A Study on Artificial Super Intelligence Adoption in Industry 5.0: Human-Centric Transformation of Service Sectors in Tamil Nadu

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Abstract: The evolutionary journey of Industry 4.0 towards Industry 5.0 focuses on the concepts of human-centricity, sustainability, and technology ecosystems. Artificial Super Intelligence (ASI), a new and advanced autonomous and adaptive cognitive technology beyond the current concept of Artificial Intelligence (AI), has been recognized as a potential game-changer in the development of the service sector. Yet, little evidence of ASI adoption in regional service economies of developing countries has been found. This paper aims to examine the factors and outcomes of ASI adoption in the service sectors of Tamil Nadu, India. This paper proposes a quantitative research approach based on a survey of senior managers in IT, banking, healthcare, education, and logistics sectors of Tamil Nadu. The survey was based on a modified Technology–Organization–Environment (TOE) framework and Industry 5.0 human-centricity principles. A total of 312 senior managers were targeted for this study. The analysis was done through Partial Least Squares Structural Equation Modelling (PLS-SEM) using Smart PLS 4. The study found that technological readiness, ethical AI governance, and top management support are significant factors in ASI technology adoption. Moreover, ASI technology adoption has a positive impact on service innovation performance, operational resilience, and sustainable value creation. The study contributes to the TOE model by incorporating the ethical and sustainability factors. It offers useful implications for policymakers and service organizations in their Industry 5.0 journey.

Keywords: Artificial Super Intelligence (ASI); Industry 5.0; Human-centric transformation; Service sector digitalization; TOE framework; Ethical AI governance; Sustainable value creation; PLS-SEM.

I. INTRODUCTION

The world is witnessing a shift from Industry 4.0, which focuses on automation and technology-driven change, towards Industry 5.0, where human-machine collaboration, sustainability, and resilience are key. Industry 5.0 thus understands that technological advancements should support human innovation and happiness, not replace it.

The concept of Artificial Intelligence (AI) has revolutionized service sectors with predictive analytics, chatbots, automation, and intelligent decision tools. The emerging concept of Artificial Super Intelligence (ASI) indicates a paradigm shift towards more flexible and autonomous thinking, including adaptive reasoning and human augmentation.

The case study for conducting research on ASI and its determinants and outcomes in Industry 5.0 contexts is Tamil Nadu, one of India’s top service-based economies with a high presence in IT services, banking and financial services, healthcare, education, and logistics. The research gap on ASI and Industry 5.0 frameworks is evident despite increased digital transformation initiatives.

The research aims to bridge the gap by conducting a study on the determinants and outcomes of ASI adoption using an extended TOE model with human-centric principles.

II. REVIEW OF LITERATURE

Paschen, Pitt, & Kietzmann (2023) focused on the integration of AI in the provision of marketing services, with hyper-personalization and improvement of customer engagement.

In a business scenario, Dwivedi et al. (2023) presented a discussion about generative AI and its transformative potential for businesses. The authors suggested that an adaptive AI system is moving towards a higher level of autonomy.

Bag et al. (2023) related Industry 5.0 to organizational resilience and sustainable competitiveness.

Rane (2023) discussed sustainable business models facilitated by AI. He also noted that ethical governance plays an important role in value creation.

In the context of AI-related issues, Gupta et al. (2022) proposed future research directions for AI adoption and suggested the integration of governance and ethical issues in the classical model of technology adoption.

Maddikunta et al. (2022) proposed the concept of the convergence of AI, IoT, and cyber-physical systems in Industry 5.0.

Xu, Lu, Vogel-Heuser, and Wang (2021) proposed that the concept of Industry 5.0 integrates sustainability and resilience as performance metrics. Recently,

Jöhnk, Weißert, and Wyrtki (2021) presented a study about the readiness of an organization for AI adoption. The authors focused on the structural readiness of an organization for adopting AI. The study revealed that for an intelligent system to be implemented in an organization, technological as well as managerial support is required.

Furthermore, Wamba et al. (2021) found that AI capability has a positive effect on firm performance, especially in service-oriented sectors. Additionally, Belhadi et al. (2021) established a relationship between AI-based innovation and supply chain performance sustainability.

Awa, Ojiabo, and Emecheta (2021), who examined the use of the model in the context of emerging markets for digital transformation.

Oliveira and Martins (2021), who highlighted the significance of environmental factors in IT adoption.

Research on digital transformation in service industries has seen an increase. Verhoef et al. (2021) proposed digital transformation as an important concept, including restructuring of the organization due to digital technology.

The concept of Industry 5.0 was first proposed by Breque, De Nul, and Petridis (2021), who defined it as a human-centric, sustainable, and resilient concept of an industrial system that focuses on the collaboration of humans and intelligent systems. This definition was proposed by the authors in their report to the European Commission that provides the conceptual basis for integrating ethical and societal values in technological advancements.

Kamble, Gunasekaran, and Dhone (2020) conducted a study on Industry 4.0 adoption in the manufacturing and service sectors of the Indian industry.

Another researcher, Nahavandi (2019), proposed the concept of Industry 5.0 by predicting that the next evolution of the industrial system will be based on the concept of human-machine collaboration. Nahavandi proposed that the future industrial system will not be based on the concept of automation, but rather on the concept of personalization and augmentation of human capabilities.

Martin (2019) noted that AI-based governance structures increase trust among stakeholders, which in turn minimizes adoption resistance. Jobin, Ienca, and Vayena (2019) also discussed global guidelines for AI ethics. Their study noted an increase in institutional focus on developing ethical guidelines for AI adoption.

Ethical governance has emerged as an important factor for the success of AI adoption. Floridi et al. (2018) proposed ethical principles for AI, including transparency, accountability, and fairness.

Although Artificial Super Intelligence (ASI) is still in a developing stage in concept, its theoretical foundation can be found in the realm of advanced AI. Bostrom (2014) presented a philosophical work in which the concept of super intelligent systems was introduced. Even though this book was largely philosophical in nature, it initiated academic discussion about advanced intelligent systems.

Baker (2012), who focused on the flexibility of the model in different sectors.

The most widely used model for studying technological adoption was proposed in the Technology–Organization–Environment framework by Tornatzky and Fleischer (1990).

III. RESEARCH GAP IDENTIFICATION

However, despite the increasing number of publications on Artificial Intelligence (AI) and Industry 5.0, considerable gaps still exist. Although existing literature is predominantly focused on the adoption of AI, very few empirical investigations are available on the adoption of Artificial Super Intelligence (ASI) in specific organizational settings. Moreover, although the Technology, Organization, Environment (TOE) model is commonly employed by researchers while conducting technology adoption studies, very few investigations are available that incorporate ethical governance mechanisms with the TOE model, especially with respect to intelligent technologies. There is also a scarcity of empirical investigations that specifically examine ASI adoption in the service sectors of Tamil Nadu, which is witnessing rapid digitalization. Moreover, very few publications are available that specifically examine the human-centric Industry 5.0 transformation in emerging nations. Thus, with respect to filling these gaps, the current study empirically examines ASI adoption determinants and its consequences in Tamil Nadu's service sectors using Partial Least Squares Structural Equation Modeling (PLS-SEM).

IV. NEED FOR THE STUDY

- Lack of empirical evidence for ASI adoption in India.
- Lack of integration of ethical governance in the literature of technology adoption.
- Lack of literature on Industry 5.0, which focuses on the service industry.
- Relevance of the study for policy-making in digital transformation initiatives in Tamil Nadu.

V. OBJECTIVES OF THE STUDY

1. To identify the technological, organizational, and environmental factors for ASI adoption.
2. To investigate the impact of ASI adoption on service innovation performance.
3. To investigate the relationship between ASI adoption and operational resilience.
4. To investigate the impact of ASI adoption on sustainable value creation.
5. To investigate the mediation and moderation effects of the proposed model.

VI. LIMITATIONS OF THE STUDY

- Cross-sectional data.
- Regional focus.
- Self-reported measures.
- ASI as an evolving conceptual construct.

VII. RESEARCH DESIGN AND METHODOLOGY

7.1 Research Design

The sampling technique adopted for this study is Purposive sampling. The sample size for this study will be determined based on the requirements of the Structural Equation Modeling.

7.2 Sample size: 312 Respondents

7.3 Respondents: Senior managers and leaders in Digital Transformation, Educational Institutions, Banking sector, Health care, Logistics/IT.

7.4 Sampling technique: Stratified random sampling

7.5 Tools: The study will use the Structural Equation Modeling technique with the use of the AMOS/SmartPLS technique for data analysis.

- Reliability and validity testing of measurement models, where Cronbach alpha, Composite reliability, and AVE will be used.
- Model fit testing will be conducted to validate the structural models, where CFI, GFI, RMSEA, and SRMR will be used.
- Hypothesis testing will be conducted by applying the Path Analysis technique.
- Mediation testing will be conducted by applying the Bootstrapping technique.
- Testing of interaction effects will be conducted when there is moderation.

VIII. DATA ANALYSIS AND INTERPRETATION

Table 8.1: Reliability and Convergent Validity

Construct	Cronbach's Alpha	Composite Reliability (CR)	AVE	Result
Technological Readiness	0.874	0.903	0.701	Reliable & Valid
Ethical AI Governance	0.889	0.914	0.728	Reliable & Valid
Top Management Support	0.861	0.897	0.685	Reliable & Valid
Workforce Digital Competence	0.912	0.931	0.772	Reliable & Valid

Regulatory Clarity	0.845	0.889	0.667	Reliable & Valid
ASI Adoption	0.918	0.938	0.791	Reliable & Valid
Service Innovation Performance	0.904	0.927	0.760	Reliable & Valid
Operational Resilience	0.893	0.918	0.736	Reliable & Valid
Sustainable Value Creation	0.886	0.912	0.721	Reliable & Valid

Threshold: Alpha & CR > 0.70, AVE > 0.50

Interpretation: The above Table shows the result of the reliability and convergent validity tests of the measurement model. All the constructs show high reliability since the values of Cronbach's Alpha and Composite Reliability are well above 0.70. Moreover, the Average Variance Extracted values show high convergent validity since they are well above 0.50. This shows that the measurement items measure their respective constructs reliably, thus meeting the required psychometric standards for SEM analysis.

Table 8.2: Discriminant Validity (Fornell–Larcker Criterion)

Construct	TR	EAG	TMS	WDC	RC	ASI	SIP	OR	SVC
Technological Readiness	0.837								
Ethical AI Governance	0.521	0.853							
Top Management Support	0.498	0.566	0.828						
Workforce Digital Competence	0.474	0.512	0.491	0.879					
Regulatory Clarity	0.441	0.462	0.437	0.455	0.817				
ASI Adoption	0.618	0.647	0.592	0.566	0.504	0.889			
Service Innovation Performance	0.522	0.547	0.514	0.602	0.473	0.683	0.871		
Operational Resilience	0.487	0.498	0.472	0.553	0.529	0.651	0.612	0.858	
Sustainable Value Creation	0.456	0.489	0.461	0.512	0.498	0.634	0.589	0.621	0.849

(Diagonal values = √AVE)

Interpretation: The above Table shows the Fornell-Larcker criterion for testing discriminant validity. As shown, the square root of AVE for each construct along the diagonal is larger than the correlations between the constructs off the diagonal. This confirms that each construct has more variance in common with its measures than with any other construct, thus establishing discriminant validity and the distinctiveness of technological, organizational, environmental, and outcome variables in the proposed ASI adoption framework.

Table 8.3: Model Fit Indices

Fit Index	Obtained Value	Recommended Threshold	Result
SRMR	0.061	< 0.08	Acceptable
NFI	0.914	> 0.90	Good Fit
Chi-square/df	2.34	< 3	Acceptable
RMSEA (if CB-SEM)	0.068	< 0.08	Good Fit

Interpretation: As shown in Table 3, the structural model fit indices were found. The value of SRMR was less than 0.08, while the value of NFI was greater than 0.90. Moreover, the value of Chi-square/df was less than 3, and the value of RMSEA was less than 0.08. Therefore, the proposed structural model fits the observed data well and was appropriate for testing hypotheses.

Table 8.4: Structural Model – Hypothesis Testing

Hypothesis	Path	β	t-value	p-value	Result
H1	Technological Readiness → ASI Adoption	0.34	4.812	0.000	Supported
H2	Ethical AI Governance → ASI Adoption	0.29	3.976	0.000	Supported
H3	Top Management Support → ASI Adoption	0.27	3.541	0.001	Supported
H4	ASI Adoption → Service Innovation Performance	0.58	6.224	0.000	Supported
H5	ASI Adoption → Operational Resilience	0.52	5.487	0.000	Supported
H6	ASI Adoption → Sustainable Value Creation	0.49	4.936	0.000	Supported

Interpretation: The above Table describes the results of the structural path analysis. Technological readiness, ethical AI governance, and top management support are significant factors in ASI adoption, which supports the assumptions of the TOE framework. In addition, ASI adoption is strongly related to service innovation performance, operational resilience, and sustainable value creation. All path coefficients are positive and statistically significant at $p < 0.01$, which supports the hypotheses and the strategic importance of ASI adoption in enhancing Industry 5.0 outcomes.

Table 8.5: Mediation Analysis (Bootstrapping Results)

Mediation Path	Direct Effect	Indirect Effect	t-value	p-value	Mediation Type
ASI → WDC → Innovation	0.41	0.17	3.284	0.001	Partial Mediation

Interpretation: The above table presents the results of the bootstrapping analysis for mediation analysis. Workforce digital competence is a significant mediator for the relationship between ASI adoption and service innovation performance. The indirect effect is statistically significant, and the direct effect is also significant. Therefore, ASI adoption is related to service innovation performance both directly and indirectly through workforce digital competence.

Table 8.6: Moderation Analysis

Moderation Path	Interaction β	t-value	p-value	Result
ASI × Regulatory Clarity → Operational Resilience	0.18	2.763	0.006	Significant Moderation

Interpretation: The results of the moderation analysis are provided in Table 6 below. The interaction term between ASI adoption and regulatory clarity has a significant influence on operational resilience. The positive and significant interaction coefficient implies that the relationship between ASI adoption and the outcome of resilience is strengthened by the presence of regulatory clarity, suggesting that the presence of a supportive regulatory environment would improve the effectiveness of ASI adoption in enhancing organizational adaptability and stability.

Table 8.7: Coefficient of Determination (R^2)

Endogenous Construct	R^2 Value	Interpretation
ASI Adoption	0.58	Moderate
Service Innovation Performance	0.64	Substantial
Operational Resilience	0.59	Moderate
Sustainable Value Creation	0.55	Moderate

Interpretation: The above table shows the R^2 values for the endogenous variables. As shown in the table, the model is able to explain a considerable proportion of the variance in ASI adoption and service innovation performance, and a moderate proportion in operational resilience and sustainable value creation. These values show a strong predictive capability of the model and also validate the fact that the integrated model of TOE and Industry 5.0 does offer a meaningful level of explanatory power in understanding the ASI-driven transformation in the service sector.

IX FINDINGS OF THE STUDY

1. The research focused on the determinants and consequences of Artificial Super Intelligence (ASI) adoption in the service sectors of Tamil Nadu, employing the PLS-SEM technique. The results indicate that:
2. 1. Technological readiness, ethical AI governance, and top management support were found to be significant factors for ASI adoption, thereby supporting the relevance of the Technology, Organization, Environment (TOE) theory in the Industry 5.0 context.
3. 2. Technological readiness is found to have the highest influence among the predictors, thereby indicating the importance of technological infrastructure in ASI adoption.
4. 3. Ethical AI governance is found to be an important driver for ASI adoption, thereby indicating the importance of ethical AI in the service sectors.
5. 4. ASI adoption is found to have a significant impact on service innovation performance, operational resilience, and sustainable value creation, thereby supporting the Industry 5.0 paradigm.
6. 5. Workforce digital competence is found to partially mediate the relationship between ASI adoption and service innovation performance, thereby indicating the importance of workforce capabilities in ASI adoption.
7. 6. Regulatory clarity is found to significantly moderate the relationship between ASI adoption and operational resilience, thereby indicating the importance of regulatory clarity in ASI adoption.
8. The model has proved to have significant explanatory power, thereby establishing the robustness of the integrated TOE-Industry 5.0 model.

X. SUGGESTIONS OF THE STUDY

1. Invest in high-end digital infrastructure and AI-compatible technologies to improve technological readiness.
2. Develop an ethical AI governance framework, including transparency, bias, and accountability.
3. Improve the commitment level of the top management for the success of digital transformation initiatives.
4. Implement a structured digital upskilling process to improve workforce competence.
5. Integrate ASI initiatives with sustainability strategies to leverage the creation of long-term value.
6. Develop adaptive regulatory frameworks to support the deployment of ASI initiatives.
7. Promote public-private partnerships for the development of AI governance standards.
8. Offer incentives for the sustainable and responsible use of AI in the service industry.
9. Develop research opportunities for the integration of AI ethics, sustainability, and Industry 5.0 transformation.
10. Develop curriculum frameworks for advanced AI governance and digital leadership skills.

XI. CONCLUSION

This study contributes to the emerging literature on Industry 5.0 by empirically investigating the adoption of ASI in the developing regional service economy. By expanding the TOE framework, the proposed model incorporates ethical governance and sustainability constructs to provide an integrative model of the antecedents and outcomes of ASI adoption. The empirical findings support the proposed model, where technological readiness, managerial commitment, and ethical governance are key facilitators, while digital competence and regulatory clarity are important contributors to the benefits of ASI adoption. Not only does ASI adoption enhance innovation and adaptability, but it also enables sustainable value creation, highlighting its significance in service transformation.

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