is closely tied to where KTT work becomes legally, commercially, or reputationally high stakes. Taken together, the matrix indicates that current adoption is driven by cross-cutting language assistance and selective enablement, while more specialized, end-to-end process support remains limited to isolated cases. This process-oriented baseline provides the point of comparison for the next step, where we apply the same module mapping to the desired AI use cases to contrast today’s concentrations with the areas where interviewees expect the strongest future leverage.

AI Use Cases Expressed as Need/Potential Mapped to KTT Reference Model Modules: Matrix 4

Table 4: Matrix 4 - AI Use Cases as Desired Capabilities Mapped to KTT Reference Model Modules (Etzkorn et al., 2025a)

Use Case × KTT Module	M1	M2	M3	M4	M5	M6	M7	M8	M9	M10
D1: Privacy-compliant LLM infrastructure & governance								X		
D2: Automated research (market, patent, trend, funding scans)		X		X	X	X				
D3: Contact/lead matching & outreach (target customers, contact persons, email drafting)							X		X	X
D4: Workflow & documentation agents (meeting transcripts, summarization, to-dos, automated documentation, compliance)			X					X	X	
D5: LLM-based summarization of large document collections (corpus QA)	X	X			X	X		X		
D6: Technology/market triage across the entire data corpus (input agent, internal triage)		X	X	X		X				X
D7: Business model/business case generation (spin-offs)										X
D8: Internal knowledge & asset search and expert finder (on-premises LLM/RAG)							X	X		
D9: Automated content generation (reports, slides, social media, matching reports, courses)			X				X	X		X

X = AI use case that is expressed as a need or potential within the defined module.

M1: Research; **M2**: Technology and method identification; **M3**: Transfer case processing; **M4**: Invention processing; **M5**: Patent research and processing; **M6**: Market research; **M7**: Contact management; **M8**: Knowledge management; **M9**: Contract management (licensing); **M10**: Spin-off management

Matrix 4 maps the AI use cases articulated as desired or high-potential to the 10 modules of the KTT reference model. Rows represent the defined AI use cases (D1-D9), and columns represent the modules (M1-M10). An "X" indicates that interviewees associated the respective AI use case with the corresponding task area/module, i.e., as a future target capability or high-leverage opportunity for that part of the transfer process. In contrast to the "in active use/pilot phase" mapping, this matrix makes visible where interviewees expect AI to generate the next wave of value along the end-to-end KTT workflow.

Overall, the mapping shows a clear shift from today's predominantly language-centric, low-risk applications toward process-integrated capabilities that cluster around three leverage zones: first, upstream intelligence and screening (M2-M4); second, evidence-building for IP and markets (M5-M6); and third, downstream partner engagement and exploitation (M7-M10). At the same time, several desired categories are anchored in knowledge management (M8), reflecting the need for a reusable, organization-wide information backbone.

In the upstream phases of discovery, intake, and early case handling (M2-M4), desired applications cluster most strongly where opportunities are identified, structured, and routed. Desired applications concentrate strongly on the early modules where opportunities are identified, structured, and routed. Automated research/scanning (D2) spans M2, M4, M5, and M6, indicating demand for continuous market/patent/trend/funding monitoring that feeds both invention-related work and subsequent evaluation. Technology/market triage over the full database (D6) is positioned across M2-M4 as well as M6 and M10, suggesting a strong need for AI-supported prioritization and routing of heterogeneous inputs before they become formal transfer cases. In addition, workflow/documentation agents (D4) are linked to M3 (transfer case processing), highlighting the expectation that agentic support can reduce coordination and documentation overhead already at the case-handling stage.

In the evidence-building phase for IP and market evaluation (M5-M6), a second concentration emerges around the analytical core of KTT evaluation, where evidence for IP and market decisions is built. LLM-based summarization of large document sets/corpus QA (D5) is associated with M1, M2, M5, M6, and M8, reflecting the need to synthesize large corpora (internal reports, patent material, market information) into actionable summaries and Q&A-style access. Together with D2 (automated research), this points to a future operating mode in which AI helps generate and maintain the evidence base required for patentability assessment, market sizing, and commercialization argumentation.

In downstream commercialization and external engagement (M7-M10), desired AI use cases focus on the outward-facing and formalization-heavy parts of KTT. Contact/lead matching and outreach (D3) maps to M7 (contact management) and extends into M9 (contract management (licensing) and M10 (spin-off management), indicating expectations of AI support not only for identifying and approaching partners, but also for preparing follow-up artifacts that connect to licensing and venture pathways. Automated content production (D9) similarly spans M3, M7, M8, and M10, consistent with producing transfer-facing materials (reports, slides, matching outputs) that support outreach, internal coordination, and venture-related communication. Finally, business model/business case generation (D7) is located exclusively in M10, underscoring that interviewees view this as a specialized but high-impact capability for spin-off work rather than a general-purpose tool.

As a knowledge backbone and governance anchor (M8), several desired categories converge on knowledge management (M8), pointing to the role of an organization-wide backbone and enabling conditions for scaling. Privacy-compliant infrastructure/governance (D1) is positioned here as an enabling layer; internal knowledge/asset search and expert finding (D8) maps to M7-M8 and both D5 and D9 also connect to M8. Taken together, this suggests that interviewees increasingly conceptualize "scaling AI in KTT" as dependent on institutional memory, discoverability of internal assets, and compliant operating conditions, rather than isolated tool adoption.

In sum, Matrix 4 highlights that future AI leverage is expected primarily where KTT work requires first, continuous information acquisition and screening; second, synthesis of large heterogeneous evidence bases; and third, high-throughput external engagement and formalization. This provides a process-oriented contrast to the current "in active use/pilot phase" footprint and helps explain why many interviewees emphasize governance, integrated data access, and workflow embedding as prerequisites for the next maturity stage.

Conclusion, Limitations and Outlook

Conclusion

Based on 12 expert interviews, we provide a first comparative, process-oriented map of AI use cases in KTT in German public NURIs, distinguishing what is already in active use or pilot phase from what is envisioned as high-potential future capability. We do not claim that individual AI applications such as text generation, summarization, or search are novel in themselves. Rather, our key novelty lies in developing a status-aware AI use-case taxonomy (in active use/pilot phase/desired) and combining it with reusable matrix artifacts (Use Cases × Interviews; Use Cases × KTT Modules) that make adoption gaps and maturity patterns comparable across institutions and KTT modules. A next step is to extend the KTT reference model by Etzkorn et al. (2025a) by integrating concrete data objects, the system/tool landscape and the AI use cases into an expanded, module-consistent reference model to be documented and published, enabling future operationalization, benchmarking, and impact evaluation.

Contributions

Our research contributes in three ways. First, we contribute to IS research by conceptualizing AI in KTT as a form of process augmentation for knowledge-intensive and cross-organizational transfer work. Rather than treating AI applications as isolated tools, our findings show how AI use cases can be understood as recurring augmentation mechanisms that support information retrieval, knowledge structuring, evidence synthesis, decision support, and workflow/communication activities across the KTT process. While the present study remains exploratory and inductive in nature, this process-augmentation perspective provides a conceptual starting point for future IS research on AI-enabled KTT capabilities, maturity, and impact. Second, we develop an empirically grounded, status-aware AI use-case taxonomy based on 12 expert interviews that distinguishes between “in active use” and “pilot phase”, as well as desired and high-potential applications, thereby making adoption gaps and maturity patterns comparable. Third, we provide reusable matrix artifacts, namely AI use cases by interviews and AI use cases by KTT reference model modules, which enable operationalization for future research, particularly as a basis for maturity models and benchmarking across KTT units. They can also support cross-institutional learning by helping larger and smaller NURIs compare adoption patterns, identify shared implementation challenges, and transfer lessons learned across organizational contexts. Beyond these research contributions, the findings also offer practical implications for managerial practice. For KTT leadership, the matrices provide a roadmap for prioritizing AI initiatives by module and maturity stage, from low-threshold language and content work toward integrated scanning, triage, and workflow automation. The findings highlight that scaling depends on enablement, notably privacy-compliant infrastructure and governance, especially in sensitive IP and partner-facing modules. This also points to key implementation barriers, including data privacy requirements, governance arrangements, infrastructure availability, and organizational readiness for integrating AI into established KTT workflows. Finally, the desired AI use-case portfolio identifies high-leverage priorities for KTT resource allocation and implementation planning. Institutions can use the matrices to prioritize AI investments stepwise: first by establishing privacy-compliant infrastructure and governance, then by scaling low-threshold language and documentation support, and subsequently by integrating higher-impact applications such as automated research and evidence synthesis, corpus-level summarization, partner matching and outreach, and documentation agents.

Limitations

This study has several limitations. First, the empirical basis is a small qualitative sample of 12 expert interviews with a strong focus on German public non-university research institutions. This focus was deliberately chosen in line with the scope of our research. While the multi-NURI design across several German public research institutions supports analytical comparison, findings are not statistically generalizable to other research-performing organizations such as universities, universities of applied sciences, or companies. We therefore view the concrete prevalence and implementation status of individual use cases as context-bound to German public NURIs. By contrast, the broader process-augmentation mechanisms and the status-aware mapping logic may be analytically transferable to other knowledge-intensive transfer contexts and provide a basis for future comparative IS research. In addition, the interviewees represent a mix of roles and responsibility scopes within KTT, which may shape how AI use is perceived and reported. Second, the results rely on self-reported accounts. Interview data reflect participants' perceptions of current practice, pilots, and future needs and may be affected by recall bias, selective reporting, and differences in individual familiarity with AI tools. We did not independently verify implementations or measure actual usage intensity. Third, the identified AI use cases are consolidated as inductive categories. This abstraction supports comparison and matrix building, but it may hide relevant differences in granularity, implementation variants, and organizational embedding. Some categories can cover heterogeneous solutions, ranging from ad hoc tool use to integrated systems, which limits comparability of maturity within a category.

Future Work

Future research should further theorize AI-enabled KTT by developing and testing a more coherent process-oriented framework that explains how AI augmentation mechanisms translate into KTT capabilities and measurable transfer outcomes. Future research should validate and extend the AI use-case taxonomy and matrices through a larger-N survey across NURIs and additional KTT contexts. A survey design could test prevalence, drivers, and barriers by module and enable benchmarking and maturity assessments at scale. In addition, future work should move from mapping to impact evaluation by measuring effects of AI use on operational and outcome-related metrics. Relevant dimensions include time and throughput (cycle times, workload reduction), quality (accuracy, consistency, compliance, stakeholder satisfaction), and transfer outcomes (e.g., lead generation, licensing activity, contract cycle time, spin-off progression). Combining surveys with behavioral data, process logs, and quasi experimental designs would strengthen causal inference and support evidence-based roadmaps for AI deployment in KTT.

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