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Integrating artificial intelligence into business processes: how to enhance customer–machine interactions amid industry convergence

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Abstract

Purpose – This research illustrates how companies can leverage Artificial Intelligence (AI) within the context of industry convergence to foster stronger customer-machine interaction. We aim to unveil how convergence occurs within industries and what AI-enabled mechanisms help exploit these developments.

Design/methodology/approach – AI is increasingly adopted within convergent service industries. Such integrations are employed to shape customer–machine interactions across business processes. Yet existing research rarely examines AI use under conditions of industry convergence while also tracing effects across the full input–process–output (IPO) chain. To address this gap, we conduct a qualitative, multi-case study inductive design, set in the MedTech industry. This approach enables a holistic, end-to-end examination of AI outcomes across the IPO chain, while preserving the organizational and industry context in which convergence occurs.

Findings – Results reveal industries face different pathways amid industry convergence, leading to the following types of output: non-convergence, symmetric convergence, asymmetric convergence. Furthermore, we identified stage-specific AI mechanisms and classified them according to their impact on customer acceptance of machines.

Originality/value – This research introduces an industry convergence input–process–output (ICIPO) model, reframing the original framework around this phenomenon. Moreover, it provides mapping for AI mechanisms amid industry convergence, allowing managers to improve customer-machine interactions across business processes.

Keywords Industry convergence, Artificial intelligence, Customer-machine interactions,
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1. Introduction

Artificial intelligence (AI) is shifting from a discrete tool to an infrastructural layer embedded in products and service operations across industries (Nicolescu and Tudorache, 2022; Klein and

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Martinez, 2023). Its most consequential effects arise when AI directly mediates customer–machine interactions. Through conversational agents, clinical decision support, or automated triage, these AI integrations shape trust, transparency and perceived control (Yang and Park, 2011; Shahid Iqbal *et al.*, 2018). In these customer-centric contexts adopting AI-enabled solutions can foster value co-creation through responsiveness and personalization, but it can also strain relationships and trigger value co-destruction when interaction expectations are violated (Vargo and Lusch, 2008; Lumivalo *et al.*, 2024). At the same time, firms rarely deploy AI as a standalone artifact, but they embed it across the entire input–process–output (IPO) chain (Khvatova *et al.*, 2023). These process redesigns increasingly intersect with industry convergence. As boundaries erode and hybrid segments emerge, industry-specific data and capabilities travel from outside their traditional domains (Greenstein and Khanna, 1997; Curran *et al.*, 2010; Lee *et al.*, 2018). Such convergence tends to intensify in tech-driven settings. Thus, AI functions as an enabler of convergence within service contexts that involve advanced tech for customer interactions (Neuwirth, 2015; Thomas, 2020; Sick *et al.*, 2019; Haefner *et al.*, 2021).

Despite these developments, existing research rarely connects the three elements that determine outcomes: (1) convergence as cross-industry recombination, (2) AI as a customer-facing interaction mediator and (3) business-process design as the mechanism that embeds AI into work (Greenstein and Khanna, 1997; Khvatova *et al.*, 2023; Nicolescu and Tudorache, 2022). IPO studies typically model value creation as an internal transformation of inputs into outputs within a focal system (Ilgen *et al.*, 2005). Convergence research distinguishes input-side and output-side shifts, but mostly at the sector level, offering limited visibility into how specific initiatives re-route activities across stages and boundaries (Curran *et al.*, 2010). Consequently, we still lack an explanation of how convergence unfolds across industries, redirecting companies' IPO chains and how AI can be employed in this context to manage customer–machine interactions. Further developments have led scholars to investigate how AI is integrated within business processes (Khvatova *et al.*, 2023). To fill this gap and investigate our theoretical speculations, we built the study around the following research question: *"How to leverage AI within industry convergence to strengthen customer-machine interactions?"*. To answer this, we pursue two objectives: (1) develop a stage-spanning framework that explains how convergence occurs in the IPO chain; and (2) identify guidelines to help firms diagnose whether stage-specific AI mechanisms amid industry convergence improve or worsen customer–machine interactions.

We ground our analysis in four theoretical lenses. First, thanks to *Absorptive capacity* (Zahra and George, 2002), we frame convergence as a condition that expands and recombines firms' knowledge bases, explaining how cross-industry inputs can be acquired, assimilated, transformed and exploited. Second, the *IPO model* (Ilgen *et al.*, 2005) specifies where AI enters workflows and how effects propagate from inputs to processes and outputs. Third, Amelia *et al.* (2022) provide *customer-acceptance factors* for AI-enabled solutions, letting us interpret outcomes as drivers or barriers for customer–machine interactions. Finally, building on Geum *et al.* (2016), we operationalize convergence as boundary crossings along the IPO sequence, distinguishing within- and cross-industry pathways. In coding, we routed each instance to an IPO stage, classified its industry locus and crossing pattern and assessed its likely acceptance impact before aggregating mechanisms into higher-order constructs. Methodologically, we adopt an inductive multi-case qualitative design (Yin, 2018) because AI integration amid convergence is still emergent and requires rich process evidence. We focus on MedTech because AI adoption is accelerating in healthcare and patient acceptance is decisive for outcome success. The study examines three cases, selected for active AI initiatives and clear Med–Tech coupling. We triangulate interviews with managers, technicians and customers with secondary materials to strengthen interpretive robustness. Data analysis was conducted by employing NVivo [15] and by adopting the methodology of Gioia *et al.* (2013). Its progression from informant-centric concepts to aggregate dimensions supports rigorous theory building and systematic cross-case comparison, directly serving our objectives.

Results show that AI-enabled initiatives in MedTech generate distinct output patterns depending on how far they re-route theIPO chain across industry boundaries. We identify (1) null-convergent outputs when inputs and processes remain within either MED or TECH; (2) semi-convergent outputs when boundary crossing occurs once (at the input stage or at the process stage), producing asymmetric pathways (MED→TECH or TECH→MED); and (3) fully convergent outputs when boundaries are crossed twice (MED→TECH→MED or TECH→MED→TECH), yielding reciprocal value propositions. These findings allowed us to formulate three core propositions. First, we developed an *industry convergence input-process-output (ICIPO) model* to illustrate where convergence occurs and how each pathway leads to different outcomes. Second, we conceptualize *stage-specific AI mechanisms amid convergence* to explain how companies improve (drivers) or worsen (barriers) customer-machine interactions amid industry convergence, at every stage of the IPO chain. Third, to provide *diagnostic guidance*, by mapping each mechanism: what outcome they provide on customer acceptance of machines (driver/barrier); at what stage of the IPO chain they occur (input stage or output stage); at what level they cross or don't cross industry boundaries (intra-industry or inter industry); finally what is the output type generated (null-convergent, semi-convergent or fully convergent). Overall, our work extends IPO and convergence theory by showing that AI can redirect value creation across industries in patterned ways and that cross-industry recombination can be effective, ambivalent or dysfunctional depending on customer-acceptance frictions, not only learning potential.

Beyond its theoretical contributions, this study offers actionable implications. For managers, ICIPO provides a practical diagnostic to locate AI initiatives along the IPO chain, allowing them to understand which type of convergent output is being created. Furthermore, our research assesses whether mechanisms act as drivers or barriers of customer–machine acceptance. Our guidelines help anticipate effective, ambivalent, or dysfunctional outcomes and target improvements. For policymakers, the results support regulations that consider the impact of convergence within service settings. Future research should extend ICIPO through comparative studies across other converging fields or by adopting quantitative designs to test the correlation between newly discovered variables.

2. Literature review

2.1 Towards industry convergence through developing AI integration

Industry convergence is intended as the process by which a new industrial segment emerges as the boundaries of existing ones blur and merge, leading to a final state in which new industries are created (Greenstein and Khanna, 1997; Curran *et al*., 2010; Lee *et al*., 2018). A frequently cited example of such an emergent hybrid industry is the field of functional foods and nutraceuticals, located at the intersection between the food and pharmaceutical sectors (Bröring *et al*., 2006; Curran, 2013). Here, industry convergence has led to products and value chains that cannot be clearly classified as either "food" or "drug", but instead constitute a distinct industry segment with its own actors, regulatory challenges and competitive dynamics (Bröring and Cloutier, 2008; Bornkessel *et al.*, 2016). Examples such as this highlight the potential of industry convergence to break apart barriers and foster competitive differentiation (Neuwirth, 2015; Thomas, 2020). By lowering structural and cognitive boundaries between sectors, convergence facilitates the transfer and recombination of knowledge and capabilities across industries (Cohen and Levinthal, 1990). It also encourages firms to adapt and share business models beyond traditional industry borders, in line with open innovation arguments about leveraging external ideas and pathways to market (Chesbrough, 2003; Kwon *et al*., 2020).

There is a difference, however, between convergence as a general phenomenon and industry, according to research conducted in the 1990s (von Delft, 2013). For the OECD, convergence is "the blurring of technical and regulatory boundaries between sectors of the economy" (OECD, 1992). Since the late 1990s, further developments have emphasized overlaps in value propositions, technologies and markets (Choi and Valikangas, 2001) illustrated the importance of industry-specific knowledge (Pennings and Puranam, 2001, September); highlighted the sequential process by which these elements converge from different domains (Hacklin *et al.*, 2009). Literature agrees that industry convergence unfolds along two dimensions: inputs, when new technological fields span previously separate industries and create shared platforms; and outputs, when demand fuses so products become interchangeable or hybridize in use (Bröring *et al.*, 2006). Convergence can also be substitutive, replacing original industries or complementary, creating an additional segment that coexists with them (Boehlje *et al.*, 2011). By increasing the diversity and complementarity of external technological and market knowledge, industry convergence can foster the development of firms' absorptive capacity, understood as their ability to acquire, assimilate, transform and exploit external knowledge (Zahra and George, 2002).

The first evidence of convergence has been observed in sectors related to information technology, telecommunications and consumer electronics (Curran *et al.*, 2010). Established digital technologies – such as big data analytics, blockchain and AI – are now considered mature and reliable by both industry stakeholders and end users and are widely recognized as key enablers of digital transformation (Akter *et al.*, 2022; Aldoseri *et al.*, 2024; Deliu and Olariu, 2024). Their integration into business processes enables innovative digital work models and reduces the risk of failure associated with the introduction of novel solutions to the market (Kaplan and Haenlein, 2019; Tohãnean *et al.*, 2020). Furthermore, these technologies are typically framed as enablers of end-to-end process redesign and continuous improvement across the business process lifecycle, from process discovery and modelling to monitoring and optimization (Dumas *et al.*, 2018; Baiyere *et al.*, 2020). More specifically, process mining and machine-learning approaches are increasingly used in BPM to diagnose process performance and support data-driven redesign decisions (Van Der Aalst, 2016; Weinzierl *et al.*, 2024). Overall, technology helps sustain trust among stakeholders in the initial phases of collaboration, for example, through transparent data infrastructures and blockchain-based architectures (Barrane *et al.*, 2021; Shi *et al.*, 2021).

AI denotes computational systems that autonomously analyze data, adapt their behavior through learning and support or execute decisions typically requiring human judgment and reasoning (Raisch and Krakowski, 2021; Berente *et al.*, 2021). Within management, AI increasingly augments decision-making, automates routine supervisory tasks and supports data-driven strategic analysis, reshaping managerial roles while enabling new forms of algorithmic and collaborative governance (Noponen, 2019; Keding, 2021). Furthermore, AI management approaches embed ethical principles to align algorithmic decisions with social, environmental and economic sustainability objectives (Goralski and Tan, 2020; Brendel *et al.*, 2021). Embedding AI into a company workflow enables it to redesign core processes, thus driving industry convergence (Katz, 1996; Haefner *et al.*, 2021). Therefore, offering firms opportunities to respond to crises and create new value by recombining knowledge, technologies and markets (Stieglitz, 2007; Weaver, 2007). However, studies also point out potential barriers introduced by a mismanaged convergence, such as knowledge or competence gaps between specialized actors (Sick *et al.*, 2019) and conflicts with existing strategies (Broring, 2010).

2.2 Artificial intelligence as a tool to enhance customer-machine interactions

Within customer-centric fields, how consumers engage with providers can enable value co-creation or threaten relationships (Vargo and Lusch, 2008; Lumivalo *et al.*, 2024). Customer–machine interactions are service encounters where customers co-create value with technologies rather than employees (Larivière *et al.*, 2017; Zhang *et al.*, 2018). Research on Self-Service-Technologies (SSTs) shows that technology encounters deliver convenience and control but can also generate frustration and service failures, making satisfaction contingent on ease of use and perceived service quality (Meuter *et al.*, 2000). Subsequent studies clarify that intuitive, reliable, time-saving systems foster satisfaction and reuse, whereas complexity, errors and delays undermine them (Yang and Park, 2011; Shahid Iqbal *et al.*, 2018). Individual differences further shape outcomes: technology-ready and experienced customers perceive greater efficiency, while insecurity or anxiety can make encounters stressful (Lin and Hsieh, 2007; Kelly *et al.*, 2010).

AI-based chatbots and service robots extend these insights by adding conversational quality, social presence and human-like traits (e.g. warmth, empathy), and by making outcomes sensitive to the fit between machines, staff and the broader service context (Nicolescu and Tudorache, 2022; Borghi *et al.*, 2023; Klein and Martinez, 2023). Doubts arise when AI is opaque, unreliable or removes meaningful human support, increasing customer effort and lowering perceived fairness (Coelho and Farias, 2025). Accordingly, AI's effects are conditional on transparency, escalation to humans and context fit (Ostrom *et al.*, 2018). This conditionality also appears in work examining AI integration across industries, which emphasizes designing customer-facing interactions alongside task allocation between automation and employees (Wirtz *et al.*, 2018). Across domains, the most robust value is often framed as automating routine tasks while augmenting human capabilities, positioning AI as embedded in processes rather than only at the interface (Davenport and Ronanki, 2018; Cannavale *et al.*, 2022; Murire, 2024).

Process perspectives connect interaction outcomes to implementation choices. Mapping an IPO chain helps specify where AI enters workflows and how operational changes translate into customer-facing experiences (Ilgen *et al.*, 2005; Khvatova *et al.*, 2023). In healthcare, event-log studies reconstruct patient and administrative pathways to detect bottlenecks and deviations and to support evidence-based redesign (Rebuge and Ferreira, 2012; Rojas *et al.*, 2016). Robotic process automation (RPA) in hospital information systems similarly targets monitoring and improving complex workflows in ways that can shape user experience and service reliability (Agostinelli *et al.*, 2020; Syed *et al.*, 2020). Beyond back-office automation, Frontline Service Robots (FSR) combine physical presence and AI capabilities to engage customers in socially framed encounters, which differentiates them from earlier SST interactions (Lee *et al.*, 2017). Consistent with this trajectory, FSR deployments span tourism, retail and healthcare, indicating that customer–machine interactions increasingly occur through embodied, interactive interfaces (Odekerken-Schröder *et al.*, 2022).

Empirical studies further suggest that AI tools – from productivity systems to service chatbots – can improve operational efficiency and service quality, motivating continued refinement and scaling in service industries (Misischia *et al.*, 2022; Czarnitzki *et al.*, 2023). These developments have particular relevance in healthcare, where digital platform diffusion creates new patient value streams (Hermes *et al.*, 2020), consistent with the view that technology is a dominant force in healthcare change (Thimbleby, 2013). AI is central to this shift and is frequently linked to the "fourth medical revolution" aimed at improving decision-making through intelligent systems (Sarker *et al.*, 2021; El-Sherif *et al.*, 2022, February). Within the medical industry – firms that develop, produce and commercialize pharmaceutical and therapeutic products – AI supports discovery, clinical development and patient stratification, potentially accelerating pipelines while reducing attrition and adverse events (Liebenau, 1987; Bajwa *et al.*, 2021; Alowais *et al.*, 2023). AI also supports forecasting, quality control and regulatory compliance across data-intensive supply chains (Gadde and Kalli, 2021; Ali *et al.*, 2023).

In parallel, AI deployment debates increasingly frame patients as active customers of digital services, with AI-enabled tools mediating patient–machine encounters similarly to service interactions in other industries (Leone *et al.*, 2021; Kumar *et al.*, 2023). Recent research highlights the factors influencing customer acceptance towards AI-based technologies, including: utilitarian aspect; social interaction; customer responses toward FSR; customer perspective of the company brand; individual and task heterogeneity (Amelia *et al.*, 2022). Other studies claim patients evaluate AI integration in terms of convenience, responsiveness and perceived quality of care (Chew and Achananuparp, 2022). Furthermore, cross-domain integration can deepen customer relationships by aligning AI capabilities with established routines (Selvarajan, 2021; Magas and Kiritsis, 2022). However, if mismanaged, AI can also amplify inequities and induce automation bias in high-stakes settings (Obermeyer *et al.*, 2019; Seyyed-Kalantari *et al.*, 2021; Parasuraman and Manzey, 2010; Abdelwanis *et al.*, 2024). Overall, these developments support a shift from isolated offerings toward orchestrated, data-rich health solutions with durable strategic advantages (Troilo *et al.*, 2017).

2.3 Theoretical speculations

Literature has shown that industry convergence between the Tech sector and healthcare, specifically through the integration of Information and Communication Technology (ICT) within companies' processes (Eidam *et al.*, 2017). Furthermore, AI integration in the Med sector is increasing rapidly, thus leading to an additional industry segment existing alongside traditional domains (Bajwa *et al.*, 2021; Alowais *et al.*, 2023). The convergence between the Tech industry and the Med industry has therefore occurred in a complementary way rather than substitutive (Boehlje *et al.*, 2011), leading to the MedTech industry. This allows existing companies to access opportunities to share knowledge and develop new capabilities (Stieglitz, 2007; Weaver, 2007). By employing absorptive capacity (Zahra and George, 2002), we assume convergence enables firms to acquire, assimilate, transform and exploit external knowledge across industry boundaries. AI becomes a vehicle for such knowledge sharing by codifying and scaling routines that can be transferred and recombined across partners (Raisch and Krakowski, 2021; Berente *et al.*, 2021). When Med actors adapt AI to regulated workflows, medical routines change and new capabilities emerge, while Tech actors redesign AI to fit clinical constraints and absorb domain expertise, creating reciprocal learning opportunities (Cohen and Levinthal, 1990; Haefner *et al.*, 2021).

Drawing from the traditional IPO model (Ilgen *et al.*, 2005), and empirical research on how convergence unfolds (Geum *et al.*, 2016), it is possible to translate these learning opportunities into concrete stage-specific design choices. At the input stage, convergence widens firms' exposure to heterogeneous technological and market knowledge, supporting acquisition and early assimilation of external signals and capabilities (Cohen and Levinthal, 1990; Zahra and George, 2002). AI and adjacent digital technologies act as enabling infrastructures that make cross-industry inputs useable and stable enough to be embedded in organizations (Akter *et al.*, 2022; Raisch and Krakowski, 2021). At the process stage, firms redesign workflows to combine internal routines with newly assimilated knowledge, which aligns with transformation and process reconfiguration logics (Haefner *et al.*, 2021; Dumas *et al.*, 2018). At the output stage, exploitation becomes visible in deliverables and new value propositions that reflect hybridized capabilities and markets (Bröring *et al.*, 2006; Greenstein and Khanna, 1997). Mismanaged convergence can still create competence gaps and strategic conflict, constraining absorption across stages (Sick *et al.*, 2019; Broring, 2010).

Since AI mechanisms amid convergence operate along the IPO chain, then their customer-facing consequences should also be examined stage by stage to unveil more deeply how customer-machine interactions unfold (Larivière *et al.*, 2017; Zhang *et al.*, 2018). Consistent with the acceptance factors identified for AI-based technologies, firms can shape early expectations at the input stage through design and governance choices that signal utilitarian value, social interaction quality and brand credibility (Amelia *et al.*, 2022; Ostrom *et al.*, 2018). At the process stage, embedding AI into workflows determines reliability, speed and service quality, which are central determinants of technology-mediated evaluations (Davenport and Ronanki, 2018; Yang and Park, 2011). Process visibility and redesign approaches further connect operational performance to interaction outcomes by reducing errors, delays and bottlenecks (Van Der Aalst, 2016; Rebuge and Ferreira, 2012). At the output stage, AI-mediated interfaces (e.g. chatbots or robots) can enhance responsiveness and social presence, but effects remain contingent on context fit and escalation to humans (Nicolescu and Tudorache, 2022; Wirtz *et al.*, 2018). Acceptance can deteriorate when systems are opaque or remove meaningful human support, increasing effort and lowering perceived fairness (Coelho and Farias, 2025). In healthcare, these risks are amplified because AI can exacerbate inequities and trigger automation bias in high-stakes decisions (Obermeyer *et al.*, 2019; Parasuraman and Manzey, 2010).

3. Method

3.1 Research setting

To answer our research question, we employed an inductive, multi-case study qualitative approach (Yin, 2018). A qualitative design was appropriate because the study examines organizational processes, meanings and coordination practices around AI initiatives that are difficult to capture through pre-specified variables alone. We adopted an inductive logic to allow constructs and relationships to emerge from the data in a setting where theory is still developing and where categories are likely to be context-dependent. Finally, a multi-case design increased analytic leverage by enabling systematic comparison across organizations and projects, strengthening robustness through replication logic and helping distinguish case-specific idiosyncrasies from recurring patterns. Regarding data collection, we gathered both primary and secondary data to strength solidity and ensure data triangulation (Yin, 2018). This study combines ethnographic elements (indirect observations) with multiple qualitative data sources (interviews, statements, internal and external documents). For data analysis, we chose the Gioia *et al.* (2013) methodology because the study aims at inductive theory building – deriving an integrative ICIPO framework that links informant-level accounts of AI integration to higher-order dimensions of value creation under Med–Tech convergence. For data analysis, we adopted the Gioia *et al.* (2013) methodology because it provided a transparent and systematic procedure for moving from empirical material to theoretical constructs. More specifically, it allowed us to progress from first-order concepts generated through NVivo coding of primary and secondary data, to second-order themes developed through their combined interpretation using two theoretical lenses (Geum *et al.*, 2016; Amelia *et al.*, 2022), and finally to aggregate dimensions derived from the combination of two second-order themes within the IPO pathway. Overall, this methodology offered a cleaner reporting architecture, more explicit construct development and effective cross-source synthesis, compared to other approaches.

The empirical arena is Med–Tech convergence. We chose Med–Tech because AI-driven coupling is both fast-moving and highly regulated in medical settings, thus forcing adaptation between industries. Furthermore, the underlying mechanisms (e.g. data sharing, platformization, partnership structuring and workflow embedding) are not sector-specific, so insights can transfer easily to other convergence settings. We operationalized Med-Tech as observable cross-industry coupling evidenced by at least one of the following: (1) formally documented partnerships between medical/healthcare and technology actors, (2) co-development or integration of AI-enabled digital capabilities into healthcare workflows or (3) shared platform/data/process infrastructures spanning the medical and technology domains.

Based on these criteria, we identified three case studies:

(1) Alira Health operates across the life-sciences value chain. It supports medical and pharmaceutical companies with consulting, clinical development, market access and digital health execution. Geographically, it is anchored in North America with projects and partnerships spanning Europe. Its activities include regulated healthcare, patient pathways and evidence generation. In parallel, the firm increasingly works with technology actors to scale data-driven services and improve patient and clinician interactions. A clear example is its collaboration with Workday, a cloud platform for enterprise finance and HR. In this setting, Workday can be used to streamline internal operations, improve workforce planning and strengthen service delivery across complex healthcare programs. The partnership illustrates how med-sector firms adopt enterprise tech to improve responsiveness and coordination.

(2) Pieces develops clinical software used in high-acuity settings such as perioperative care, anesthesia, ICU and procedural areas. Its products focus on documentation, workflow orchestration and operational visibility for hospitals. Its deployments are concentrated in North America with a broader footprint across hospital networks, including parts of Europe. As providers demand more predictive and personalized interactions, the company is incorporating technology partners and AI-enabled capabilities into its ecosystem. Public materials point to machine-learning functionality for operating room efficiency, including predicting case times to improve scheduling and utilization. Furthermore, it also maintains a partner network that includes Caresyntax, which positions itself as an AI-powered surgical intelligence platform. This combination signals a shift from pure clinical documentation toward decision support and smarter customer-facing workflows.

(3) Kelyon operates at the intersection of healthcare delivery and digital services. It is anchored in Southern Europe, with initiatives extending to wider European stakeholders. Its purpose is the development of solutions to support care pathways, prevention and patient engagement. Specifically, it focuses on improving communication between citizens and clinicians. This medical-sector grounding has pushed the firm toward deeper collaboration with technology and AI research actors. A central example is its strategic alliance with Fondazione Bruno Kessler (FBK) to co-develop AI-based healthcare applications. The collaboration includes work on virtual assistant concepts, including MaIA, designed to provide guided information and support for women's health. These initiatives illustrate how the company uses AI to strengthen customer interactions while aligning with clinical credibility and public-health goals.

3.2 Data collection

Data were collected from diverse sources, combining secondary data (indirect observation, public declaration, online documentation, archival record and indirect interview) with primary data (13 anonymous semi-structured interviews). Secondary evidence was gathered over a 24-month window (June 2023–June 2025) to ensure temporal coverage and to avoid overstating longitudinal depth beyond what the dataset can support. We treated observations as ethnographic-influenced fieldwork elements rather than full ethnography, adhering to core requirements of (1) systematic fieldnote production (time-stamped notes written immediately after each event), (2) explicit separation of observation from inference (notes capture who/what/when before interpretation), (3) reflexive memoing on researcher assumptions and potential bias and (4) triangulation across independent sources before elevating any observation to a reported claim. Secondary sources were included when they (1) referenced AI-enabled initiatives affecting customer–company interaction, (2) evidenced Med–Tech coupling per our operational definition and (3) were attributable to identifiable organizations or reputable publishers. Exclusion criteria removed unverifiable commentary, duplicate re-postings and promotional claims lacking corroboration. Reliability was managed by treating public declarations as claims and cross-checking key assertions against archival records, multiple documents, or interview testimony.

Primary data consisted of 13 anonymous direct interviews, distributed across the three case studies to enable within-case depth and cross-case comparison. The sample included six consumers, four managers and three technicians. The interviews were conducted between June 2023 and June 2025 and lasted 25–60 min each. We used a semi-structured, ethically grounded protocol aligned with Kvale (2007), consisting of a common set of question blocks and role-specific probes. The common blocks addressed: (1) background and involvement, (2) description and timeline of the AI initiative and (3) inputs, process changes and outputs (IPO logic). Role-specific probes focused on customer–machine interaction and acceptance (consumers), organizational implementation and value expectations (managers), and technical architecture/data, integration and monitoring/override practices (technicians). The wording and order were adapted to the interviewee and case, while the same domains were covered in all interviews using follow-up prompts (e.g. requests for concrete examples and critical incidents). Sample adequacy was assessed via thematic sufficiency: recruitment stopped when later interviews predominantly refined existing themes rather than introducing substantively new mechanism categories.

All primary and secondary materials were consolidated in NVivo [15] to build a unified qualitative evidence base with traceability. Each item was imported with metadata (case affiliation, source type, date/month and stakeholder category) to support structured retrieval and transparent linkage between claims and evidence. First, we organize the dataset into three cases and source-type classifications (interview vs. observation vs. document/public/archival). Second, we store and code transcripts, fieldnotes and documents within a single auditable repository. Finally, we maintain an audit trail through dated memos documenting inclusion decisions, evolving code definitions and negative-case notes. During analysis preparation, NVivo queries (e.g. text search, matrix coding queries) were used to check whether emerging themes were supported across multiple source types and roles, strengthening triangulation readiness. Where more than one researcher coded overlapping subsets, NVivo's coding comparison functionality was used as a diagnostic tool to flag divergences and trigger reconciliation discussions; codebook refinements were recorded in project memos to prevent coder drift and preserve transparency from raw excerpts to reported findings.

3.3 Data analysis

Guided by the Gioia methodology, we analyzed the gathered material through an inductive sequence that preserves qualitative rigor while allowing us to move from empirical observations to theoretical constructs (Gioia *et al*., 2013). Using NVivo [15], we first conducted within-case coding of interview excerpts alongside pertinent secondary materials, generating first-order concepts that remained anchored in informants' expressions and the terminology appearing in the dataset. These codes captured concrete manifestations of AI integration and customer–company interaction across increasingly hybrid med–tech settings. We then cycled iteratively between the evolving concepts and the broader dataset to articulate second-order themes, tightening code definitions through systematic comparison across both sources and cases. Finally, we synthesized the themes into aggregate dimensions that reflect distinct pathway outcomes of AI-enabled value creation under conditions of industry convergence. NVivo supported traceability throughout by linking excerpts to coding nodes, enabling structured cross-case interrogation and recording analytic decisions through memos and successive re-coding. Table 1 maps the progression from first-order concepts to second-order themes and, ultimately, to aggregate dimensions.

To move from first-order concepts to second-order themes, we combined the interpretation of primary interview data and secondary materials, guided by two theoretical lenses. Drawing from Geum *et al*. (2016), we derived a convergence-sensitive IPO routing logic to locate each AI integration in the value creation chain and to determine whether it remained within an industry or crossed between industries. Furthermore, by employing the propositions from Amelia *et al*. (2022), we assessed whether an integration functioned as a driver (enhancing perceived usefulness, ease, trust, or relational support) or a barrier (creating friction, exclusion, distrust, or reduced human touch). Using NVivo [15], we then (1) assigned each excerpt to its industry locus (MED vs TECH) and path locus (Input-to-Process vs Process-to-Output), (2) coded whether the mechanism was intra-industry (MED-to-MED; TECH-to-TECH) or inter-industry (MED-to- TECH; TECH-to- MED) and (3) applied excerpt-path "coding cues" to classify it as a driver or barrier of customer acceptance. This produced 16 second-order themes: eight Input-to-Process mechanisms (four drivers and four barriers) and 8 Process-to-

Table 1. Data analysis

1ST order concept	2ND-order themes	Aggregate dimensions
Alira Health		
"The synergies among our Regulatory, Clinical and Real-World Evidence (RWE) practices and CROS NT's global biometrics capabilities will enhance Alira Health's unique ability to serve clients across their solutions lifecycle." *"CROS NT is delighted to join Alira Health to better serve our clients by providing a complete portfolio of services and solutions. We are excited to contribute to Alira Health's mission of healthcare transformation, creating value for patients. Our experienced team of professionals will deliver value through our combined services, accelerating innovation and delivering tomorrow's standard of care to patients."*	Clinical evidence base	Effective null convergence
"We are privileged to collaborate with the Patient Empowerment Network. Together, we empower patients to take charge of their healthcare experiences through the utilization of meaningful data that patients own and have control over [. . .] In today's context, prioritizing patients and granting them and their support networks the capacity to chart their healthcare paths is of utmost importance. We firmly believe that well-informed, respected, and engaged patients are more likely to make informed decisions, leading to improved health outcomes. As patients gain access to this growing resource of healthcare and treatment information, they become better equipped to be advocates for their own well-being [. . .] We are excited to establish this partnership with Alira Health and the Health Storylines app," said Tracy Rode, Executive Director at the Patient Empowerment Network [. . .] We are confident that this will provide our community of patients and caregivers with an additional resource to effectively oversee their well-being and flourish." *"If you are medically diagnosed with a schizophrenia or a related brain disorder, my wish is you find the same hope I did by simply using this priceless app."* *"At Alira Health we invest a lot of time in building our family around very core values. We believe in: being inclusive . . . being courageous . . . being honest . . . being accountable . . . [and] elevating others"* *"This is a fantastic application . . . It gives you the opportunity to track not only medication use, but also daily moods and habits [. . .] you are able to see patterns over time."*	Personalized care gains	

(*continued*)

Table 1. Continued

1ST order concept	2ND-order themes	Aggregate dimensions
“Gustave Roussy is leading a transformational shift in cancer prevention, and we are honored to support them with SpherePX [. . .] Our technology bridges the gap between research and real-world care, ensuring that high-risk individuals receive the personalized prevention plans they need. By integrating digital health solutions with real-world evidence, we can drive earlier interventions and improve long-term outcomes.”	Clinical data for AI	Effective symmetric convergence
“The innovative part of our approach is how we engage with patients. The Alira Health difference is we do not recruit patients for only a particular Clinical and RWE study. We already have patients active on our platforms using our technology to manage their conditions, and we empower them with education on what it means to be part of a study and partner with them all along. We now have over 160,000 patients on our technology platforms.”		
“SpherePX’s Proven Market Expertise: – 60+ Clinical Studies, – 150K+ Patients Engaged, – 50+ Therapeutic Areas, – 20+ Countries, – 15+ Languages”		
“SpherePX’s Monitoring Capabilities: reduce administrative burden (automate documentation and workflows so teams can focus on care); streamline patient management (automate documentation and workflows so teams can focus on care); access real-time data (monitor study performance and patient input as its captured)”	Monitoring improves outcomes	
“I use it (Health Storylines app) everyday to keeping track of vitals and taking my medication. I love the fact that you can journal your feelings and reflect on emotions and what got you to where you are now. You can even input your moods and keep track of your upcoming appointments. [. . .] I definitely would recommend”		
“This app has so many ways to track your lifestyle and see not only what your triggers are and how often they show up. It’s a great app and I would recommend it to anyone.”		

(*continued*)

Table 1. Continued

1ST order concept	2ND-order themes	Aggregate dimensions
"This is a great app for me since I like tracking my health when I get sick. It's a lot easier to make conclusions when you have analytics." *"The integration has been profound. Our financial, staffing, and travel management systems now speak the same language, thanks to Workday [. . .] We see Workday as a partner in our growth, not just as a platform. It's about enhancing our data quality and capabilities to support strategic analysis and decision-making,"*	Data-driven delivery	Effective asymmetric convergence
"Patient stories are powerful advocacy tools. We are now in the age that enables us to use advanced technology to unfold these stories – as a result, the newest patient-reported, evidence-based tools allow patient advocacy groups to capture analytics and insights into the journey of each patient and leverage these data points to deliver better care, helping patients, their families, and care teams." *"AI solutions are designed to allow real-time information, enabling practitioners to focus on a much smaller pool of patients and obtain a clear and complete dataset. In addition, the data collection and analysis present that a clearer image of patient information allows a greater focus on personalized care and the real needs of individuals"*	Clinical data for AI	
"We are extremely pleased to acquire CROS NT's Biometrics services globally. The synergies among our Regulatory, Clinical and Real-World Evidence (RWE) practices and CROS NT's global biometrics capabilities will enhance Alira Health's unique ability to serve clients across their solutions lifecycle. The addition of CROS NT will also enable Alira Health to expand our direct clinical operations in Europe. We embrace CROS NT's commitment and passion to being a visionary in clinical research and are proud to welcome CROS NT CEO, Paolo Morelli, and his team to our fast-growing company." *"Project Interception is being implemented at six medical centers, with approximately 490 patients enrolled and 85 healthcare professionals engaged. The long-term goal is to expand the program to 30 sites across France, ultimately reaching 2,000 patients per site each year. As the initiative grows, Gustave Roussy and Alira Health invite healthcare institutions, policymakers, and patient advocacy groups to collaborate in advancing global cancer prevention efforts."*	Tech scaling friction	Dysfunctional null convergence
"The Medication Tracker, Symptom Tracker, and Vitals are not working for me, but everything else is absolutely wonderful! [. . .] This app treats the whole patient, mind, body, and soul – not just the physical aspects of your illness." *"We had to think globally and act swiftly to address our growing pains. We were tasked with unifying a workforce that was rapidly scaling across various countries and cultures."*	Delivery instability	
Pieces Clinical Solutions		

(*continued*)

Table 1. Continued

1ST order concept	2ND-order themes	Aggregate dimensions
"Digital platforms ensure the interaction of patients with medical institutions and provides support to medical staff in the course of accompanying the patient."	AI workflow support	Effective symmetric convergence
"I've been with Picis as a client for several hospitals in the past 18 years and always had great experience with the performance of their solutions."		
"Picis was the only vendor that could deliver on all our objectives and provide the necessary integration with our other hospital information systems."		
"None of my colleagues would want to return to a paper record because we now realize the many benefits of computerized anesthesia charting."		
"Picis is the core system that provides near real-time data to help clinicians make informed decisions."		
"The drug delivery systems (DDS) market is undergoing a structural transformation, driven by the rapid expansion of biologics, intensified competition in GLP-1s and biosimilars, and the growing demand for patient-centric and sustainable solutions. Devices are no longer viewed simply as delivery tools; they are becoming platforms for differentiation, real-world evidence generation, and healthcare system efficiency. [. . .] DDS providers are embedding digital features and co-developing devices with patients to improve adherence tracking, generate real-world evidence, and enhance usability in diabetes, GLP-1 therapies, and rare chronic diseases. Sustainability is becoming a critical priority, with reusable injectors, eco-packaging, and greener manufacturing aligned with PPWR 2035 and ESG commitments now essential in pharmaceutical partnerships and procurement decisions."	Clinical-digital modules	
"AI mechanisms allow healthcare facilities to develop new and digital solutions that simplify the complex healthcare value chain and adapt to the digitization phenomenon."		
"The global biosimilar market has matured significantly in recent years, with the US and EU leading this expansion [. . .] Regulatory advances, such as the IRA and updated FDA guidance on biosimilar interchangeability, are driving this growth. With patent expirations and increasing biosimilar approvals, the market is on track to surpass $64 billion by 2028. This represents a significant shift in healthcare, delivering the benefits of biologics at reduced costs and expanding patient access while alleviating financial pressures on health systems."		
"Biopharma companies partner with contract development and manufacturing organizations (CDMOs) to receive end-to-end drug-device continuum support that enhances efficiency, scalability, and speed to market. CDMOs are investing heavily to expand capabilities upstream in design, automation, digital manufacturing, and downstream in drug product development and fill-finish."		
"We are bringing to market a new model of solutions and services that are promoting the democratization of life sciences research."		

(*continued*)

Table 1. Continued

1ST order concept	2ND-order themes	Aggregate dimensions
"AI Assistant Feature Suite for Patients and Clinicians: Conversational Study Support (give users instant answers about the study through a conversational chat interface with an AI assistant trained on your protocol); AI-enhanced questionnaires (attach an AI assistant that listens to dictation, transcribes the output, interprets the meaning using your AI model, and maps the output directly to structured eCRF fields; Automated data extraction (pre-populate forms with data extracted from medical records)" *"AI is used to enhance internal processes related to both product realization and service provision."* *"AI solutions allow start-up entrepreneurs and companies to get feedback from medical peers before proceeding with the commercialization of products. A large audience coverage allows users to convey the idea to potential investors, and partners, assess potential demand, and so on. An important feature of the platform is the combination of private and public funding opportunities that have gone through the securities review process."*	Platform automation readiness	Effective asymmetric convergence
"Prevention and Care Management Activities: Patient Support Programs that ensure patient engagement and adherence as well as health care professional coordination throughout the care pathway; Patient Remote Monitoring that reinvents the link between the patient and healthcare professionals with our state-of-the art prevention and monitoring technologies; Primary Prevention at Work offers value-added services to your employees with health risk screening solutions in the workplace; Risk Screening Campaigns like cardio-metabolic risk screening campaigns with certified nurses within companies, public places, thanks to our state-of the art digital solution and connected devices" *"AI integration enables healthcare systems to create value for patients and the different actors involved by achieving a suitable trade-off between high-quality care and cost containment."*	Monitoring improves outcomes	

(*continued*)

Table 1. Continued

1ST order concept	2ND-order themes	Aggregate dimensions
“Technology alone won’t enroll patients in clinical studies; it’s an enabler which you can combine with clinical expertise and patient engagement to succeed in recruitment. You need deep knowledge and experience to make technology beneficial, and you must include the human component. I’ve seen companies fail when they relied totally on technology and left out the human interaction, especially when it comes to not just finding patients but convincing them to participate. For example, we were running a study in an older population living with diabetes, and because digital technology was the only option for participation, these patients felt they couldn’t be a part of the study because they didn’t have smartphones.” *“Digital advertising allows us to reach out to potential targets for study participation. We use display ads to mobilize patients to a landing page where we explain the benefit of the study and the type of person who would be perfect for this study. People register themselves as a potential participant and then we share more information with them. This technology allows us to cast a wide net for finding patients, while also enabling a seamless experience in the background to capture patient information, connect patients with the PI, and communicate with them going forward. This is, of course, combined with off-line techniques, such as engaging with patient associations.”*	Digital exclusion risk	Dysfunctional asymmetric convergence
“Another issue is that the sponsor often considers enrollment the responsibility of the principal investigator (PI) and the study team at the hospital. This situation results in frustration on all sides. The study team doesn’t have the time or bandwidth because they’re running multiple studies and have numerous responsibilities. Don’t expect the study team to solve recruitment for you. Certainly, one of your strategies can be to talk to the investigator, but you need to find a way to support them and work collaboratively.” *“Through constant optimization and a rigorous human-in-the-loop review process, Pieces reaches low summary error rates. Their AI agents allow personalization down to the individual doctor level.”*	Trial execution delays	
Kelyon		
“high quality and in-depth data are necessary for current analyses but difficult to obtain,” *“Digital solution brings together stakeholders such as healthcare providers, clinical evaluators, and payers, thus affecting the speed and quality of medical services.”*	Clinical-tech misfit	Dysfunctional symmetric convergence
“I would like a simpler app.” *“A more formal chatbot.”*	Trust adoption friction	

(*continued*)

Table 1. Continued

1ST order concept	2ND-order themes	Aggregate dimensions
"I also see a challenge in patients' willingness to participate in a clinical study. Patients are reluctant to participate for various reasons, including their physical abilities, lack of transportation, and the time commitment, including time away from work (which can affect income) or family. Sometimes patients don't trust the clinical study process and have concerns about receiving a drug that's not approved or a device that's not cleared. These very human issues can further limit your patient population."	Clinical input constraints	Dysfunctional asymmetric convergence
"Sometimes limited budgets and lack of knowledge of other options, can make them think they should stick to traditional approaches, such as relying on the PI, but what's been done for years doesn't necessarily work anymore. And PIs are concentrating on the investigation and they simply cannot handle everything. So I think that sponsors should think a little bit outside of the box, and consider strategies that may take them beyond their comfort zone."		
"Another major challenge related to that is that studies are seldom co-designed with patients. During the co-design process, patients can provide input as to what will work and what won't, identifying logistical problems in the proposed study protocol and letting you know what's truly feasible. For example, you can ask patients if the number of times they would be expected to visit the hospital is possible, rather than assuming that it will be. If sponsors involve patients in study planning early on, they can significantly improve patient recruitment."	Co-design gaps	
"We are a global company with the mission to humanize healthcare and life sciences, in partnership with patients, through innovative technologies and expert guidance. We feel accountable at every turn of the biopharma and medical technology development cycle. We are bringing to market a new model of solutions and services promoting the democratization of life sciences research"		

(*continued*)

Table 1. Continued

1ST order concept	2ND-order themes	Aggregate dimensions
"You need deep knowledge and experience to make technology beneficial, and you must include the human component. I've seen companies fail when they relied totally on technology and left out the human interaction, especially when it comes to not just finding patients but convincing them to participate. For example, we were running a study in an older population living with diabetes, and because digital technology was the only option for participation, these patients felt they couldn't be a part of the study because they didn't have smartphones." *"Through a tele-monitoring and online training model, Moira contributes to improving the quality of life of patients and their care givers by facilitating development of care pathways tailored to the unique needs of each patient and family."*	Digital exclusion risk	Ambivalent symmetric convergence
"Implementing digital solutions, such as Artificial Intelligence mechanisms helps developing innovative products or new ways of delivering care." *"The objective of Project Interception is to reduce the risk of stage 2 or higher (or equivalent) malignant tumors by 30% over five years by identifying individuals at increased risk of cancer as early as possible and offering them a personalized course of screening and prevention. Research shows that up to 40% of cancer cases are preventable, yet traditional screening methods often fail to address individual risk factors. Project Interception shifts the focus from late-stage diagnosis to proactive, personalized prevention and monitoring, leveraging digital health solutions to enhance both patient engagement and clinical decision-making."*	Clinical-digital modules	

(*continued*)

Table 1. Continued

1ST order concept	2ND-order themes	Aggregate dimensions
"AI mechanisms are designed for long-term participation in complex clinical trials and offers a virtual assistant for study participants to increase engagement. The patented design of the solution motivates study participants to continue procedures and adapts to the needs of the individual participant. The company's clients receive prevention drop-out and maximize compliance with proprietary engagement strategies that autonomously promote adherence." *"An AI Assistant Feature Suite for Study Administrators: Build Custom AI Assistants (quickly create AI assistants using tailored prompts and uploaded study documents); Targeted AI deployment (decide exactly where and how each assistant functions. Attach a specific assistant to an individual question, entire questionnaire, or place an informational chatbot on the study landing page); Smart Access to Study Insights enable real-time answers to queries about your study or participants pulled from pre-defined fields in your study database or connected systems."*	AI workflow support	Ambivalent asymmetric convergence
"Operationally, I have seen that a sponsor or CRO often selects one strategy to boost recruitment, and then waits to see if that strategy will work. The problem with that is, six months will pass and if that strategy wasn't successful, they've delayed their timeline, wasted money, and have not solved the problem. In fact, you probably have to execute on 20 different strategies simultaneously, and continuously assess them and re-evaluate if needed." *"Build in defined time points and risk mitigation right from the beginning of the project, and anticipate recruitment issues because no matter what, it's not going to be easy. You can't just set a target metric and then come back six months, twelve months, even 24 months later to find that you are way behind." [. . .] "These delays can result in having to resubmit protocols, which costs still more time and money. It's not just that you're losing the opportunity for recruitment; the consequences to your company can be enormous."*	Trial execution delays	
"We adopted a minimal viable product approach, which allowed us to leverage the core functionalities quickly and lay the groundwork for future enhancements," *"Flora is an innovative modular platform designed to optimize collaboration among healthcare professionals, facilitate workflow management, and improve efficiency in multicenter settings. Thanks to secure and rapid sharing of clinical data, Flora enables physicians, specialists, and supervisors to coordinate effectively, ensuring an unprecedented continuity of care."*	Platform automation readiness	Ambivalent null convergence
"The chatbot and the app sometimes freeze or won't let me continue." *"Integrating new digital tools into existing information systems requires investment, training, and a cultural shift among healthcare professionals – processes that are not immediately feasible."*	Delivery instability	

Output mechanisms (four drivers and four barriers), spanning eight intra-industry and eight inter-industry integrations across MED and TECH. For example, excerpts describing the use of regulatory/clinical/RWE assets to enable AI-supported trial operations were coded as *"Clinical evidence base"* (MED Input-to-MED Process; intra-industry; driver). Conversely, excerpts describing a lack of patient co-design and feasibility blind spots that impede digital build and deployment were coded as *"Co-design gaps"* (MED Process-to-TECH Output; inter-industry; barrier).

Finally, we identified nine aggregate dimensions representing the type of result obtained after a distinct pathway from input-to-process-to-output. Aggregate dimensions were classified from pairs of second-order themes. These joint interpretations led to the following dimensions: (1) convergence degree, determined by the number of industry crossings along the IPO sequence (Input→Process→Output) and (2) customer acceptance impact, derived from the joint effect of the two themes on customer acceptance.

(1) Convergence degree depended on the classification of two second-order themes as intra-industry or inter-industry. When both themes are intra-industry (MED→MED→MED or TECH→TECH→TECH), no industry crossing occurs, leading to "null convergence". If only one is inter-industry (either at Input→Process or Process→Output) then one industry crossing takes place, leading to "asymmetric convergence". Finally, if both are inter-industry (MED→TECH→MED or TECH→MED→TECH) then two industry crossings emerge, leading to "symmetric convergence".

(2) Customer acceptance impact was assessed by the categorization of two second-order themes as either driver (D) or barrier (B). When both themes were drivers (D + D), the resulting configuration was "effective". Conversely, if both themes were barriers (B + B), the resulting configuration was "dysfunctional". Finally, if one theme was a driver and the other a barrier (D + B or B + D), the resulting configuration was "ambivalent".

This yields nine aggregate dimensions, deriving from the combination of convergence degree (null/asymmetric/symmetric) and customer acceptance impact (effective/dysfunctional/ambivalent). For instance: "Clinical evidence base" (intra-industry, driver) + "Co-design gaps" (inter-industry, barrier) is a pathway classified as asymmetric convergence + ambivalent configurations, therefore leading to an *"Ambivalent asymmetric convergence"* outcome. Figure 1 presents the "Convergent Output Matrix," which synthesizes the nine possible combinations arising from the intersection between the three categories of convergence degree and the three outcomes of customer acceptance impact.

4. Findings

4.1 Within industry pathways: null convergence outcomes

The findings are presented at two analytical levels: second-order themes are directly grounded in the combined interpretation of interview and secondary material, whereas the nine aggregate outcome categories represent a higher-order configurational synthesis derived from pairing those themes across the IPO pathway. Results reveal how inputs define process within industry borders, leading to non-convergent outputs. Null convergence describes pathways in which AI-related inputs are mobilized and translated into processes that remain anchored within a single industry logic. Therefore, outputs are not derived from reconfigurations of industry boundaries. In these cases, capabilities, resources or platforms define processes within the same domain – either medical or technology – where routines are embedded into workflows. Customer-machine interactions stay domain-bound: patient touchpoints are clinically governed, while TECH users experience automation and decision support. Outputs remain "single industry" in character: medical processes generate MED outcomes (e.g.

		Convergence degree		
		Null	**Asymmetric**	**Symmetric**
Customer acceptance impact	**Effective**	Effective non-convergence	Effective asymmetric convergence	Effective symmetric convergence
	Dysfunctional	Dysfunctional non-convergence	Dysfunctional asymmetric convergence	Dysfunctional symmetric convergence
	Ambivalent	Ambivalent non-convergence	Ambivalent asymmetric convergence	Ambivalent symmetric convergence

Figure 1. Convergent output matrix. Source: Authors' research

prevention, trials), while technology processes generate TECH outputs (e.g. integration, analytics). Below we represent intra-industry pathways for MED (Figure 2) and TECH (Figure 3), showing how inputs (I) define processes (P) and outputs (O).

In the MED pathway, healthcare-native inputs include: clinical expertise, regulatory and real-world evidence capabilities and clinical operational capacity. They are positioned as the basis for implementing AI-enabled routines in care and research settings. These inputs are translated into MED processes that reorganize prevention and care delivery without shifting the locus of value creation into the technology industry. Project Interception exemplifies this logic: the initiative aims to reduce malignant tumor risk by 30% over five years through early identification of high-risk individuals. Furthermore, it fosters the delivery of personalized screening and prevention pathways, supported by health solutions that enhance engagement and decision-making. The process remains embedded in clinical institutions (implemented across multiple medical centers with professionals and patients), and its outputs are framed as healthcare outcomes. These encompass earlier interventions, scalable prevention infrastructure as the program expands to additional sites, prevention and monitoring. In parallel, patient engagement inputs (education, advocacy and patient-reported data practices) are operationalized through medical routines that support adherence and participation. In this manner, they shape customer-machine interactions as clinician-supervised guidance rather than autonomous service. Overall, the pathway reflects MED inputs being absorbed into MED processes that culminate in MED outputs, consistent with null convergence.

In the TECH pathway, inputs are framed as platform capabilities and organizational infrastructures enabling AI workflows inside the technology domain. SpherePX and related

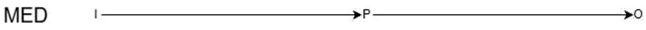

Figure 2. Null convergence (MED). Source: Authors' research

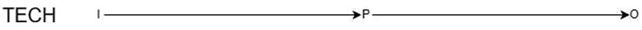

Figure 3. Null convergence (TECH). Source: Authors' research

platform features are presented as digital inputs, including monitoring tools that automate documentation and workflows and provide real-time study performance. The aim is to consolidate information for operational oversight, so user–machine interaction centers on dashboards, alerts and task automation. The same logic appears in the HRIS transformation narrative, where the organization describes unifying systems for a rapidly scaling workforce and moving toward integration across fields. In this manner, platforms "speak the same language", enhancing data quality and decision-making. These inputs translate into TECH processes centered on automation, integration and analytics, improving how digital work is performed and governed. Outputs remain technology-centric: improved operational visibility, higher-quality data infrastructures and decision-support capabilities strengthening platform performance and scalability. These TECH processes strengthen the technological system itself rather than producing a hybrid industry output. To summarize, TECH inputs become TECH processes generating TECH outputs, determining null convergence.

Across null convergence pathways, customer–machine interactions reinforce a single-industry logic. In MED, interaction is clinically governed: AI supports clinician-supervised prevention and research routines (e.g. risk identification and personalized screening nudges inside programs like Project Interception), producing non-convergent outputs such as earlier intervention rates, adherence improvements and scalable prevention infrastructure. In TECH, interaction is primarily "operator-to-platform": dashboards, workflow automation and analytics guide study teams or administrators (e.g. SpherePX monitoring and HRIS integration). In this domain, non-convergent outputs include system interoperability, operational visibility and decision-support performance.

4.2 Unidirectional cross-industry pathways: asymmetric convergence outcomes

Our findings also unveil circumstances in which industry boundary crossing occurs once along the IPO chain. We define asymmetric convergence pathways where convergence emerges either at the input stage (when resources or evidence from one domain shape processes in the other) or at the process stage (when routines anchored in one domain are mobilized to produce outputs in the other). In both cases, the output is "semi-convergent", it reflects cross-industry influence, but integration is not reciprocal across the full chain. Furthermore, interaction effects are one-way, as AI touchpoints adopt the destination industry's service norms. This produces unidirectional patterns, running either from MED-to-TECH (Figure 4) or from TECH-to-MED (Figure 5).

In MED-to-TECH asymmetric convergence, MED inputs shape technology-side processes, leading to MED-oriented TECH offerings. Therefore, convergence occurs at the input level: medical resources supply the informational content and operating constraints that technology teams translate into TECH routines. In this pattern, evidence and clinical requirements are operationalized through platform processes, such as structured capture of patient inputs, automated monitoring and analytics-enabled oversight. These processes generate TECH outputs in the form of digital infrastructures, dashboards, or AI-enabled service features shaping patient-facing touchpoints for patients. Otherwise, when convergence occurs at the process level, MED inputs first define MED processes, and boundary crossing happens when those processes are converted into TECH outputs. Here, prevention and care management routines are formalized into modular digital services and connected-device solutions that can be packaged, standardized and replicated across contexts. In both variants, the resulting TECH output retains a MED imprint because it is oriented around clinical journeys and health management objectives. Yet it is delivered as a technology artefact designed for deployment and scaling through digital systems. Therefore, MED-to-TECH reflects a one-time boundary crossing that redirects MED knowledge or routines into TECH outputs.

TECH-to-MED asymmetric convergence follows the same unidirectional logic, but with TECH as the point of departure. When convergence occurs at the input level, we found that

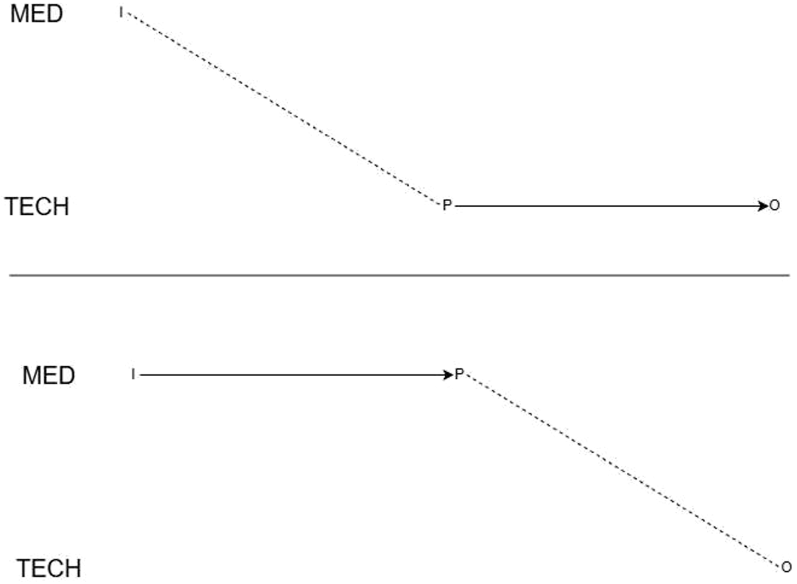

Figure 4. Asymmetric convergence (MED-to-TECH). Source: Authors' research

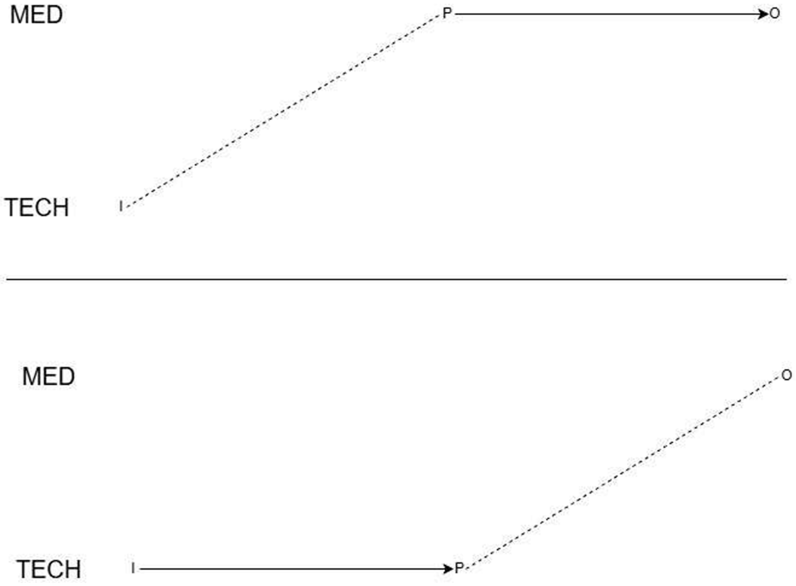

Figure 5. Asymmetric convergence (TECH-to-MED). Source: Authors' research

platform infrastructures, automation features and AI-enabled tools enter and reshape MED processes. In this pattern, capabilities such as conversational study support, automated extraction from medical records and monitoring functions become embedded in clinical and trial workflows, therefore, altering how documentation, oversight and patient management are performed. TECH inputs define the process layer inside MED settings, while outputs remain MED in character: improved operational execution of studies or more continuous management of patients through digitally enabled routines. When convergence occurs at the process level, TECH inputs first consolidate into TECH processes (e.g. integrated data pipelines, real-time performance visibility and workflow automation) and boundary crossing occurs when these processes are applied to generate MED outputs. Here, technology-enabled execution supports prevention and monitoring programs, strengthens care pathway coordination and expands access through connected infrastructures. Across both pathways, the MED output carries a TECH imprint because delivery depends on automation and real-time data. Once again, the cross-industry transfer occurs only once. This yields semi-convergent outputs characterized by unidirectional integration from TECH toward MED.

In semi-convergent pathways, customer–machine interaction changes by assimilating the other industry logic, at the stage in which convergence happens. In MED-to-TECH, input-stage convergence (Clinical data for AI) turns clinically defined needs into platform interactions (e.g. structured patient self-reporting, automated check-ins and analytics-enabled oversight). In this way, patients and study teams increasingly engage through dashboards and prompts rather than clinician-led touchpoints. When clinical-tech misfit emerges, these same interactions feel irrelevant or burdensome. At the process stage, medical routines are repackaged as clinical-digital modules, but co-design gaps can reduce usability and trust. In TECH-to-MED, input-stage AI workflow support introduces chatbots/RPA-like assistance into clinical workflows, yet digital exclusion risk and trust adoption friction can constrain uptake. At the process stage, data-driven delivery and monitoring can improve outcomes, unless delivery instability makes interactions unreliable.

4.3 Bidirectional cross-industry pathways: symmetric convergence outcomes

Finally, our study identifies cases where boundary crossing occurs twice in the IPO chain. Symmetric convergence describes pathways where inputs originate in one domain, shape processes in the other and then generate outputs that return to the originating domain. The resulting output is fully convergent because value creation depends on reciprocal integration across MED-TECH boundaries, not one-sided transfer. This reciprocity aligns customer-machine interaction design with execution feedback. Empirically, these pathways can unfold in two manners. First, when MED evidence and engagement assets are operationalized through TECH processes to produce MED outcomes (Figure 6). Second, when TECH capabilities are embedded into MED processes that then generate TECH outputs (Figure 7).

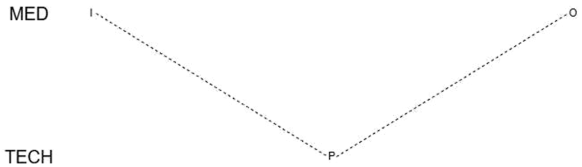

Figure 6. Symmetric convergence (MED-to-TECH). Source: Authors’ research

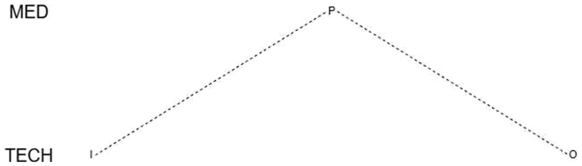

Figure 7. Symmetric convergence (TECH-to-MED). Source: Authors’ research

In MED-to-TECH symmetric pathways, convergence unfolds as a two-step loop in which MED inputs are first absorbed by TECH processes and then consistently returned to the MED domain as outcomes. First, clinical expertise, real-world evidence and patient engagement knowledge specify what must be measured. For instance, how risk should be identified or how patient–machine interactions are supported. Second, these inputs are translated into TECH processes that operationalize medical intent through digital execution. This logic is reflected in efforts to bridge research and real-world care by coupling evidence with health solutions. In this manner, prevention programs can be delivered through monitoring, real-time capture and automated coordination rather than relying solely on manual clinical routines. As the TECH process layer takes over the work of scaling, it becomes the vehicle through which MED programs are enacted across sites and populations. The output then "returns" to medicine through earlier interventions, personalized prevention pathways and improved long-term outcomes. The fully convergent outcome in this pathway is therefore a MED value proposition (e.g. prevention, monitoring and improved outcomes) whose feasibility and reach are produced through technology-mediated execution rather than through clinical processes alone.

Otherwise, TECH-to-MED symmetric pathways, the loop runs in the opposite direction: TECH inputs enter MED processes, and those processes generate TECH outputs that reshape the originating domain. The path starts with platform infrastructures and AI-enabled tools introduced into clinical and trial settings to support execution. Once embedded, these digital capabilities become part of MED processes. Applications include trial operations, patient engagement routines and coordination across stakeholders, creating clinician and patient interactions with the tools. As these processes run, they generate operational learning, validation signals and workflow requirements that feed back into the design of scalable digital offerings. For instance, results suggest AI and digital solutions improve both service provision and product realization. Therefore, what happens inside medical execution becomes a development input for technology systems. Over time, the MED process environment shapes how technology is configured, what features are built, how modules are standardized and how solutions are packaged for broader deployment. The fully convergent outcome here is a TECH deliverable (e.g. platform features, service models or modular components) whose structure and legitimacy are produced through medical execution and coordination.

In fully convergent pathways, human–machine interaction evolves through a closed loop: what users need at the interface is defined in one domain, operationalized in the other, and then validated by outcomes that feed back to refine the interaction. In MED-to-TECH symmetric pathways, clinical data for AI and strong evidence foundations specify interaction rules (e.g. when to prompt, what to capture, when to escalate), which technology turns into scalable touchpoints (monitoring, automated check-ins, decision-support visibility) that return as personalized care gains. Features such as monitoring improve outcomes, unless clinical-tech misfit or trust adoption friction makes the experience feel opaque or impersonal. In TECH-to-MED symmetric pathways, AI workflow support and platform readiness embed automation into clinical routines. For instance, shifting interaction from manual work to supervising AI outputs (confirming, correcting, escalating). Clinical use then generates signals that return to TECH (what prompts fit consultation flow, what traceability is needed for accountability, and where escalation must be frictionless). Conclusively, they become refined clinical-digital modules and more reliable data-driven delivery. Digital exclusion risk and co-design gaps can still stall adoption and weaken feedback.

5. Discussions

Our study unveils how convergence unfolds between the MED and TECH industries, identifying patterns across the entire IPO chain. The previously highlighted pathways to the MED-TECH industry are illustrated in Figure 8: the *Industry Convergence IPO model (ICIPO)* provides a comprehensive view of stage-specific AI mechanisms happening within

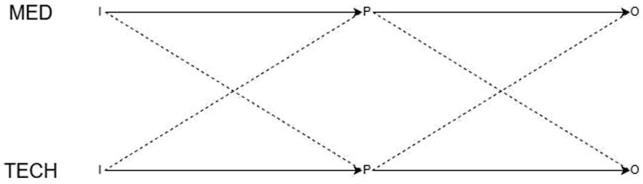

Figure 8. Industry convergence IPO model. Source: Authors' research

the same industry (*intra-industry mechanisms*), represented with full lines and crossing between industries (*inter-industry mechanisms*), represented with dotted lines. While classic IPO work largely treats value creation as a within-system sequence (and notes that outcomes can become new inputs over time), our ICIPO shows that AI can redirect the IPO chain across industry boundaries in patterned ways (zero/one/two crossings), making convergence an observable process architecture rather than a background condition. This extends convergence research by translating "input-side" vs "output-side" convergence into stage-specific crossing points along IPO, and by showing symmetric (two-crossing) convergence as a distinct pathway type. It also challenges a purely capability-optimistic absorptive-capacity view by showing that cross-industry knowledge recombination can be effective, ambivalent or dysfunctional depending on customer–acceptance frictions, not just learning potential.

Across cases, our results show that AI mechanisms may either stay within industry boundaries or cross them, shaping convergence at different points along the IPO chain. *Null convergence* occurs when inputs configure processes and outputs within the same domain (MED→MED→MED or TECH→TECH→TECH), yielding non-convergent outputs. *Asymmetric convergence* occurs when boundaries are crossed once – either at the input stage (e.g. MED inputs shaping TECH processes, or TECH inputs shaping MED processes) or at the process stage (MED or TECH processes generating outputs in the other domain) – yielding semi-convergent outputs. *Symmetric convergence* occurs when boundaries are crossed twice (MED→TECH→MED or TECH→MED→TECH), yielding fully convergent outputs. In parallel, AI mechanisms affect customer–machine interactions in two ways: as drivers (D), thus improving acceptance (e.g. usefulness, ease, trust), or as barriers (B), thus reducing acceptance (e.g. friction, exclusion, distrust). Combining these effects across linked stages produces *effective* (D + D), *ambivalent* (D + B/B + D), or *dysfunctional* (B + B) outcomes. Table 2 maps convergence degree against customer acceptance impact, allowing for simple visualization of which pair of AI mechanisms produces which type of outputs across the converging IPO chains.

At the input-to-process stage, AI integration hinges on how industry-specific resources are converted into operational routines. Within the medical domain, *Clinical evidence base (D)* captures situations in which regulatory expertise, clinical knowledge and real-world evidence provide a stable foundation for embedding AI into clinical and research workflows. When such inputs are available and legible, medical processes can be configured around prevention, monitoring and trial operations in ways that sustain downstream value creation; when execution conditions deteriorate, however, the same input strength may not translate into smooth process performance. The counterpart, *Clinical input constraints (B)*, reflects limitations in the availability, quality or accessibility of medical data and participation prerequisites, which restrict the ability to operationalize AI reliably and can set the pathway on a weaker trajectory from the start. Crossing industry boundaries at the input stage, *Clinical data for AI (D)* reflects moments where medical evidence and patient-related information are sufficiently structured to define technology-side routines, allowing platforms to operationalize clinical intent into digital workflows. Yet these cross-domain transfers are not frictionless: *Clinical-tech misfit (B)* captures misalignment between clinical realities and technology assumptions, such as feasibility blind spots or insufficient grounding in patient routines, which weakens translation from medical inputs into technology processes.

Table 2. Mapping AI mechanisms to convergence pathways and customer acceptance impact

AI mechanism	Effects on customer-machine interactions	Customer acceptance impact	Industry pathway	Crossing level	Output type
Clinical evidence base + Personalized care gains	D + D	Effective	Intra-industry	No crossing	Null-convergent output
Platform automation readiness + Data-driven delivery			Intra-industry		
Clinical evidence base + Trial execution delays	D + B	Ambivalent	Intra-industry		
Clinical input constraints + Personalized care gains			Intra-industry		
Platform automation readiness + Delivery instability			Intra-industry		
Tech scaling friction + Data-driven delivery			Intra-industry		
Clinical input constraints + Trial execution delays	B + B	Dysfunctional	Intra-industry		
Tech scaling friction + Delivery instability			Intra-industry		
Clinical data for AI + Data-driven delivery	D + D	Effective	Inter-industry (MED→TECH→TECH)	Input stage	Semi-convergent output
AI workflow support + Personalized care gains			Inter-industry (TECH→MED→MED)		
Clinical evidence base + Clinical-digital modules			Inter-industry (MED→MED→TECH)	Process stage	
Platform automation readiness + Monitoring improves outcomes			Inter-industry (TECH→TECH→MED)		
Clinical data for AI + Delivery instability	D + B	Ambivalent	Inter-industry (MED→TECH→TECH)	Input stage	
Clinical-tech misfit + Data-driven delivery			Inter-industry (MED→TECH→TECH)		
AI workflow support + Trial execution delays			Inter-industry (TECH→MED→MED)		
Digital exclusion risk + Personalized care gains			Inter-industry (TECH→MED→MED)		
Clinical evidence base + Co-design gaps			Inter-industry (MED→MED→TECH)	Process stage	
Clinical input constraints + Clinical-digital modules			Inter-industry (MED→MED→TECH)		
Platform automation readiness + Trust adoption friction			Inter-industry (TECH→TECH→MED)		
Tech scaling friction + Monitoring improves outcomes			Inter-industry (TECH→TECH→MED)		
Clinical-tech misfit + Delivery instability	B + B	Dysfunctional	Inter-industry (MED→TECH→TECH)	Input stage	
Digital exclusion risk + Trial execution delays			Inter-industry (TECH→MED→MED)	Input stage	
Clinical input constraints + Co-design gaps			Inter-industry (MED→MED→TECH)	Process stage	
Tech scaling friction + Trust adoption friction			Inter-industry (TECH→TECH→MED)	Process stage	
Clinical data for AI + Monitoring improves outcomes	D + D	Effective	Inter-industry (MED→TECH→MED)	Double crossing	Fully convergent output
AI workflow support + Clinical-digital modules			Inter-industry (TECH→MED→TECH)	Double crossing	
Clinical data for AI + Trust adoption friction	D + B	Ambivalent	Inter-industry (MED→TECH→MED)	Double crossing	
Clinical-tech misfit + Monitoring improves outcomes			Inter-industry (MED→TECH→MED)	Double crossing	
AI workflow support + Co-design gaps			Inter-industry (TECH→MED→TECH)	Double crossing	
Digital exclusion risk + Clinical-digital modules			Inter-industry (TECH→MED→TECH)	Double crossing	
Clinical-tech misfit + Trust adoption friction	B + B	Dysfunctional	Inter-industry (MED→TECH→MED)	Double crossing	
Digital exclusion risk + Co-design gaps			Inter-industry (TECH→MED→TECH)	Double crossing	

Within the technology domain, *Platform automation readiness (D)* denotes mature digital infrastructures and capabilities that enable AI to be embedded into workflow automation, monitoring and analytics routines, supporting consistent execution and scale. The opposing pattern, *Tech scaling friction (B)*, reflects the integration debt and coordination strain that emerge when systems, teams and data infrastructures expand faster than standardization can keep pace, constraining process reliability. Finally, when technology inputs enter medical processes, *AI workflow support (D)* captures the embedding of digital tools into clinical routines to enable operational work, whereas *Digital exclusion risk (B)* reflects input-side access constraints that limit who can participate and therefore whether AI-enabled processes can be enacted broadly.

At the process-to-output stage, AI-enabled routines determine whether operational execution converts into measurable customer and system outcomes. Within the medical domain, *Personalized care gains (D)* captures clinical and preventive routines that translate AI-enabled monitoring, engagement and decision support into improved patient value, such as earlier interventions or more tailored prevention pathways. These outcomes become visible when processes stabilize and scale across settings; when clinical operations become strained, the pathway can instead be pulled toward *Trial execution delays (B)*, where recruitment bottlenecks, protocol frictions and slow iteration reduce performance and limit realized benefits, even if upstream inputs were strong. When medical processes generate technology outputs, *Clinical-digital modules (D)* captures the translation of prevention and care routines into standardized digital components that can be packaged, deployed and replicated through platforms. This conversion is most effective when clinical routines are compatible with modularization and scaling; when they are not, *Co-design gaps (B)* emerges, reflecting misalignment between process design and user feasibility, which can undermine the usefulness of resulting digital offerings.

Within the technology domain, *Data-driven delivery (D)* reflects analytics- and automation-centered routines that produce outputs such as improved operational visibility, decision support and scalable platform performance. Yet execution can also be undermined by *Delivery instability (B)*, where rapid growth or fragmented infrastructures degrade the reliability and consistency of digital outputs. When technology processes produce medical outputs, *Monitoring improves outcomes (D)* captures how real-time oversight, automated workflows and connected infrastructures translate into better coordination, sustained engagement and stronger prevention or management results. However, these outputs are contingent on acceptance dynamics; *Trust adoption friction (B)* reflects downstream barriers that reduce uptake and limit the extent to which technology-enabled routines translate into patient value, particularly when solutions are perceived as impersonal, exclusionary or misaligned with clinical expectations. Across the model, these process-to-output mechanisms explain why similar convergence degrees can yield divergent outcomes: stable routines amplify benefits, whereas operational, design and trust frictions attenuate or reverse them.

6. Implications and conclusions

This study uses an exploratory, inductive qualitative design and Gioia-style coding to explain how AI integration generates value across the full IPO chain amid MED–TECH convergence. The main contribution is the ICIPO framework, which extends classic IPO (Ilgen *et al.*, 2005) and convergence literature (Geum *et al.*, 2016) in two ways. First, by showing that AI can keep activities within one domain or redirect them across industry boundaries at different stages. Second, boundary-crossing interactions produce varying types of outputs. Beyond this, the study contributes to the AI and customer–machine interaction literature (Amelia *et al.*, 2022) by linking *where* AI is embedded in the IPO chain (input vs process vs output) to *how* customers experience and evaluate AI-mediated encounters. Specifically, it identifies stage-specific AI mechanisms that act as drivers or barriers of customer acceptance, clarifying why similar AI solutions can enable value co-creation in some settings but trigger acceptance erosion in others (Vargo and Lusch, 2008; Lumivalo *et al.*, 2024). By mapping these mechanisms onto convergence pathways, ICIPO offers an explanatory bridge between workflow design choices and customer-facing interaction outcomes.

For managers, ICIPO can be used as an empirically informed diagnostic map for assessing AI initiatives amid convergence. Based on the patterns observed in our cases, teams can first locate an initiative along the pathway (Input→Process or Process→Output) and determine whether it is intra-industry or inter-industry. This helps clarify whether the initiative is primarily oriented toward improving execution within one domain or toward enabling boundary crossing between domains. Managers can then assess whether the relevant mechanism appears to act as a driver or barrier of customer–machine interactions, thereby indicating whether the combined pathway is more likely to generate effective, ambivalent, or dysfunctional outcomes. In practical terms, this means using the framework to identify where stronger evidence and data foundations are needed, where hybrid workflows require clearer human escalation and where execution learning should be translated into more useable and trustworthy service configurations.

For policy makers, the findings imply that AI-driven convergence should be governed as a hybrid MED-TECH space rather than as separate medical and technology regimes. Therefore, policy should align approval, reimbursement and liability with data-intensive services. Furthermore, it is crucial to invest in interoperable data standards and secure infrastructures for clinical and real-world data use. In parallel, safeguards are needed for privacy, transparency and auditability of algorithmic decisions. Finally, targeted measures should reduce digital exclusion through accessibility requirements and support for smaller providers and vulnerable groups.

7. Limitations and future research

Despite its contributions, it is crucial to highlight some research limitations. First, it examines MED–TECH convergence through a small set of cases, which supports analytical generalization but limits broad representativeness. Second, the evidence base is primarily qualitative; therefore, the correlation between the identified variables are not proven yet. Third, the observation window is bounded, meaning longer-run shifts in business models, regulation and patient outcomes may not yet be fully visible.

Future work can extend ICIPO through comparative, longitudinal and mixed-method designs. Comparative studies could apply the framework across additional MED-TECH settings and other converging fields (e.g. FinTech, mobility–energy, agro-biotech) to test whether the same null, asymmetric and symmetric pathways recur and to refine boundary conditions. Longitudinal research could follow initiatives as they move across stages, documenting how outputs become new inputs and how convergence trajectories stabilize or reverse over time. Quantitative operationalization could translate the pathway categories and acceptance profiles into measurable indicators, enabling tests of associations with adoption, performance, safety and equity outcomes. Finally, deeper inclusion of MED-TECH actors would clarify how contested expectations shape AI integration and whether “effective” convergence is sustained in everyday practice.

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