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# University–industry collaboration for AI-driven service innovation

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## Abstract

**Purpose** – Service innovation is undergoing a fundamental transformation due to digitization, sustainability imperatives, platformization and particularly the rapid diffusion of artificial intelligence (AI). AI-driven service innovation requires specialized and domain-specific expertise, which is increasingly derived from university–industry collaboration (UIC) contexts. However, UICs are often prone to failure, and new, uncertain and ambiguous characteristics of AI can further exacerbate these challenges. This paper, therefore, explores how UICs can be successfully managed to develop and deploy AI-driven service innovations.

**Design/methodology/approach** – A qualitative, illustrative case study research design featuring expert interviews and secondary data sources was employed to analyze multiple UIC contexts, with a focus on understanding AI-driven service innovation. The interpretive thematic analysis revealed inductive data-driven insights that were used to refine and augment deductive insights from the literature.

**Findings** – A framework for enhancing the success of UIC for AI-driven service innovation is proposed, based on illustrative case data, alongside theoretical perspectives from UIC, service-dominant logic and service ecosystems. The framework incorporates the mechanisms for thriving partnerships and defines how AI-driven stakeholder value can be enhanced. Therein, it identifies key enablers, processes/practices and outcomes/benefits of UIC for AI-driven service innovation. The conclusion brings together theoretical and practical implications from the framework and presents a future research agenda.

**Originality/value** – Prior literature has primarily examined UIC for technological, product and process innovation. To the best of the authors' knowledge, this is the first study to focus on UIC collaborations for service innovation, specifically in AI contexts. It synthesizes existing literature and insights from successful UIC in the



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context of AI to develop a novel framework to guide further theory development, practical collaborations and policy design.



**Keywords** Service innovation, Artificial intelligence, University–industry collaborations, Open innovation, Illustrative case study

**Paper type** Research article



## 1. Introduction

Technological forces, such as artificial intelligence (AI), are altering the service landscape, shifting consumer expectations, enhancing data-driven personalization and accelerating global "grand challenges" (Buckley *et al.*, 2017). Advancements in AI are forcing service organizations to rethink traditional service delivery assumptions, innovate continuously and collaborate with research partners to commercialize novel AI-driven service innovations more effectively. University–industry collaboration (UIC) can enhance innovation performance by making available research expertise, creative problem-solving and access to new knowledge (Ankrah and Omar, 2015; Perkmann *et al.*, 2013; Verreynne *et al.*, 2025) and is particularly important in extremely competitive and rapidly changing environments that require differentiation. Universities increasingly embrace "third mission" objectives, expanding their societal roles beyond teaching and research to include entrepreneurial engagement and innovation (Nelles and Vorley, 2010). Through cross-disciplinary expertise, ethical oversight and a long-term orientation, universities complement service firms' market knowledge, data assets and commercialization capacity (Benoit *et al.*, 2019). Together, these complementarities enable collaborations to embed innovation more deeply, ensuring it evolves, regenerates and delivers sustained value for service firms, customers and society. However, UIC, while ideal in theory, often fails in practice. This is attributed to diverse factors well established in the literature, such as barriers to trust and commitment (O'Dwyer *et al.*, 2023) and bureaucracies and incentive challenges (Siegel *et al.*, 2003). Therefore, understanding how to better manage UIC has attracted considerable attention (e.g., Perkmann and Walsh, 2007).

An important yet under-researched avenue for successful UIC management lies in the context of AI-driven service innovation. Such a context is a particularly fruitful one for UIC research, as the pace of AI model development, ethical dilemmas and implementation challenges often outstrips the absorptive capacity of service firms alone (Kaartemo and Helkkula, 2024; McMahon, 2025). These capacity shortcomings suggest that successful collaboration with what Etzkowitz (2004) terms "entrepreneurial universities" is an order-qualifier for service firms' survival.

Prior literature on the enablers of successful UIC has emphasized knowledge transfer, commercialization, trust, culture and intellectual property (IP) (e.g., Sjöö and Hellström, 2019; O'Dwyer *et al.*, 2023). Yet, the emergence of AI introduces new and complex service dynamics relating to human–AI interaction (Kaartemo and Helkkula, 2024) and ethics and governance (McMahon, 2025). These dynamics draw on established concepts such as trust (Kriz, 2009) and partnerships (Prigge, 2005), and extend them into contexts where the technology itself is an active co-creator. AI, for example, has enabled robo-advisors in financial services (Marti *et al.*, 2024), diagnostic devices in healthcare (van Riel *et al.*, 2025) and agents that support sustainable decision-making in transport and energy (Witell *et al.*, 2016). While AI-driven service innovations are complex in nature and increasingly demand the expertise and input of stakeholders external to service firms (i.e., research and technology partners), little is currently known as to how UICs are best managed in AI service contexts.

Therefore, a central research problem emerges: *how are successful UIC partnerships managed for AI-driven service innovation?* While UIC research has identified factors such as trust, absorptive capacity and governance structures, much less is known about how these elements function under the conditions created by AI – rapid model iteration, data dependency, and heightened ethical and regulatory scrutiny. At the same time, research on AI-driven service innovation has scantly addressed how cross-sector partnerships can be organized to support the practical realities of AI development and deployment. Together, these gaps highlight the need for empirically grounded insight into how UICs can be effectively managed in the context of AI-driven service innovation.

To address this problem, this study builds on prior research into AI-driven service innovation (Vargo *et al.*, 2024; Mariani and Borghi, 2024) and extends it by foregrounding the role of UIC in cultivating such innovations. Drawing on insights from the UIC, service and AI literatures, supplemented with illustrative case evidence comprising expert interviews and secondary data, we develop a framework that captures the success factors and enablers of co-created innovation in AI service contexts. By focusing on UIC in the context of AI, this paper extends prior service innovation research that has traditionally emphasized intra-firm processes, supplier networks or customer engagement (Janeiro *et al.*, 2013). We argue that AI introduces novel dynamics, such as human–AI collaboration, model drift and responsible governance, which require new forms of knowledge exchange and sustained co-creation. Addressing these dynamics offers both theoretical and practical contributions: advancing our understanding of service innovation and guiding firms and universities to co-develop practices that ensure innovation remains not only technologically cutting-edge but also socially responsible.

## 2. Conceptual framing

### *2.1 Service innovation and AI*

Service innovation has long been central to innovation studies, particularly since the rise of the service economy in the late 20th century. Early work viewed it through a product lens, focusing on improvement and differentiation (Witell *et al.*, 2016; Lusch and Nambisan, 2015). Over time, scholars recognized its distinct nature and developed service-specific theories emphasizing value co-creation between providers and customers (Gustafsson *et al.*, 2020). In services, value arises through customer experiences and shared sense-making rather than provider-defined outputs (Akaka *et al.*, 2015; Kindstrom *et al.*, 2013). As a result, service innovation often targets enhanced delivery processes, efficiency and satisfaction through collaboration across service ecosystems (Lusch and Nambisan, 2015). Over time, however, scholars recognized that service innovation involves unique challenges and opportunities, leading to the development of service-specific theories and models (Gustafsson *et al.*, 2020). Advancements in service innovation are now inherently linked to digital and new technologies, with AI underpinning many of these.

AI is fundamentally reshaping service ecosystems, transforming how value is created, delivered and experienced across a wide range of service sectors, including finance, healthcare, education, entertainment and hospitality (As'ad *et al.*, 2024; Wirtz *et al.*, 2023). Its capacity for autonomous learning and real-time decision-making allows organizations to reimagine service processes and relationships (Huang and Rust, 2018; Berente *et al.*, 2021). AI agents are also being designed to nudge both managers and consumers toward more sustainable decisions in transport and healthcare contexts (Witell *et al.*, 2016). Collectively, these developments illustrate AI's potential to augment and even redefine service innovation as data-driven, adaptive and deeply personalized.

Despite its potential to transform service innovation, implementing AI in the service context and beyond comes with significant challenges. Many organizations struggle to operationalize AI due to limitations in data quality, system integration and talent availability (McDonald, 2024). The technology's rapid evolution also heightens ethical and social concerns, such as bias, fairness, transparency and job displacement, that may erode public trust (Berente *et al.*, 2021; Wirtz *et al.*, 2023). Managing these challenges requires more than technical solutions: it demands organizational learning, ethical governance and cross-sector collaboration. Universities, in particular, play a vital role in this process, advancing research on responsible AI, fostering interdisciplinary skills and helping firms and policymakers co-design adaptive service ecosystems capable of harnessing AI for inclusive, sustainable innovation.

*2.2 The role of UIC for AI-driven service innovation*

UICs have been extensively researched and are important vehicles for enhancing innovation, performance outcomes (Tseng *et al.*, 2020) and economic growth (Perkmann *et al.*, 2013). UIC offers a promising channel for “open innovation” (Chesbrough, 2011), where organizations leverage external networks to develop novel ideas (Perkmann and Walsh, 2007). Through collaborative projects, universities and industries can gain access to complementary resources, exchange knowledge, share risks, lower costs and enhance legitimacy (Ankrah and Omar, 2015). However, universities and industries operate differently with different cultures and norms (Bruneel *et al.*, 2010). Intermediaries are often leveraged to facilitate collaborative projects and bridge the divide between partners (de Wit-de Vries *et al.*, 2019). For example, governments can play an important role as they develop tax benefits and grant policies to support collaborative efforts (Szücs, 2018). This is elaborated through the “triple-helix framework,” which examines the innovation outcomes resulting from the interaction between government, university and industry (Etzkowitz and Leydesdorff, 2000).

Research on UIC identifies multiple determinants of success spanning internal, relational and technical factors. Internal determinants include firm size and age (Triguero *et al.*, 2015; Castrogiovanni *et al.*, 2012), absorptive capacity (Hervas-Oliver *et al.*, 2012), collaborative experience (Bjerregaard, 2009) and strategic orientation (van Rijnsoever *et al.*, 2017). Smaller or younger firms often lack the dynamic capabilities and human capital necessary to exploit academic partnerships effectively, implying that successful collaborations require sufficient internal competencies to absorb and apply external knowledge (Cao *et al.*, 2026). Relational factors, such as trust, openness and communication, are equally critical (Rosli *et al.*, 2018). The literature further highlights technical factors, such as goal alignment and IP management, as central enablers of collaboration success (Sjöö and Hellström, 2019; O’Dwyer *et al.*, 2023). Conversely, barriers include conflicting organizational cultures (Schulze-Krogh and Calignano, 2020), mismatched project timelines (Karlsson *et al.*, 2007) and insufficient institutional support (Biro, 2015). Outcomes of collaboration extend well beyond firm-level outputs and lead to higher-level dynamic open innovation networks (Chesbrough, 2003) with mutual benefits for UIC partners. Firms benefit through enhanced research and development (R&D) intensity (Motohashi, 2008), improved innovation (Cao *et al.*, 2026) and stronger performance and legitimacy (Jones and de Zubielqui, 2017), while universities gain enriched research agendas, co-publications and validated societal impact (Perkmann *et al.*, 2013).

Yet, despite decades of research guiding policy and practice, UIC studies have predominantly focused on technological, product and process innovation, where universities contribute technical expertise and talent while firms lead commercialization (Ankrah and Omar, 2015). However, the emergence of AI and digital technologies introduces new dimensions that existing frameworks struggle to capture. AI-related collaborations demand interdisciplinary expertise, robust data-management capabilities, continuous model monitoring, and ethical oversight to manage algorithmic bias and transparency (e.g., Moser *et al.*, 2022; Gama and Magistretti, 2023). These challenges are particularly pronounced when innovation outcomes transition toward services and experience-based value creation (Favoretto *et al.*, 2022).

Extending these insights to AI-driven service innovation underscores the growing importance of cross-sector partnerships linking computer science, data analytics, ethics and business scholarship. Effective AI-driven service innovation collaborations require not only traditional enablers such as trust, absorptive capacity and clear communication, but also new competencies in data stewardship, explainability and human–AI governance. Specifically, universities can play a pivotal role as boundary-spanning institutions, co-creating knowledge and ensuring that AI-enabled services remain innovative, ethical and socially beneficial.

While the integration of AI into services presents new challenges, we view UIC, when managed effectively to mitigate barriers and promote success, as crucial to developing novel and ongoing service innovations in a dynamic and volatile environment. UICs seek to address several key challenges faced by service firms. First, AI integration into services is inherently complex, involving not just the application of existing algorithms but also the co-creation of new models and technologies tailored to specific industry and customer needs (Bock *et al.*, 2020; Huang and Rust, 2021). This complexity demands a deeper, and sometimes nuanced understanding of how AI algorithms and technologies can be integrated into service processes (Huang and Rust, 2018). These often differ significantly from other traditional forms of innovation, and hence, require not only industry but also research expertise (via UICs) to delve more deeply into the complexities and forge new understandings of how AI-driven service innovation is to be embedded into the service ecosystem (Kaartemo and Helkkula, 2024).

Second, as mentioned prior, AI introduces significant ethical and regulatory challenges, particularly in areas such as data privacy, algorithmic bias and decision-making transparency (e.g., Wirtz *et al.*, 2023). UICs can address these challenges directly, focusing on how these issues can be navigated for various stakeholders (i.e., customers, employees) in line with established ethical guidelines, to ensure compliance with regulatory standards, as well as for the broader societal "good" while still fostering innovation.

Third, AI-driven service innovation often requires different approaches to knowledge transfer and commercialization than other types of innovation. For example, AI models and algorithms may be more difficult to patent and protect, and their commercial value may depend heavily on data access and management (Akter *et al.*, 2023). Research conducted by universities can provide insights into how industry partners can effectively navigate these challenges, ensuring that AI-driven service innovations can be successfully brought to market.

Fourth, AI-driven service innovation typically requires expertise from multiple disciplines, including computer science, data science, ethics, business and the specific service domain of application (e.g., healthcare, finance). This interdisciplinary nature of AI projects adds layers of complexity to these innovations, and multi-disciplinary expertise can be gleaned from UICs. Universities, with their diverse academic communities, are well-positioned to foster such interdisciplinary collaborations, which can be mobilized and leveraged to support the development of AI-driven service innovation.

Last, the sustained use of AI is challenged by its self-learning nature, which necessitates ongoing monitoring of AI models for "drift" and fine-tuning to ensure continued good performance while reducing the risk of bias (Rahwan *et al.*, 2019). This can be difficult for service organizations, particularly those that are resource-poor or lack relevant in-house technical capabilities (Wirtz *et al.*, 2023), as is often the case with start-ups and small to medium enterprises (SMEs). Ongoing involvement of universities can ensure service organizations can assess the performance of their AI solutions and reduce risks related to reliance on AI for decision-making. At the same time, industry partners can provide the real-world context needed to ensure the practical applicability of these innovations. While UICs address numerous challenges faced in embedding AI-driven service innovation, research is needed to understand how such collaborations can and should be managed effectively, and how their different perspectives can be integrated to drive sustained stakeholder value.

## 3. Methodology

We adopted a qualitative case study design, which involved expert interviews with identified UIC participants (i.e., CEO, Co-founder/Managing Director, senior leader, senior academics) (Van Audenhove and Donders, 2019) across diverse AI-driven service innovation case examples from service contexts primarily in Australia, supplemented with secondary data. The case study adopted a realist-inspired contextualized explanation approach (Welch *et al.*, 2022) to enable deep insight into complex phenomena and facilitate an understanding of relationships between context, mechanisms and outcomes (Piekkari and Welch, 2011).

### *3.1 Case design and data selection*

Each case involved a distinctive UIC collaboration or series of UIC collaborations linked to an individual or a cluster of common individuals. This meant that cases were typically limited to one industry but could span diverse areas. Four illustrative cases were purposively sampled and confirmed for inclusion based on evidence of service innovation supported through UICs (Patton, 2002). The cases were sourced from the healthcare, consulting and hospitality service sectors. Our abductive qualitative approach (Dubois and Gadde, 2002) indicated that our illustrative cases reflected *constrained variation* (Eisenhardt, 1989), meaning that there was sufficient commonality across cases to compare them, but there were also nuances between cases (e.g., service sector; innovation dynamics; view of AI in the collaboration). Through ongoing qualitative investigation of each case, it became evident that each case could be classified as a "success case" in terms of UIC for AI-driven service innovation (see Table 1 for an overview of the illustrative cases). While success cases and a survivor bias have their limitations (Odlin and Benson-Rea, 2021), a focus on success as a common outcome across all cases allowed us to compare explanatory factors more uniformly, given consistent endpoints. It is also important to note that, as a "real-time" study, our consideration of "success" is evaluated at a point in time.

As indicated in Table 1, UIC was a key feature of each case, as was the pursuit of co-creating ongoing value through novel service opportunities and AI in various forms, from more traditional to more contemporary applications (Akter *et al.*, 2023). Each case presented a unique service ecosystem comprising UIC partnerships, specific institutions and resourcing activities, which added complexity to our selection. However, they were all considered a part of the broader national service innovation ecosystem, which normalized cultural and institutional aspects specific to Australia (e.g., funding availability, IP norms, legal frameworks, university processes) (Kriz *et al.*, 2022).

Data were collected through expert interviews and secondary data sources, including company/research project artifacts (i.e., reports, websites, press releases, video footage) (the secondary data sources obtained for each case are also featured in Table 1). Obtaining multiple sources of data culminated in a more robust data collection process that combined the strengths of primary and secondary data (Yin, 2014) (Table 1 summarizes the sources collected for each case). For example, a well-established limitation of interview data is recall bias. In contrast, secondary data provide factual historical information, event specificity and quantitative details that complement subjective qualitative perspectives captured in interviews (Yin, 2014). In total, five experts were interviewed (with one expert interviewed multiple times to elicit deeper insights and for confirmatory purposes), leading to eight interviews in total, and the interviewees spanned both university and industry to promote a more balanced perspective [1]. The approach was consistent with a realist ontology and subjectivist epistemology (Wynn and Williams, 2012), and the case design was cross-sectional as opposed to longitudinal, given our focus on understanding perceptions of UIC in relation to AI service innovation at a point in time.

Rather than following a strict interview protocol, interviews were conversational and semi-structured (Adams, 2015). Interview questions were relevant to the interviewee and their context and focused on the types and structures of collaborations; initiation and partner selection; motivations and objectives; processes, dynamics and challenges; and results and impact. Interviews lasted approximately 45 min to 1 h and were recorded and transcribed. Two members attended most interviews to enhance the rigor of the interview process.

### *3.2 Data analysis*

Interviews were manually thematically analyzed to make sense of broader and more holistic categories, concepts, ideas, commonalities and contrasts (Maxwell and Miller, 2008). Drawing upon aspects of a descriptive phenomenological approach (Sundler *et al.*, 2019), transcripts were reviewed to promote immersion in the data and to consider the different meanings interviewees conveyed regarding AI and UIC for service innovation. This process encouraged the detection of unusual or novel perspectives (e.g., reflections from multiple interviewees that AI was simply a tool and to be careful of exaggerating its hype; the

**Table 1.** Illustrative UIC success case overviews

| Illustrative success case context | Service innovation (including classification of innovation novelty) | UIC partners | Data collection sources |
|---|---|---|---|
| *Case I: Healthcare service industry: AI-driven diagnostic tools* | Development of AI-driven service innovations, such as an AI-driven tool[a] for early disease detection. This healthcare service innovation created value by not only improving patient outcomes but also reducing healthcare costs (new to market/world innovations) | (1) University (medical researchers) (2) Industry (e.g., service firm – hospital, corporate technology partner) | Interviewees: Two senior academics (i.e., university), with one of the academics interviewed multiple times Secondary data sources: website material, institute videos |
| *Case II: Hospitality service industry: algorithmic (AI) nudging tool* | Development of sustainable hotel innovations based on AI algorithms and machine learning to drive profit for hotel chains through "green nudging" (von Zahn *et al.*, 2025) to incentivize environmentally friendly customer behavior (incremental innovation) | (1) University (business school researchers) (2) Industry (e.g., service firm – hotel provider) | Interviewee: Senior academic (i.e., university) Secondary data sources: Presentation transcript, presentation slides, website material |
| *Case III: Healthcare service industry: AI-driven oral health tools* | Development of an AI-supported oral health innovation to support accuracy in scans and better diagnostic support for customers. Partnership collaboration focused on activities such as validation and AI software enhancement, with a focus on the industry partner becoming an international leader in its offering. AI recognized as an essential tool to enhance customer experience and enhance service delivery (new to market/world innovation) | (1) University (oral health and engineer researchers) (2) Industry (SME software and hardware service provider for oral health and publicly funded research agency) | Interviewee: CEO (i.e., software and hardware service firm) Secondary data sources: video documentary, website material, press release, public interview |

(*continued*)

**Table 1.** Continued

| Illustrative success case context | Service innovation (including classification of innovation novelty) | UIC partners | Data collection sources |
|---|---|---|---|
| *Case IV: Healthcare and consulting service industries: AI-driven workforce productivity and wellbeing tools* | Development of machine learning and AI-driven, organizational-level innovations addressing intelligence solutions for healthcare worker productivity and decision-making, as well as psychological health innovations that provide assistive tools and diagnostics to enhance mental health/wellbeing for healthcare workers (new to market/world innovation) | (1) University (interdisciplinary researchers within a research center)<br>(2) Industry (e.g., SME AI service firm) | Interviewee: CEO/co-founder/Managing Director SME AI service firm (ex-academic researcher) (i.e., industry)<br>Secondary data sources: website material, research center website |

**Note(s)** [a]In the discussion of a "tool," we concur with Vargo and Lusch's (2008) service dominant logic and rather than physical tools (or goods), our focus is on the activities and services derived from such tools and that require value co-creation

**Source(s):** Authors' own work

importance placed on key individual people in a collaboration, rather than larger organizations and institutions) and led to the emergence of broader patterns and themes.

Patterns became clear when interviews were compared; for instance, nuanced approaches to trust emerged across many of the interviews and could be contrasted: one interviewee highlighted how trust was valuable at different institutional levels, another focused on how trust could be built through dialogue, and another explored trust and temporality. Broader themes were developed (e.g., "initiating deliberate and strategic partnerships," "win-win," "trust") and further interpreted in relation to other identified themes. Iterative reviewing of transcripts and reflection in conjunction with an understanding of existing theory and literature prompted an inductive data-driven and deductive literature-driven approach (i.e., abductive) (Dubois and Gadde, 2002).

This process enabled interpretive inquiry to facilitate inferences and exploration around meaning from both the data and the literature (Saldaña, 2014). In line with a subjectivist epistemology, such an analytical approach prompted a hermeneutic perspective that provided an alternative to conventional positivist qualitative analytical approaches (Mees-Buss *et al.*, 2020; Valtakoski and Glaa, 2024). Secondary data (e.g., presentation transcripts, press releases, company website material and video transcripts) were also analyzed as part of the triangulated illustrative case design (Easton, 2010; Nolen and Talbert, 2011) and were used to obtain additional factual detail and promote a "chain of evidence" (Yin, 2014). Due to their breadth (e.g., websites with multiple pages and extensive page links), rather than thematically analyzing the entirety of the secondary material, secondary sources were employed in targeted ways for directed purposes of "fact-finding" and "fact-checking" or for broader case contextualization to supplement the primary data. As discussed in the following section, a conceptual framework was developed drawing on illustrative case evidence (both primary and secondary) to refine and augment insights from the literature.

## 4. Findings and discussion

A synthesis of existing literature combined with exploratory insights from our illustrative case data resulted in the formation of a framework (Table 2) showing that UIC for AI-driven service

**Table 2.** Integrated dimensions of successful AI-driven service innovation through UIC

| Dimension | Enablers | Processes/practices | Outcomes/benefits | Illustrative case examples |
|---|---|---|---|---|
| Mutuality<br>✓ Value co-creation<br>✓ Alignment<br>✓ Governance<br>(e.g., Ankrah and Al-Tabbaa, 2015; Bruneel *et al.*, 2010; Katirai and Nagato, 2024) | • Clear IP management<br>• Actively managed ownership<br>• Supportive and responsive institutional and governance structures<br>• Information accuracy and aligned timing expectations<br>• Mutual understanding of AI's value for all stakeholders | • Research centers focused on data and AI<br>• Industry professionals with advanced research training<br>• Practical ethical processes and frameworks<br>• Research collaboration agreements with industry AI service providers | • Create new markets and technological opportunities for global differentiation for both parties<br>• Identifying reciprocal advantages<br>• Enhanced value creation for all partners | *Case II:* The value derived from this AI-driven service innovation was multifaceted, including enhanced personalization and a better customer experience for hotel guests. Value also stemmed from potential cost reductions for the hotel providers, while simultaneously enhancing brand recognition by targeting their sustainability profiles<br>*Case III:* Timing alignment between partners, R&D benefits, trust, and clarity of ownership and responsibility were important themes in nurturing a successful partnership |
| Relational embeddedness<br>✓ Trust<br>✓ Communication<br>✓ Empathy<br>(e.g., Ankrah and Al-Tabbaa, 2015; Bruneel *et al.*, 2010; Cao *et al.*, 2026) | • Understand pain points and how AI could be leveraged to solve problems<br>• Empathize to understand mindsets around AI utility<br>• Orchestrate trusted partnerships<br>• Build open communication channels and a shared language<br>• Effectively boundary span | • Maintain linkages with the research community<br>• Ongoing dialogue<br>• Establishment of affiliate and adjunct positions at universities and/or within research centers<br>• Crossover activities for AI capability development | • Long-term engagement strategy<br>• Lower transaction costs<br>• Enhanced access to data and consumer populations to sustain value drivers | *Case III:* A deliberate and ongoing engagement strategy with universities was valued. Partnerships with senior university staff were highlighted as a key mechanism for effectively facilitating trust<br>*Case IV:* The academic/university's natural proclivity for a "deep-seated distrust" was identified as a key barrier. However, the role of the former university researcher, who was involved in multiple companies and had extensive and well-established university networks, led to genuine trust and boundary-spanning opportunities |

(*continued*)

**Table 2.** Continued

| Dimension | Enablers | Processes/practices | Outcomes/benefits | Illustrative case examples |
|---|---|---|---|---|
| Complementary capabilities<br>✓ AI expertise<br>✓ Data access<br>✓ Absorptive capacity<br>(e.g., Ankrah and Al-Tabbaa, 2015; Benoit *et al.*, 2019; Verreynne *et al.*, 2021) | • Viewing AI as a research tool<br>• Deliberate joint PhD supervision and resource sharing<br>• Opportunities for talent development across the partnership<br>• Understanding the expertise and skills of each party | • Data control in AI model development<br>• Alignment in relation to data access<br>• Validating the algorithms and ensuring interpretability checks | • Future talent pool, joint publication and internships<br>• Invisible-by-design AI integration | *Case I:* The collaboration had historically led to patent protection for the research, which was critical for the healthcare provider by differentiating its products and services and enhancing its reputational assets in the global healthcare market. However, AI and new tools were only useful if the partner could integrate them to add commercial value<br>*Case IV:* Managing data ownership was identified as a major UIC hurdle due to the university partner's differing mental models of data and the need for broader system and institutional change |

**Source(s):** Authors' own work

innovations are most successful when partners co-evolve across three integrated dimensions: (1) *Mutuality – Value co-creation, alignment, governance*; (2) *Relational embeddedness – Trust, communication, empathy*; and (3) *Complementary capabilities – AI expertise, data access, absorptive capacity.*

These dimensions interact through collaboration enablers – structured processes and institutional supports – that shape the practices, outputs and long-term value of the collaboration within broader service ecosystems (see Table 2). These dimensions and their associated enablers, processes/practices and outcomes/benefits are explained in the ensuing sections.

### *4.1 Mutuality: value co-creation, alignment, governance*

Ensuring mutually beneficial aspects for both university and industry partners in AI service innovation collaboration was essential. Service innovation embraces diversity to leverage the unique strengths that partners bring to the collaboration. However, regularly reviewing progress ensures that the collaboration continues to meet the evolving needs of both parties. Institutional support, including clear IP agreements and access to funding, is essential for facilitating collaborations. Universities and industries must ensure that policies and agreements are in place to protect the interests of all parties and support long-term collaboration. They need to establish robust IP management frameworks and seek joint funding opportunities (e.g., grants) to provide financial stability and legal clarity throughout the collaboration.

The co-development of AI-driven prototypes and iterative experimentation are key processes in successful collaborations. Universities and industries should foster environments where innovation can thrive through collaborative R&D efforts. They should create dedicated R&D teams that include members from both the university and industry partner(s), with a focus on iterative development and continuous feedback, and the use of agile methodologies to ensure rapid prototyping and refinement. Partners must work together to establish and adhere to ethical guidelines that govern the development and deployment of AI technologies. They should develop and implement ethical guidelines specific to AI-driven service innovation and regularly review guidelines in an evolving technological landscape. Universities and industry partners should invest in maintaining and expanding these collaborations to create robust innovation ecosystems. They should establish long-term agreements and interdisciplinary collaborative networks (e.g., research centers) that extend beyond individual projects. Creating platforms for ongoing collaboration, such as innovation hubs or joint research centers, to explore opportunities for AI-driven service innovation, nurtures future ecosystems. Navigating value co-creation, alignment and governance is complex for UIC partnerships in general, but likely to be acute in the case of AI and its rate of development, which, as indicated by Stanford research, is “outpacing Moore’s Law” (Saran, 2019). AI’s speed of progress can be attributed to deep learning advances, the proliferation of data, investment exposure and increasing computational capacity (California Learning Resource Network, 2025). While AI adds complexity, we observed enablers, processes/practices and outcomes that can promote mutuality in relation to AI-driven service innovations.

*4.1.1 Enablers.* Institutional elements, such as IP issues, can pose barriers to UIC (Ankrah and Omar, 2015), and therefore, *clear IP management* between industry and the university acts as an enabler of mutuality. As one interviewee involved in several AI service innovation ventures highlighted, clinical IP management was key: “We have very clear boundaries of protecting the IP and separating the IP from the university and work within the company . . .” (CEO/co-founder, Case IV). Where AI is central to the service firm’s business model, talent and data intelligence are critical resources, and *managing ownership* between partners is important to clarify. As one interviewee highlighted, this was managed and defined very deliberately: “Who owns the scientific outputs? . . . we clearly define that. We haven’t encountered many issues at this stage, and as such we haven’t found it challenging or that hard to collaborate with universities” (CEO, Case III).

*Supportive institutional and governance structures* can navigate potential conflicts to ensure both parties' interests are protected. For example, formal governance structures (e.g., formal protocols around interpretability of machine learning results, medical device frameworks, executive steering committees, boards, advisory panels and governance committees) are important in UIC partnerships. For example, in Case I, clear protocols were in place for one industry partner around quality assurance for AI and machine learning: "So they have in-house measures around interpretability of machine learning results. So they have guidelines around that at what point it becomes explainable and interpretable" (Academic, Case I). Similarly, medical device frameworks were essential in ensuring that the partner was assured that any collaborative activity was executed in such a way that was consistent with the partner's parameters, as identified by one Academic (Case I):"[partner] will have an agreement because it's a medical device . . . and so we have to work within that approved framework. So they already have pre-frameworks, and we can only operate within those frameworks." The academic also highlighted that specific governance structures were often implemented in direct response to the funding source and its requirements, rather than standardized: ". . . it's stipulated by the funding body. So when we're developing the [technology], we had a steering committee. Because it was stipulated that you must have a steering committee . . . so the project was industry led, but it had to have a governance structure which was informed by [university] people and industry people."

In terms of the function of the advisory committee for AI projects in Case I, they typically comprised industry partner representatives who understood the enterprise's goals and vision, in addition to a technical industry representative who had a practical understanding around feasibility and the practicality of the project based on their knowledge of the enterprise. Broader university advisory teams were also an important component. The influence of institutional and governance structures was also evidenced in Case IV when the CEO/co-founder highlighted the value of centers that had governance frameworks that were embedded in the UIC collaboration: ". . . industry partners sit on the executive panel and they contribute to the way the Institute is going and what's happening and the directions that they're taking." As emerged through the case, such centers can target innovative UIC "partnership models" where industry is deliberately brought together with the university in ways that carefully manage any competitive tensions to ensure practical and applied research-driven outcomes for society.

In terms of PhD projects, the CEO/co-founder (Case IV) also highlighted that such centers could also embed governance around PhD supervision in terms of industry involvement and diverse project teams:

> So every PhD student had to have an industry supervisor and an industry sort of companion that . . . would top up the PhD scholarship . . . they would then, in return, spend 1/3 of the PhD with the industry partner and the idea was that the project they were working on was kind of a project that the industry partner would benefit from, it was of interest to them, but it was still sort of within the research space.

Furthermore, when PhD projects were part of the UIC, annual progress reviews served as a key institutional and governance mechanism. This ensured industry supervisors had opportunities to confirm that the necessary advisory support and guidance were being provided for the university PhD candidate. This also included AI skill development; for example, in Case IV (which featured a former university researcher who had recently taken up roles in industry), industry provided AI expertise to support knowledge and skill development at the university. However, it was acknowledged that putting too many controls in place can be problematic, and trust still needed to play an important role in the joint supervision as part of an industry-supervised PhD project:

> . . . there may be some sort of need for reporting. You know, like when we when we co supervise . . . we meet together as supervisors or you know, there are reviews every year . . . and so that there is a way of controlling what's going on without needing to be . . . dictatorial about it . . . (CEO/co-founder, Case IV).

Another enabler was *information accuracy*: “Sometimes communication is a little bit of a challenge between some of our researchers and our AI engineers. At the senior level, we don’t find that there’s that many issues, but at the, you know, more of the technical and clinical levels we find that sometimes information can get lost” (CEO, Case III). Furthermore, the evolving landscape for AI-driven service firms and the novel application of AI in service innovation present a contested space, made more challenging by the rate of AI evolution. As the CEO (Case III) highlighted, “Having the commercial pressures really makes you have to move and progress the project a lot faster . . ..” However, aligning university and industry timeframes, while an enabler of mutuality, was recognized as a challenge, given the varied motivations and operating environments in universities, as opposed to industry. As the CEO (Case III) pointed out, their expectations regarding timing and deadlines were “quite strict.” He acknowledged this could be a challenge in some cases for partners:

> We don’t have the luxury of spending so much time researching particular areas, but at the same time we have to do it thoroughly. So, there’s always a balance. That’s probably the biggest challenge.

However, the CEO was also cognizant that “we’re all human” and highlighted “we miss deadlines as well,” acknowledging that sometimes deadlines were challenging to achieve, no matter what side of the partnership dichotomy you were on, but reflected that better communication could help to better synchronize timing between partners. Therefore, ensuring *aligned timing expectations* was important: “I guess sometimes the expectations around when the data is going to be supplied and feedback around whether we need additional data, [is what] we can improve on” (CEO, Case III). One way of effectively managing this, as revealed in Case I, was through monthly meetings with external partners, and with milestones being regularly reviewed and adjusted when necessary.

Sometimes industry processes also had implications for academic publishing cycles. In Case I, for example, getting approval on a publication from a partner, given their input into the project, was relatively prompt, but could take two to four weeks as standard practice, in view of the IP protection assessment that had to be in place on the part of the multinational partner, prior to publication. This process also served as a feedback mechanism to drive future investigations more closely aligned with industry goals over the next five years.

Furthermore, *mutual understanding of AI’s value* was deemed important, with university partners placing greater value on increased knowledge and application of AI, and industry partners needing to deliver value to shareholders through profitability. A desirable outcome for industry is AI delivering the goal of increased profitability. As one interviewee identified: “It’s a hotel . . . it’s a profit business. All they care about is profit. They don’t care about whether it’s AI generating it or anyone else . . .” (Academic, Case II). However, the black box nature of AI brought additional complexity when it came to a shared understanding of the value derived from AI service innovations: “I guess it’s the black box nature of ML [machine learning] . . . there is always a disconnect between where we are and where everyone else is. So we are the forefront of developing methods, right? So, we are leading if you like . . . So that’s the disconnect” (Academic, Case I).

*4.1.2 Processes/practices.* University *research centers focused on data and AI* with strong industry participation were perceived as a crucial component for genuinely bringing together university and industry partners to engage. An example of one such center was identified as playing an important role in fusing academic and industry interests on real-world contemporary challenges (e.g., industry-based projects), with the center specializing in data and AI related challenges: “What was really interesting and exciting for us about this endeavor was that this was an Institute designed with an industry model” (CEO/co-founder, Case IV).

Another process supporting mutuality was the presence of *industry professionals with advanced research training*, which, in turn, promoted UIC’s AI work. This was the case for a PhD-qualified practitioner who had joined a well-respected machine learning/AI firm. As the interviewee reflected: “When I was working at [company C], one of the things that I really,

really loved about the company was that they were not just building products and commercializing them, they were also looking into research . . . this was ‘my place’, not only because it was industry-based, but it was still research” (CEO/co-founder, Case IV).

Successful UIC is also enabled by the integration of ethical and regulatory frameworks to ensure responsible innovation (Alkire *et al.*, 2024). Universities and other research bodies have a key role to play in designing *practical ethical processes and frameworks* to incentivize compliance with and responsible, reasonable practices in relation to AI research. However, the industry is also developing its own standards, given the importance of ethical compliance, particularly in light of the new ethical dilemmas posed by AI (Wang, 2023). Microsoft’s Empowering Responsible AI Practice and its recent 2024 Responsible AI Transparency Report (Microsoft, 2024) is one such example. Some governments are also leading the way in this space by developing AI ethics principles as well as AI safety standards. For example, Australia introduced in 2019 a set of AI ethics principles (Australian Government, 2019), followed by a voluntary AI safety standard outlining a set of 10 AI guardrails (Australian Government, 2024), with work now ongoing to introduce a mandatory AI safety standard for high-risk settings (Commonwealth of Australia, 2024) and an AI Safety Institute (Australian Government, 2025) to support best practice regulation on an ongoing basis. However, one of the challenges identified in one interview was the cost associated with ethical compliance due to having to adhere to multiple policies and standards, creating bureaucracy and process constraints: “Ethics is an issue for us. Not because we can’t do it, it’s because you have to go through [hospital] ethics and you have to go through [university] ethics. It’s many hurdles” (Academic, Case I).

While these were consistently managed, they did pose additional complexity. To better navigate this complexity, one industry partner established its own AI group to oversee related ethical issues. Ongoing communication with internal university ethics teams was emphasized as a way to ensure ethics processes could be reasonably managed and compliance achieved. As an interviewee reflected, in general any ethics project in a university setting benefitted from ethics teams that communicate regularly with researchers to achieve mutually desirable outcomes, both from an ethical and research performance perspective: “It’s also trust by now . . . we just have to work through it . . . because ultimately ethics doesn’t want to prevent research, right . . . you just have to figure it out on a case-by-case basis” (Academic, Case II). In addition to reasonable ethics processes, it was also important to have *research collaboration agreements with industry AI service providers*: “Our research collaboration agreement is . . . we clearly define what role each party plays, and we bring the IP to the table. If we’re talking about AI diagnostics, then you know [the industry partner] has all the IP, we bring all that to the table” (CEO, Case III).

*4.1.3 Outcomes/benefits.* Achieving UIC mutuality to catalyze AI-driven service innovations can *create new markets and technological opportunities for global differentiation for both partners*. “Win-win” value creation was therefore an important outcome for both UIC parties. From the perspective of the CEO in Case III, this meant forming “strategic collaborations” and it was important for the service firm to “structure it in such a way that it’s mutually beneficial for both parties.” In AI-driven service innovation, not only do universities and industry need to see clear benefits from the collaboration, but so do the end customers. For example, in the oral health case (Case III), the superior AI-driven service innovation enabled by strategic collaboration allowed patients to more easily interpret their results, providing greater clarity and peace of mind.

Navigating mutual benefits and *identifying reciprocal advantages* is important. While end users and customers are motivated by the value proposition of enhanced user experiences, universities are incentivized to translate and apply their research to real-world problems (i.e., a broad view perspective). At the same time, industry partners seek innovations that can be commercialized or integrated into their existing products (i.e., a narrow view perspective) (Wang, 2023). Despite such perspective variations, when combined they add real value, as each party brings something to the table as part of an ambidextrous team and ultimately produces a superior result for both. This was summarized by one interviewee as a “win-win-

win" (Academic, Case I) necessary to initiate collaborations, identifying that multiple stakeholders needed to realize value:

> . . . We want to win because we want them to use our methods; clinicians want to win because they want to improve the process so as to make better decisions, and the patients want to win because they want to have better outcomes.

Across cases, mutuality served as the foundational mechanism for enabling successful collaboration. Clear governance boundaries, transparent expectations and shared understandings of AI's value reduced coordination frictions and created stability in otherwise fast-moving technological environments. These patterns suggest that successful UICs in AI contexts require a balance of formal structure and ongoing reciprocal adjustment, enabling partners to jointly navigate uncertainty while retaining strategic alignment.

*4.2 Relational embeddedness: trust, communication, empathy*

AI and smart service systems add new frontiers to an understanding of trust and communication (Wetzels *et al.*, 2025). These changes suggest that while human-technology interactions and AI possibilities are transforming, humans still may have an edge over AI in terms of being able to demonstrate empathy (Wei, 2025). Such inherently human traits, including empathy, reinforce the need for AI to be carefully integrated into service innovations, and human relational embeddedness remains arguably more important than ever in UIC service innovation partnerships. Trust is a cornerstone of successful collaborations. Prioritizing the development of strong personal and professional relationships between university researchers and industry stakeholders is key. Regular communication, transparency and the delivery of commitments are essential practices for building and maintaining trust over time. This suggests establishing trust-building initiatives, such as joint workshops, regular updates and collaborative decision-making processes, to ensure that both parties feel valued and invested in the partnership.

*4.2.1 Enablers.* In the context of UIC, it was important for researchers to understand that AI for the sake of AI, or as a "pet" research project, was of limited benefit for industry (service firms) if it failed to deliver outcomes to address service industry challenges. Rather, the need to *understand pain points and how AI could be leveraged* to address them was more important. One interviewee revealed the need for researchers to *empathize to understand mindsets around AI utility*: "Certainly none of our industry partners get excited about AI. As for the purpose of AI, they only get excited if the AI solves the problem" (Academic, Case II).

Another enabler for relational embeddedness was the ability to *orchestrate trusted partnerships*. As one interviewee explained, trust to support their AI-driven service innovation was facilitated through top-down partnerships: "Building that trust with the senior managers is really important. So, we have a very close relationship with the senior people at the University ... and from there it flows through the project, and so that's how we build the trust" (CEO, Case III).

Trust is built over time through repeated interactions and successful outcomes (Barnes *et al.*, 2002), and one academic interviewee mentioned that accessing consumer populations (patients) to continue to test AI models was now significantly easier based on the greater familiarity and trust that had been built over time with the industry partner's market: "This was really hard 10 years ago because we couldn't get anyone. Because we have been around so long now [working with the service firm], I would say it's actually really easy. Because they know us, we [are able to] just put flyers out, saying that this is our study . . ." (Academic, Case I). A similar theme was brought out by the former university researcher (Case IV), who was working in multiple AI ventures and whose trust had come from the ability to *effectively boundary span* between industry and academia: "I usually collaborate or speak to most people that I've already had a pre-established relationship with . . . Once you build the trust, people trust you ongoingly . . . trust is important."

*4.2.2 Processes/practices.* A service firm CEO/co-founder interviewee, who had been formerly at a university, had demonstrated the value of being able to *maintain linkages with the* *research community* in addition to fostering *ongoing dialogue*, and highlighted: “Basically, I continued conversation with all my connections that I had when I was in academia” (CEO/co-founder, Case IV). The interviewee also highlighted that, while there was a “deep-seated distrust between industry and academia,” this could be resolved through simple practices such as “talking to each other and conversation” (CEO/co-founder, Case IV).

Initiatives such as government-funded Industry Fellowships, ensuring government funding is targeted toward applied industry needs, as well as the *establishment of affiliate and adjunct positions at universities and/or within research centers*, were also an important process for promoting relational embeddedness of AI collaboration opportunities. The previously mentioned interviewee, who held an adjunct position, was an affiliate with a research center and was well-connected with universities, highlighting the value of such *crossover activities for AI capability development* for academics and PhD researchers:

> All these connections allow me to talk to the [academic] group leaders and professors and say, hey, how about we do this research, and maybe I can help with expanding some of your AI capabilities. I’m co supervising 3 PhD students. They’re working on theses directly relevant to the domains that they work within. But I’m helping them . . . upskill them in AI.

*4.2.3 Outcomes/benefits.* The enablers and processes/practices discussed can prompt a *long-term engagement strategy* and ultimately *lower transaction costs*. Furthermore, UIC interactions expose partners to different perspectives:

> The feedback that I’ve received from the university participants . . . they say that there’s a different lens that we both approach problems from, and I think it benefits who we work with from the universities. To see how we commercialize and roll things out. So yeah, there’s definitely mutual benefits there. (CEO, Case III)

Taken together, these practices illustrate that relational embeddedness functions as a collaborative risk-reduction mechanism. Trust, familiarity and frequent informal exchanges enabled partners to surface problems early, coordinate decisions more efficiently and adapt jointly as AI models evolved. Importantly, relational embeddedness compensated for areas where formal governance alone was insufficient, for example, managing ambiguity around data quality, evolving technical requirements or unexpected shifts in project direction. These findings reinforce that enduring interpersonal and inter-organizational relationships are not peripheral but central to successful UIC in AI-driven service innovation.

### *4.3 Complementary capabilities: AI expertise, data access, absorptive capacity*

AI expertise in relation to UIC extends beyond generic AI uses, such as Large Language Models, and is rather more specific to the needs of the partnership and the backgrounds of the partners involved. This requires specialized knowledge and access to data, but also absorptive capacity as a dynamic capability (Zahra and George, 2002) on the part of both the university and industry to benefit from the knowledge and commercial partnership. Here, one may consider success as having engaged in a productive collaboration. Access to data and specialized resources is critical for AI-driven service innovations. Universities and industry should formalize data-sharing agreements that outline clear terms for data access, usage and ownership, ensuring that both parties benefit from shared resources. Specifically, they should develop clear data-sharing protocols and legal agreements that protect the interests of both universities and industry partners while facilitating smooth access to necessary data and tools. For collaborations to be sustained, both parties and all stakeholders involved must see clear, mutual benefits.

*4.3.1 Enablers.* Domain knowledge was a difficult-to-replicate resource (Barney, 1991) in a UIC partnership, particularly in relation to AI and machine learning. One interviewee described their passion for the field and specific skills and reflected how it influenced their choice of partnerships: “I always liked maths and analytical methods . . . ML is very mathy and involves a lot of analytical tools. We are doing what we enjoy doing, and that's the best thing. We try not to do projects because we can. We try to do projects because we want to do it" (Academic, Case I).

Respondents *viewed AI as a research tool* that enhances performance, especially in managing large datasets and tackling complex problems. As revealed by one interviewee, AI provided critical research functionality: "Of course we use machine learning, which is AI to predict . . . basically to find the optimal model from which we can predict . . . using the empirical data" (Academic, Case II). It also became apparent through interviews that AI was a more general term involving diverse activities and, therefore, understanding how AI was being used in UIC projects was essential in generating a deeper understanding of its utility: "AI is a broad term. It's everything from clustering to, you know, ChatGPT . . . AI can be anything from a data analysis method right through to . . . something intelligent that's learning and starting to become human" (Academic, Case II).

Another interviewee recognized digital technology and AI as akin to other research tools: "I guess it's like any other tool research tool. We use it to explore various ideas, so that's really been something. Over the last 5 to 10 years, this accelerated, certainly in collaboration with partners" (Senior leader, Case I). However, it was important to note that machine learning had advantages over traditional models, which were helpful in collaborations with industry partners, and as one interviewee explained: ". . . we want to try something different because traditional model[s] we knew they weren't fantastic . . ." (Academic, Case I).

Furthermore, context mattered, including the nature of the AI models used, and in particular, service settings such as healthcare, in which certain boundaries were in place to regulate AI. When it came to collaborations, AI-driven service innovations for healthcare service providers were guided by original models developed by the academic research team through a collaboration, rather than requiring ongoing relearning interventions by the research team: "There are AI models that continually learn and adapt . . . those are usually not able to be used in the medical setting, because it's not well defined in terms of how they behave" (Academic, Case I).

Initiating deliberate and strategic partnerships was a critical enabler to support complementary capabilities, particularly given the speed of AI and competitive activity. The importance of strategic partnerships to maintain a point of difference in a competitive market was exemplified by one interviewee, who highlighted, "We're looking to partner with other leading universities" (CEO, Case III).

*Deliberate joint PhD supervision* potentially enabled absorptive capacity by ensuring PhDs could access knowledge and insights from individuals involved in AI-focused service firms, as well as by facilitating *resource sharing* (e.g., infrastructure). This was important in training the next generation of researchers and *talent development*. In terms of advisory team composition in PhD projects, industry could play an important role, and for example, in Case I, for projects involving one particular industry partner, it was typical to have two advisors from industry alongside two university advisors.

In practice, PhD students can be co-located with service firms in a physical office as part of their candidature, which ensures opportunities to regularly engage with industry. This model was practiced in Case IV, where PhD students had the "best of both worlds":

> They come into my office and they work on a thesis for their PhD. And you know, that's just the work that they do. It helps me with the supervision because I get to see them every week . . . at the same time, I'm helping them because I'm giving them some sort of access to an internship, where they can work a day a week or so at my company on the commercial side of things and understand how this works (CEO/co-founder).

In Case I, one example was explored where the university had provided the supervision via a center, but the industry provided in-kind and resourcing support, including the assignment of key service firm staff to individual projects. Here, it involved two people: a technical expert and a person familiar with technology integration within existing medical imaging systems. The technical person would also liaise with international experts within the service firm where additional support was required (this generally occurred for all projects to ensure the relevant expertise could be tapped). This extended to specific training by the industry partner (service firm) on their medical devices for the PhD student:

> We're in the center . . . we do research projects, where we come up with projects for PhD students . . . And this was the project . . . using machine learning . . . but the question then is OK, we can [technically] do that, but how do we implement . . . we need [a service firm partner's expertise] . . . to help with that . . . So we talked to [our service firm partner] and they said, it's a good idea and we'll give you support, so we went ahead with the PhD project . . . the [service firm's experts] trained the student in how to modify the system (Academic).

*Understanding the expertise and skills of each party* was important. Universities played a key role in research and testing to support industry commercialization, and as highlighted by an interviewee, "One of the things we've found while working with the [University] ... is that they're very technical and very strong" (CEO, Case III). Universities brought access to supplementary data and hardware (i.e., Case III). However, industry often provided direct access to data (e.g., Case I), could present the ideal setting for field experiments (i.e., Case II), and in some instances, industry, rather than university, was driving AI skill and capability development in UIC research projects (i.e., Case IV). This reinforced that, depending on the fluidity of an innovation ecosystem, when individuals could move in and across university and industry spheres, this permitted knowledge generation from both partners.

Understanding the strengths that each party brought was important, and to excel at AI, this required support from leading research experts: "We've just entered a three-year partnership with Research Partner A and that's to support the development of our AI software. So, we've gotten the backing of some of the best AI engineers in Australia" (CEO, Case III). An evolving research partnership network also meant that a repertoire of AI expertise could be accumulated for industry partners to support commercial activity, and the aforementioned interviewee reflected on their dynamic partnership landscape: "So, we're entering into a collaboration with them soon as well . . . They've got a lot of AI expertise" (CEO, Case III).

Integration of specific expertise, including AI and machine learning, was also important. As one interviewee explained, the research team's backgrounds had changed over time to emphasize a real interest in machine learning-based projects and recruiting for the required capability for AI-driven service innovation: "We shifted over the years . . . we are going for ML. We have people that come through computer science backgrounds and people with ML backgrounds, people with physics and mathematics backgrounds" (Academic, Case I).

*4.3.2 Processes/practices.* Data may require "cleaning" or involve other access challenges, which can require additional investments to manage (Benoit *et al.*, 2019). Besides data access, *data integration* can operate as a key barrier (or enabler) within resource sharing. On the one hand, collaborators may use different systems for data management, which causes interoperability issues. For example, hospitals use specific systems (such as Picture Archiving and Communication Systems) to store imaging data, and academics may use a different system. Since data is stored in different formats and categories as required by different systems, it can take time and effort for academics to process data for research purposes. On the other hand, academics have expertise in cutting-edge approaches to evaluating data quality (Sadiq *et al.*, 2011), more efficient approaches to curating data (Chen *et al.*, 2020), and have the required training in strategies to integrate it (Dong and Rekatsinas, 2018).

While UIC can facilitate critical data access (Wang, 2023), there is the challenge of acquiring and using high-quality data from stakeholders for AI research to capture value. One interviewee emphasized the importance of *data control in AI model development*. They highlighted "I like to have control over everything. I used to do projects where someone else give[s] you the data and you apply the method to see how it works. The problem with it is that you can't change how you got the data, especially for machine learning, you need full control on how you collect the data because that's important, 'rubbish in and rubbish out' as we say"

(Academic, Case I). These sentiments aligned well with the well-established "garbage in, garbage out" concept in data quality academic literature (Sadiq and Indulska, 2017).

Collaboration with industry was crucial for accessing large datasets essential for training AI models. The issue of *alignment in relation to data access* was also acknowledged by one interviewee:

> There's no point in coming up with a project where I can't actually access data. So, because we have an existing collaboration with [Hospital A], we know we can access data if we have a well-structured project. So, it's called alignment . . . we need to align ourselves with somewhere where we can actually get the data, relevant data. Aligning in terms of where can I actually physically get the data in my hands. (Academic, Case I)

Finally, processes and practices were in place to ensure the interpretability of AI outputs. In one case (Case I), this meant that the industry partner played a key role in *validating the algorithms and ensuring interpretability checks* were in place.

*4.3.3 Outcomes/benefits.* The value of access to data, as well as resources more broadly, including talent, emerged as a concept that linked to complementary capabilities and supported *context-relevant innovation*. For example, the CEO (Case III) pointed out that the university brought access to "subject matter experts" and the information and knowledge that PhD candidates and graduates could bring to the service firm. While the service firm already had data, the CEO noted that universities brought "additional data sets," and this provided "a lot of recognition" for activities such as grants. There were "quite significant benefits to collaborating with the top universities." While this benefited the industry, it also offered advantages for university partners by bringing together these complementary capabilities as part of a customized collaboration design. Specifically, PhD students could be exposed to commercial realities, critical for their future development and building a skilled *future talent pool*: "For graduate students to have studies published with commercial companies [is important]. They [also] get to work with some of our engineers as well, and we think that they're some of the best engineers in Australia" (CEO, Case III).

There were also several other spillover benefits that emerged through collaborative activity (e.g., *joint publications*), with *internships* with collaborators a future possibility for one AI service firm: "We've got joint presentations that come out of it . . . there are also joint papers and conference posters. There's a lot of visibility for us, as well as the universities. We're not averse to opening up internships or providing, you know, that kind of training to the people we collaborate with" (CEO, Case III). However, in the case of joint publications, partners may face an extensive approval process to ensure IP protection, and any potential reputational risks need to be mitigated (e.g., Case I).

*Invisible-by-design AI integration* was also an important consideration for outcomes derived through complementary capabilities. Because of its disruptive nature, AI is often integrated into existing technologies to enhance their functionality and reduce pushback to adoption (Sibbald *et al.*, 2024). For example, in medical imaging, AI was used to automate processes such as positioning and image reconstruction, thereby streamlining workflows: "It's AI that does all the positioning for you" (Academic, Case I).

AI can expedite the R&D process by automating routine tasks, facilitating simulation and modeling and enabling rapid prototyping. This is particularly beneficial in UIC, where time-to-market is a critical factor (Verreynne *et al.*, 2021). As one interviewee from industry highlighted, while timeline expectations are driven by differences in needs, in general research partner engagement had been exceptional and had resulted in an excellent service experience in terms of the value they had received from the collaboration: "They've exceeded our expectations . . . they've expanded on the scope as well as provided a lot more in-depth analysis, more so than what we expected" (CEO, Case III).

AI can help reduce the time required to develop, test and refine service innovations, leading to faster implementation and impact. One interviewee acknowledged the efficiency opportunities for AI and machine learning in particular that he was focused on delivering in his role: "I am in the business of making better predictions . . . developing the methods to make it better, faster and more accurate" (Academic, Case I). AI also enables the development of highly personalized services by analyzing individual customer data and preferences. This level of customization is increasingly expected by consumers and can be a key differentiator in competitive markets. For UIC, this means that AI can help create tailored solutions that meet specific customer needs. In Case III, this meant that patients were able to better understand their diagnoses and alleviate uncertainties through the AI-based offerings. These insights collectively suggest that if UIC for AI-driven service innovation is successful, there is potential for new ecosystem emergence (Kriz *et al.*, 2022) built on AI and machine learning capability and expertise, creating new and niche global markets.

Across cases, complementary capabilities translated into successful outcomes only when paired with sufficient absorptive capacity on both sides. Technical expertise without interpretive capability, or data access without shared problem understanding, was insufficient for generating value. The cases demonstrate that capability complementarity in AI-intensive settings is inherently relational: partners must not only contribute distinct resources but also be able to integrate, refine and apply each other's expertise as part of a two-way (i.e., "coupled") open innovation exchange involving collaboration and co-creation (Candi and Kahn, 2025, p. 13). This underscores that successful UIC requires deliberate investment in capability alignment, not merely capability possession.

## 5. Conclusions and future research agenda

We present a theoretical framework for successful UIC in AI-driven service innovation (see Table 2), grounded in the co-evolution of mutuality, relational embeddedness and complementary capabilities. By unpacking how these dimensions interact through structured enablers and co-creative processes, the framework highlights both the complexity and the opportunity inherent in UICs as part of an open innovation network (Huizingh, 2011). In doing so, it responds to recent calls for a clearer understanding of collaborative innovation involving AI technologies (Wirtz and Stock-Homburg, 2025).

### *5.1 Theory and practice implications*

Our paper makes several contributions. First, our framework reframes UIC as co-evolutionary. Traditional models of UIC often emphasize linear technology transfer or contractual problem-solving (Perkmann *et al.*, 2013). However, the AI service innovation context is dynamic, uncertain and recursive, requiring what we describe as co-evolutionary approaches. AI systems, particularly those using machine learning or generative models, do not have static functions or predictable outcomes. Their value depends on continuous tuning, data input, contextual feedback and learning across deployment cycles. In this environment, mutuality (e.g., shared key performance indicators, risk-sharing agreements), trust-based relational governance and mutual absorptive capacity are not just enablers but prerequisites for sustained innovation (Cao *et al.*, 2026). Our framework contributes to existing literature by rebalancing attention from "who brings what" to "how partners grow together." In doing so, it complements the resource-based view, which traditionally highlights the competitive advantage gained from unique resources (Barney, 1991), by incorporating the relational view (Dyer and Singh, 1998) and by emphasizing inter-organizational advantage derived from joint learning, open innovation and capability development.

Second, we show how mutuality shifts from a transactional to a transformational mode. Mutuality encompasses shared goals, risk tolerance, IP models and performance indicators. In AI-driven service innovation, this dimension is especially critical. For instance, firms may want fast, application-ready tools, while universities seek to publish novel algorithms. These tensions can create misaligned incentives, undercutting collaborative potential (Bruneel *et al.*, 2010). However, mechanisms such as milestone-based governance, shared IP ownership and joint success metrics can foster mutual commitment and help transition from transactional projects to transformational partnerships. This aligns with service-dominant logic which posits that value is co-created through interaction rather than embedded in products or technologies (Vargo and Lusch, 2008). By viewing AI services not as "solutions" but as value-in-use platforms, mutuality can be seen as an ongoing negotiation of relevance, trust and shared benefit.

Third, we address relational embeddedness and the importance of trust. AI collaborations often involve opaque technologies, long development cycles, significant uncertainty, ethical considerations, co-development of resource (data) sharing infrastructures and invisible-by-design adoption strategy – factors that increase the importance of relational embeddedness. Relational theories suggest that under such conditions, formal contracts are insufficient to govern behavior (Verreynne *et al.*, 2021, 2025). Instead, trust, prior familiarity and informal norms often determine whether collaborations succeed. Furthermore, empirical studies have shown that successful university–industry partnerships tend to be embedded in long-term relationships, often facilitated by boundary-spanning individuals or "translation zones" in the form of research centers or embedded researcher programs (Ankrah and Al-Tabbaa, 2015). In our framework, embeddedness enables not just smoother knowledge exchange but also the mutual adjustment of expectations and iterative problem-solving, especially critical when the service "output" of an AI model may be unpredictable or require domain-specific fine-tuning.

Fourth, complementary capabilities recognize that AI-driven service innovation requires the integration of computational, domain-specific and organizational knowledge. Universities often provide technical expertise in data science, machine learning or human–AI interaction design, while service firms provide data, problem contexts, regulatory insight and access to users. However, capability complementarity alone is insufficient; what matters is whether each partner has the absorptive capacity to recognize, internalize and apply the knowledge gained from the other (Zahra and George, 2002). This becomes especially salient in generative AI projects where model performance is highly contingent on context and usage patterns. When partners can meaningfully exchange and adapt capabilities, such as co-supervision of PhDs, sharing datasets or testing models in operational environments, the resulting services are more likely to be impactful.

Fifth, across all three dimensions, collaboration enablers, namely data governance frameworks, facilitators and shared infrastructure, play a mediating role. Such mechanisms facilitate open innovation (Chesbrough, 2011). In AI service contexts, this includes technical enablers (e.g., innovation sandboxes), legal mechanisms (e.g., data-sharing agreements) and human enablers (e.g., embedded fellows). The interaction of these enablers with mutuality, embeddedness and capabilities suggests UIC for AI-driven service innovation is not a single event, but a system of evolving interdependencies. The Triple Helix model (Etzkowitz and Leydesdorff, 2000) as a policy framework can further institutionalize these collaborations by linking universities, firms and government bodies around shared missions, especially important when public value is at stake (e.g., AI in healthcare).

Finally, integrating AI into service innovation through UIC presents a range of practical implications that can significantly enhance the effectiveness and impact of these partnerships. Managers and leaders should reflect on the key dimensions and associated enablers, processes/practices and outcomes/benefits to constructively debate and agree on target strategies that can help them successfully pursue UIC AI-driven service innovation. Context matters, and the illustrative case insights here, while revealing, should be critically evaluated by both university and industry experts already involved in collaboration, or contemplating collaboration, in terms of how they could best be applied or adapted in relation to diverse UIC settings.

*5.2 Future research agenda*

We provide recommendations for future research streams and a prospective agenda that seeks to enhance the field theoretically and managerially moving forward. Table 3 outlines these

**Table 3.** Future research domains related to value creation for AI-driven service innovation

| Domains | Future research opportunities/questions | Theoretical relevance | Managerial relevance |
|---|---|---|---|
| *Ethical dimensions* | • What are the future ethical dilemmas posed by increasingly autonomous AI systems in service innovation? How can they be addressed to ensure equitable development and deployment of AI? | • Builds on ethics and trust theories and issues such as AI autonomy, privacy, bias, fairness and accountability in AI-driven services (Floridi and Cowls, 2022; Wirtz *et al.*, 2023) | • Identifying and addressing potential ethical issues will ensure responsible deployment of AI, enable regulatory compliance and help to maintain public trust |
| *UIC dimensions* | • What are the specific capabilities needed to enable UICs in AI-driven service innovation? How do they differ from those of traditional product innovation UICs?<br>• What innovative models of UIC will emerge to drive technological advancements? How can future UICs be structured to adapt to rapidly changing technological landscapes?<br>• What role will evolving government policies play in shaping the future of UIC?<br>• How can future IP frameworks be designed to better support collaborative innovation to which AI contribute? What are the challenges associated with IP rights?<br>• What future best practices will emerge for effective knowledge transfer between universities and industries in AI projects? | • Builds on theories of dynamic capability and alliance and collaboration to show strategic and adaptive partnerships over time (Teece, 2009)<br>• Based on open innovation and UIC literature that explores new models that can enhance the effectiveness of UICs (Cao *et al.*, 2026)<br>• Grounded in policy and regulatory theories, such as the triple helix framework, exploring how government interventions can facilitate or hinder collaborations (Etzkowitz and Leydesdorff, 2000)<br>• Explores the complex interplay between IP rights, open innovation and knowledge sharing (Perkmann and Walsh, 2007)<br>• Grounded in knowledge management and transfer theories, exploring how best practices can evolve to support AI projects (Argote and Ingram, 2000) | • New models based on co-creation principles can enhance the effectiveness of UICs and create both better research questions and faster commercialization<br>• Addressing these challenges can help to facilitate the smooth sharing of knowledge between universities and industry partners, clarifying the role of AI<br>• Understanding the impact of government policies helps stakeholders navigate regulatory environments and leverage policy support to enhance collaboration outcomes<br>• Clarifying the IP rights of different collaborators will streamline negotiations for UIC<br>• Co-creation models will lead to improved science and improved outcomes for service organizations |

(*continued*)

**Table 3.** Continued

| Domains | Future research opportunities/questions | Theoretical relevance | Managerial relevance |
|---|---|---|---|
| *AI-driven service innovation* | • How can AI-driven service innovation remain adaptive to changing stakeholder needs? What are the value drivers for the various stakeholders in embedding AI innovations? How might AI-driven service innovation dynamics unfold longitudinally as part of a complex innovation process?<br>• How will advancements in AI shape the future of personalized customer experiences in service industries?<br>• What emerging technologies could complement AI to overcome current barriers in traditional service sectors? How can AI be effectively integrated into existing service delivery models to enhance customer experience and operational efficiency?<br>• What success factors will be critical for future interdisciplinary teams working on AI-driven service innovation? | • Drawing on theories of technology adoption and human-computer interaction, these questions examine how AI can enhance personalization, a key factor in customer satisfaction and loyalty (Huang and Rust, 2018) and extend on broader innovation process theories of Andrew Van de Ven and others<br>• Builds on theories of technological innovation and diffusion, examining how complementary technologies can enhance AI's impact in service sectors (Vendrell-Herrero *et al.*, 2017)<br>• Delves into the intersection of service innovation and AI, drawing on theories of service innovation (e.g., Vargo and Lusch, 2008) and AI adoption (e.g., Rogers, 2003)<br>• Based on team dynamics and interdisciplinary collaboration, exploring the factors that contribute to successful teamwork (Edmondson and Harvey, 2018) | • Enhanced personalization will continue to help businesses tailor their service offerings, but an over-reliance on AI may create the opposite effect<br>• Complementary technologies may help businesses integrate AI more effectively and overcome adoption barriers and enhance overall service delivery<br>• Understanding the effective integration of AI can lead to the development of innovative service solutions, improved customer satisfaction and increased organizational productivity<br>• Teamwork is essential for UICs. Therefore, it is crucial that interdisciplinary teams with diverse backgrounds collaborate well to ensure UIC success |

**Source(s):** Authors' own work

recommendations in terms of three broad thematic future research domains that underpin value creation for AI-driven service innovation, namely, (1) ethical dimensions, (2) UIC dimensions and (3) AI-driven service innovation. Each of these domains offers the opportunity for further unique and salient contributions to be made to both theory and service management practice. This paper positions UIC derived service innovation as a means to ensure that AI-driven service innovations become embedded and mutually beneficial as part of a co-creation network, rather than one-off interventions. UIC provides a powerful mechanism for achieving this, particularly in fast-moving technological fields such as AI. By leveraging the distinctive strengths of universities and industry partners, AI-driven service innovations can be cultivated to create lasting value for firms, customers and society.

As indicated in Table 3, key future questions emerge from this research, for example: *What emerging technologies could complement AI to overcome current barriers in traditional service sectors? How can AI be effectively integrated into existing service delivery models to* *enhance customer experience and operational efficiency? What role will evolving government policies play in shaping the future of UIC?* Such questions offer fruitful areas for research in the evolving era of service innovation.

## Note

1. As experienced collaborators, interviewees were evaluated as comprising a mature and experienced understanding of the partners' university/industry worldviews. A selection of the interviewees also either hold, or held, positions in their career across both university and industry (or external organizations to the university), which enhanced their understanding of diverse worldviews. Including interviews with more balanced perspectives promoted a holistic understanding.

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