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RESEARCH

AI-enhanced competency transfer hubs: a conceptual framework for university-industry engagement and knowledge sharing

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Abstract
This paper introduces a framework for AI-driven competency transfer hubs, designed to facilitate effective knowledge exchange and collaboration between universities and industries. These hubs leverage artificial intelligence technologies like machine learning and natural language processing to enhance the efficiency and effectiveness of information flows between academic institutions and industry partners, optimizing the whole knowledge-sharing process. Using the TCM-ADO framework the paper consolidates existing perspectives and offers practical suggestions on how to incorporate AI technologies into competency hubs. The discussion further delves into outlining key layers of such hubs including AI-powered knowledge extraction and enrichment, knowledge customization, adaptive project management as well as collaboration outcome enhancement and feedback optimization. A set of key elements for AI-enhanced competency transfer hubs was also developed and presented including the issues of technical alignment, advanced AI integration as well as value aspects. The study wraps up by exploring key areas of application in the establishment of AI-enhanced competency transfer hubs and their wider societal significance.

Keywords AI-enhanced knowledge transfer · University-industry collaboration · Machine learning in knowledge hubs · Natural language processing (NLP) for innovation · Competency transfer hubs · Long-term competitiveness in AI-driven hubs

JEL Classification A2 · I2 · M1 · O3

1 Introduction

Artificial intelligence (AI) is revolutionizing a wide range of different industries such as healthcare, manufacturing or finance by accelerating innovation and enhancing operational efficiencies (Abulibdeh et al., 2024; Sharma et al., 2022; Kumar et al., 2023). One of AI's most promising transformative roles lies in fostering university-industry collaborations,

Extended author information available on the last page of the article where academic institutions generate cutting-edge research and industries apply these advancements for real-world impact (Zhai et al., 2021; Bukhari et al., 2021). University-industry collaborations take various forms, including internships, joint research projects, technology licensing, and consulting agreements. However, traditional university-industry partnerships often struggle with challenges such as misalignment in research and industry timelines, cultural differences, delayed knowledge dissemination and inefficiencies in knowledge transfer (Yin et al., 2023; Sharma et al., 2023; Alexandre et al., 2022; Nsanzumuhire & Groot, 2020). In addition, an arrangement of a university-industry collaboration requires an extensive knowledge exchange which is also not free from some costs related to absorptive capacity building or associated with risks of omitting or leaking important information (Vivona et al., 2023). These issues are particularly pronounced in AI-related fields due to the rapid pace of technological advancements, necessitating novel, AI-driven mechanisms to bridge the gap between academia and industry.

This study aims to develop a conceptual framework for AI-enhanced competency transfer hubs (CTHs) to enhance knowledge exchange between universities and industries as implementation of such knowledge-sharing routines is one of the key mechanism to establish strong university-industry collaborations and support its evolutionary trajectory (O'Dwyer et al., 2023). CTHs are structured, technology-enhanced platforms designed to systematically facilitate knowledge transfer, optimize competency alignment and improve the efficiency of university-industry collaborations. Unlike traditional models such as technology transfer offices or research consortia, AI-enhanced CTHs leverage AI-based technologies like machine learning (ML) or natural language processing (NLP) to streamline knowledge sharing, personalize competency mapping and automate industry-academia matchmaking (Serrano-Ruiz et al., 2024; Malik et al., 2021a, 2021b; Panchendrarajan & Zubiaga, 2024). By doing so these hubs can significantly improve the scalability, adaptability, and efficiency of knowledge transfer (Luthra et al., 2024; O'Dwyer et al., 2023; Olan et al., 2022; Hartmann & Henkel, 2020).

Despite an extensive research on university-industry collaboration models, there are still a lot of significant gaps in these area (Zhou & Baines, 2024). Among others, the role of AI in optimizing knowledge transfer also remains significantly underexplored. Prior works such as the Triple Helix model (Schartinger et al., 2002; Etzkowitz & Leydesdorff, 2000) emphasize the importance of government, academia, and industry collaboration, but lack adaptability to the fast-evolving AI landscape. Similarly, studies based on the knowledge transfer frameworks (Nonaka & Takeuchi, 1995) and open innovation theory (Chesbrough, 2006; Gassmann & Enkel, 2004) highlight the need for structured collaboration mechanisms, but do not fully address AI's role in automating, scaling, and enhancing knowledge exchange. This research addresses this issue by investigating the effectiveness of AI-powered CTHs in improving the scalability and adaptability of knowledge transfer to keep pace with rapid advancements in AI technologies (Janiesch et al., 2021; Trappey et al., 2021). Thus, to bridge this gap, this study is guided by the following research question (RQ): How can AI-enhanced CTHs improve the efficiency, scalability, and adaptability of university-industry knowledge exchange?

This study argues that AI-driven CTHs serve as a complementary mechanism rather than a replacement of traditional model, enhancing them through automated competency matching, real-time industry-academia interaction and AI-assisted knowledge synthesis. By automating knowledge transfer and dynamically aligning research outputs with industry needs, AI-enhanced CTHs reduce collaboration inefficiencies and improve the adaptability of partnerships to AI-driven technological advancements (O'Dwyer et al., 2023). Unlike conventional knowledge transfer processes, which can take years, such CTHs facilitate real-time data-driven decision-making to align research with industry priorities, funding opportunities, and commercialization pathways (Rossoni et al., 2024; Albats et al., 2022; Rajalo & Vadi, 2017).

Universities can benefit from AI-enhanced CTHs by simplifying the process of commercializing research to match industry requirements effectively, while industries can leverage these hubs to access academic research resources, lower costs, and accelerate innovation (Bukhari et al., 2021). Thus, AI-enhanced CTHs have the potential to redefine how universities and industries collaborate in the era of AI-driven technological innovation, fostering more agile, productive, and impactful partnerships. Furthermore, AI-powered partnerships must emphasize fairness, transparency and accountability, ensuring that ethical governance remains central to these interactions (Dwivedi et al., 2021; Schiff, 2022). The study also provides insights for policy-makers, highlighting the importance of investing in AI-driven knowledge-sharing frameworks to foster sustainable university-industry collaborations and drive long-term competitiveness (Wiroonrath et al., 2024).

The rest of the paper is organised as follows. The next section is devoted to the review of the relevant literature and conceptual grounding. Section 3 presents the development of the conceptual model including the development of AI-enhanced CTH concept, defining its' core elements and integration of advanced AI. Section 4 discusses the findings and highlights key implications of the presented framework while Sect. 5 concludes and provides some key areas for further research.

2 Literature review and conceptual grounding

In today's dynamically evolving technological landscape AI is playing a significant role in driving innovation in various industries (Abulibdeh et al., 2024). With the increasing impact of AI there is a growing demand for partnerships between institutions and businesses to maximize its benefits effectively. The studies emphasize the importance of literature synthesis by delving into the realms of AI research and university-industry partnerships alongside competency transfer hubs (Zhou & Tang, 2020; Fountaine et al., 2019). This process entails the examination and integration of insights from studies through a methodical procedure that starts with pinpointing pivotal themes and theoretical voids derived from past publications.

In studies there has been an in depth exploration of the utilization of AI tools like machine learning (ML) and natural language processing (NLP) in different scenarios involving knowledge transfer (Casillo et al., 2022; Mosey et al., 2014). However, with the rise of AI and other cutting-edge technologies conventional university-industry partnership models might face challenges in keeping pace with the changes and intricate nature of innovation processes (Tolin & Piccaluga, 2024; Thomas & Paul, 2019; Ferreira & Carayannis, 2019; Jain et al., 2009). This research delves into the efficacy of university-industry collaboration pointing out its key challenges and how AI can improve this interaction process. Through combining these observations and findings the research establishes a solid groundwork for crafting the suggested structure. Furthermore, the TCM-ADO framework (Rahat et al., 2024; Paul & Criado, 2020; Paul et al., 2017) is also incorporated in this section to steer the basis of this research endeavour.

2.1 University-industry collaboration

Nowadays, in many countries around the world one of the main direction of innovation policy refers to the encouragement of more intensive commercialization of university knowledge (Zhou & Baines, 2024). Therefore, universities have become an essential part of regional entrepreneurial ecosystems and even form such ecosystems at their own (Audretsch et al., 2025; Correia et al., 2024). These university-based entrepreneurial ecosystems (UEE) may involve a lot of different actors, including but not limited to technology transfer offices, academic founders, external entrepreneurs, investors and business incubators (Prokop, 2021; see also Hayter et al., 2018 for an extensive review of the key elements of the UEE). Recent studies (e.g. Prokop, 2022) show that more advanced UEE with more actors being involved also promote the corresponding growth of commercialisation as well as boost entrepreneurial activities of university students and alumni. So that, the creation of UEE is now considered as quite a hot, but still poorly understood topic in the literature (Correia et al., 2024; Abreu & Grinevich, 2024). In addition, universities play a key role in promoting sustainable entrepreneurship and supporting innovations that address big social or environmental challenges (Civera et al., 2024). To ensure such a sustainable UEE, universities have to engage in various collaborations with different stakeholders among those university-industry collaborations are one of the most critical.

University-industry collaborations have long been recognized as essential drivers of technological progress, innovation, and economic development. Although the precise measurement of impacts of such collaborations remains challenging, a recent review by Cohen et al. (2025) summarized 25 possible impacts being important not only for the university and the industry, but also for the society as a whole. The Triple Helix model conceptualized by Etzkowitz and Leydesdorff (2000) underscores the significance of partnerships among universities, industries, and governments in fostering a knowledge-based economy (Hailu, 2024; Link et al., 2021). In this model universities act as knowledge generators, industries serve as knowledge consumers, while governments establish regulatory frameworks to support and enhance collaboration (Ideland & Serder, 2023). While the Triple Helix model remains influential, it does not fully account for the increasing complexities of knowledge transfer in the world of rapidly evolving technological landscapes. For instance, AI's rapid advancement is blurring the boundaries between academic research and industrial applications, necessitating more dynamic, data-driven collaboration mechanisms.

Traditional knowledge transfer models have highlighted the importance of structured mechanisms to ensure that academic research translates into practical innovations. Schartinger et al. (2002) explored knowledge flows between universities and industries, emphasizing the need for formalized processes to improve collaboration efficiency. However, their study also highlighted persistent challenges, including misaligned research priorities, differences in institutional cultures, and inefficiencies in knowledge transfer. These challenges are further exacerbated by the accelerated pace of AI development, which demands agile and scalable collaboration frameworks (Wiroonrath et al., 2024; Raisch & Krakowski, 2021; Hayter et al., 2021).

Existing theoretical models such as Open Innovation (Chesbrough, 2006; Gassmann & Enkel, 2004) and Absorptive Capacity Theory (Cohen & Levinthal, 1990) provide additional insights into how firms identify, assimilate, and apply external knowledge with knowledge combination capability (Yu et al., 2022). Open Innovation highlights the necessity of university-industry engagement to foster knowledge exchange (Luthra et al., 2023; Sethi et al., 2021), while Absorptive Capacity Theory explains why some firms are better positioned to integrate academic research into industrial applications especially open-innovation based by emphasizing the role of knowledge-oriented leadership (Gonzalez, 2024). However, these models are also not fully helpful to address how AI can enhance and automate the knowledge transfer process, particularly in high-tech industries where real-time data exchange and predictive analytics are crucial for success.

In contrast, recent empirical studies have demonstrated that AI-driven solutions can significantly enhance knowledge transfer between academia and industry. Janiesch et al. (2021) and Trappey et al. (2021) emphasize the role of machine learning (ML) and natural language processing (NLP) in improving collaboration by automating knowledge discovery, facilitating interdisciplinary connections and accelerating the transfer of research insights into practical applications. Similarly, research by Albats et al. (2022) and Alexandre et al. (2022) highlights how digital intermediaries (including AI-enhanced platforms) are transforming university-industry partnerships, making knowledge transfer more efficient, scalable, and industry-relevant.

Despite these advancements, many existing university-industry partnerships remain reliant on traditional collaboration models, which struggle to keep pace with the rapidly evolving AI landscape. Rajalo and Vadi (2017) and Rossoni et al. (2024) argue that delays in knowledge transfer, inefficiencies in project alignment, and slow commercialization cycles are key barriers that prevent academia and industry from fully leveraging research advancements. Addressing these challenges requires new, AI-powered mechanisms that facilitate real-time knowledge exchange, dynamic competency alignment, and automated collaboration management.

To bridge this gap, AI-enhanced CTHs may offer a novel, technology-driven approach to university-industry collaboration. These hubs leverage AI technologies including predictive analytics, NLP-driven knowledge curation and automated skill-matching systems to create more adaptive, scalable, and high-impact collaboration frameworks (Serrano-Ruiz et al., 2024; Malik et al., 2021a; Panchendrarajan & Zubiaga, 2024; Mosey et al., 2014). Unlike traditional knowledge transfer offices or research consortia, such CTHs provide a real-time, data-driven solution that aligns academic expertise with industry needs, enhances research commercialization, and fosters more agile, responsive collaboration structures.

2.2 Knowledge transfer and AI

Effective knowledge transfer is the cornerstone of successful university-industry collaboration, enabling the translation of academic research into real-world applications that drive innovation and economic growth. Historically, knowledge transfer has been conceptualized through structured, institution-driven frameworks such as technology transfer offices (TTOs), joint research initiatives, and university-industry consortia (Schoen et al., 2014). The Knowledge Transfer Theory (see Nonaka & Takeuchi, 1995) emphasizes the systematic codification and exchange of knowledge, reinforcing the importance of formalized mechanisms in facilitating knowledge diffusion between academia and industry. However, contemporary research increasingly suggests that knowledge transfer is not solely an institutionalized process, but also thrives in decentralized, organic, and individual-driven exchanges, where personal networks, informal collaborations, and departmental initiatives play a significant role (Harfouche et al., 2023).

The complexity of knowledge exchange between universities and industries has intensified with the advent of AI, which disrupts traditional transfer mechanisms by enabling real-time, scalable, digital business configurations and automated knowledge sharing and creation into platform based settings (Moraes et al., 2023; Bereznoy et al., 2021). Unlike conventional knowledge transfer models that rely on human mediation and structured exchanges, AI introduces adaptive mechanisms capable of enhancing both formal and informal knowledge flows (Birkstedt et al., 2023). Machine learning (ML), natural language processing (NLP), and predictive analytics facilitate the automatic identification, extraction, and dissemination of knowledge, transforming static, linear transfer models into dynamic, self-sustaining ecosystems that align research advancements with industry needs in real time.

University-industry collaboration also faces challenges due to misalignment between academic research cycles and industry innovation timelines, hindering efficient knowledge transfer (Wiroonrath et al., 2024; Raisch & Krakowski, 2021). Traditional models, characterized by centralized, bureaucratic structures, struggle to meet industry demands, particularly in fast-evolving fields such as biotechnology. Conversely, decentralized, informal exchanges among researchers and industry practitioners provide agility, but lack scalability and structured integration into innovation ecosystems (Rajalo & Vadi, 2017; Rossoni et al., 2024). This fragmentation necessitates a hybrid approach that combines institutional mechanisms with decentralized knowledge flows and AI also may help to do it.

Thus, AI-driven CTHs provide a scalable, hybrid solution by integrating institutional oversight with decentralized collaboration. AI-powered matchmaking algorithms enhance research-industry connections by identifying optimal collaboration opportunities in real-time (Harfouche et al., 2023). AI also facilitates interdisciplinary synergies, enabling cross-sector knowledge integration beyond traditional university-industry consortia (Birkstedt et al., 2023). Moreover, NLP-driven knowledge extraction systematically captures insights from conferences, workshops, and informal collaborations, ensuring tacit knowledge is not lost, but integrated into structured knowledge exchange frameworks (Janiesch et al., 2021; Trappey et al., 2021).

2.3 TCM-ADO framework

The foundation of this study is built upon the TCM-ADO framework introduced by Paul et al. (2017), and referenced by researchers, such as Rahat et al. (2024) and Paul and Criado (2020). This framework offers an approach to conducting research in intricate areas, like university-industry partnerships, encompassed within two main elements: TCM (Theory, Context and, Methodology) and ADO (Antecedents, Decisions, Outcomes). By bringing these elements in a manner the framework provides a structured method for exploring how university-industry partnerships function and the impact of AI on enhancing these interactions:

- *Theory (T)*: Our theoretical basis relies on well-established frameworks such as Knowledge Transfer Theory (Nonaka & Takeuchi, 1995), Open Innovation (Chesbrough, 2006; Gassmann & Enkel, 2004) and Socio-Technical Systems Theory (Trist, 1981; van Eijnatten, 2013). Knowledge Transfer Theory offers perspectives on the methods for sharing knowledge between institutions and businesses as discussed by Govind and Küttim (2016). In contrast, Open Innovation Theory underscores the significance of engaging with partners to foster innovation as highlighted by Wiroonrath et al. (2024). Socio-Technical Systems Theory explores the interplay between technological components within organizations (Davis et al., 2014; Walker, 2015). This theory provides a framework for examining how AI is integrated into efforts between academia and industry. All three theories combined provide a basis for grasping how AI-enhanced CTHs can improve the sharing of knowledge and collaboration processes effectively.
- *Context (C)*: The main focus of the study is on partnerships between universities and industries, especially those being significantly influenced by the continuously progressing of AI technologies (Olan et al., 2022; Schiff, 2022; Dwivedi et al., 2021). It also delves into the obstacles encountered by traditional collaboration methods such as schedules differences, cultural divergences and difficulties in sharing knowledge. In placing this study in the field of AI technologies domains the research seeks to meet the demand for flexible and adaptable collaboration frameworks that can match the progress of innovations.
- *Methodology (M)*: The study is focused around theoretical aspects aims to enhance university-industry collaborations through AI-driven CTHs (Papadopoulos et al., 2022). It incorporates well-known theories within the TCM-ADO framework to develop a systematic and inventive conceptual model. This study does not rely on collecting data; instead it carefully combines literature with theoretical perspectives and secondary sources to put forward and confirm the conceptual model by emphasizing important connections between ideas and setting the groundwork for futher empirical studies.
- *Antecedents (A)*: Antecedents are the reasons why AI-enhanced CTHs are needed in collaborations between universities and industries. These reasons include the paced changes in AI technology, the growing complexity of AI innovations and the limitations of knowledge transfer methods. The reasons also involve the increasing need for interactive collaboration frameworks that enable sharing of information between academic institutions and businesses (Stylos et al., 2021; Benitez et al., 2020).
- *Decisions (D)*: Decisions involve the steps universities and industries take to establish AI-driven CTHs (Zhou & Tang, 2020; Fountaine et al., 2019). Such decisions involve implementing AI tools like machine learning (ML) and natural language processing (NLP) to automate the transfer of knowledge process. Additionally, adopting platforms for work and establishing governance structures for fair and transparent decision making are also key steps outlined by Trappey et al. (2021) and Zhu et al. (2020). The choices taken by both institutions and industries greatly impact the effectiveness of these hubs dedicated to enhancing competency through AI technologies.
- *Outcomes (O)*: The results of incorporating AI-enhanced CTHs in university industry partnerships are known as outcomes (Caloghirou et al., 2021). These outcomes encompass knowledge transfer processes that are both more efficient and scalable and lead to faster cycles of innovation along with improved collaboration between academia and industry partners. Additionally, these outcomes highlight the potential for AI-enhanced

CTHs to stimulate advancements in the field of AI and bring about broader societal advantages through enhanced university-industry collaborations.

This study utilizes the TCM-ADO framework (Lim et al., 2021; Paul et al., 2017) to present a method, for exploring how university industry collaboration mechanisms and AIs involvement enhance knowledge transfer processes efficiently. Additionally, the framework establishes a basis, for comprehending how competency transfer hubs improved by AI can overcome the constraints of collaboration approaches fostering better partnerships in the realm of AI. This research adds to existing knowledge by conducting an examination of the factors that impact the effectiveness of collaborations improved by AI technology, in university industry partnerships and offers guidance, for studies in this area.

3 Conceptual model development

3.1 AI-driven competency transfer and collaboration framework

The new AI-Enhanced Competency Transfer and Collaboration Framework aims to strengthen relationships between universities and industries by streamlining knowledge sharing processes and enhancing collaboration scalability for results. This innovative approach tackles obstacles faced in partnerships like differing schedules and cultures while emphasizing the importance of flexibility in project coordination (Zhang & Liu, 2022; Palvia et al., 2021). The setup consists of four layers, working together to facilitate effective knowledge sharing processes (Wu et al., 2021; Saratchandra & Shrestha, 2022).

3.1.1 Layer 1: knowledge extraction and enrichment

The initial step involves gathering and processing data to establish a base for further knowledge sharing. By utilizing machine learning techniques for data scraping and aggregation purposes, academic articles in journals along with patents and reports from the industry are compiled into a database. Subsequently, a Knowledge Graph is created using natural language processing techniques to generate a representation linking research subjects and prospects (Secundo et al., 2021). The module for enhancing knowledge uses entity recognition to provide context to the information. This helps ensure that the knowledge is customized to suit collaboration purposes like product development or research innovation (Mikalef et al., 2020).

3.1.2 Layer 2: automated knowledge transfer and customization

This layer utilizes AI tools to adjust and share information in a way that fits each individual needs by dealing with concerns regarding terminology clarity and practical usability. Language processing powered summarization simplifies research discoveries for industry professionals to ensure shared understanding. Interactive AI elements may be useful to respond to inquiries and explain complicated subjects effectively which helps connect the divide between academic and industry knowledge. In addition, to promoting teamwork translation models that utilize natural language processing help align language with terms commonly used in the industry. This fosters coherent communication among individuals (Palvia et al., 2021; Casillo et al., 2022).

3.1.3 Layer 3: scalability, coordination, and adaptive project management

The third layer assists in managing day-to-day tasks effectively to facilitate responsive teamwork efforts. By using AI-based analytics for resource planning and adjusting schedules in line with academic and business schedules, organizations can achieve better alignment with their goals (Battisti et al., 2022). Additionally, utilizing natural language processing tools for scheduling and translation purposes helps coordinate collaborations across fields of expertise, which is especially beneficial for global teams (Nguyen & Mougenot, 2022; Franke & Foerstl, 2020). Moreover, the use of AI in streamlining workflows and analyzing aspects has been noted to provide adaptability and alignment of project schedules. This enables teams to swiftly adjust to emerging insights and changes in the market landscape (Valle Cruz & García-Contreras, 2023).

3.1.4 Layer 4: collaboration outcome enhancement and feedback optimization

The last stage strengthens collaboration results by providing feedback and adaptable methods. Machine learning techniques support impact analysis and monitor job collaboration performance indicators like outcomes and stakeholder contentment (Deng et al., 2023). Additionally, NLP-driven sentiment analysis evaluates communication emotions and team interactions (Birjal et al., 2021). This phase also integrates a knowledge preservation component that saves insights and top notch strategies in a database resulting in an accessible knowledge source for upcoming initiatives. Long term team compatibility measures enhance fit and team formation strategies to boost collaboration efficiency as time goes by (Xu & Correia, 2024).

By using this AI model to collaborate between universities and industries can break through obstacles and adjust flexibly to achieve meaningful and lasting results collaboratively. This structure encourages a scalable method for sharing knowledge and managing projects demonstrating its importance as a tool for optimizing university-industry partnerships.

3.2 Defining the core elements of an AI-enhanced competency transfer hub

Considering the aspect of the research work, the analytical approach focuses on evaluating the theoretical robustness and its practical applicability of the proposed framework as suggested by Reed et al. (2021). The evaluation involves a review of how the framework corresponds with established theories and models while also delving into its ability to tackle the research queries raised earlier in the study. Moreover, potential constraints of the framework are explored alongside recommendations for studies aimed at enhancing and validating the model.

As detailed in Table 1, the implementation and success of the suggested AI-driven CTHs hubs depend on key variables spanning financial, technological, and regulatory categories, etc. These include essential factors such as capital investment, AI tools availability, skill development initiatives, compliance with ethical standards, which all together cre-

Table 1 Key variables of AI-Driven knowledge hubs

Variable Category	Key Variables
Funding & Financial	Capital investment, operational budget, return on investments
Technological	High-performance computing, data quality, AI tools, cybersecurity
Skills Development	Skill level, training programs, interdisciplinary readiness
Governance	Organizational structure, IP/data sharing, stakeholder engagement
Performance Metrics	Project success, innovation output, employment outcomes
Collaborative Culture	Partnership alignment, incentive structures, communication tools
R&D Scope	Target research areas, scalability, readiness levels
Regulatory & Ethical	Compliance, ethical standards, environmental impact

Source: Authors

ate a structured foundation for the competency transfer process. By aligning resources and expertise from both academia and industry, AI-Enhanced CTHs provide a robust framework for converting research insights into scalable, real-world applications.

To fully comprehend the systems working effectively involves outlining its components that form the basis of its functionality and success. The key components consist of automation and scalability, knowledge management and curation, stakeholder integration, personalized learning, ethical governance, and performance monitoring effectively contribute to the operation of CTHs empowered by AI technology in fostering quality knowledge exchange within partnerships with brands (Arya et al., 2024) and, between universities and industries.

3.2.1 Automation and scalability

The AI-driven CTHs are automation tools that change mechanism of knowledge transfer into up-to-date systems (Chen, 2020). Automation involves leveraging AI advancements to simplify the identification of collaboration chances and aligning skills with industry demands while overseeing the exchange of knowledge between these sectors (Lu et al., 2020). For instance, machine learning algorithms can be employed to search through collections of studies and business patents spotting connections that would have been missed through manual methods. By automating these functions, AI-hubs reduce the workload for universities and businesses, allowing for faster and more effective partnerships to form.

Furthermore, automation plays a role in AI-enhanced CTHs along with scalability as a factor to consider. Traditional partnerships between universities and industries often face challenges when it comes to scalability due to the resource processes involved in transferring knowledge (O'Dwyer et al., 2023; Lundberg & Öberg, 2021; Nsanzumuhire & Groot, 2020). With AI-enhanced CTHs scalability is inherently incorporated into the system making it possible to oversee collaborations simultaneously. Utilizing cloud-based AI infrastructure guarantees that the central hub can manage datasets and multiple collaborations simultaneously while facilitating interactions among various stakeholders without compromising the efficiency of knowledge dissemination.

3.2.2 Knowledge management and curation

The AI-enhanced CTH focuses on managing and organizing knowledge to enhance collaboration between academia and industry (Sowa et al., 2021). This process includes storing and retrieving industrial information with the help of AI technologies like NLP and ML to automate sorting and accessing data within the hub. For example, NLP algorithms can be used to examine articles, patents and industry summaries extracting findings and classifying them according to their pertinence to particular sectors or research fields. This guarantees that business collaborators can conveniently find the academic studies for their requirements while scholars can also pinpoint industrial hurdles that match their capabilities.

The process of curation also includes creating a knowledge base that evolves over time by integrating research discoveries and industry trends (Jarrahi et al., 2023). This repository acts as a database expanding through inputs from institutions and industry collaborators to keep the knowledge up to date and applicable consistently. When AI is employed in curating this information the hubs increases its usefulness for universities and industries alike by facilitating effective partnerships.

3.2.3 Stakeholder integration

Successful collaboration between universities and industries necessitates the blending of players, such as academic researchers and industry experts while also possibly involving government entities or regulatory bodies (Awasthy et al., 2020). A key aspect of the AI-enhanced CTHs is its capacity to unite these stakeholders on a platform to promote communication and maximize each participant input in the collaborative endeavour among knowledge assimilation application and knowledge transformation capacities (Ju et al., 2023). Intelligent matchmaking algorithms used in AI tools are vital for bringing stakeholders by evaluating the abilities and requirements of academic and industrial partners to suggest collaborations with high potential value (Gupta et al., 2022). For instance, a university AI research lab could be matched with a healthcare company aiming to enhance its systems through AI integration. The central hub also enables communication among parties involved by utilizing AI-powered collaboration tools to promote sharing of information and problem-solving capabilities.

Moreover, stakeholder integration involves making sure that various individuals are in sync with their objectives and anticipations. AI applications can be utilized to develop customized dashboards for every stakeholder granting them access to updates regarding initiatives the significance of research discoveries and the economic potential of innovations (Gill et al., 2019). This guarantees that all stakeholders are kept in the loop and involved thereby enhancing the likelihood of results.

3.2.4 Personalized learning and adaptive training

AI-enhanced CTHs offer personalized learning and adaptive training for stakeholders to bridge the gap between industry professionals seeking upskilling in technologies and academic researchers looking to understand industrial applications (Bhutoria, 2022). Through the use of AI technology, the hub customizes learning experiences to meet the requirements of each stakeholder. Personalized learning systems powered by AI utilize machine learning algorithms to evaluate users existing skill levels and suggest tailored training resources such as research papers or case studies to enhance their knowledge base. For instance, a manufacturing professional could receive learning materials focusing on the application of AI in maintenance, whereas an academic scholar might be directed towards industry reports discussing the current obstacles in AI-driven automation.

In addition, personalized training feature guarantees that educational journeys will change as users make progress. When participants finish training sessions or participate in partnerships between academia and industry AI-based tools will adjust their learning routes to present subjects or switch attention to new areas of interest. This guarantees that both educational and industrial members stay updated on the developments in their fields promoting better and more influential collaborations.

3.2.5 Ethical governance and compliance

When universities and industries work together with AI technology in the mix it brings up issues that need attention for fairness and transparency. The hubs that help transfer skills using AI should have rules in place for dealing with ethics concerns like protecting data privacy copyrights and potential biases in AI algorithms (Bankins & Formosa, 2023). In the hubs ethical governance framework lays the foundation of establishing rules and procedures for sharing data to facilitate collaboration between universities and industries while safeguard sensitive information integrity intact. AI technologies can streamline compliance monitoring by verifying data sharing practices adhere to privacy laws like the General Data Protection Regulation (GDPR) in Europe or similar regulations (Gao et al., 2023). These AI-powered compliance solutions not only enhance collaboration efficiency, but also ensure its legality and ethicality.

Another crucial element of governance involves tackling biases in AI algorithms that could influence the outcomes of collaborations. For instance, to illustrate if an AI algorithm suggests collaboration prospects unknowingly favor universities or industries due to biased data input. Therefore, the central system should incorporate procedures for examining and rectifying any biases within the algorithms to guarantee chances for all stakeholders to engage in efforts.

3.2.6 Performance monitoring and continuous improvement

In AI-enhanced CTHs ultimate component lies in the performance monitoring and ongoing enhancement aspect crucial for its effectiveness to efficiently track collaboration outcomes and spot areas needing improvement while making adjustments to enhance collaborations (Steidl et al., 2023). AI technology is essential in this process as it offers analytics and performance dashboards that provide insights into the effectiveness of current collaborations. For example, AI algorithms can examine data from previous university-industry initiatives to forecast the elements that are likely to facilitate successful knowledge exchange with ambidextrous innovation strategy modes (Weerasinghe & Dedunu, 2021; Papa et al., 2020). This enables the hubs to anticipate and tackle challenges like conflicting objectives or limitations in resources before they escalate into hurdles.

Furthermore, those performance monitoring systems that are powered by AI allow for feedback loops. As partnerships evolve stakeholders have the opportunity to share their insights into what's effective and where enhancements could be made (Tong et al., 2021). Through AI tools this feedback is applied to enhance the hubs operations ensuring that future collaborations build upon the knowledge gained from projects (Sjödin et al., 2021). This approach not only enhances the effectiveness of sharing knowledge, but fosters creativity by consistently enhancing the teamwork process.

All these factors offer a structure for assessing and developing AI-driven CTHs that promote ethical partnerships between universities and industries in a sustainable manner (see, Table 2). Through examination of each of these aspects academic institutions can establish AI CTHs that optimize outcomes, facilitate knowledge exchange and fulfil both research and business objectives effectively.

Table 2 Technical alignment for AI-Driven hubs

Category	Key Elements
1. Advanced Data Infrastructure	*Cloud Computing & Storage*: Scalable, accessible cloud solutions for managing large data volumes. *Data Lakes & Warehousing*: Store unstructured and structured data for seamless access and analysis. *Data Integration*: Use interoperability standards (APIs, schemas) to integrate academic and industry data sources.
2. AI and ML Platforms	*Customizable ML Models*: Platforms for training and deploying models tailored to specific research needs. *AutoML*: Tools to automate model prototyping, supporting users with varying expertise. *Collaborative Coding*: Environments like Jupyter Notebooks for real-time team collaboration on experiments.
3. Knowledge Management Tools	*Collaborative Repositories*: Shared spaces (e.g., Git, Confluence) for documents, outputs, and findings. *Searchable Databases*: AI-powered search capabilities for intuitive information retrieval. *IP and Publication Management*: Tools for tracking intellectual property, patent applications, and publications.
4. Data Security & Privacy Controls	*Role-Based Access Control (RBAC)*: Access management by user roles (e.g., researchers, partners). *Data Encryption*: Ensure sensitive data protection and regulatory compliance (e.g., GDPR). *Audit Trails*: Logs for tracking data access and usage to enhance transparency and compliance.
5. Communication & Collaboration	*Integrated Communication Tools*: Real-time communication suite (e.g., Slack, Teams) for video, chat, and project management. *Hybrid Meeting Spaces*: Support for both virtual and physical collaboration, with AI-enhanced transcription and translation. *Digital Whiteboards*: Interactive tools for brainstorming and idea mapping.
6. Performance & Collaboration Metrics	*Analytics Dashboards*: AI-driven dashboards to monitor project progress and metrics. *Knowledge Sharing KPIs*: Track data usage, transfer rates, and joint outputs. *Predictive Analytics*: Assess project viability and prioritize impactful projects.
7. Skill Development Modules	*Online Learning*: Industry-focused AI and data science training modules. *Workshops & Certifications*: Expert-led programs to address skill gaps. *Hackathons*: Innovation challenges for hands-on AI learning in a collaborative setting.
8. Interdisciplinary Research	*Cross-Disciplinary Modules*: Structures that encourage collaboration between AI and domain experts. *Resource Sharing*: Flexible access to tools, lab spaces, and personnel for cross-departmental projects.

Source: Authors

3.3 Advanced AI integration

3.3.1 Hybrid AI models

There is a development in AI research that involves using hybrid AI models that blend symbolic AI with sub-symbolic AI techniques such as deep learning and machine learning. These hybrid models have the potential to enhance the AI-assisted CTHs by enhancing interpretability and efficiency in decision making for university-industry partnerships (Zhan et al., 2022; Sjödin et al., 2021). Hybrid AI systems combine the capabilities of reasoning (logical inference and rule-based knowledge structures) and machine learning techniques to recognize intricate patterns in extensive datasets (Benbya et al., 2020). When it comes to competency transfer scenarios hybrid AI models can fulfil the following roles:

1. *Semantic Knowledge Mapping*: Mapping semantic knowledge may help to match research findings such as papers and patents with the requirements of various industries in a more effective manner. The symbolic aspect maintains connections and categories while machine learning enhances precision and significance by adapting from datasets (Janiesch et al., 2021).
2. *Dynamic Resource Allocation*: Hybrid approaches can be utilized to forecast and distribute resources in response to evolving project requirements and technological advancements effectively utilizing both rule-based frameworks for consistency and machine learning for adapting to real-time data inputs to maintain responsiveness to changes as highlighted by Zhou et al. (2021).
3. *Advanced Personalization*: Advanced customization is a feature of the model that enables tailored interactions between industry players and educational establishments. Machine learning algorithms are constantly adjusting their grasp of user preferences. Alongside this the symbolic aspect ensures that the model stays in line with aims and objectives for knowledge transfer (Janiesch et al.,2021).

3.3.2 Explainability and interpretability in AI

The concept of Explainable AI (XAI) has been getting recognition because it allows for understandable decision-making processes (Saeed & Omlin, 2023). Integrating XAI into the AI-enhanced CTHs framework ensures that both academic and industry collaborators can rely on and comprehend the decisions made by AI systems as it:

1. *Improving Trust in AI-Driven Decision-Making*: When it comes to partnerships and project management in university-industry collaborations some stakeholders may be cautious about trusting AI for choices if they're unclear about how the AI comes to its recommendations. XAI offers a glimpse into the logic behind the suggestions made by AI regarding partnerships, resource distribution and project oversight (Arrieta et al., 2020). This transparency becomes crucial in industries where ethical considerations and adherence to norms hold particular importance (e.g. biotechnology, cybersecurity).
2. *Domain-Specific Explainability*: In some specific fields certain explanations methods should be customized to suit requirements. For example, in healthcare technology collaborations XAI can clarify the basis of recommendations for research projects. On

the other hand, in AI partnerships XAI may concentrate on elucidating model choices in algorithmic language giving important insights to both non specialist and technical individuals (Minh et al., 2022).

3. *Feedback Loops and Continuous Learning*: By incorporating XAI into the AI-enhanced CTHs design and functionality as suggested by Keding and Meissner (2021) users can offer feedback on AI-generated decisions to enhance the quality and pertinence of its recommendations - an approach that enhances transparency and adaptability while refining performance progressively.

3.3.3 Ethical AI considerations in university-industry collaboration

The integration of AI-driven CTHs in university-industry collaboration presents critical ethical challenges that extend beyond technical implementation. While AI enhances decision-making efficiency, collaboration matchmaking and knowledge dissemination, its deployment in research ecosystems necessitates a robust ethical framework to mitigate risks related to algorithmic bias, autonomy, data privacy, and governance (Hagendorff & Medling, 2023; Schiff, 2022). As AI takes on a centralized role in research partnerships, ensuring transparency, accountability and inclusivity in AI-generated recommendations becomes an imperative.

A major concern is algorithmic bias in AI-powered recommendation systems, which influence partner selection, funding allocation and knowledge exchange. If AI models are trained on historically skewed datasets, they may reinforce existing academic hierarchies, favoring well-established institutions and dominant research fields while marginalizing emerging disciplines and early-career researchers (Bankins & Formosa, 2023). To mitigate this risk bias detection and mitigation techniques should be embedded within AI models to ensure fairness and equitable collaboration opportunities. Additionally, XAI frameworks must be employed to provide clear, interpretable reasoning for AI-driven recommendations, fostering trust and transparency in research matchmaking. Furthermore, human-in-the-loop oversight should allow academic experts to review and adjust AI-generated suggestions, ensuring that research autonomy and disciplinary diversity are preserved.

Data privacy, security and academic sovereignty are equally significant ethical considerations. University-industry collaborations often involve sensitive intellectual property, proprietary datasets, and personal researcher information, necessitating strict adherence to global data protection regulations such as GDPR in Europe and CCPA in the U.S. (Gao et al., 2023; Tang et al., 2023). AI-driven CTHs must incorporate differential privacy and homomorphic encryption to ensure secure data exchanges. Additionally, federated learning architectures should be leveraged, allowing AI models to train on decentralized datasets without directly accessing proprietary information. Ensuring academic sovereignty protocols is crucial so that institutions maintain control over their intellectual contributions while benefiting from AI-enhanced collaboration.

As AI facilitates cross-border research partnerships, ethical challenges related to data sovereignty, regulatory divergence and geopolitical risks must be addressed (Bamdad et al., 2022). AI-driven CTHs should implement adaptive AI compliance frameworks that dynamically adjust to jurisdiction-specific legal and ethical standards. Moreover, decentralized AI governance models should be established to prevent concentration of decision-making authority, ensuring equitable access to knowledge-sharing resources and services, understating relationship employees' commitment to reach sustainable performance goals (Zhang & Liu, 2022; Mahajan et al., 2024). Ethical interoperability mechanisms must also be developed to harmonize international AI-driven collaboration frameworks in sectors such as healthcare, defense, and high-stakes AI ethics research.

Another pressing concern is over-centralization in AI-driven research management, which may compromise academic autonomy by imposing rigid, data-driven evaluation criteria that undervalue interdisciplinary and unconventional research. Overreliance on AI-based CTHs could also diminish human intuition and creativity in forming research partnerships while favoring institutions with superior AI infrastructure, creating power imbalances. To counter these risks, AI-powered CTHs should adopt a hybrid governance approach, integrating automated intelligence with human agency. This requires implementing decentralized AI governance models, allowing researchers to override AI-driven recommendations when necessary, and enabling personalized collaboration filters, where researchers define their own preferences and research priorities. Additionally, mechanisms for contestability should be established, allowing academics to challenge AI-generated rankings and request alternative matches to maintain research diversity and inclusivity.

Ultimately, while AI-driven CTHs hold immense potential to revolutionize knowledge exchange, their implementation must be ethically grounded to safeguard fairness, academic sovereignty, and researcher autonomy. Embedding bias mitigation strategies, privacy-preserving AI, decentralized governance, and contestability mechanisms will ensure that AI serves as an enabling tool rather than a controlling force in university-industry collaboration, fostering an inclusive, transparent, and innovation-driven research ecosystem.

3.3.4 Cross-domain applications of AI in competency transfer

AI-enhanced CTHs offer an opportunity to support collaborations across different fields of our fast-paced technological world (Gao et al., 2023). Interdisciplinary teamwork and cross-domain partnerships play an important role in driving innovation. AI serves as a valuable tool in connecting diverse areas of expertise and enabling collaborations that were previously out of reach, without advanced technological support:

1. *Interdisciplinary Research Collaboration*: AIs knack for combining information from fields enhances the effectiveness of partnerships that involve disciplines (Pan & Froese, 2023). Take AI tools as an example, they can uncover connections between areas like agriculture and finance, propose chances for collaboration between them. This exchange of ideas is especially valuable in CTHs where several industries meet.
2. *Facilitating AI-Driven Innovation in Niche Fields*: To support advancements in niche industries or new sectors effectively and promote collaborations among fields like nanotechnology and aerospace companies can be facilitated by utilizing cutting edge technologies with the help of AI (Malik et al., 2021b). For example, AI could assist in bringing the expertise of a university nanotechnology department and an aerospace company for joint materials research to develop solutions.
3. *Cross-Sector Skill Transfer*: AI tools in the CTHs can aid in transferring skills and competencies across sectors by recognizing skills acquired from AI or data analytics work (Nan & Huang, 2024). This encourages professionals to explore opportunities in industries and broadens collaboration prospects.

3.3.5 AI-driven strategic foresight in competency transfer hubs

One aspect of AI in university-industry partnerships that is frequently not given attention is the capacity of AI to offer foresight– the capability to anticipate forthcoming trends and identify potential opportunities and risks in advance effectively. AI-powered strategic foresight can serve as a valuable asset in CTHs by aiding universities and industries in anticipating technological changes and market shifts proactively in the following fields:

1. *Predictive Analytics for Emerging Technologies*: Utilizing AI-driven predictive analysis can track patent submissions and market trends to spot technologies with the potential to revolutionize sectors (Tekic & Füller, 2023). When this function is incorporated into the CTHs framework educational institutions and businesses can foresee ventures and stay ahead in the innovation game.
2. *Scenario Planning and Risk Mitigation*: AI tools are also valuable for scenario planning purposes as they assist stakeholders in examining scenarios resulting from different collaboration approaches (Ganesh & Kalpana, 2022; Neuhofer et al., 2021). For instance, AI has the capability to model the effects of a regulatory structure on partnerships enabling universities and businesses to proactively prepare for diverse potential outcomes.
3. *Long-Term Strategic Alliances*: AI-driven foresight also aids in creating enduring relationships that grow with technological progressions and introduce strategic alliances between universities and industries (Liu & Maas, 2021). This approach resonates with the CTHs' objective of nurturing innovation and sharing of knowledge.

The comprehensive discussion on these advanced hybrid elements of AI-driven hubs are summarized in Table 3.

4 Discussion and key implications

The use of AI models for the development of AI-enhanced CTHs brings an innovative approach to partnerships between universities and industries. These models greatly improve the understanding of information and decision-making processes within collaborative environments (Steidl et al., 2023; Rahat et al., 2024). This part delves deeper into the impact of AI models and their links to the TCM-ADO framework (Table 4):

Theory (T): Hybrid AI models expand on Knowledge Transfer Theory by facilitating connection of academic research like papers and patents to industry requirements. They blend symbolic AI for logical relationships and structured taxonomies with machine learning for enhancing accuracy through data analysis and past collaborations (Jarrahi et al., 2023). This combined approach strengthens university-industry partnerships for benefits.

Context (C): In the fields such as biotechnology and cybersecurity where technological advancements occur swiftly and constant learning is essential for progress, collaborative efforts driven by AI play an important role in facilitating real-time information sharing and adaptability to meet the ever-changing technological requirements (Trunk et al., 2020). This ability of AI models to adjust dynamically supports decision making processes.

Table 3 Advanced elements of AI-Driven CTHs

Category	Key Elements
Advanced AI Integration	*Hybrid AI Models*: Combines symbolic AI with machine learning for interpretability and pattern recognition. *Semantic Knowledge Mapping*: Matches research with industry needs by combining AI and ML techniques. *Dynamic Resource Allocation*: Uses hybrid AI to adapt resource distribution in real time.
Explainability and Interpretability	*Trust in Decision-Making*: Ensures transparent AI recommendations for project management and resource allocation. *Domain-Specific Explainability*: Tailors XAI explanations for fields like healthcare. *Feedback Loops*: Incorporates user feedback on AI decisions to enhance system adaptability.
Ethical AI Considerations	*Interdisciplinary Collaboration Ethics*: Integrates bias detection in recommendations to prevent discrimination. *Data Privacy and Security*: Employs encryption and compliance with data regulations like GDPR. *Cross-Border Ethics*: Adheres to international standards for secure data sharing across borders.
Cross-Domain Applications	*Interdisciplinary Collaboration*: Facilitates partnerships across fields by recognizing intersections (e.g., finance and agriculture). *Innovation in Niche Fields*: AI supports novel collaborations (e.g., nanotechnology and aerospace). *Cross-Sector Skill Transfer*: Identifies transferable skills, enhancing collaboration.
AI-Driven Strategic Foresight	*Predictive Analytics*: Tracks emerging tech through patent and market data for trend forecasting. *Scenario Planning*: Models regulatory and market impacts to support proactive collaboration. *Long-Term Alliances*: *Encourages* enduring partnerships that evolve with tech advancements.

Source: Authors

Methodology (M): The construction of the framework for the AI-enhanced CTHs is shaped by examining models in knowledge transfer and AI in a methodical manner (Papadopoulos et al., 2022). By combining machine learning with reasoning in this process ensures that partnerships are not simply effective, but also customized to meet the specific requirements of different industries. Hybrid AI models provide an approach for enhancing knowledge transfer with AI technology by maintaining a blend between academic research outcomes and practical industry applications.

Antecedents (A): These hybrid AI systems tackle issues by simplifying the process of organizing information and enhancing the distribution of resources while encouraging disciplinary cooperation that takes advantage of AIs analytical strengths.

Decisions (D): Decisions within this framework primarily focus on how universities and industries opt for AI technologies to improve collaboration. They decide to utilize AI-powered tools like natural language processing or machine learning to streamline the knowledge

Table 4 TCM-ADO framework for AI-driven CTHs

TCM-ADO Component	Application in AI-Driven CTHs for University-Industry Collaboration
Theory (T)	*Knowledge Transfer Theory*: Facilitates structured sharing of knowledge between academia and industry, emphasizing effective knowledge dissemination (Nonaka & Takeuchi, 1995). *Open Innovation Theory*: Highlights collaborative innovation with external partners to foster technological progress (Chesbrough, 2006). *Socio-Technical Systems Theory*: Examines integration of AI technology in collaborative systems, enhancing interactions between technical and human components (Trist, 1981). Together, these theories provide a foundation for AI-driven competency hubs.
Context (C)	*AI-Driven Collaborative Environment*: Focuses on partnerships within high-impact fields (e.g., healthcare, biotech, cybersecurity) where AI enhances adaptability and rapid information sharing (Olan et al., 2022). *Addressing Collaboration Barriers*: Tackles common issues such as cultural differences, knowledge transfer challenges, and the need for adaptable, real-time collaborative frameworks. *Dynamic Technological Adaptation*: Aligns with the fast-paced, evolving needs of high-tech sectors, supporting agile, technology-driven decision-making.
Methodology (M)	*Conceptual Model Development*: Combines Knowledge Transfer and Open Innovation theories with socio-technical perspectives to establish a structured model for AI-enhanced knowledge sharing (Papadopoulos et al., 2022). *AI-Driven Techniques*: Utilizes AI methodologies, such as NLP and hybrid AI models, to automate and personalize the knowledge transfer process. *Hybrid AI Models*: Integrates symbolic and machine learning techniques to bridge academic research with industry needs, enhancing adaptability and knowledge application.
Antecedents (A)	*Need for Advanced Collaboration Models*: Driven by rapid AI advancements, complex innovations, and limitations in traditional knowledge transfer methods. *Interactive Framework Requirements*: Growing demand for adaptive, real-time collaboration tools that facilitate efficient knowledge sharing between academia and industry (Stylos et al., 2021). *AI-Enhanced Competency Needs*: Complexity in AI applications necessitates advanced frameworks for knowledge and competency transfer across disciplines.
Decisions (D)	*AI Tool Selection*: Universities and industries choose AI tools (e.g., machine learning, NLP) to enhance automation and personalize knowledge transfer processes (Zhou & Tang, 2020). *Governance and Ethical Standards*: Implementation of fair and transparent decision-making structures, ensuring ethical compliance and IP protection in collaborations (Trappey et al., 2021). *Platform Integration*: Decision to use integrated, virtual collaboration platforms to facilitate smooth, AI-driven interactions and resource allocation.
Outcomes (O)	*Enhanced Knowledge Transfer Efficiency*: AI enables faster, scalable knowledge sharing processes, fostering more efficient university-industry collaborations (Caloghirou et al., 2021). *Accelerated Innovation Cycles*: AI-enabled hubs support quicker transitions from academic research to industry application, closing the gap between theory and practice. *Societal and Economic Impact*: Potential to advance AI fields and generate broader societal benefits through optimized university-industry partnerships, driving economic growth and innovation.

Source: Authors

acquisition processes and facilitate personalized suggestions (Malik et al., 2021a, b; Brem et al., 2021).

Outcomes (O): The outcomes focused around enhancing effectiveness and expandability in sharing knowledge procedures and boosting innovation timelines while bridging the gap between studies and industry requirements (Chowdhury et al., 2022; Caloghirou et al., 2021). Hybrid AI models pave the way for innovation by tuning AI-generated suggestions through user feedback loops constantly (Centobelli et al., 2025).

Thus, the suggested AI-enhanced CTHs framework pushes the boundaries of Knowledge Transfer Theory further introducing a responsive system for collaborations between universities and industries It also act as a catalyst for open innovation through its' assistance in developing collaboration platforms (Wiroonrath et al., 2024). Finally, hybrid AI models play an important role in assisting decision making by incorporating XAI to CTHs to ensure transparency and trustworthiness in AI-powered decisions (Yoon & Kim, 2024). In high stakes scenarios involving human AI interactions XAI guarantees that decisions made are fair and transparent by applying Socio-Technical Systems Theory principles.

The idea of *AI-powered CTHs* for sharing skills and knowledge, as presented and discussed in this study, holds the potential to significantly enhance the productivity and outcomes of university-industry partnerships. AI-powered systems introduce novel approaches for knowledge workers' innovative behavior related to information exchange, fostering greater involvement, positive spillovers and alignment within innovation ecosystems to keep pace with the fast-evolving technology landscape (Song et al., 2023; Jha & Basu, 2024).

In this section we also examine the practical implications and impacts of using AI-powered platforms for transferring knowledge and skills between universities and industry partners, identifying areas that would interest researchers and professionals alike. To illustrate how advancements in AI can transform the university-industry relationship we reference Table 5, which outlines the key value aspects of AI-driven CTHs, including strategic foresight, cognitive digital twins, ecosystem intelligence, etc. These value aspects emphasize how AI can optimize collaboration dynamics and amplify the social and economic benefits of university-industry partnerships, providing a framework for maximizing mutual gains in inward and outward knowledge transfer and innovation, especially during public to private collaborations with R&D-driven multinational incumbents and new comers (Park et al., 2022; Singh et al., 2025).

The practical impacts of AI-powered CTHs extend broadly, positively affect universities as well as businesses and decision makers alike. For institutions, like universities, the primary advantage lies in the commercialization of research outcomes facilitated by AI technology which matches scholarly research results with industry demands instantly leading to better synchronization with the market and decreased inefficiencies. An illustration of this can be seen at the Technology Licensing Office at Massachusetts Institute of Technology (MIT) where artificial intelligence is already leveraged to accelerate patent assessments and pinpoint industry partners enabling commercialization processes (MIT PatentScout (2024). Universities that adopt such systems can enhance innovation by connecting academic research with industry needs to stimulate economic progress as patents are typically considered as both an important measure of innovation output (Vismara, 2014) and a signaling mechanism about technological discoveries (Milani & Neumann, 2022).

Table 5 Value aspects of AI-Driven CTHs

Category	Advanced Value Aspects
Strategic Foresight and Innovation Forecasting	*Anticipatory Innovation Mapping*: Predicts future technology trends to align research and industry priorities *Scenario-Based Decision Making*: Models impacts of various strategic decisions for proactive planning. *Risk Propensity Analysis*: Evaluates R&D risk factors to prioritize high-return, calculated-risk projects.
Cognitive Digital Twins for Competency Transfer	*Dynamic Knowledge Transfer Models*: Digital twins of projects capture expertise for knowledge continuity. *Project Lifecycle Prediction*: Forecasts the complete project lifecycle to pre-empt challenges. *Customized Learning Pathways*: Provides personalized skill-building based on individual needs and project roles.
AI-Powered Ecosystem Intelligence	*Real-Time Ecosystem Monitoring*: Tracks internal and external trends for adaptive decision-making. *Collaboration Insights*: Identifies high-performing team dynamics for optimized collaboration. *Automated Competency Gap Analysis*: Highlights skills shortages and recommends training/hiring.
Advanced Ethical and Responsible AI Governance	*Automated Ethical Compliance Monitoring*: AI ensures ongoing adherence to ethical guidelines. *Diversity and Inclusion Metrics*: Evaluates inclusivity in research outcomes for equitable innovation. *Cross-Border Ethical Compatibility*: Ensures compliance with international regulations in global projects.
Hyper-Personalized Knowledge Curation	*On-Demand Knowledge Repositories*: Provides real-time, personalized access to curated resources. *Adaptive Content and Expertise Matching*: Recommends collaborators and resources suited to each user's needs. *Real-Time Insights Translation*: Simplifies complex data for easy cross-disciplinary collaboration.
Impact Amplification and Social Value Generation	*Social Impact Assessment*: AI assesses societal impact, from sustainability to social equity. *Inclusive Innovation Models*: Ensures underrepresented voices are included in research and development. *Knowledge Spillover to Local Economies*: Supports regional economic growth through knowledge sharing.
High-Fidelity Resource Optimization	*Resource Efficiency Models*: Optimizes resource use, aligning with sustainability goals. *Circular Economy Initiatives*: Promotes reuse of data and models across sectors for extended innovation value. *Sustainability Impact Simulation*: Models environmental impact of projects to support eco-friendly practices.

Source: Authors

Furthermore, AI has the potential to assist universities in amplifying the impact of their research on society as a whole in response to the growing demand for demonstrating significance (de Silva et al., 2024). Through the examination of data sets AI systems can pinpoint societal issues like climate change and public health emergencies and establish connections between these problems and pertinent academic investigations. For instance, Stanford University has directed its AI research efforts toward addressing climate change by linking studies on energy with industries on sustainable solutions (Standford University, 2023). By using these applications effectively universities can connect their research goals with the needs of society and establish themselves as influential catalysts for bringing about positive transformations. This synchronization not only enhances the reputation of universities, but is also draws in funding opportunities and attracts skilled individuals and possible partners for collaboration.

CTHs enhanced with AI technologies also help dismantle the barriers between different departments within universities by encouraging collaboration across disciplines (Wu, 2022). AI has the ability to examine data from various fields and identify connections that might be missed otherwise. This feature enables the development of solutions that span areas of expertise to address intricate problems effectively. The framework has resulted in advancements such as AI-powered analysis for healthcare services has solidified the academic institutions' position as a frontrunner in AI and healthcare advancements.

In the practical scenarios AI-powered CTHs play a vital role in connecting research with industry schedules. By incorporating analytics into these platforms companies are able to stay informed about the developments in academia promptly leading to quicker launches of new products. Through offering updates on research trends AI technologies assist industry collaborators in keeping up with innovations help them remain competitive in rapidly changing markets. Furthermore, businesses leverage AI-generated insights to predict research paths, integrating them into their R&D approaches to stay ahead in the market competition.

AI-powered CTHs also help to cut down costs associated with collaborations between universities and industries that typically require a lot of negotiation and monitoring expenses for projects. By automating these tasks like connecting projects with industry partners and keeping track of project advancements in real time using AI technologies. These streamlining saves time and resources needed for collaborations and also makes it easier for smaller companies to participate in partnerships. As a result, using AI-powered CTHs makes academic resources more accessible to industry players promoting innovation across fields.

One more benefit for businesses is the opportunity to tap into the research and knowledge base in advanced fields like augmented reality (AR) or biotechnology to stay ahead of the competition in rapidly evolving industries where it's tough to keep up with relevant developments naturally. For instance, AI-enhanced CTHs keep an eye on publications as well as patents and research outcomes to keep industry collaborators updated about the most recent progress and insights. This ability ensures that companies receive a flow of concepts and technological breakthroughs that allow them to stay at the forefront of innovation.

Policymakers can leverage AI-enhanced CTHs to aid and tune national innovation strategies (Lundvall & Rikap, 2022). Such CTHs play a role in promoting knowledge exchange between academic institutions and industries to ensure that research funding supports overarching economic goals like progress in renewable energy initiatives and healthcare advancements. By utilizing AI-generated data insights governments can pinpoint industry sectors where academic research can make an impact on innovation and allocate resources accordingly. This focused strategy enhances the use of funds by directing research resources towards partnerships that offer the societal benefits.

AI-powered CTHs also enable decision makers to oversee the results of partnerships between universities and industries to guarantee that government funds support advancements in technology and research development. By using AI technologies CTHs can monitor performance indicators like the quantity of partnerships established, market release timings and success rates in commercializing innovations, helping decision makers make well informed choices on funding and strategic planning. This method grounded in data

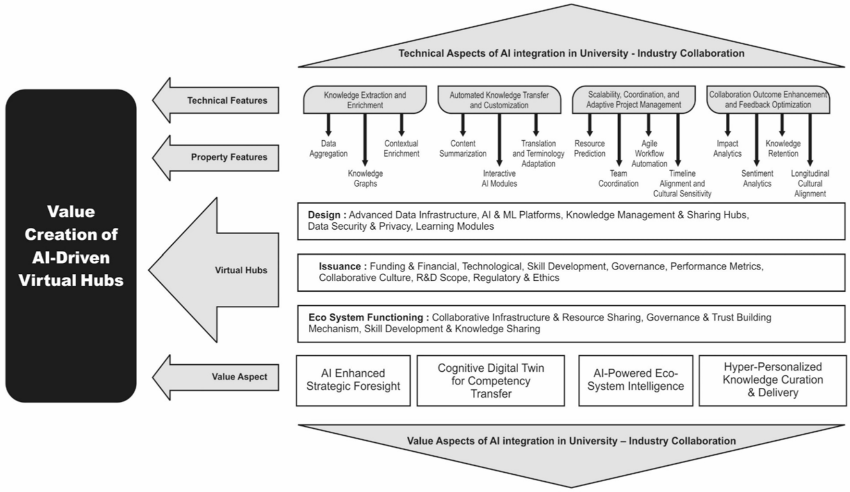

Fig. 1 Analysis Framework
Source: Authors

facilitates prompt modifications in how resources are distributed, ensuring that systems promoting innovation continue to operate and endure over time.

As illustrated in conceptual framework (Fig. 1), these AI-driven CTHs integrate various technical features, design elements, and value aspects that enhance the collaboration ecosystem. The figure highlights key components, such as AI-enabled knowledge extraction, customization, adaptive project management, and outcome optimization, which collectively contribute to a robust framework for effective university-industry collaboration. By incorporating these structured elements policymakers and stakeholders can maximize the potential of AI-enhanced CTHs to drive impactful and sustainable innovation.

5 Conclusion & future directions

The practical implications of AI-driven CTHs for universities, businesses and policymakers are extensive. These hubs provide a method for collaboration between universities and businesses facilitating knowledge exchange, accelerating innovation processes and increasing societal influence between older and younger employees as a mechanism of knowledge generation and access (Fasbender et al., 2021). By utilizing AI advancements like machine learning and natural language processing, universities and businesses can break through obstacles to collaboration and establish more flexible and adaptable innovation environments.

Universities benefit from AI-powered CTHs that simplify the process of bringing research to market and increase their influence on society, while boosting cooperation across fields of study. Industries find these hubs useful for cutting costs during transactions and gaining access to the research findings to speed up the introduction of ideas and enhance their competitive advantage. Policymakers have the opportunity to utilize AI-enhanced CTHs in promoting national innovation agendas and aligning investments with strategic priorities as well as fostering collaboration between sectors while monitoring the effectiveness of collaborations between universities and industries. Together, these impacts demonstrate the potential of AI-enhanced competency hubs to drive sustainable, cross-field innovation.

One of the limitations of the current study is that its' main emphasis has been on machine learning and natural language processing seen as AI technologies for CTHs. However upcoming investigations might probe into other AI-based tools like computer vision or blockchain to drive advancements in collaborations between universities and industries by streamlining more knowledge transfer procedures. One way this could work is, by using computer vision to examine information from studies like medical images or satellite data and link it to practical uses in various industries. The use of blockchain could also be a solution to oversee property securely and follow the development of projects to guarantee both sides have clear insight into the transfer of knowledge.

Further studies could also investigate how AI improved CTHs influence innovation results in the long run instead of just focusing on the immediate advantages of AI in enhancing collaboration and cutting transaction costs as discussed in this paper. It's crucial to evaluate the effects of these hubs on industries' long-term competitiveness and the sustainability of academic research. Scholars may explore if sectors that partner with universities via AI-driven hubs witness innovation cycles and better market performance along with enhanced long-term expansion when compared to those that do not collaborate in such a manner. Likewise, academic institutions could assess if AI-powered hubs contribute to the development of more resilient funding models for research and increased academic autonomy and generating new absorption pathways for assimilation, dissemination and sedimentation of knowledge (Yoshino et al., 2025; Cerchione et al., 2023; Iaia et al., 2023).

In discussions about the utilization of AI in sharing knowledge various ethical issues have been brought up specifically concerning data privacy, biases and the need for transparency. It would be beneficial for studies to delve into ways to tackle these dilemmas when creating and executing AI driven platforms for transferring competencies. Experts may explore ways in which AI systems can be created to guarantee fairness and inclusivity in sharing knowledge so that everyone involved (regardless of their scale and resources) can equally enjoy the advantages of collaborating with AI technology. Moreover, research could look into how AI-powered CTHs can be managed to maintain openness and responsibility especially when AI-driven choices hold economic consequences.

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References

Abreu, M., & Grinevich, V. (2024). The entrepreneurial University: Strategies, processes, and competing goals. *The Journal of Technology Transfer*, *49*, 1991–2034.

Abulibdeh, A., Zaidan, E., & Abulibdeh, R. (2024). Navigating the confluence of artificial intelligence and education for sustainable development in the era of industry 4.0: Challenges, opportunities, and ethical dimensions. *Journal of Cleaner Production*, 140527.

Albats, E., Alexander, A. T., & Cunningham, J. A. (2022). Traditional, virtual, and digital intermediaries in university-industry collaboration: Exploring institutional logics and bounded rationality. *Technological Forecasting and Social Change*, *177*, 121470.

Alexandre, F., Costa, H., Faria, A. P., & Portela, M. (2022). Enhancing university–industry collaboration: The role of intermediary organizations. *The Journal of Technology Transfer*, *47*(5), 1584–1611.

Arrieta, A. B., Díaz-Rodríguez, N., Del Ser, J., Bennetot, A., Tabik, S., Barbado, A., & Herrera, F. (2020). Explainable artificial intelligence (XAI): Concepts, taxonomies, opportunities and challenges toward responsible AI. *Information Fusion*, *58*, 82–115.

Arya, V., Sethi, D., & Hollebeek, L. D. (2024). Using augmented reality to strengthen consumer/brand relationships: The case of luxury brands. *Journal of Consumer Behaviour*. https://doi.org/10.1002/cb.2419

Audretsch, D. B., Khurana, I., Dutta, D. K., & Tamvada, J. P. (2025). Creating effective university innovation and entrepreneurial ecosystems: A commitment system perspective. *The Journal of Technology Transfer*, *50*, 169–191.

Awasthy, R., Flint, S., Sankarnarayana, R., & Jones, R. L. (2020). A framework to improve university–industry collaboration. *Journal of Industry-University Collaboration*, *2*(1), 49–62.

Ayala-Gaytán, E., Villasana, M., & Naranjo-Priego, E. (2024). University entrepreneurial ecosystems and graduate entrepreneurship. *The Journal of Entrepreneurship*, *33*(1), 88–117.

Bamdad, S., Finaughty, D. A., & Johns, S. E. (2022). Grey areas': Ethical challenges posed by social media-enabled recruitment and online data collection in cross-border, social science research. *Research Ethics*, *18*(1), 24–38.

Bankins, S., & Formosa, P. (2023). The ethical implications of artificial intelligence (AI) for meaningful work. *Journal of Business Ethics*, *185*(4), 725–740.

Battisti, S., Agarwal, N., & Brem, A. (2022). Creating new tech entrepreneurs with digital platforms: Meta-organizations for shared value in data-driven retail ecosystems. *Technological Forecasting and Social Change*, *175*, 121392.

Benbya, H., Davenport, T. H., & Pachidi, S. (2020). Artificial intelligence in organizations: Current state and future opportunities. *MIS Quarterly Executive*, *19*(4).

Benitez, G. B., Ayala, N. F., & Frank, A. G. (2020). Industry 4.0 innovation ecosystems: An evolutionary perspective on value cocreation. *International Journal of Production Economics*, *228*, 107735.

Bereznoy, A., Meissner, D., & Scuotto, V. (2021). The intertwining of knowledge sharing and creation in the digital platform based ecosystem. A conceptual study on the lens of the open innovation approach. *Journal of Knowledge Management*, *25*(8), 2022–2042.

Bhutoria, A. (2022). Personalized education and artificial intelligence in the united States, China, and India: A systematic review using a human-in-the-loop model. *Computers and Education: Artificial Intelligence*, *3*, 100068.

Birkstedt, T., Minkkinen, M., Tandon, A., & Mäntymäki, M. (2023). AI governance: Themes, knowledge gaps and future agendas. *Internet Research*, *33*(7), 133–167.

Brem, A., Giones, F., & Werle, M. (2021). The AI digital revolution in innovation: A conceptual framework of artificial intelligence technologies for the management of innovation. *IEEE Transactions on Engineering Management*, *70*(2), 770–776.

Bukhari, E., Dabic, M., Shifrer, D., Daim, T., & Meissner, D. (2021). Entrepreneurial University: The relationship between smart specialization innovation strategies and university-region collaboration. *Technology in Society*, *65*, 101560.

Caloghirou, Y., Giotopoulos, I., Kontolaimou, A., Korra, E., & Tsakanikas, A. (2021). Industry-university knowledge flows and product innovation: How do knowledge stocks and crisis matter? *Research Policy*, *50*(3), 104195.

Casillo, F., Deufemia, V., & Gravino, C. (2022). Detecting privacy requirements from user stories with NLP transfer learning models. *Information and Software Technology*, *146*, 106853.

Centobelli, P., Cerchione, R., Oropallo, E., Papa, A., & Palermo, S. (2025). Digital knowledge management in agile self-tuning organisations: A multiple case study. *Journal of Knowledge Management*, *29*(1), 222–246.

Cerchione, R., Centobelli, P., Oropallo, E., Magni, D., & Borin, E. (2023). Knowing what you don't know: A tertiary study on knowledge management. *Journal of Knowledge Management*, *27*(9), 2548–2578.

Chen, Y. (2020). IoT, cloud, big data and AI in interdisciplinary domains. *Simulation Modelling Practice and Theory*, *102*, 102070.

Chesbrough, H. (2006). Open innovation: Researching a new paradigm. *Oxford University Press Google Schola*, *2*, 15–25.

Chowdhury, S., Budhwar, P., Dey, P. K., Joel-Edgar, S., & Abadie, A. (2022). AI-employee collaboration and business performance: Integrating knowledge-based view, socio-technical systems and organisational socialisation framework. *Journal of Business Research*, *144*, 31–49.

Civera, A., Meoli, M., & Vismara, S. (2024). The sustainability of academic entrepreneurial ecosystems. *Research handbook on entrepreneurial ecosystems* (pp. 339–351). Edward Elgar Publishing.

Cohen, W. M., & Levinthal, D. A. (1990). Absorptive capacity: A new perspective on learning and innovation. *Administrative Science Quaterly*, *35*(1), 128–152.

Cohen, M., Fernandes, G., & Godinho, P. (2025). Measuring the impacts of university–industry R&D collaborations: A systematic literature review. *The Journal of Technology Transfer*, *50*, 345–374.

Correia, M. P., Marques, C. S., Silva, R., & Ramadani, V. (2024). Academic entrepreneurship ecosystems: Systematic literature review and future research directions. *Journal of the Knowledge Economy*, *15*, 17498–17528.

Davis, M. C., Challenger, R., Jayewardene, D. N., & Clegg, C. W. (2014). Advancing socio-technical systems thinking: A call for bravery. *Applied Ergonomics*, *45*(2), 171–180.

de Silva, D., Kaynak, O., El-Ayoubi, M., Mills, N., Alahakoon, D., & Manic, M. (2024). Opportunities and challenges of generative artificial intelligence: Research, education, industry engagement, and social impact. *IEEE Industrial Electronics Magazine*.

Deng, H., Duan, S. X., & Wibowo, S. (2023). Digital technology driven knowledge sharing for job performance. *Journal of Knowledge Management*, *27*(2), 404–425.

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.

Etzkowitz, H., & Leydesdorff, L. (2000). The dynamics of innovation: From National systems and mode 2 to a triple Helix of university–industry–government relations. *Research Policy*, *29*(2), 109–123.

Fasbender, U., Gerpott, F. H., & Unger, D. (2021). Give and take? Knowledge exchange between older and younger employees as a function of generativity and development striving. *Journal of Knowledge Management*, *25*(10), 2420–2443.

Ferreira, J. J., & Carayannis, E. G. (2019). University-industry knowledge transfer-unpacking the black box: An introduction. *Knowledge Management Research & Practice*, *17*(4), 353–357.

Fountaine, T., McCarthy, B., & Saleh, T. (2019). Building the AI-powered organization. *Harvard Business Review*, *97*(4), 62–73.

Franke, H., & Foerstl, K. (2020). Understanding politics in PSM teams: A cross-disciplinary review and future research agenda. *Journal of Purchasing and Supply Management*, *26*(3), 100608.

Ganesh, A. D., & Kalpana, P. (2022). Future of artificial intelligence and its influence on supply chain risk management–A systematic review. *Computers & Industrial Engineering*, *169*, 108206.

Gao, B., Wang, Y., Xie, H., Hu, Y., & Hu, Y. (2023). Artificial intelligence in advertising: Advancements, challenges, and ethical considerations in targeting, personalization, content creation, and ad optimization. *Sage Open*, *13*(4), 21582440231210759.

Gassmann, O., Enkel, E. (2004). Towards a theory of open innovation: three core process archetypes. *Proceedings of The R&D Management, & Conference, Lisbon, Portugal, July 6–9*.

Gill, S. S., Tuli, S., Xu, M., Singh, I., Singh, K. V., Lindsay, D., & Garraghan, P. (2019). Transformative effects of IoT, blockchain and artificial intelligence on cloud computing: Evolution, vision, trends and open challenges. *Internet of Things*, *8*, 100118.

Gonzalez, R. V. D. (2024). The impact of potential and realized absorptive capacity on open innovation: The moderating role of knowledge-oriented leadership. *Journal of Knowledge Management*.

Govind, M., & Küttim, M. (2016). International knowledge transfer from university to industry: A systematic literature review. *Research in Economics and Business: Central and Eastern Europe*, *8*(2), 5–25.

Gupta, S., Modgil, S., Kumar, A., Sivarajah, U., & Irani, Z. (2022). Artificial intelligence and cloud-based collaborative platforms for managing disaster, extreme weather and emergency operations. *International Journal of Production Economics*, *254*, 108642.

Hagendorff, T., & Meding, K. (2023). Ethical considerations and statistical analysis of industry involvement in machine learning research. *Ai & Society*, 1–11.

Hailu, A. T. (2024). The role of university–industry linkages in promoting technology transfer: Implementation of triple helix model relations. *Journal of Innovation and Entrepreneurship*, *13*(1), 25.

Harfouche, A., Quinio, B., Saba, M., & Saba, P. B. (2023). The recursive theory of knowledge augmentation: Integrating human intuition and knowledge in artificial intelligence to augment organizational knowledge. *Information Systems Frontiers*, *25*(1), 55–70.

Hartmann, P., & Henkel, J. (2020). The rise of corporate science in AI: Data as a strategic resource. *Academy of Management Discoveries*, *6*(3), 359–381.

Hayter, C. S., Nelson, A. J., Zayed, S., & O'Connor, A. C. (2018). Conceptualizing academic entrepreneurship ecosystems: A review, analysis and extension of the literature. *The Journal of Technology Transfer*, *43*, 1039–1082.

Hayter, C. S., Fischer, B., & Rasmussen, E. (2021). Becoming an academic entrepreneur: How scientists develop an entrepreneurial identity. *Small Business Economics*, 1–19.

Iaia, L., Nespoli, C., Vicentini, F., Pironti, M., & Genovino, C. (2023). Supporting The implementation of AI in business communication: The role of knowledge management. *Journal of Knowledge Management*, *28*(1), 85–95.

Ideland, M., & Serder, M. (2023). Edu-business within the triple helix. Value production through assetization of educational research. *Education Inquiry*, *14*(3), 336–351.

Jain, S., George, G., & Maltarich, M. (2009). Academics or entrepreneurs? Investigating role identity modification of university scientists involved in commercialization activity. *Research Policy*, *38*(6), 922–935.

Janiesch, C., Zschech, P., & Heinrich, K. (2021). Machine learning and deep learning. *Electronic Markets*, *31*(3), 685–695.

Jarrahi, M. H., Askay, D., Eshraghi, A., & Smith, P. (2023). Artificial intelligence and knowledge management: A partnership between human and AI. *Business Horizons*, *66*(1), 87–99.

Jha, S., & Basu, S. (2024). Knowledge spillovers between R&D-driven incumbents and start-ups in open innovation: A systematic review and Nomological network. *Journal of Knowledge Management*.

Ju, X., Wang, G., & Fu, Y. (2023). Linking networking capability and ambidextrous innovation strategies: The mediating roles of knowledge assimilation application and knowledge transformation application. *Journal of Knowledge Management*, *27*(6), 1534–1561.

Keding, C., & Meissner, P. (2021). Managerial overreliance on AI-augmented decision-making processes: How the use of AI-based advisory systems shapes choice behavior in R&D investment decisions. *Technological Forecasting and Social Change*, *171*, 120970.

Kumar, P., Dwivedi, Y. K., & Anand, A. (2023). Responsible artificial intelligence (AI) for value formation and market performance in healthcare: The mediating role of patient's cognitive engagement. *Information Systems Frontiers*, *25*(6), 2197–2220.

Lim, W. M., Yap, S. F., & Makkar, M. (2021). Home sharing in marketing and tourism at a tipping point: What do we know, how do we know, and where should we be heading? *Journal of Business Research*, *122*, 534–566.

Link, A. N., van Hasselt, M., & Vismara, S. (2021). Going public with public money. *Small Business Economics*, *57*, 1419–1426.

Liu, H. Y., & Maas, M. M. (2021). Solving for X?'Towards a problem-finding framework to ground long-term governance strategies for artificial intelligence. *Futures*, *126*, 102672.

Lu, Y., Xu, X., & Wang, L. (2020). Smart manufacturing process and system automation–a critical review of the standards and envisioned scenarios. *Journal of Manufacturing Systems*, *56*, 312–325.

Lundberg, H., & Öberg, C. (2021). Teachers, researchers, but not innovators? Rethinking university-industry collaboration. *Journal of Business & Industrial Marketing*, *36*(13), 161–173.

Lundvall, B. Å., & Rikap, C. (2022). China's catching-up in artificial intelligence seen as a co-evolution of corporate and National innovation systems. *Research Policy*, *51*(1), 104395.

Luthra, A., Dixit, S., & Arya, V. (2023). Evaluating the impact of faculty development on employee engagement practices in higher education: Analysing the mediating role of professional development. *The Learning Organization*, *31*(4), 565–584.

Luthra, A., Arya, V., Dixit, S., Roy, H., & Sasso, P. (2024). Knowledge management is no more a Gray area in the tourism industry in India–a study on transformation leadership and executive communication. *Journal of Knowledge Management*, *28*(6), 1711–1745.

Mahajan, V., Sharma, J., Singh, A., Bresciani, S., & Alam, G. M. (2024). Knowledge sharing behavior of service sector's employees to attain sustainable development goals. *Journal of Knowledge Management*.

Malik, A., De Silva, M. T., Budhwar, P., & Srikanth, N. R. (2021a). Elevating talents' experience through innovative artificial intelligence-mediated knowledge sharing: Evidence from an IT-multinational enterprise. *Journal of International Management*, *27*(4), 100871.

Malik, A., Sharma, P., Pereira, V., & Temouri, Y. (2021b). From regional innovation systems to global innovation hubs: Evidence of a quadruple Helix from an emerging economy. *Journal of Business Research*, *128*, 587–598.

Mikalef, P., Boura, M., Lekakos, G., & Krogstie, J. (2020). The role of information governance in big data analytics driven innovation. *Information & Management*, *57*(7), 103361.

Milani, S., & Neumann, R. (2022). R&D, patents, and financing constraints of the top global innovative firms. *Journal of Economic Behavior and Organization*, *196*, 546–567.

Minh, D., Wang, H. X., Li, Y. F., & Nguyen, T. N. (2022). Explainable artificial intelligence: A comprehensive review. *Artificial Intelligence Review*, 1–66.

MIT PatentScout (2024). MIT PatentScout™ Secure Patent Search Tool, Accessed on October 2024, available at: https://tlo.mit.edu/understand-ip/mit-patentscouttm-secure-patent-search-tool

Moraes, G. H. S. M. D., Fischer, B., Salles-Filho, S., Meissner, D., & Dabic, M. (2023). More than one way to get there: A configurational view on performance drivers in knowledge-intensive entrepreneurship. *Journal of Knowledge Management*, *27*(11), 205–230.

Mosey, S., Rasmussen, E., & Wright, M. (2014). The influence of university departments on the evolution of entrepreneurial competencies in spin-off ventures. *Research Policy*, *43*(1).

Nan, M., & Huang, L. (2024). Innovation ecosystems: A Cross-Industry examination of knowledge flows and collaboration dynamics. *Journal of the Knowledge Economy*, 1–39.

Neuhofer, B., Magnus, B., & Celuch, K. (2021). The impact of artificial intelligence on event experiences: A scenario technique approach. *Electronic Markets*, *31*(3), 601–617.

Nguyen, M., & Mougenot, C. (2022). A systematic review of empirical studies on multidisciplinary design collaboration: Findings, methods, and challenges. *Design Studies*, *81*, 101120.

Nonaka, I., & Takeuchi, H. (1995). *The knowledge creating company: How Japanese companies create the dynamics innovation*. Oxford Univ. Press.

Nsanzumuhire, S. U., & Groot, W. (2020). Context perspective on university-industry collaboration processes: A systematic review of literature. *Journal of Cleaner Production*, *258*, 120861.

O'Dwyer, M., Filieri, R., & O'Malley, L. (2023). Establishing successful university–industry collaborations: Barriers and enablers deconstructed. *The Journal of Technology Transfer*, *48*(3), 900–931.

Olan, F., Arakpogun, E. O., Suklan, J., Nakpodia, F., Damij, N., & Jayawickrama, U. (2022). Artificial intelligence and knowledge sharing: Contributing factors to organizational performance. *Journal of Business Research*, *145*, 605–615.

Palvia, P., Ghosh, J., Jacks, T., & Serenko, A. (2021). Information technology issues and challenges of The Globe: The world IT project. *Information & Management*, *58*(8), 103545.

Pan, Y., & Froese, F. J. (2023). An interdisciplinary review of AI and HRM: Challenges and future directions. *Human Resource Management Review*, *33*(1), 100924.

Panchendrarajan, R., & Zubiaga, A. (2024). Synergizing machine learning & symbolic methods: A survey on hybrid approaches to natural Language processing. *Expert Systems with Applications*, *251*, 124097.

Papa, A., Chierici, R., Ballestra, L. V., Meissner, D., & Orhan, M. A. (2020). Harvesting reflective knowledge exchange for inbound open innovation in complex collaborative networks: An empirical verification in Europe. *Journal of Knowledge Management*, *25*(4), 669–692.

Papadopoulos, T., Sivarajah, U., Spanaki, K., Despoudi, S., & Gunasekaran, A. (2022). Artificial intelligence (AI) and data sharing in manufacturing, production and operations management research. *International Journal of Production Research*, *60*(14), 4361–4364.

Park, J. S., Chang, J. Y., & Lee, T. (2022). The impacts of inward knowledge transfer and absorptive capacity on the turnover of host country nationals in MNE subsidiaries: A multilevel modeling approach. *Journal of Knowledge Management*, *26*(11), 1–21.

Paul, J., & Criado, A. R. (2020). The Art of writing literature review: What do we know and what do we need to know? *International Business Review*, *29*(4), 101717.

Paul, J., Parthasarathy, S., & Gupta, P. (2017). Exporting challenges of SMEs: A review and future research agenda. *Journal of World Business*, *52*(3), 327–342.

Prokop, D. (2021). University entrepreneurial ecosystems and spinoff companies: Configurations, developments and outcomes. *Technovation*, *107*, 102286.

Prokop, D. (2022). The composition of university entrepreneurial ecosystems and academic entrepreneurship: A UK study. *International Journal of Innovation and Technology Management*, *19*(6), 2250020.

Rahat, N., Sahni, S., & Nasim, S. (2024). Mapping sustainability practices in the healthcare sector: A systematic literature review and future research agenda. *International Journal of Consumer Studies*, 48(1), e12997.

Raisch, S., & Krakowski, S. (2021). Artificial intelligence and management: The automation–augmentation paradox. *Academy of Management Review*, *46*(1), 192–210.

Rajalo, S., & Vadi, M. (2017). University-industry innovation collaboration: Reconceptualization. *Technovation*, *62*, 42–54.

Reed, M. S., Ferré, M., Martin-Ortega, J., Blanche, R., Lawford-Rolfe, R., Dallimer, M., & Holden, J. (2021). Evaluating impact from research: A methodological framework. *Research Policy*, *50*(4), 104147.

Rossoni, A. L., de Vasconcellos, E. P. G., & de Castilho Rossoni, R. L. (2024). Barriers and facilitators of university-industry collaboration for research, development and innovation: A systematic review. *Management Review Quarterly*, *74*(3), 1841–1877.

Saeed, W., & Omlin, C. (2023). Explainable AI (XAI): A systematic meta-survey of current challenges and future opportunities. *Knowledge-Based Systems*, *263*, 110273.

Saratchandra, M., & Shrestha, A. (2022). The role of cloud computing in knowledge management for small and medium enterprises: A systematic literature review. *Journal of Knowledge Management*, *26*(10), 2668–2698.

Schartinger, D., Rammer, C., Fischer, M., & Fröhlich, J. (2002). Knowledge interactions between universities and industry in Austria: Sectoral patterns and determinants. *Research Policy*, *31*(3), 303–328.

Schiff, D. (2022). Education for AI, not AI for education: The role of education and ethics in National AI policy strategies. *International Journal of Artificial Intelligence in Education*, *32*(3), 527–563.

Schoen, A., van Pottelsberghe, B., & Henkel, J. (2014). Governance typology of universities' technology transfer processes. *The Journal of Technology Transfer*, *39*, 435–453.

Secundo, G., Shams, S. R., & Nucci, F. (2021). Digital technologies and collective intelligence for healthcare ecosystem: Optimizing internet of things adoption for pandemic management. *Journal of Business Research*, *131*, 563–572.

Serrano-Ruiz, J. C., Ferreira, J., Jardim-Goncalves, R., & Ortiz, Á. (2024). Relational network of innovation ecosystems generated by digital innovation hubs: A conceptual framework for the interaction processes of DIHs from the perspective of collaboration within and between their relationship levels. *Journal of Intelligent Manufacturing*, 1–41.

Sethi, D., Pereira, V., & Arya, V. (2021). Effect of technostress on academic productivity: E-engagement through persuasive communication. *Journal of Global Information Management (JGIM)*, *30*(5), 1–19.

Sharma, M., Luthra, S., Joshi, S., & Kumar, A. (2022). Implementing challenges of artificial intelligence: Evidence from public manufacturing sector of an emerging economy. *Government Information Quarterly*, *39*(4), 101624.

Sharma, K., Arya, V., & Mathur, H. P. (2023). New higher education policy and strategic plan: Commensurate India's higher education in global perspective. *FIIB Business Review*, 23197145221125351.

Singh, N., Salwan, P., Kumar Mangla, S., & Vrontis, D. (2025). Impact of dimensions of absorptive capacity on multinationals' reverse knowledge transfer: From an Indian context. *Journal of Knowledge Management*, *29*(1), 171–203.

Sjödin, D., Parida, V., Palmié, M., & Wincent, J. (2021). How AI capabilities enable business model innovation: Scaling AI through co-evolutionary processes and feedback loops. *Journal of Business Research*, *134*, 574–587.

Song, J., Jiao, H., & Wang, C. (2023). How work-family conflict affects knowledge workers' innovative behavior: A spillover-crossover-spillover model of dual-career couples. *Journal of Knowledge Management*, *27*(9), 2499–2525.

Sowa, K., Przegalinska, A., & Ciechanowski, L. (2021). Cobots in knowledge work: Human–AI collaboration in managerial professions. *Journal of Business Research*, *125*, 135–142.

Standford University (2023). Sustainability and AI. Accessed on October 2024, available at: https://hai.stanford.edu/sites/default/files/2023-01/HAI_IndustryBrief6_v8.pdf

Steidl, M., Felderer, M., & Ramler, R. (2023). The pipeline for the continuous development of artificial intelligence models—Current state of research and practice. *Journal of Systems and Software*, *199*, 111615.

Stylos, N., Zwiegelaar, J., & Buhalis, D. (2021). Big data empowered agility for dynamic, volatile, and time-sensitive service industries: The case of tourism sector. *International Journal of Contemporary Hospitality Management*, *33*(3), 1015–1036.

Tang, H., Xie, Y., Liu, Y., & Boadu, F. (2023). Distributed innovation, knowledge re-orchestration, and digital product innovation performance: The moderated mediation roles of intellectual property protection and knowledge exchange activities. *Journal of Knowledge Management*, *27*(10), 2686–2707.

Tekic, Z., & Füller, J. (2023). Managing innovation in the era of AI. *Technology in Society*, *73*, 102254.

Thomas, A., & Paul, J. (2019). Knowledge transfer and innovation through university-industry partnership: An integrated theoretical view. *Knowledge Management Research & Practice*, *17*(4), 436–448.

Tolin, G., & Piccaluga, A. (2024). University-industry knowledge transfer in the agri-food: A systematic literature review. *Knowledge Management Research & Practice*, 1–14.

Tong, S., Jia, N., Luo, X., & Fang, Z. (2021). The Janus face of artificial intelligence feedback: Deployment versus disclosure effects on employee performance. *Strategic Management Journal*, *42*(9), 1600–1631.

Trappey, A., Trappey, C. V., & Hsieh, A. (2021). An intelligent patent recommender adopting machine learning approach for natural Language processing: A case study for smart machinery technology mining. *Technological Forecasting and Social Change*, *164*, 120511.

Trist, E. L. (1981). *The evolution of socio-technical systems* (Vol. 2, p. 1981). Toronto: Ontario Quality of Working Life Centre.

Trunk, A., Birkel, H., & Hartmann, E. (2020). On the current state of combining human and artificial intelligence for strategic organizational decision making. *Business Research*, *13*(3), 875–919.

Valle-Cruz, D., & García-Contreras, R. (2023). Towards AI-driven transformation and smart data management: Emerging technological change in the public sector value chain. *Public Policy and Administration*, 09520767231188401.

van Eijnatten, F. M. (2013). Developments in socio-technical systems design (STSD). *A handbook of work and organizational psychology* (pp. 61–88). Psychology.

Vismara, S. (2014). Patents, R&D investments and post-IPO strategies. *Review of Managerial Science*, *8*, 419–435.

Vivona, R., Demircioglu, M. A., & Audretsch, D. B. (2023). The costs of collaborative innovation. *The Journal of Technology Transfer*, *48*, 873–899.

Walker, G. (2015). Come back sociotechnical systems theory, all is forgiven…. *Civil Engineering and Environmental Systems*, *32*(1–2), 170–179.

Weerasinghe, I. M. S., & Dedunu, H. H. (2021). Do demographic factors matter in university-industry knowledge exchange? A study based on Sri Lankan university system. *Journal of Knowledge Management*, *25*(5), 973–988.

Wiroonrath, S., Phanniphong, K., Somnuk, S., & Na-Nan, K. (2024). Impact of leader support on open innovation: The mediating role of organizational culture, intellectual property, and collaboration. *Journal of Open Innovation: Technology Market and Complexity*, *10*(3), 100333.

Wu, Z. (2022). Understanding teachers' cross-disciplinary collaboration for STEAM education: Building a digital community of practice. *Thinking Skills and Creativity*, *46*, 101178.

Wu, J. Y., Yang, C. C., Liao, C. H., & Nian, M. W. (2021). Analytics 2.0 for precision education. *Educational Technology & Society*, *24*(1), 267–279.

Xu, F., & Correia, A. P. (2024). Adopting distributed pair programming as an effective team learning activity: A systematic review. *Journal of Computing in Higher Education*, *36*(2), 320–349.

Yin, X., Li, F., Chen, J., & Zhai, Y. (2023). Innovating from university–industry collaboration: The mediating role of intellectual capital. *Journal of Intellectual Capital*, *24*(6), 1550–1577.

Yoon, J., & Kim, C. (2024). Positive emodiversity in everyday human-technology interactions and users' subjective well-being. *International Journal of Human–Computer Interaction*, *40*(3), 651–666.

Yoshino, M., Sadlek, B., Yarime, M., & Ali, A. (2025). Knowledge absorption pathways for eco-innovation: An empirical Analysis of small And medium-sized enterprises in the European union. *European Journal of Innovation Management*, *28*(2), 426–453.

Yu, X., Washida, Y., & Sasaki, M. (2022). Impact of qualified gatekeepers on team absorptive capacity: The mediating role of knowledge combination capability. *Journal of Knowledge Management*, *26*(11), 259–292.

Zhai, X., Chu, X., Chai, C. S., Jong, M. S. Y., Istenic, A., Spector, M., & Li, Y. (2021). A review of artificial intelligence (AI) in education from 2010 to 2020. *Complexity*, *2021*(1), 8812542.

Zhan, Z. H., Shi, L., Tan, K. C., & Zhang, J. (2022). A survey on evolutionary computation for complex continuous optimization. *Artificial Intelligence Review*, *55*(1), 59–110.

Zhang, X., & Liu, S. (2022). Understanding relationship commitment and continuous knowledge sharing in online health communities: A social exchange perspective. *Journal of Knowledge Management*, *26*(3), 592–614.

Zhou, R., & Baines, N. (2024). To what extent do universities' formal and informal knowledge exchange activities interact: Evidence from UK HE-BCI survey. *The Journal of Technology Transfer*, *49*, 1145–1175.

Zhou, R., & Tang, P. (2020). The role of university knowledge transfer offices: Not just commercialize research outputs! *Technovation*, *90*, 102100.
Zhou, Q., Zhao, D., Shuai, B., Li, Y., Williams, H., & Xu, H. (2021). Knowledge implementation and transfer with an adaptive learning network for real-time power management of the plug-in hybrid vehicle. *IEEE Transactions on Neural Networks and Learning Systems*, *32*(12), 5298–5308.
Zhu, R., Tu, X., & Huang, J. (2020). Using deep learning based natural Language processing techniques for clinical decision-making with EHRs. *Deep Learning Techniques for Biomedical and Health Informatics*, 257–295.

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