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Designing a Business Model for AI-Based Service-Oriented Enterprises Using a Foresight Approach

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Abstract

The present study was conducted with the aim of examining service-oriented business models based on artificial intelligence (AI) using a foresight approach. This research is qualitative, exploratory in nature, and grounded in grounded theory methodology, conducted according to the Strauss and Corbin approach (1998). Data were collected through semi-structured interviews with 15 experts from industry, academia, and technology institutions and were analyzed using open, axial, and selective coding. As a result, 22 conceptual categories were identified across six main dimensions: causal conditions, contextual conditions, intervening factors, core phenomenon, strategies, and consequences. The core category was identified as "Designing a Business Model for AI-Based Service-Oriented Enterprises Using a Foresight Approach." According to the findings, factors such as weak technological infrastructure, cultural resistance, insufficient specialized training in the AI domain, and a lack of supportive policies were among the key barriers to the implementation of this model. On the other hand, strategies such as the intelligent automation of processes, formulation of modern standards, and the development of employees' digital skills were introduced as key enablers for the realization of the model. The consequences of implementing this model include enhanced productivity, improved product quality, and the advancement of service-oriented businesses. By presenting a localized and data-driven model, this study can serve as a strategic framework for guiding industrial managers, policymakers, and educational centers in the path toward digital transformation and the development of AI-based service-oriented businesses.

Keywords: Service-oriented businesses, Artificial Intelligence, Foresight approach

1. Introduction

In recent years, the convergence of artificial intelligence (AI) and service-oriented business models has emerged as a transformative force in contemporary industries, enabling organizations to rethink their value propositions, operational models, and customer interactions. The integration of AI into service-centric business strategies not only enhances efficiency but also redefines the dynamics of value creation and value capture, particularly within digital ecosystems (Agarwal et al., 2022). This paradigm shift is especially significant in the context of "digital servitization," where firms increasingly adopt digital technologies to augment traditional services or introduce new ones that meet evolving customer expectations (Sjödin et al., 2020).

AI-driven service business models have become a focal point in strategic foresight and innovation agendas, largely due to their potential to facilitate real-time data analysis, automate processes, and personalize offerings at scale (Kim, 2023). These capabilities not only lead to higher operational productivity but also allow firms to remain competitive in an increasingly volatile and technology-driven market. The shift toward digital-first services necessitates a transformation in core organizational capabilities, demanding digital literacy, dynamic capabilities, and a deep understanding of how AI technologies impact both internal processes and customer-facing services (Akhtar et al., 2019).

The Fourth Industrial Revolution (Industry 4.0) and the forthcoming Industry 5.0 underscore the importance of leveraging AI not just for automation, but for creating intelligent, responsive, and customer-centric services (Zeb et al., 2022). As companies navigate this transformation, foresight approaches become crucial in anticipating market trends, identifying emerging technologies, and designing future-proof business models. This anticipatory capacity enables firms to develop strategic responses to complex challenges such as cultural resistance to technology, the need for upskilling, and weak policy support (Belk et al., 2023).

Research shows that the successful implementation of AI-based service models is often contingent on overcoming significant institutional, infrastructural, and cultural barriers. For instance, organizational ambidexterity—the balance between exploration and exploitation—is key to fostering innovation while maintaining operational stability (Andrade et al., 2022). Similarly, entrenched hierarchical structures and rigid bureaucratic systems can hinder the agile transformation required for digital servitization (Rajabpour & Alizadeh, 2024). The lack of specialized human resources and coordination between departments often exacerbates these limitations, highlighting the need for comprehensive capability development and cultural change management (Brennan & Kirby, 2022).

The AI value chain within service-oriented enterprises is increasingly shaped by data-centric capabilities. As illustrated in the literature, firms that invest in big data capabilities and cultivate data-savvy teams are better positioned to drive performance and innovation (Akhtar et al., 2019). The evolution from product-centric to service-centric business logic also requires organizations to embrace open innovation, collaborative ecosystems, and platform-based business models (Luoto et al., 2017). These shifts call for a reconfiguration of traditional business structures to accommodate new forms of value exchange, including digital platforms, knowledge networks, and real-time feedback mechanisms (Cui & van Esch, 2023).

Moreover, AI facilitates the development of intelligent decision-making systems that can autonomously monitor operations, predict failures, and provide adaptive customer experiences. These capabilities are instrumental in operationalizing digital transformation and achieving strategic agility (Crupi et al., 2022). As firms collect and analyze vast amounts of customer data, the importance of ethical AI practices and customer-centric design becomes more pronounced. Research indicates that customers increasingly expect seamless, personalized, and responsive services, making AI a critical enabler of competitive differentiation in the service sector (Cui & van Esch, 2023; Kim, 2023).

Additionally, the integration of AI into service models contributes to enhanced environmental, social, and governance (ESG) performance by promoting operational sustainability, improving resource efficiency, and enabling proactive risk management (Moro-Visconti et al., 2023). In this context, the alignment of AI with sustainable development goals and responsible innovation practices becomes a strategic imperative. This is particularly relevant in sectors where compliance with safety, quality, and ethical standards is paramount (Brei, 2020).

One of the key frameworks for conceptualizing AI-based service innovation is the idea of value orchestration, which emphasizes dynamic stakeholder engagement, modular service offerings, and data-enabled customization (Palo et al., 2019). This approach aligns closely with the notion of digital ecosystems, wherein multiple actors co-create value through interconnected platforms and technologies. In such ecosystems, AI not only enables real-time data exchange but also facilitates trust-building and adaptive governance (Bharadwaj et al., 2022; Sjödin et al., 2020).

Furthermore, digital transformation in service-based industries cannot be disentangled from the broader socio-technical systems within which they operate. Public policies, regulatory frameworks, and institutional readiness significantly affect the adoption and scalability of AI-driven models (Brennan & Kirby, 2022; Rajabpour & Alizadeh, 2024). For instance, the lack of supportive regulations or misalignment between safety and innovation standards can create friction in the deployment of advanced technologies (Aggarwal et al., 2022). Similarly, the digital divide and uneven access to enabling infrastructure pose challenges for inclusive and equitable adoption (Zeb et al., 2022).

To address these challenges, several scholars advocate for systemic interventions including investment in education and digital skills, fostering academia-industry collaboration, and establishing knowledge-sharing platforms (Alizadeh & Ghasemi, 2023; Alizadeh et al., 2024). Such interventions are crucial for building organizational readiness and cultivating a culture of continuous learning and innovation. The literature also emphasizes the significance of developing domain-specific training programs and AI-focused curricula that align with industry needs (Singh et al., 2022).

From a methodological standpoint, grounded theory approaches have proven valuable in exploring the dynamic interplay between AI, organizational processes, and service innovation. These approaches enable researchers to inductively build theoretical models grounded in empirical data, thereby capturing the complexity and contextual nuances of digital transformation (Carleo et al., 2019). This methodological rigor is especially important in future-oriented research that seeks to inform strategy and policy design in emerging technology domains.

The synthesis of existing scholarship highlights a multifaceted view of AI-driven service innovation—one that encompasses technological, organizational, cultural, and regulatory dimensions. As digital technologies become increasingly pervasive, there is a growing need for integrative models that capture the strategic, operational, and experiential elements of service transformation (Konzett, 2022). These models must be adaptable to various contexts, scalable across sectors, and grounded in a foresight-based approach that anticipates future challenges and opportunities (Alizadeh et al., 2024).

In conclusion, the design and implementation of AI-based service business models require a holistic and anticipatory perspective that aligns technological innovation with organizational capabilities and societal values. The literature provides a comprehensive foundation for understanding how AI can be leveraged to transform service delivery, enhance customer value, and promote sustainable competitiveness (Agarwal et al., 2022; Andrade et al., 2022; Belk et al., 2023). This study builds upon these insights to develop a grounded model for AI-driven service business transformation, offering strategic guidance for managers, policymakers, and educational institutions navigating the future of work and value creation in the digital era.

2. Methods and Materials

The present study is classified as qualitative research. Due to the existing theoretical gap, this study adopted the systematic approach of Strauss and Corbin (1998) for grounded theory in the field of quality and safety management, which served as the main qualitative research approach. This method seeks to offer a model for deeply understanding quality and safety management. The grounded theory approach is a type of qualitative research method that inductively applies a series of systematic procedures to develop a theory about the phenomenon under study.

The statistical population consisted of academic experts and specialists in the fields of service-oriented businesses and artificial intelligence. A total of 15 participants were selected using purposive sampling based on the snowball technique. Interviewees were asked to introduce other experts in the field, which reflects the snowball sampling approach commonly used in qualitative research. The concept of purposive sampling in qualitative studies implies that the researcher selects participants because they can effectively contribute to understanding the research problem and the core phenomenon.

For data collection, in-depth semi-structured interviews were conducted. Prior to the interviews, a summary of the research design, definitions of key terms used in the study, along with the main research questions and objectives, were sent to the interviewees via email, Telegram, or in person to prepare them for the interview. At the beginning of each interview session, a brief explanation of the research procedures was provided. The characteristics of the participants involved in the research process are presented in Table 1.

Table 1.Characteristics of the Participants in the Research Process

Educational Level	Field of Study	Position	No.
PhD	Business	Executive Vice President	1
M.A.	IT Management	Planning Deputy	2
PhD	Economics	CEO	3
PhD	Executive Management	Deputy Minister	4
M.A.	Technology Management	Company Vice President	5
PhD	Technology Management	Parliamentary Representative	6
M.A.	Economics	Planning Deputy	7
PhD	Technology Management	Executive Vice President	8
PhD	Economics	Executive Vice President	9
PhD	Public Administration	Member of Parliament	10
M.A.	Technology Management	Planning Deputy	11
M.A.	Technology Management	Executive Vice President	12
PhD	Technology Management	University Professor	13
PhD	Technology Management	University Professor	14
PhD	Strategy	University Professor	15

On the other hand, according to Creswell and Creswell (2018), qualitative researchers must employ validation strategies in every study to ensure the credibility of their findings. In this research, validation was carried out through dual coding by two researchers (peer debriefing and member checking). Coding was independently conducted by the researcher and a colleague. The extracted codes were compared, and Cohen's Kappa coefficient was calculated at 86.9%, with a significance value of 0.001, indicating almost perfect agreement between the two coders.

Moreover, in addition to the researcher, the supervisor and advisor professors, as well as three experts in the fields of service-oriented businesses and artificial intelligence, reviewed the identified categories and the model. Their feedback was used to enhance and enrich the model. For member checking, given their relevant academic backgrounds, the results of coding, categorization, and modeling were shared with three of the interviewees. Based on their feedback, necessary revisions and refinements were made.

3. Findings and Results

In this study, data were documented simultaneously with the collection of interviews using audio recordings and concurrent note-taking, based on the Strauss and Corbin (1998) approach. The content of the interviews was transcribed into text files, and data analysis and coding were conducted accordingly. Following the review of the data obtained from the transcripts of 15 interviews, 22 categories were extracted, as shown in tables below.

Causal Conditions

In this model, causal conditions are the events that create and explain situations and issues related to a phenomenon, clarifying why and how individuals and groups respond in specific ways. These conditions include categories that directly affect the business models of AI-based service-oriented enterprises using a foresight approach, or are factors that generate and develop the phenomenon. The categories related to causal conditions are shown in Table 2.

Table 2. Causal Categories (Main, Subcategories)

No.	Subcategory	Sample Concepts Extracted from Interviews	Interviewee Code
1	Weak Technological Infrastructure	Lack of digital infrastructure in production lines / Incompatibility of existing equipment with Industry 4.0 / Obsolete control systems / Limited access to real-time data / Weak automation / Absence of sensors and intelligent systems	P1, P2, P4, P5, P6
2	Cultural and Organizational Resistance	Preference for traditional over technological methods / Fear of data transparency / Lack of acceptance at managerial levels / Conflict with hierarchical culture / Concerns over job displacement / Distrust in new technologies	P1, P10, P12, P9, P11, P3
3	Insufficient Training and Awareness	Lack of technology-oriented educational programs / Deficient skills in digital domains / Unawareness of safety 4.0 requirements / No experience with smart tools / Traditional view on quality / Lack of familiarity with data analysis	P12, P7, P5, P6
4	Weak Macro-Level Supportive Policies	Absence of governmental incentives / Lack of specialized consulting from policy institutions / Weak digital transformation roadmaps / Lack of financial support for industries / Challenges in obtaining smart technology permits / Ineffective intermediary institutions	P10, P14, P5

Contextual Conditions

Contextual conditions refer to a specific set of features related to the phenomenon, generally pointing to the location of events and occurrences. These include factors without which the realization of the quality and safety management model under Industry 4.0 is not feasible. They form the conditions under which strategies are implemented to manage, control, and respond to the phenomenon. These conditions consist of a collection of contextual concepts, categories, and variables. In this study, the main contextual factors for the quality and safety management model under Industry 4.0 are shown in Table 3.

Table 3. Contextual Categories (Main, Subcategories)

No.	Subcategory	Sample Concepts Extracted from Interviews	Interviewee Code
1	Traditional and Inefficient Organizational Structure	Centralized and slow decision-making / Resistance of management layers to change / Heavy bureaucracy / Lack of agility in responding to technological changes / Rigid hierarchical structure / Ignoring internal innovation	P9, P11, P12, P7
2	Lack of Specialized Human Resources	Shortage of skilled labor in technology / Absence of practical Industry 4.0 knowledge / Lack of motivation for learning / Weak data literacy / Failure to update employee capabilities / Limited specialization	P1, P2, P9, P11

3	Lack of Interdepartmental Coordination	Lack of effective communication among departments / Siloed decision-making / Overlapping activities / Conflicts between safety and production units / No common implementation framework / No data sharing	P13, P15, P12
4	Financial Problems and Budget Constraints	Lack of capital for modernization / Inadequate R&D budget allocation / Low prioritization of safety in resource allocation / No funding for technology training / Limitations in purchasing smart equipment / Financial instability	P1, P2, P3, P6, P7, P10

Intervening Conditions

Intervening conditions include more general factors such as time, space, and culture that act as facilitators or inhibitors of strategy implementation. These conditions operate to either enable or restrict actions/interactions in a specific context. Each condition forms a spectrum whose influence ranges from very distant to very direct. In this study, the intervening categories are presented in Table 4.

Table 4. Intervening Categories (Main, Subcategories)

No.	Subcategory	Sample Concepts Extracted from Interviews	Interviewee Code
1	Role of Technological and Academic Institutions	University collaboration in designing service-oriented business models / Technical consulting from incubators / Research support from technology parks / Development of local platforms / Specialized training programs / Engagement with top academic institutions	P2, P3, P4, P11, P12, P14
2	Existence of Knowledge and Communication Networks	Presence of industrial clusters / Sharing experiences of successful firms / Innovation exchange platforms / Networking with tech companies / Interaction between industry and academia / Experience-sharing meetings on service-oriented businesses	P14, P13, P7
3	Access to Digital Infrastructure	Availability of stable internet networks / Possibility of using cloud platforms / Availability of data collection systems / Integration of control systems with monitoring software / Use of IoT / Data analytics infrastructure	P1, P7, P8, P9, P10, P12

Core Category

The phenomenon under investigation must be central, meaning that all other main categories can be linked to it and that it appears repeatedly in the data. This implies that in all or almost all cases, there are indicators pointing to this concept. The core category refers to the idea or phenomenon that serves as the foundation and axis of a process to which all other main categories are related. In this study, the core category is presented in Table 5.

Table 5. Core Categories (Main, Subcategories)

No.	Subcategory	Sample Concepts Extracted from Interviews	Interviewee Code
1	Designing an Integrated Model for Service-Oriented Businesses	Integration of intelligent systems with service-oriented business requirements / Design of smart alert systems / Alignment between safety and quality standards / Process-oriented approach to service-oriented businesses / Modeling service-oriented businesses in a digital environment / Data-driven error analysis	P1, P7, P8, P9, P10, P12
2	Reengineering Processes of Service-Oriented Businesses	Re-analysis of workflows using digital tools / Elimination of quality bottlenecks / Increased automated monitoring of operations / Electronic documentation of processes / Simplification of quality control pathways / Data integration using a foresight approach	P3, P4, P5, P6, P10, P13, P14
3	Development of Employees' Digital Skills	Designing Industry 4.0-based training programs / Motivating technological learning / Training on intelligent systems / Empowerment in safety data analysis / Training in quality control dashboards / Fostering a culture of continuous learning	P1, P2, P8, P10, P12, P9, P11

Strategies

Strategies are in fact the plans and actions that result from the core category and ultimately lead to outcomes. Strategies consist of a series of measures taken to manage, lead, or respond to the phenomenon under investigation. In this study, the categories of strategies are shown in Table 7.

Table 6. Strategy Categories (Action/Reaction, Main, Subcategories)

No.	Subcategory	Sample Concepts Extracted from Interviews	Interviewee Code
1	Formulation and Implementation of Industry 4.0 Standards	Developing hybrid guidelines / Creating digital process control checklists / Using data-driven KPIs / Expanding digital requirements in service-oriented business processes / Alignment with global standards / Localization of successful models	P3, P4, P5, P6, P10, P13, P14
2	Implementation of Targeted AI-Based Training Programs	Designing educational platforms for service-oriented businesses / In-service training on Industry 4.0 tools / Enhancing safety digital literacy / Developing error analysis competencies / Training on control dashboards / Foresight-focused workshops	P1, P2, P5, P7, P9
3	Intelligent Automation of Service-Oriented Business Systems	Use of intelligent alert systems / Real-time process monitoring / Development of service-oriented businesses / Cloud integration of equipment / Automated error reporting / Real-time AI data analysis	P4, P5, P6, P10, P15, P14, P13, P7, P8, P11

4	Institutionalization of a Digital Transformation Culture	Creating an environment for change acceptance / Strengthening manager-employee relationships / Identifying transformation leaders in AI / Conducting interactive team sessions / Learning from successful cases / Enhancing employee ownership of change	P1, P2, P8, P11, P12

Outcomes

Outcomes refer to the outputs or results of actions and reactions. Based on open coding, the concepts related to the outcomes of the model were extracted, and then, through iterative movement between themes and concepts, the main outcome categories were identified and labeled. Table 8 presents the categories and concepts related to the outcomes.

Table 7. Outcome Categories (Action/Reaction, Main, Subcategories)

No.	Subcategory	Sample Concepts Extracted from Interviews	Interviewee Code
1	Increased Foresight-Based Organizational Productivity	Reduction in rework / Faster error detection / Decreased production downtime / Improved equipment efficiency / Enhanced unit coordination / Effective use of operational data	P2, P3, P4, P5, P13, P9, P11, P12, P15
2	Enhanced Quality of Service-Oriented Businesses	Increased accuracy of service-oriented businesses / Reduced deviation from smart standardization / Continuous quality data monitoring / Lower product return rates / Higher customer satisfaction / Data-driven product development	P1, P12, P9, P11, P7
3	Improved Status of Service-Oriented Businesses	Reduced challenges in service-oriented businesses / Smart work environments / Enhanced staff awareness / Rapid AI response / Service business analytics / Use of smart service-oriented businesses	P3, P5, P6, P10, P15, P14, P7, P8, P14

The paradigmatic model of this study was developed based on the Strauss and Corbin paradigmatic framework. Given the identified factors and conditions, the process and model of AI-based service-oriented businesses were designed using a foresight approach. Explaining the generating factors of this phenomenon was also the main concern of this research. Figure 1 illustrates the relationships among the categories based on the paradigmatic model, following evaluation and confirmation by the study participants.

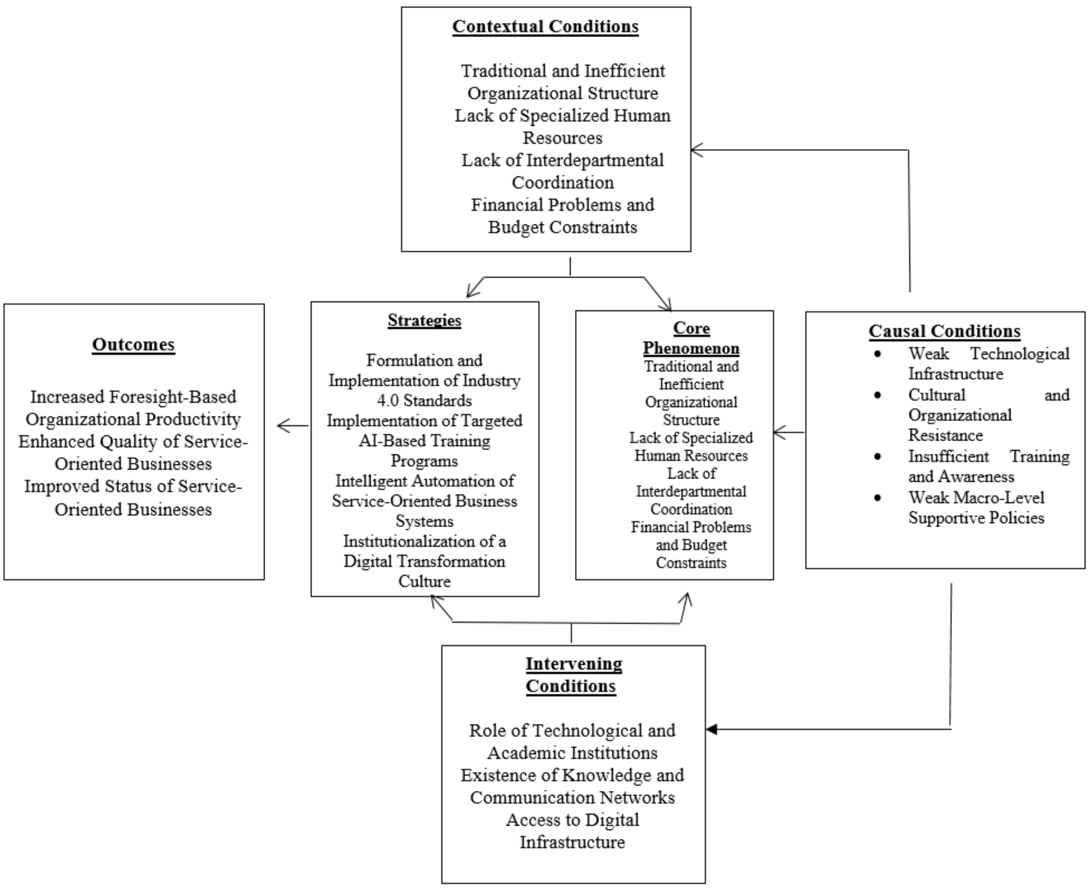

Figure 1. Paradigmatic Model of the Study

4. Discussion and Conclusion

The findings of the present study, aimed at designing AI-based service-oriented business models using a foresight approach, reveal a multifaceted paradigm grounded in six principal components: causal conditions, contextual conditions, intervening conditions, core category, strategies, and consequences. These components, extracted from expert interviews and systematically categorized, provide a data-driven, locally contextualized, and strategically robust model for guiding AI integration in service enterprises.

The causal conditions identified—such as weak technological infrastructure, cultural and organizational resistance, insufficient training and awareness, and lack of supportive macro policies—highlight foundational barriers to the adoption of AI-based service models. These findings align with prior research underscoring the challenges of technological and organizational readiness. For instance, infrastructural limitations have long been recognized as a critical bottleneck in AI deployment, especially in industries with legacy systems incompatible with Industry 4.0 technologies (Konzett, 2022; Zeb et al., 2022). The absence of real-time data capture tools, intelligent automation, and robust sensor networks hinders the implementation of adaptive service models that rely on dynamic feedback loops and continuous monitoring (Bharadwaj et al., 2022).

Cultural resistance and lack of acceptance at managerial levels, as reported in this study, mirror the findings of Andrade et al., who emphasize the inhibiting role of rigid hierarchical structures and managerial inertia in embracing ambidextrous innovation strategies (Andrade et al., 2022). Furthermore, the lack of digital literacy and training, particularly in safety and quality analytics, resonates with the observations of Akhtar et al., who argue that skill gaps in big data interpretation and AI deployment undermine organizational performance (Akhtar et al., 2019). The literature consistently suggests that human capital development is a critical enabler of AI-driven transformation, and organizations must move beyond ad-hoc training to institutionalize continuous learning mechanisms (Alizadeh et al., 2024).

The contextual conditions, particularly traditional organizational structures, departmental silos, and budget constraints, reflect deeper systemic issues. These factors compromise the agility and responsiveness of service-oriented firms, which are essential characteristics in AI-integrated ecosystems (Luoto et al., 2017). As confirmed by Sjödin et al., value creation and capture in AI-based models are heavily dependent on structural flexibility and interdepartmental collaboration (Sjödin et al., 2020). The lack of coordination between safety and production units, for example, not only delays response times but also generates conflicting priorities that weaken overall system coherence. Moreover, financial instability and low prioritization of safety in resource allocation further limit the firm's ability to invest in long-term digital strategies (Belk et al., 2023).

Intervening conditions, such as the role of universities, the availability of knowledge networks, and access to digital infrastructure, serve as both accelerators and moderators of transformation. The involvement of academic institutions in designing AI-enabled business solutions is in line with findings by Carleo et al., who argue that research collaborations foster contextual innovation and bridge the gap between theory and practice (Carleo et al., 2019). Likewise, networking platforms and innovation ecosystems, as discussed by Crupi et al., provide firms with access to shared resources, success stories, and strategic templates that can be customized to local needs (Crupi et al., 2022).

The core category of the study—designing an integrated model for AI-based service-oriented businesses—centers on three sub-themes: model integration, business process reengineering, and digital skill development. The emphasis on system integration and coordination between quality and safety standards aligns with recent efforts to build holistic, responsive, and intelligent systems that support value co-creation (Kim, 2023). The literature identifies integrated AI systems as critical enablers of data-driven decision-making, real-time monitoring, and predictive analytics, all of which are necessary for the evolution of service-dominant business logic (Cui & van Esch, 2023). Business process reengineering, as observed in the present study, reinforces the need for lean, data-centric workflows capable of eliminating inefficiencies and increasing service reliability—a concept that parallels findings by Agarwal et al. on digital servitization and process innovation (Agarwal et al., 2022).

The role of digital upskilling as part of the core transformation is further supported by evidence from Singh et al., who emphasize that organizational competence in AI requires not only technical fluency but also the cultivation of interpretative and ethical reasoning around data use (Singh et al., 2022). This study adds depth by highlighting how firms can create a sustainable learning culture through targeted training, motivational strategies, and the introduction of continuous development platforms. These elements are essential in mitigating resistance to change and fostering digital maturity across the organization (Alizadeh & Ghasemi, 2023).

In terms of strategies, the study identified four major pathways: formulating and implementing Industry 4.0 standards, executing AI-based training programs, automating service systems, and institutionalizing a culture of digital transformation. These strategies converge on a central objective—enhancing organizational agility and responsiveness through intelligent infrastructure and human-centric design. The development of KPI-based performance standards and the localization of global best practices echo the framework proposed by Palo et al., who view servitization as an ongoing negotiation between institutional expectations and business innovation (Palo et al., 2019).

Moreover, the proactive implementation of educational platforms and AI simulation tools supports the literature's call for context-specific upskilling programs that are aligned with industry requirements (Aggarwal et al., 2022). As noted by Brennan and Kirby, the lack of specialized AI education continues to hamper deployment, particularly in regulated industries like health and manufacturing (Brennan & Kirby, 2022). The study's identification of interactive workshops and AI scenario planning reflects best practices in digital foresight and strategic learning (Huntingford et al., 2019).

The automation of service-oriented systems, involving smart alert platforms and real-time data monitoring, confirms the essential role of AI in enhancing operational efficiency and minimizing human error. As discussed by Brei and Bharadwaj, intelligent systems play a pivotal role in predictive maintenance, fault detection, and customer satisfaction (Bharadwaj et al., 2022; Brei, 2020). Likewise, embedding AI into enterprise systems contributes to building adaptive capabilities that are responsive to customer feedback and market volatility (Moro-Visconti et al., 2023).

Finally, the institutionalization of a digital transformation culture—including leadership buy-in, staff empowerment, and the recognition of AI champions—reinforces the argument made by Belk et al. regarding the socio-technical nature of AI implementation (Belk et al., 2023). Encouraging a shift in organizational mindset is not merely a supplementary initiative; rather, it is foundational to the success of AI integration and business model renewal (Alizadeh et al., 2024).

The study's outcomes provide empirical support for these theoretical insights. The implementation of the AI-driven service model resulted in improved productivity, higher service quality, and enhanced organizational learning. The reported reduction in production downtime and increase in data utilization confirm the practical value of digital transformation in service businesses. These findings parallel those of Sjödin et al. and Kim, who both demonstrate how strategic alignment and process innovation contribute to enhanced value capture and stakeholder satisfaction (Kim, 2023; Sjödin et al., 2020).

Despite the strengths of this study, certain limitations should be acknowledged. The qualitative nature of the research limits the generalizability of the findings to broader populations. The sample size of 15 experts, while suitable for grounded theory, may not fully capture the diversity of perspectives across industries. Additionally, the study focuses primarily on organizations within a specific regional and technological context, which may influence the salience of certain conditions and strategies. Moreover, potential biases may have emerged during the interview process or data coding, despite triangulation efforts.

Future studies should consider expanding the sample size and incorporating quantitative or mixed-method approaches to validate and refine the proposed model. Longitudinal research could offer valuable insights into the evolving nature of AI adoption and the sustainability of business model innovations over time. Researchers might also explore cross-sectoral comparisons or conduct international studies to examine cultural and regulatory variances in AI integration. Examining customer perspectives and behavioral responses to AI-enabled services could further enrich the understanding of value creation in digital ecosystems.

To effectively implement AI-based service business models, organizations must prioritize infrastructure investment, particularly in intelligent data systems and cloud platforms. Leadership should foster a culture of experimentation and learning by supporting innovation labs, cross-functional teams, and continuous training programs. Collaborations with universities, tech firms, and policy institutions should be strengthened to ensure alignment with global standards and local needs. Finally, firms should approach AI adoption not as a one-time project but as an ongoing strategic transformation embedded within every layer of the organization.

Ethical Considerations

All procedures performed in this study were under the ethical standards.

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Conflict of Interest

The authors report no conflict of interest.

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