

DO AUTOMATION AND DATA ALWAYS IMPROVE EFFICIENCY? THE MEDIATING ROLE OF TECHNOLOGY READINESS IN SERVICE CONTEXTS

Sri Astuti Mualimin¹, Mega Utami², Ramlawati³, Serlin Serang⁴

^{1,2,3}Universitas Muslim Indonesia, Makassar, South Sulawesi, Indonesia

Email penulis:

srikhalilah01@gmail.com¹; megautami20011215@gmail.com²; anis.saleh@umi.ac.id³



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Abstract: *This study examines whether service automation and customer data utilisation consistently improve service efficiency, with a particular focus on the mediating role of the Technology Readiness Index. Using a quantitative approach, data were collected from 160 employees working in digitally enabled service organisations and analysed using Partial Least Squares Structural Equation Modelling. The findings reveal that service automation does not directly affect service efficiency, whereas customer data utilisation significantly enhances it. Technology readiness emerges as a critical determinant, exerting the strongest direct influence on service efficiency. Furthermore, technology readiness fully mediates the relationship between service automation and service efficiency, indicating that automation contributes to performance only when it enhances individuals' readiness to engage with technology. In contrast, the mediating effect of technology readiness in the relationship between customer data utilisation and service efficiency is not supported. These results suggest that different digital technologies operate through distinct mechanisms, highlighting the importance of human readiness in realising the benefits of automation. This study contributes to the literature by challenging deterministic views of digital transformation and emphasising the conditional role of technology in improving organisational performance.*



INTRODUCTION

The accelerating adoption of digital technologies has significantly reshaped the landscape of service operations, prompting organisations to reconsider how efficiency is conceptualised and achieved (Halik, Halik, et al., 2026). In contemporary service environments, service automation and customer data utilisation are increasingly viewed as critical enablers of improved performance (Halik et al., 2024). Service automation, supported by artificial intelligence, machine learning, and self-service technologies, is often associated with faster processing times, reduced operational costs, and improved consistency. At the same time, the growing availability of customer data allows organisations to gain deeper insights into customer behaviour, enabling more accurate decision-making and more responsive service delivery. However, the assumption that these technological advancements will automatically improve service efficiency warrants closer scrutiny.

Recent studies indicate that the outcomes of automation and data utilisation are not universally positive. While some organisations report substantial efficiency gains, others experience limited benefits due to challenges in implementation and adoption (Bortolotti & Romano, 2012; Rust & Huang, 2012). One important explanation for this variation lies in the concept of Technology Readiness Index, which reflects an individual's or organisation's

propensity to embrace and use new technologies. Technology readiness captures both enabling factors, such as optimism and innovativeness, and inhibiting factors, such as discomfort and insecurity. Empirical research shows that higher levels of readiness tend to support more effective technology adoption, whereas lower levels often result in resistance or ineffective use (Blut & Wang, 2020; Lee et al., 2022).

In addition, the use of customer data introduces further complexity into the service process. Although data driven strategies can improve decision quality and operational responsiveness, they require adequate analytical capabilities and organisational support to translate data into meaningful actions (Mikalef & Krogstie, 2020). Without these capabilities, the potential benefits of customer data may not be fully realised. Similarly, service automation can produce unintended consequences if it is implemented without careful consideration of human factors (Verhoef et al., 2021). For example, excessive reliance on automated systems may reduce flexibility or weaken customer engagement, which can ultimately affect perceived service quality (Rust & Huang, 2012).

The empirical literature reveals mixed findings regarding the relationship between digital technologies and service efficiency. Some studies demonstrate positive effects, while others highlight inconsistencies that depend on contextual and behavioural factors (Verhoef et al., 2021; Wirtz et al., 2018). These inconsistencies suggest that the relationship between automation, data utilisation, and efficiency is not purely direct, but may be influenced by mediating variables. In this context, technology readiness emerges as a key explanatory mechanism that may clarify why similar technological investments lead to different outcomes across organisations.

Table 1. Empirical Evidence on Digital Technology and Service Efficiency

Study	Context	Key Findings	Implications
Rust & Huang (2012)	Artificial intelligence in services	Automation improves efficiency but may reduce human interaction	Balance between technology and human involvement is necessary
Mikalef & Krogstie (2020)	Data driven organisations	Data utilisation enhances performance when supported by capabilities	Capability development is essential
Verhoef et al. (2021)	Digital transformation	Performance outcomes vary across organisations	Contextual and organisational factors matter
Sahetapy et al. (2025)	Technology readiness	Readiness influences technology adoption outcomes	Human readiness determines effectiveness

Source: Quoted from previous research (2026)

Despite the rapid expansion of digital technologies in service contexts, many organisations still struggle to achieve consistent improvements in efficiency. Investments in automation and data driven systems are often made without sufficient attention to the readiness of individuals and organisations to adopt and utilise these technologies effectively. This gap can lead to suboptimal outcomes, where advanced technologies fail to deliver their expected value. Therefore, it is essential to investigate the mediating role of technology readiness in order to better understand how and when service automation and customer data utilisation contribute to service efficiency.

Based on the conceptual background and identified research gaps, this study seeks to address the following research questions:

1. To what extent does service automation influence service efficiency
2. To what extent does customer data utilisation influence service efficiency
3. How does service automation affect technology readiness

4. How does customer data utilisation affect technology readiness
5. To what extent does technology readiness influence service efficiency
6. Does technology readiness mediate the relationship between service automation and service efficiency
7. Does technology readiness mediate the relationship between customer data utilisation and service efficiency

LITERATURE REVIEW

Grand Theory: Technology Readiness as a Socio-Technical Enabler

This study is primarily grounded in the Technology Readiness Index, which explains how individuals and organisations differ in their propensity to adopt and utilise new technologies. Technology readiness is conceptualised as a multidimensional construct consisting of optimism, innovativeness, discomfort, and insecurity (Blut & Wang, 2020). These dimensions collectively determine whether technology adoption leads to effective utilisation or operational inefficiencies.

Recent evidence suggests that technology readiness plays a central role in shaping technology-related outcomes, particularly in digital service environments. A meta-analysis by Blut and Wang (2020) demonstrates that technology readiness significantly influences technology usage and performance outcomes, both directly and indirectly through behavioural mechanisms. More recent research further expands this perspective by positioning technology readiness as part of a broader socio-technical continuum that links readiness, adoption, and performance outcomes in digital transformation contexts (Joshi et al., 2025).

From a theoretical standpoint, this study also aligns with the Technology Acceptance Model and its extensions, which emphasise perceived usefulness and ease of use as key determinants of technology adoption (Ma & Liu, 2004). However, unlike these models, technology readiness focuses on inherent predispositions rather than situational perceptions, making it particularly relevant for explaining variability in outcomes across similar technological implementations.

Service Automation and Service Efficiency

Service automation refers to the use of advanced technologies such as artificial intelligence, machine learning, and robotic systems to perform service-related tasks with minimal human intervention. In theory, automation enhances efficiency by reducing processing time, minimising human error, and improving consistency in service delivery (Rust & Huang, 2012; Wirtz et al., 2018).

Empirical findings support this argument, showing that automation-driven systems can significantly reduce operational costs and improve productivity. For instance, recent studies report measurable efficiency gains in organisations adopting AI-based systems, including reductions in operational costs and improvements in decision-making quality (Prince, 2024). However, the relationship is not universally positive. In some cases, automation may introduce rigidity, reduce flexibility, or create service failures when human judgement is required (Sahetapy et al., 2025; van der Burg et al., 2019).

This suggests that the impact of automation on service efficiency is conditional rather than deterministic. Without adequate readiness, organisations may fail to fully leverage automated systems, resulting in suboptimal outcomes. Thus:

H1: Service automation has a positive effect on service efficiency

Customer Data Utilisation and Service Efficiency

Customer data utilisation refers to the ability of organisations to collect, process, and apply customer related information to improve service performance. In the context of digital transformation, data driven decision making has become a key strategic capability (Bouwman et al., 2019; Sahetapy et al., 2025).

The literature indicates that effective use of customer data can enhance operational efficiency by improving forecasting accuracy, personalising services, and optimising resource allocation. However, these benefits depend heavily on the organisation's analytical capabilities and readiness to transform data into actionable insights (Verhoef et al., 2021).

Recent studies highlight that organisations often face challenges in integrating data into operational processes, leading to a gap between data availability and actual performance improvement (Du et al., 2021). This reinforces the argument that data utilisation alone is insufficient without supporting capabilities and readiness mechanisms. So, hypothesis 2 proposed as follow:

H2: Customer data utilisation has a positive effect on service efficiency

Technology Readiness and Service Efficiency

Technology readiness has been widely recognised as a determinant of performance outcomes in technology enabled environments. It influences how effectively individuals interact with systems, adapt to technological changes, and utilise digital tools in their tasks (Rizana et al., 2025).

Empirical research shows that higher levels of technology readiness are associated with improved operational efficiency, as individuals are more capable of adapting to new systems and leveraging technological features effectively (SRIBOONLUE et al., 2024). Conversely, low readiness can lead to resistance, errors, and inefficient use of systems.

Moreover, recent studies emphasise that readiness is not merely an individual trait but also an organisational capability that includes infrastructure, skills, and strategic alignment (Techanamurthy et al., 2025). This broader perspective strengthens the argument that technology readiness plays a pivotal role in determining the success of digital transformation initiatives.

H3: Technology readiness has a positive effect on service efficiency

Service Automation and Technology Readiness

While technology readiness is often conceptualised as an antecedent, recent perspectives suggest that it can also evolve through exposure to technology. Service automation provides repeated interaction with digital systems, which can enhance users' familiarity, confidence, and competence (Bortolotti & Romano, 2012).

From the perspective of the Technology Readiness Index, such exposure can strengthen optimism and innovativeness while reducing discomfort and insecurity. Empirical evidence supports this view, indicating that continuous interaction with automated systems enhances users' technological confidence and adaptability (Rust & Huang, 2012).

However, this relationship depends on the quality of implementation. Poorly designed systems may increase frustration and resistance, thereby reducing readiness. Nevertheless, in well managed contexts, automation is expected to foster higher levels of technology readiness.

H4: Service automation has a positive effect on technology readiness

Customer Data Utilisation and Technology Readiness

Customer data utilisation also contributes to the development of technology readiness through cognitive and behavioural mechanisms. Engaging with data analytics tools requires users to develop digital competencies and analytical skills, which enhance their confidence in using technology.

Mikalef and Krogstie (2020) highlight that organisations adopting data driven approaches tend to exhibit higher levels of digital capability and readiness. Through continuous engagement with data systems, users become more comfortable with technology, thereby reducing uncertainty and increasing perceived control (Halik, Lambe, et al., 2026; Sahetapy et al., 2025).

Nonetheless, the complexity of data systems may pose challenges. If systems are overly complex or lack usability, they may increase discomfort and reduce readiness. Therefore, the positive effect of data utilisation on readiness is contingent upon system design and organisational support.

H5: Customer data utilisation has a positive effect on technology readiness

The Mediating Role of Technology Readiness

The inconsistent findings in prior research regarding the impact of automation and data utilisation on efficiency suggest the presence of an underlying mechanism. Technology readiness provides a compelling explanation for this inconsistency.

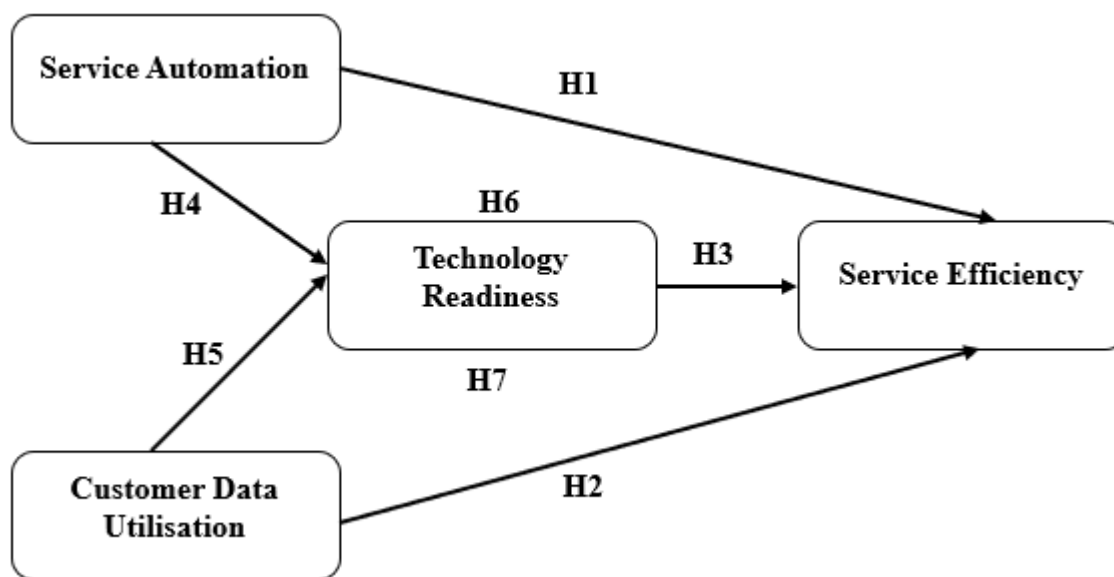
From a theoretical perspective, technology readiness acts as a mediator that translates technological inputs into performance outcomes. It determines whether individuals and organisations can effectively adopt and utilise automation and data driven systems.

Empirical studies indicate that readiness often exerts indirect effects on performance through behavioural and operational pathways (Blut & Wang, 2020). This reinforces its role as a critical mechanism linking digital technologies to efficiency outcomes.

H6: Technology readiness mediates the relationship between service automation and service efficiency

H7: Technology readiness mediates the relationship between customer data utilisation and service efficiency

Before presenting the conceptual framework, the relationships among the key constructs are synthesised based on the theoretical arguments and empirical evidence discussed in the preceding sections. The proposed model integrates service automation and customer data utilisation as primary antecedents of service efficiency, while positioning technology readiness as a mediating mechanism that explains how these technological factors translate into performance outcomes. This framework reflects the view that efficiency gains from digital technologies are not solely determined by their adoption, but also by the extent to which individuals and organisations are prepared to engage with and utilise them effectively. Accordingly, the conceptual framework of this study is illustrated in **Figure 1**.



Source: Author (2026)

Figure 1. Conceptual Framework

RESEARCH METHOD

This study adopts a quantitative research design to examine the relationships among service automation, customer data utilisation, technology readiness, and service efficiency. A cross-sectional survey approach is employed, as it enables the collection of empirical data from a large number of respondents within a specific time frame (Sugiyono, 2021). This design is appropriate for testing causal relationships and mediating effects among latent constructs, particularly in studies that rely on perception-based measures. The research follows a deductive approach, where hypotheses derived from theory are empirically tested using statistical analysis.

The population of this study comprises employees working in service sector organisations that have implemented digital technologies, particularly those involving automation and data driven processes. The unit of analysis is individual employees, as technology readiness and perceptions of service efficiency are inherently behavioural and cognitive in nature. Given the absence of a comprehensive sampling frame, this study employs a non-probability sampling technique, specifically purposive sampling. Respondents are selected based on specific criteria, namely individuals who have direct experience with service automation systems and customer data utilisation tools within their organisations. This approach is considered appropriate for ensuring that respondents possess the relevant knowledge required to provide valid and reliable responses.

The sample size in this study is determined using the indicator-based rule of thumb commonly applied in Partial Least Squares Structural Equation Modelling (Hair et al., 2021). Specifically, the minimum sample size is calculated as ten times the total number of measurement indicators used in the model. Given that this study employs a total of sixteen indicators across all constructs, the minimum required sample size is therefore 160 respondents. This approach ensures adequate statistical power and stability of parameter estimates, particularly in models involving multiple latent variables and mediating relationships. This exceeds the minimum threshold and aligns with recommendations for achieving more reliable and generalisable results in structural equation modelling (Hair et al., 2021).

The study is conducted in the context of service organisations located in Indonesia, with a particular focus on urban areas where digital transformation initiatives are more prevalent.

Data collection is carried out over a period of approximately two to three months to ensure sufficient response rates and data quality. This timeframe allows for adequate follow up and validation of responses, thereby enhancing the reliability of the dataset.

In terms of data analysis, this study employs Structural Equation Modelling using Partial Least Squares, which is suitable for analysing complex models involving multiple constructs and mediating relationships. Partial Least Squares Structural Equation Modelling is particularly appropriate for exploratory and predictive research, as well as for studies with relatively small to medium sample sizes (Ghozali, 2021; Hair et al., 2021). The analysis is conducted in two stages, namely the measurement model assessment and the structural model assessment. The measurement model is evaluated based on criteria such as indicator reliability, internal consistency reliability, convergent validity, and discriminant validity. The structural model is assessed by examining path coefficients, coefficient of determination, effect size, and predictive relevance. Mediation effects are tested using bootstrapping procedures to determine the significance of indirect relationships (Hair et al., 2021).

Table 2. Measurement Items

Variable	Code	Indicators	Measurement Items	Source
Service Automation	SA1	Process automation	Service processes in my organisation are largely automated	(Rust & Huang, 2012; Wirtz et al., 2018)
	SA2	Technology integration	Advanced technologies are integrated into service delivery	
	SA3	Reduction of manual work	Automation reduces the need for human intervention	
	SA4	Operational consistency	Automated systems ensure consistent service performance	
Customer Data Utilisation	CDU1	Data driven decision making	Customer data is used to support managerial decisions	(Mikalef & Krogstie, 2020; Verhoef et al., 2021)
	CDU2	Customer insight generation	Customer data helps understand customer needs	
	CDU3	Service personalisation	Customer data is used to personalise services	
	CDU4	Operational responsiveness	Data utilisation improves service responsiveness	
Technology Readiness	TR1	Optimism	New technologies contribute positively to my work performance	(Blut & Wang, 2020; Joshi et al., 2025)
	TR2	Innovativeness	I am among the first to try new technologies	
	TR3	Discomfort	I feel overwhelmed when using advanced technologies	
	TR4	Insecurity	I am concerned about the reliability of new technologies	
Service Efficiency	SE1	Time efficiency	Services are delivered quickly in my organisation	(Agustiawan, 2024; Wirtz et al., 2018)
	SE2	Resource efficiency	Resources are used efficiently in service processes	

Variable	Code	Indicators	Measurement Items	Source
	SE3	Error reduction	Service delivery is characterised by minimal errors	
	SE4	Overall performance efficiency	Service operations achieve high levels of efficiency	

Source: Adapted from previous literature (2026)

RESULTS AND DISCUSSION

Overview of the Research Context

This study is conducted within the service sector in Indonesia, focusing on organisations that have adopted digital technologies in their operational processes. The increasing integration of service automation and customer data utilisation reflects a broader shift towards digital transformation, particularly in urban service environments. Industries such as banking, telecommunications, hospitality, and digital platforms have increasingly relied on automated systems and data-driven decision-making to enhance operational performance.

The organisations included in this study have implemented various forms of service automation, ranging from self-service technologies and chatbots to more advanced artificial intelligence-based systems. In parallel, customer data utilisation has become a strategic priority, enabling firms to better understand customer behaviour, personalise services, and improve responsiveness. Despite these advancements, variations in service efficiency remain evident, suggesting that technological adoption alone is insufficient to guarantee optimal outcomes.

Within this context, the role of Technology Readiness Index becomes particularly relevant. Differences in individuals' readiness to engage with technology may explain why similar technological implementations yield different levels of efficiency across organisations. Therefore, this study examines how service automation and customer data utilisation influence service efficiency, both directly and indirectly through technology readiness.

Data collection was carried out over a period of approximately three months using an online survey distributed to employees working in digitally enabled service organisations. A total of 160 valid responses were obtained and included in the analysis, exceeding the minimum sample size requirement and ensuring adequate statistical power for Structural Equation Modelling.

Respondent Characteristics

Understanding the demographic and professional characteristics of respondents is essential for interpreting the findings of this study. The respondents represent a diverse group of employees working in various service industries, with differing levels of experience, education, and exposure to digital technologies.

The distribution of respondents based on gender indicates a relatively balanced composition, with a slight predominance of male respondents. In terms of age, the majority of respondents fall within the productive age group, particularly between 25 and 35 years, reflecting a workforce that is generally familiar with digital technologies. Educational background shows that most respondents hold at least a bachelor's degree, suggesting a relatively high level of formal education.

From a professional perspective, respondents are primarily employed in sectors that actively engage in digital transformation, including banking, telecommunications, and digital services. In terms of work experience, a significant proportion of respondents have between three and five years of experience, indicating a moderate level of familiarity with organisational processes and technological systems.

Table 3. Respondent Characteristics (n = 160)

Category	Classification	Frequency	Percentage (%)
Gender	Male	86	53.8
	Female	74	46.2
Age	Less than 25 years	25	15.6
	25 to 35 years	78	48.8
	36 to 45 years	39	24.4
	Above 45 years	18	11.2
	Diploma	27	16.9
Education Level	Bachelor's degree	98	61.3
	Master's degree	35	21.8
	Less than 3 years	36	22.5
Work Experience	3 to 5 years	64	40.0
	More than 5 years	60	37.5
	Banking and financial services	46	28.8
Industry Sector	Telecommunications	32	20.0
	Hospitality and tourism	28	17.5
	Digital platforms and services	54	33.7

Source: Processed primary data (2026)

The distribution of respondents presented in **Table 3** provides important insights into the profile of individuals involved in this study. In terms of gender, the sample is relatively balanced, with male respondents accounting for 53.8 percent and female respondents representing 46.2 percent. This balanced composition reduces the likelihood of gender bias and enhances the generalisability of the findings across different workforce segments.

With respect to age, the majority of respondents fall within the 25-to-35-year category, representing 48.8 percent of the sample. This indicates that the study is largely dominated by individuals in their productive and technologically active years. This age group is typically more adaptable to digital technologies, which is particularly relevant given the study's focus on service automation and customer data utilisation. Meanwhile, respondents aged above 45 years constitute a smaller proportion, suggesting that perspectives from more senior employees are present but less dominant.

In terms of educational background, most respondents hold a bachelor's degree, accounting for 61.3 percent of the sample, followed by those with a master's degree at 21.8 percent. This reflects a relatively well-educated workforce, which is likely to possess the cognitive and analytical capabilities required to engage with complex technological systems. The presence of respondents with higher education levels strengthens the validity of responses, particularly for constructs related to technology readiness and data utilisation.

Regarding work experience, the largest group of respondents has between three and five years of experience, representing 40.0 percent of the sample. This suggests that many respondents have sufficient exposure to organisational processes and digital systems, while still being actively engaged in operational roles. Respondents with more than five years of experience also represent a substantial proportion, indicating that the sample captures both moderately experienced and more seasoned employees.

Finally, the distribution across industry sectors shows that the largest proportion of respondents comes from digital platforms and services, followed by banking and financial services. This is consistent with the research context, as these sectors are among the most

advanced in adopting service automation and data driven practices. The presence of respondents from telecommunications and hospitality sectors further enhances the diversity of the sample, allowing for broader applicability of the findings across different service industries.

Outer Model Evaluation

The evaluation of the measurement model is conducted to assess the reliability and validity of the constructs used in this study. This includes the examination of indicator reliability, internal consistency reliability, convergent validity, and discriminant validity. The analysis is performed using Partial Least Squares Structural Equation Modelling. See results in **Table 4**.

Table 4. Outer Model Evaluation

Construct	Code	Outer Loadings	Cronbach's Alpha	CR	AVE	HTMT (Max)
Service Automation	SA1	0.909	0.887	0.918	0.747	0.604
	SA2	0.919				
	SA3	0.843				
	SA4	0.778				
Customer Data Utilisation	CDU1	0.940	0.924	0.947	0.815	0.410
	CDU2	0.925				
	CDU3	0.920				
	CDU4	0.822				
Technology Readiness	TR1	0.878	0.878	0.883	0.733	0.643
	TR2	0.872				
	TR3	0.842				
	TR4	0.831				
Service Efficiency	SE1	0.813	0.830	0.840	0.662	0.643
	SE2	0.853				
	SE3	0.834				
	SE4	0.752				

Note: All values satisfy recommended thresholds: Outer Loadings > 0.70; AVE > 0.50; α & CR > 0.70; HTMT < 0.90 (Hair et al., 2019; Henseler et al., 2015)

Source: Primary Data Processed with Smart-PLS 4 (2026)

Indicator Reliability. Indicator reliability is assessed through outer loadings, where values exceeding 0.70 indicate that the indicators adequately represent their respective constructs (Hair et al., 2019; Haryono, 2017). As shown in **Table 4**, all measurement items exhibit outer loadings above the recommended threshold, ranging from 0.752 to 0.940. This indicates that each indicator has a strong correlation with its underlying construct and contributes meaningfully to the measurement model.

Notably, the indicators for customer data utilisation demonstrate particularly high loadings, with CDU1, CDU2, and CDU3 exceeding 0.90. This suggests a high level of consistency in how respondents perceive the role of data utilisation within their organisations. Similarly, the indicators of service automation show strong loadings, particularly SA1 and SA2, which exceed 0.90, indicating that automation processes are clearly recognised and consistently interpreted by respondents.

For the construct of technology readiness, all indicators also exceed 0.80, reflecting a robust representation of the construct's dimensions. These findings are consistent with the theoretical structure of the Technology Readiness Index, where multiple dimensions collectively capture individuals' readiness to engage with technology.

Internal Consistency Reliability. Internal consistency reliability is evaluated using Cronbach's Alpha and Composite Reliability. As presented in **Table 4**, all constructs exhibit values well above the recommended threshold of 0.70 (Hair et al., 2019). Specifically, Cronbach's Alpha ranges from 0.830 to 0.924, while Composite Reliability ranges from 0.840 to 0.947.

The highest reliability is observed in customer data utilisation, indicating that the measurement items are highly consistent in capturing the construct. While high reliability is desirable, values approaching 0.95 may also suggest potential redundancy among indicators (Hair et al., 2019). In this study, the CR value of 0.947 remains within an acceptable range, although it indicates that the indicators are closely related. Overall, these results confirm that the constructs demonstrate strong internal consistency and reliability.

Convergent Validity. Convergent validity is assessed using the Average Variance Extracted, where values above 0.50 indicate that a construct explains more than half of the variance of its indicators (Hair et al., 2019; Haryono, 2017). The AVE values for all constructs range from 0.662 to 0.815, exceeding the recommended threshold.

Customer data utilisation shows the highest AVE value of 0.815, indicating excellent convergent validity. This suggests that the indicators strongly converge in representing the construct. Similarly, service automation and technology readiness exhibit AVE values above 0.70, further confirming the robustness of the measurement model.

Service efficiency records the lowest AVE value at 0.662, although it still satisfies the required threshold. This indicates that while the construct is valid, there may be slightly greater variability in how respondents perceive service efficiency compared to other constructs.

Discriminant Validity. Discriminant validity is evaluated using the Heterotrait Monotrait ratio. All HTMT values are below the recommended threshold of 0.90, with the highest value recorded at 0.643. This indicates that each construct is empirically distinct and captures a unique conceptual domain (Hair et al., 2019; Henseler et al., 2015).

The relatively low HTMT values suggest that there is minimal overlap between constructs such as service automation, customer data utilisation, and technology readiness. This is particularly important given the conceptual proximity of these variables within digital transformation contexts.

Taken together, the results of the measurement model evaluation demonstrate that all constructs satisfy the required criteria for reliability and validity. The strong outer loadings confirm indicator reliability, while Cronbach's Alpha and Composite Reliability indicate high internal consistency. The AVE values support convergent validity, and the HTMT ratios confirm discriminant validity. These findings suggest that the measurement model is robust and suitable for further analysis of the structural relationships among variables. Consequently, the study proceeds to the evaluation of the structural model to test the proposed hypotheses.

Inner Model Evaluation

The structural model evaluation is conducted to examine the predictive power and the relationships among constructs in the proposed model (Hair et al., 2021; Haryono, 2017). This assessment includes the coefficient of determination (R square), effect size (f square), predictive relevance (Q square), and overall model fit. These metrics provide a comprehensive understanding of how well the model explains and predicts the endogenous constructs.

Coefficient of Determination (R Square). The coefficient of determination represents the proportion of variance in the endogenous constructs explained by the exogenous variables. According to Hair et al. (2019), R square values of 0.75, 0.50, and 0.25 can be described as substantial, moderate, and weak, respectively.

Table 5. R-Square

Endogenous Variable	R Square	R Square Adjusted	Interpretation
Technology Readiness	0.323	0.314	Moderate
Service Efficiency	0.373	0.361	Moderate

Source: Primary Data Processed with Smart-PLS 4 (2026)

The results indicate that the R square value for technology readiness is 0.323, meaning that service automation and customer data utilisation explain 32.3 percent of the variance in technology readiness. This level of explanatory power can be considered moderate, suggesting that while both predictors play a meaningful role, a substantial proportion of variance remains unexplained. This implies that additional factors, such as organisational culture, digital skills, or leadership support, may also influence technology readiness.

Similarly, service efficiency exhibits an R square value of 0.373, indicating that service automation, customer data utilisation, and technology readiness collectively explain 37.3 percent of its variance. This suggests a moderate level of predictive accuracy, where the model captures a meaningful but not exhaustive portion of the factors influencing service efficiency.

The adjusted R square values for both constructs are slightly lower than the original R square values, which is expected as they account for model complexity. The relatively small difference between R square and adjusted R square indicates that the model does not suffer from overfitting and maintains good generalisability.

Effect Size (F Square). The f square value assesses the contribution of each exogenous construct to the R square value of the endogenous variable. Threshold values of 0.02, 0.15, and 0.35 indicate small, medium, and large effects, respectively (Hair et al., 2019). Results presented in **Table 6**.

Table 6. F-Square Value

Relationship	F Square	Effect Size
Service Automation → Technology Readiness	0.415	Large
Customer Data Utilisation → Technology Readiness	0.025	Small
Service Automation → Service Efficiency	0.000	No effect
Customer Data Utilisation → Service Efficiency	0.110	Small
Technology Readiness → Service Efficiency	0.267	Medium

Source: Primary Data Processed with Smart-PLS 4 (2026)

The results reveal notable variation in the effect sizes across relationships. The strongest effect is observed in the relationship between service automation and technology readiness, with an f square value of 0.415, indicating a large effect. This suggests that service automation is a dominant factor in shaping technology readiness. In practical terms, exposure to automated systems appears to significantly enhance individuals' familiarity, confidence, and adaptability towards technology.

In contrast, customer data utilisation exhibits only a small effect on technology readiness, with an f square value of 0.025. This indicates that although data utilisation contributes to readiness, its impact is relatively limited compared to automation. One possible

explanation is that interacting with automated systems provides more direct and experiential learning than working with data, which may be more abstract or indirect in nature.

A particularly important finding is that service automation shows no effect on service efficiency, as indicated by an f square value of 0.000. This suggests that, when technology readiness is included in the model, the direct contribution of automation to efficiency becomes negligible. This is a strong indication of a potential full mediation effect, where the impact of automation on efficiency operates entirely through technology readiness rather than directly.

Customer data utilisation demonstrates a small effect on service efficiency, with an f square value of 0.110. This implies that data driven practices contribute modestly to efficiency improvements, although their impact is not substantial on their own.

Meanwhile, technology readiness shows a medium effect on service efficiency, with an f square value of 0.267. This highlights its critical role as a key driver of efficiency outcomes. Compared to the direct effects of automation and data utilisation, readiness appears to be the more influential factor in determining whether efficiency gains are realised.

Predictive Relevance (Q Square). Predictive relevance is used to evaluate the model's ability to accurately predict observed data points. The Q square value is calculated using the Stone–Geisser criterion, where values greater than zero indicate that the model has predictive relevance. As a rule of thumb, Q square values of 0.02, 0.15, and 0.35 represent small, medium, and large predictive relevance, respectively (Hair et al., 2019).

Table 7. Predictive Relevance (Q²)

Endogenous Variable	Q ² Value	Interpretation
Technology Readiness	0.323	Medium predictive relevance
Service Efficiency	0.373	Medium predictive relevance
Global Q²	0.575	High predictive relevance

Source: Primary Data Processed with Smart-PLS 4 (2026)

The results indicate that both endogenous constructs exhibit Q square values greater than zero, confirming that the model has predictive relevance. Specifically, technology readiness has a Q square value of 0.323, while service efficiency records a value of 0.373. These values fall within the medium predictive relevance category, suggesting that the model has a reasonable capability to predict observed outcomes.

Furthermore, the global Q square value of 0.575 indicates strong overall predictive relevance. This implies that the model performs well in predicting the endogenous constructs collectively, even though the individual R square values are moderate.

Model Fit. Model fit assessment in Partial Least Squares Structural Equation Modelling is used to evaluate how well the proposed model reproduces the observed data. Although PLS SEM is primarily prediction oriented, several global fit indices can still be used to assess the adequacy of the model, including the Standardised Root Mean Square Residual, Normed Fit Index, and discrepancy measures such as d_{ULS} and d_G (Hair et al., 2019).

Table 8. Model Fit

	Saturated Model	Estimated Model
SRMR	0.067	0.067
d_{ULS}	0.612	0.612
d_G	0.328	0.328
Chi-square	294.866	294.866
NFI	0.836	0.836

Source: Primary Data Processed with Smart-PLS 4 (2026)

The Standardised Root Mean Square Residual value of 0.067 indicates a good model fit, as it falls below the recommended threshold of 0.08 (Hair et al., 2021). This suggests that the discrepancy between the observed and predicted correlations is relatively small, indicating that the model adequately represents the data.

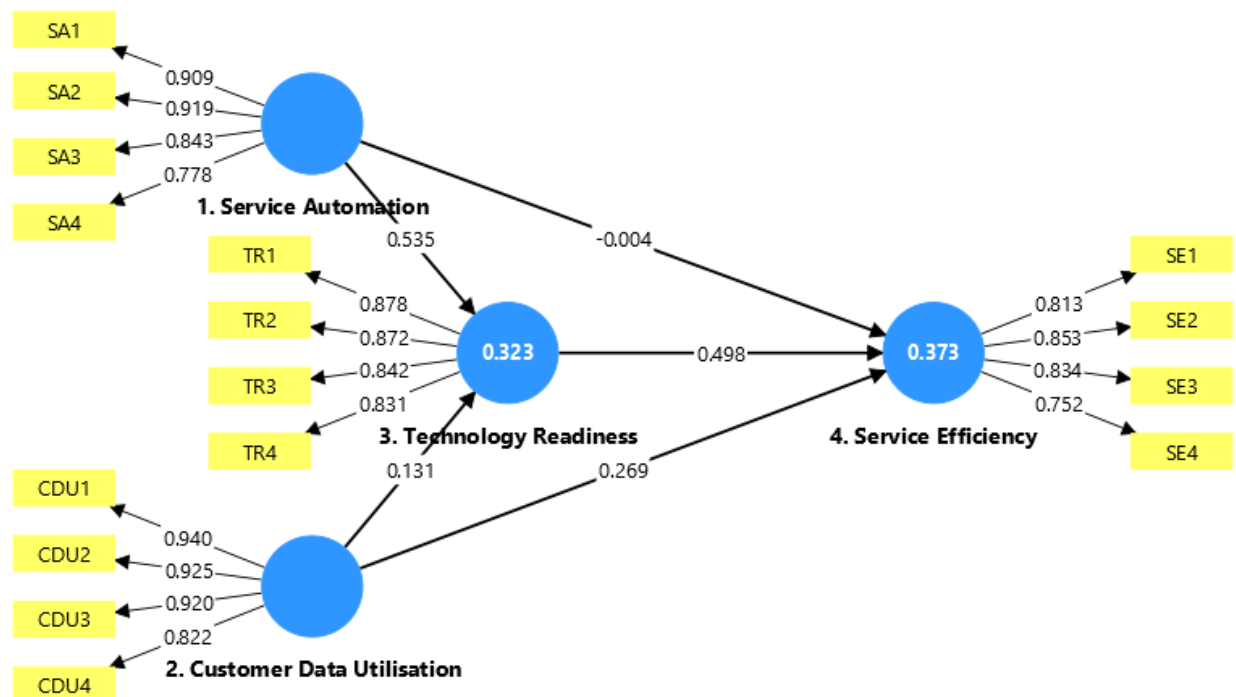
The discrepancy measures, namely d_{ULS} and d_G , also show acceptable values. Although there are no strict cut off criteria for these indices, lower values indicate better fit, and the results suggest that the difference between the empirical and model implied correlation matrices is reasonably low.

The Normed Fit Index is reported at 0.836, which is below the commonly suggested threshold of 0.90 (Hair et al., 2021). This indicates that the model fit can be considered marginal rather than excellent. However, in the context of PLS SEM, NFI values slightly below 0.90 are still acceptable, particularly in exploratory research and models involving behavioural constructs.

The Chi square value is reported for completeness, although it is not a primary criterion in PLS SEM due to its sensitivity to sample size. Therefore, it is not used as the main basis for evaluating model fit in this study.

These results suggest that the structural model is sufficiently robust to proceed with hypothesis testing and further analysis.

Before presenting the structural relationships in detail, it is important to visualise the overall model to provide a clearer understanding of the interactions among constructs. The structural equation model illustrates the direct and indirect relationships between service automation, customer data utilisation, technology readiness, and service efficiency, including the mediating role of technology readiness. This visual representation complements the statistical results and facilitates a more comprehensive interpretation of the hypothesised relationships. Accordingly, the structural model of this study is presented in **Figure 2**.



Source: Primary Data Processed with Smart-PLS 4 (2026)

Figure 2. Structure Equation Model

Hypotesis Testing. Hypothesis testing is conducted using the bootstrapping procedure in Partial Least Squares Structural Equation Modelling to examine the significance of both direct and indirect relationships. The evaluation is based on path coefficients, t statistics, and p values, where a p value below 0.05 indicates statistical significance (Hair et al., 2019). The results are summarised in **Table 9**.

Table 9. Path Coefficient and Hypotheses Testing

Hypothesis	Relation	Original Sample	Mean	SD	T-Statistics	P-Values	Description
H1	SA → SE	-0.004	-0.007	0.082	0.044	0.965	Not Supported
H2	CDU → SE	0.269	0.272	0.072	3.721	0.000	Supported
H3	TR → SE	0.498	0.501	0.084	5.957	0.000	Supported
H4	SA → TR	0.535	0.539	0.068	7.847	0.000	Supported
H5	CDU → TR	0.131	0.132	0.073	1.793	0.073	Not Supported
H6	SA → TR → SE	0.266	0.272	0.064	4.173	0.000	Supported
H7	CDU → TR → SE	0.065	0.066	0.038	1.703	0.089	Not Supported

Note: SA = Service Automation, CDU = Customer Data Utilisation, TR = Technology Readiness, SE = Service Efficiency

Source: Primary Data Processed with Smart-PLS 4 (2026)

The results reveal several important patterns that challenge conventional assumptions about digital technologies and service efficiency.

First, the relationship between service automation and service efficiency (H1) is not supported, with a path coefficient of -0.004 and a p value of 0.965. This indicates that service automation does not have a direct effect on service efficiency. This finding contradicts the widely held assumption that automation inherently improves efficiency, suggesting that its impact is not automatic and may depend on other factors.

In contrast, customer data utilisation shows a positive and significant effect on service efficiency (H2), with a coefficient of 0.269 and a p value below 0.001. This suggests that organisations that effectively use customer data are more likely to achieve higher levels of efficiency, likely due to improved decision making and responsiveness.

Technology readiness demonstrates the strongest direct effect on service efficiency (H3), with a coefficient of 0.498 and a highly significant p value. This highlights that readiness to adopt and use technology is a critical determinant of efficiency outcomes, exceeding the influence of both automation and data utilisation.

Regarding antecedents of technology readiness, service automation has a strong and significant effect (H4), with a coefficient of 0.535. This indicates that exposure to automated systems substantially enhances individuals' readiness to engage with technology. However, customer data utilisation does not significantly influence technology readiness (H5), as indicated by a p value of 0.073. This suggests that interacting with data systems alone may not be sufficient to build technological readiness.

The mediation analysis provides deeper insight into the mechanisms underlying these relationships.

The indirect effect of service automation on service efficiency through technology readiness (H6) is positive and significant, with a coefficient of 0.266. Given that the direct effect of service automation on service efficiency is not significant, this finding indicates a full

mediation effect. In other words, service automation improves efficiency only when it enhances technology readiness.

On the other hand, the indirect effect of customer data utilisation on service efficiency through technology readiness (H7) is not significant. This indicates that technology readiness does not mediate the relationship between data utilisation and efficiency. Instead, customer data utilisation appears to influence efficiency directly rather than through readiness.

DISCUSSION

Does Service Automation Improve Service Efficiency?

The findings indicate that service automation does not have a significant direct effect on service efficiency. This result challenges the dominant assumption that automation inherently enhances operational performance. Instead, the evidence suggests that automation alone is insufficient to generate efficiency gains.

A plausible explanation lies in the distinction between technology deployment and technology utilisation. Automation may streamline processes structurally, but without adequate user readiness, its potential benefits remain unrealised. Employees may struggle to adapt to automated systems, leading to underutilisation, operational friction, or even inefficiencies.

This finding contrasts with studies that report a positive relationship between automation and performance, such as Huang and Rust (2021), who argue that artificial intelligence driven systems improve service outcomes. However, the present study suggests that such effects are contingent upon human factors, particularly readiness to engage with technology. This divergence highlights an important nuance often overlooked in prior research.

Does Customer Data Utilisation Improve Service Efficiency?

Customer data utilisation is found to have a positive and significant effect on service efficiency. This indicates that organisations leveraging customer data are better able to optimise service processes, personalise interactions, and respond more effectively to customer needs.

This finding aligns with prior research demonstrating the performance benefits of data driven decision making. For instance, Mikalef and Krogtie (2020) show that data analytics capabilities enhance organisational performance through improved insights and operational responsiveness. Similarly, Sahetapy et al. (2025) emphasise the role of data in enabling digital transformation.

Unlike automation, which requires behavioural adaptation, data utilisation appears to function more directly as a decision support mechanism. Its impact on efficiency is therefore less dependent on individual readiness and more on organisational capability to process and apply insights.

Does Technology Readiness Influence Service Efficiency?

Technology readiness exhibits the strongest positive effect on service efficiency, underscoring its central role in translating technological inputs into performance outcomes. This suggests that individuals who are more optimistic, innovative, and comfortable with technology are better able to leverage digital tools to enhance efficiency.

This finding strongly supports the Technology Readiness Index, which posits that readiness determines how individuals interact with and benefit from technology. It also aligns with recent studies, such as Blut and Wang (2020), which demonstrate that technology readiness significantly influences technology adoption and usage outcomes.

Importantly, this result positions readiness not merely as a background variable, but as a core driver of performance in digital service environments.

Does Service Automation Enhance Technology Readiness?

The results show that service automation has a strong and significant effect on technology readiness. This suggests that exposure to automated systems plays a crucial role in shaping individuals' familiarity, confidence, and adaptability towards technology.

This finding is consistent with experiential learning theory, which emphasises that direct interaction with technology enhances competence and reduces uncertainty (Joshi et al., 2025). By engaging with automated systems, employees develop practical skills and psychological readiness, which in turn influence their ability to use technology effectively.

This also extends prior research by Rust and Huang (2012) demonstrating that automation does not only affect outcomes directly, but also contributes to capability building. In this sense, automation functions as a developmental mechanism, rather than merely an operational tool.

Does Customer Data Utilisation Enhance Technology Readiness?

Contrary to expectations, customer data utilisation does not significantly influence technology readiness. This suggests that working with data systems does not necessarily enhance individuals' readiness to engage with technology.

One possible explanation is that data utilisation is often embedded within routine tasks and may not require deep technological engagement. Employees may rely on pre structured dashboards or automated analytics tools, limiting opportunities for active learning or skill development.

This finding diverges from studies that emphasise the role of digital capabilities in enhancing readiness (Rizana et al., 2025). It indicates that not all forms of technology exposure contribute equally to readiness, highlighting an important distinction between passive use and active engagement with technology.

The Mediating Role of Technology Readiness

The mediation analysis reveals that technology readiness fully mediates the relationship between service automation and service efficiency. This means that automation improves efficiency only through its impact on readiness. This is a critical finding. It suggests that the effectiveness of automation is conditional upon human factors. Without sufficient readiness, automation may fail to deliver its intended benefits.

In contrast, technology readiness does not mediate the relationship between customer data utilisation and service efficiency. This indicates that data utilisation operates through a different mechanism, directly influencing efficiency without relying on readiness.

These results highlight the existence of multiple pathways through which digital technologies affect performance. Automation follows an indirect, capability-based pathway, while data utilisation follows a direct, operational pathway.

Theoretical Implications

This study makes several important contributions to the literature. First, it challenges the deterministic view of technology by demonstrating that digital investments do not automatically lead to performance improvements. Instead, the findings support a contingent perspective, where outcomes depend on mediating mechanisms such as readiness.

Second, the study extends the application of the Technology Readiness Index by positioning it as a mediator rather than merely an antecedent. This provides a more dynamic understanding of how readiness influences organisational outcomes.

Third, the study differentiates between types of digital technologies, showing that automation and data utilisation operate through distinct mechanisms. This contributes to a more nuanced understanding of digital transformation in service contexts.

Practical Implications

From a managerial perspective, the findings offer several actionable insights.

First, organisations should not assume that investing in automation will automatically improve efficiency. Instead, they must prioritise initiatives that enhance employees' technology readiness, such as training, user friendly system design, and change management programmes.

Second, customer data utilisation should be strengthened as a direct driver of efficiency. Firms should invest in data analytics capabilities, improve data quality, and ensure that insights are effectively integrated into decision making processes.

Third, managers should recognise that different technologies require different implementation strategies. Automation requires a focus on human readiness, while data utilisation requires a focus on analytical capability.

CONCLUSION, LIMITATIONS, AND FUTURE RESEARCH

This study set out to interrogate a common assumption in digital service management: that investments in automation and data inevitably translate into higher efficiency. The evidence does not support such a deterministic view. Instead, the findings reveal a more conditional and pathway dependent relationship. Service automation, while influential, does not directly enhance service efficiency. Its contribution emerges only when it cultivates the capability of individuals to engage effectively with technology. In contrast, customer data utilisation exerts a direct and meaningful influence on efficiency, suggesting that data driven practices can improve operational outcomes without necessarily reshaping individual readiness.

The central insight of this study lies in the role of Technology Readiness Index as a mechanism that converts technological exposure into performance. Technology readiness is not merely a supporting variable but a decisive factor that determines whether technological investments yield tangible benefits. This shifts the analytical focus from technology as an artefact to technology as a capability mediated by human readiness. Consequently, efficiency in digital service contexts should be understood not as a direct output of technological adoption, but as an outcome of the alignment between systems and users.

From a theoretical standpoint, the study advances a more differentiated understanding of digital transformation by demonstrating that not all technologies operate through the same causal pathways. Automation functions as a capability building mechanism, whereas data utilisation operates as an operational enabler. This distinction challenges overly simplified models that treat digital technologies as homogeneous drivers of performance.

This study underscores a critical yet often overlooked reality in the discourse on digital transformation: technology does not create value in isolation. The effectiveness of automation and data depends fundamentally on the readiness of individuals to engage with, interpret, and apply these tools in meaningful ways. In an era where organisations are racing to adopt advanced technologies, the real competitive advantage may no longer lie in the technologies themselves, but in the human capacity to make them work.

Limitations

Several limitations should be acknowledged. First, the study relies on cross sectional survey data, which constrains the ability to draw causal inferences over time. The relationships observed may evolve as organisations and individuals become more accustomed to digital technologies. Second, the use of self-reported measures introduces the possibility of common method bias, despite efforts to ensure measurement validity. Third, the sample is concentrated within digitally active service sectors, which may limit the generalisability of the findings to less digitised contexts. Finally, the model explains a moderate proportion of variance in the

endogenous constructs, indicating that other relevant variables such as organisational culture, leadership support, or digital literacy were not captured in this study.

Future Research Directions

Future research should adopt longitudinal designs to capture the dynamic nature of technology adoption and its impact on performance over time. This would provide a clearer understanding of how technology readiness develops and how its mediating role evolves. Additionally, incorporating multi source data, such as objective performance metrics or managerial assessments, would help mitigate common method bias and strengthen empirical robustness.

Further studies could also extend the model by integrating organisational level variables, including digital leadership, innovation climate, and learning orientation, to provide a more comprehensive explanation of service efficiency. Moreover, comparative studies across industries or between developed and emerging economies would offer valuable insights into contextual differences in the role of technology readiness. Finally, future research may explore alternative mediating or moderating mechanisms, such as digital competence or user engagement, to refine the understanding of how different technological investments translate into performance outcomes.

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