Examining the Role of CSR and Technological Readiness in the Intelligent Transformation of SMEs in Northern Province, Sri Lanka

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ABSTRACT

Purpose: The purpose of this research is to find out the impact of external and internal factors on the intelligent technology readiness of SMEs and the moderation effect of corporate social responsibility (CSR) on the relationship between external and internal factors and intelligent technology readiness.

Design/methodology/approach: Data were collected from owners of the SMEs. A convenient sampling technique was applied to select the respondents. A Total of 143 valid responses from SMEs in various industries participated in this survey. Data were analyzed by using confirmatory factor analysis (CFA) and Structure Equation Modeling (SEM).

Findings: The findings revealed that internal and external factors significantly influence the intelligent technology readiness of SMEs. Furthermore, corporate social responsibility (CSR)negatively moderates the relationship between external factors and the intelligent technology readiness of SMEs. However, CSR does not moderate the relationship between internal factors and the intelligent technology readiness of SMEs.

Originality: This study addresses a critical research gap by empirically testing Wang et al.'s (2022) conceptual model within the context of the SME sector, specifically in a post-conflict, resource-constrained region such as Northern Sri Lanka. This paper confirms that external factors should be considered highly for technology readiness and internal factors should be handled to incorporate intelligent technology transformation. However, corporate social responsibility is not taken high consideration by the SME sector.

Implications: The study implies that SME owners understand the intelligent technology need and implement internal changes in management practice, upskill employees, and utilize external opportunities to sustain in a competitive and tech-driven market. The intelligent technology application is vital for the economic growth of the region.

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INTRODUCTION

Intelligent transformation refers to the comprehensive integration of advanced technologies, particularly artificial intelligence to various sectors to improve efficiency, productivity, and innovation. This transformation is reshaping businesses, economics, and societies. Key aspects of intelligent transformation are digitalization, automation, natural language processing (NLP), predictive analytics, personalization, data-driven decision-making, enhanced customer experience, innovation and product development, and operational efficiency (Davenport, Guha, Grewal, and Bressgott, 2019). It has the full potential for the benefit of society. Artificial Intelligence (AI) has profoundly transformed various aspects of the world, impacting numerous fields and industries. AI has been making significant contributions in healthcare, finance, transportation, retail and e-commerce, manufacturing education, entertainment, and agriculture industries (Abrokwah-Larbi & Awuku-Larbi, 2023). Organizations create business goals and explore and implement AI to reach them. Organizations consider structure, culture, and work methods to implement AI and earn desired profits. AI technologies are complex, need high investment, time -consuming, and knowledge-intensive. Only the systematic approach proves the successful implementation of AI in organizations (BeyondMinds, 2021). Organizations can have IT expertise to implement and control AI (Bettoni, et al., 2021).

The SMEs play a prominent role by contributing to GDP, providing employment opportunities, and reducing poverty in Sri Lanka. The SME sector has been facing huge problems and challenges in Sri Lanka and they are struggling to recover from COVID -19 pandemic and economic crises. The Northern Province of Sri Lanka is a region significantly impacted by prolonged conflict. Over three decades of civil war have resulted in extensive destruction of infrastructure and natural resources. A substantial portion of the intellectual population was displaced or migrated to foreign countries. According to the central bank report, SMEs have been facing different environments across regions in Sri Lanka; compared to other provinces, SMEs in Northern Province struggling to access resources and support such as capital, labor, infrastructure facilities, government support, and policy support, (Sivatheepan et al, 2018). Entrepreneurs in the region, in particular, have experienced considerable psychological distress, rendering them reluctant to adopt new innovative technological applications that require substantial investment. SMEs are struggling to adopt the intelligent technology transformation (Wang, et al., 2022). Andersen et al., (2019) mentioned that SMEs possess inadequate capital investment, small-scale businesses, unskilled employees, and poor leadership to implement innovative technologies compared with large organizations. The implementation of the intelligent transformation of SMEs is a highlighted problem that possesses limited resources in Sri Lanka; this problem needs more research on intelligent transformation.

Previous studies were conducted on intelligent transformation in the engineering-based manufacturing industry, digital smart assembly for products, tools to predict milling operations, and machine learning in the petrochemical industry (Yi et al. 2021; Huang et al. 2020; Min et al. 2019). Krolczyk et al. (2020) conducted research regarding intelligent products and employee performance. Malik et al., (2020) researched intelligent transformation in large enterprises. Furthermore, the research on intelligent transformation was conducted in the medical, agriculture, and education fields and on human resources (Benaich and Hogarth, 2020; Knox, 2020; Malik et al., 2020). Huang and Rust (2021), Saheb et al. (2022), Kumar et al. (2019) and Orus et al. (2021) recommended the application of AI for SMEs. Whereas Xiong et al. (2022), Measures (2021), and Malik et al. (2020) proved that the AI application is risky and does not produce the desired benefits. Prior researchers investigated CSR as an independent variable (Çera & Ndou, 2024; Yang, Lai & Zhu, 2021; Sucheran, 2016; Mattera & Moreno-Melgarejo, 2012) and mediator (Kiessling, Isaksson, & Yasar, 2016). Wang et al. (2022) developed a model which explains how external and internal factors influence the technology readiness of small and medium enterprises (SMEs)in central China and the role of CSR in intelligent transformation, but this model was not tested empirically. To address this gap, the researcher tested how the external and internal factors influence on intelligent transformation of SMEs and the role of CSR in the relationship between external and internal factors and the intelligent technology readiness of SMEs.

Literature Review

Intelligent Transformation

Intelligent transformation refers to the comprehensive and strategic process of evolving and enhancing intelligent systems, capabilities, and methodologies to meet the demands of modern challenges. This involves leveraging advanced technologies, such as artificial intelligence (AI), machine learning, big data analytics, and digital tools, to improve decision-making, operational efficiency, and predictive accuracy across various domains including business, military, and education (Wang, et al., 2022). Russell (2019) explains the critical need to align AI systems with human values to ensure they act in ways that are beneficial and safe. This involves transforming traditional AI development practices to include considerations of ethical implications and control mechanisms. Businesses can achieve digital transformation by integrating advanced technologies and the importance of evolving business intelligent systems is to stay competitive (Westerman, Bonnet, & McAfee, 2014). Chui & Malhotra (2018) explored the state of AI adoption across industries and identified both advancements and challenges. They identified that there is the transformative potential for AI in enhancing intelligent operations, and also noted the barriers to data quality and integration issues. Wong et al. (2024) described how businesses are implementing AI to transform their strategic operations. It offers insights into the practical aspects of intelligent transformation through technology adoption. Kaplan & Haenlein (2019) revealed the impact of AI on global business practices and the transformation of intelligent systems. It highlights both the opportunities for innovation and the challenges related to ethical considerations and workforce adaptation.

The key components of intelligent transformation are "Data Integration and Analytics, AI and Machine Learning, Digital Tools and Platforms, Human-Machine Collaboration, and Ethical and Regulatory Considerations" (Westerman, Bonnet, & McAfee, 2014; Chui & Malhotra 2018). Data integration and analytics is utilizing big data to gather, process, and analyze vast amounts of information to derive actionable insights implementing advanced analytics platforms that integrate data from various sources to provide real-time business intelligence. AI and machine learning are deploying algorithms to automate data analysis, detect patterns, and predict future trends. It is using predictive analytics in supply chain management to forecast demand and optimize inventory. Digital tools and platforms are adopting digital tools to streamline operations and enhance decision-making processes. It is implementing IoT devices for real-time monitoring and decision support in manufacturing. Human-machine collaboration enhances human decision-making through collaborative AI systems that provide recommendations and augment capabilities. It includes AI-powered customer service chatbots that assist human agents by providing relevant information quickly. Ethical and regulatory considerations ensure that intelligent transformation initiatives comply with ethical standards and regulatory requirements. It is developing AI systems with built-in fairness and transparency features to avoid biases and ensure accountability. Intelligent transformation is an ongoing process that involves the integration of advanced technologies and methodologies to improve the effectiveness and efficiency of intelligent systems. Recent literature emphasized the need for ethical considerations, human-machine collaboration, and the adoption of digital tools to navigate the challenges and opportunities presented by this transformation (Murtarelli, Gregory, & Romenti, 2021).

Innovation Diffusion Theory with Intelligent Transformation

Applying "Innovation Diffusion Theory" to intelligent transformation helps understand the adoption process of advanced technologies within organizations (Miller, 2015). By considering factors such as relative advantage, compatibility, complexity, trialability, and observability. Organizations can strategically plan and execute their intelligent transformation initiatives. This theory describes the necessity of understanding both external and internal factors for the adoption of new technology in organizations (Fiorini, 2019; Novak, 2023).

Intelligent Transformation in the SME Sector

Intelligent transformation in the SME (Small and Medium-sized Enterprise) sector adopts advanced technologies and data-driven methodologies to enhance decision-making, operational efficiency, and competitive advantage (Jarvenpaa et al., 2021). The key aspects of intelligent transformation in SMEs are Data Analytics and Business Intelligence (BI), Artificial Intelligence (AI) and Machine Learning, Digital Tools and Automation, Customer Relationship Management (CRM) Systems and Cloud Computing. Data Analytics and Business Intelligence (BI) is implementing BI tools to collect, analyze, and visualize data to inform strategic decisions. SMEs use BI dashboards to monitor sales performance, customer behavior, and market trends. Artificial Intelligence (AI) and Machine Learning leverage AI and machine learning algorithms to automate processes, enhance customer interactions, and predict future trends. An SME using AI-powered chatbots to handle customer inquiries or machine learning models to forecast inventory needs. Digital Tools and Automation utilize digital platforms and automation tools to streamline operations and reduce manual tasks. It adopts cloud-based accounting software to automate financial reporting and invoicing. Customer Relationship Management (CRM) implements CRM systems to manage customer interactions and improve customer service. CRM uses CRM data to personalize marketing campaigns and improve customer retention rates. Cloud Computing utilizes cloud services to enhance scalability, flexibility, and cost-efficiency. SMEs migrate their IT infrastructure to the cloud to reduce costs and improve accessibility. Sivarajah et al, (2024) discussed the challenges and methods of big data analytics, highlighting how SMEs can leverage data to transform their intelligent systems despite resource constraints. Rialti et al. (2019) explored how SMEs can use social media analytics as part of their intelligent transformation to enhance marketing and customer engagement strategies.

Corporate Social Responsibility (CSR)

Corporate Social Responsibility (CSR) refers to a company's commitment to conduct its business ethically, taking into account its impact on social, environmental, and economic factors. Integrating CSR into intelligent transformation ensures that the adoption of advanced technologies like AI, machine learning, and data analytics is conducted responsibly, ethically, and sustainably (Zhao, & Gomez Farinas, 2023). Integrating CSR into intelligent transformation involves adopting ethical, sustainable, and community-focused approaches to implementing advanced technologies (Chung Tiam Fook, 2017). By prioritizing ethical data use, sustainability, community engagement, employee well-being, and transparency, organizations can ensure that their intelligent transformation initiatives contribute positively to society. Recent literature and studies provide valuable frameworks and insights to guide these efforts, ensuring that technological advancements are aligned with broader social and environmental goals (Appio, Lima, & Paroutis, 2019). Enterprise social responsibility deals with philanthropy and employee occupational health, safety, staff welfare, etc. CSR is an important factor that influences intelligent transformation while considering external and internal factors. Social responsibility played an important role in the relationship between the internal and external factors that affect the intelligent transformation of enterprises (Wang et al., 2022). Previous researchers emphasized that social responsibility is applied as an independent, dependent variable, or mediating variable (Parker et al.,2015; Brockner et al., 2007).

Factors Influencing Intelligent Transformation of Enterprises

Wang, et al., (2022) revealed the drivers of or barriers to implementing intelligent transformation into three aspects: internal aspects, external aspects, and technology readiness. To ensure a smooth and stable running system, a well-functioning interactive system with technology is essential and maybe the driver of flexible intelligent transformation (Tang and Jing, 2021). However, excessive complexity may hinder the implementation process. Undoubtedly, the collaboration between staff and machines (Seeber et al., 2020) is a key factor in the success of intelligent transformations. Managers and employees are two dimensions of internal aspects (Seeber et al., 2020). On the one hand, top management's commitment and organizational readiness are the driving forces for an enterprise to carry out the implementation (Ingalagi et al., 2021). The lack of visibility regarding AI's benefits or lack of AI understanding impedes enterprises from taking advantage of AI technologies (Aarstad and Saidl, 2019). On the other hand, employee adoption (Ingalagi et al., 2021) is also a core driver. In contrast, change resistance and lack of AI competence for employees with insufficient employee training may block the way to intelligent transformations for enterprises (Aarstad and Saidl, 2019).

Internal aspects include Enterprise development needs, implementation costs, human resources, and top management involvement. Enterprise development needs are related to scale expansion, revenue growth, and capital increase which leads to enhancement and capacity expansion. Implementation cost deals with the intelligent transformation expenses related to human and capital resources. Human resources are related to talent and the quality of workers. Top management involvement is related to senior management's enthusiasm, support, personal involvement, and overall leadership of the enterprise resource planning implementation (Karimi et al., 2007).

External factor includes competitive pressure, the convenience of AI technology, and policy support. Competitive pressure results in pressure on the enterprise which deals with the change in the external environment, demand, and product control (Deery, 2015). The convenience of AI deals with the lean operation production process with the reduction of labor intensity. Policy support is related to platform construction, policy guidance, and financial subsidies (Fornes et al., 2021).

Intelligent Transformation of Employees

The success of the intelligent transformation depends on the employee's readiness to adopt the new system. AI-based technology considers the employees' well-being which induces or encourages employees to adopt intelligent technology (Chatterjee, 2020). Intelligent technology readiness is related to employee benefits and protections. It explains the wage-related, learning cost, and organizational commitment. The wages of employees are systematically organized with work orders and linked to the piecework method. Learning costs in the initial stage are high due to the advancement of information systems and the increase in workers' workloads. However, after a break-even period, employees are knowledgeable about the system. Employees feel better and have involvement in the work and the company increases the number of employees (Chiu, Zhu, & Corbett, 2021).

According to the innovation diffusion theory, external factors are pivotal in influencing employees' intelligent transformation by shaping their perception, adoption, and integration of new technologies (Novak, 2020). External factors, Enterprise development needs, implementation costs, human resources, and top management involvement create a dynamic environment that necessitates adaptation. These factors act as external pressures or motivators, compelling employees to embrace intelligent transformation to remain competitive and relevant. The advancements in artificial intelligence (AI) and automation technologies provide employees with access to cutting-edge tools that enhance productivity and decision-making (Abrokwah-Larbi, & Awuku-Larbi, 2024). Similarly, competitive pressures from external stakeholders, including customers and industry peers, can stimulate the adoption of intelligent technologies. The dissemination of innovation through external networks, such as professional associations, collaborative partnerships, and technological ecosystems, facilitates employees' exposure to and acceptance of novel tools and practices (Davenport, & Ronanki, 2018). Furthermore, external support systems, including governmental policies, organizational training programs, and access to financial resources, also enhance the capacity of employees to undergo intelligent transformation (Altayyar, & Beaumont-Kerridge, 2016). These external factors reduce uncertainty and increase the perceived usefulness and ease of use of innovative technologies, which are critical determinants of their diffusion and successful integration within the workforce.

Based on the innovation diffusion theory, internal factors shape the organizational readiness and capacity to adopt and integrate intelligent technologies, thereby affecting the rate and success of innovation diffusion (Novak, 2020). SMEs are aiming to enhance operational efficiency, improve decision-making, or gain competitive advantages to create an environment conducive to adopting intelligent technologies (Ghobakhloo, & Ching, 2019). The alignment of these goals with employee roles fosters a sense of purpose and urgency, encouraging employees to adapt and acquire the skills needed for intelligent transformation. The financial resources required to implement intelligent technologies, including procurement, training, and maintenance costs, influence the pace and extent of adoption. High costs may pose a barrier for small and medium-sized enterprises (SMEs), limiting employees' exposure to innovative tools (Ingalagi, Mutkekar, & Kulkarni, 2021). The availability and competence of human resources within an organization are critical to the diffusion of innovation. Employees' existing skills, adaptability, and openness to learning determine how effectively they can transition to intelligent technologies. Top management's commitment and proactive involvement play a central role in fostering a culture of innovation (Ifinedo, 2011). By providing strategic direction, allocating resources, and addressing employee concerns, top management can mitigate resistance and create a supportive environment for intelligent transformation. The internal factors directly influence the organization's capacity to diffuse innovation effectively, shaping employees' attitudes and readiness toward intelligent transformation. Innovation diffusion theory underscores the importance of aligning internal factors with the technological needs and capabilities of employees to achieve successful integration of intelligent systems. Based on these above arguments, the following research hypotheses were developed:

H1: External and internal factors influence on intelligent technology readiness of SMEs

H1a: External factors influence on intelligent technology readiness of SMEs

H1b: Internal factors influence on intelligent technology readiness of SMEs

H2: CSR moderates the relationship between external factors and the intelligent technology readiness of SMEs

H3: CSR moderates the relationship between internal factors and the intelligent technology readiness of SMEs

Methodology

Wang et al., (2022) developed a model related to both internal and external factors and their impacts on intelligent transformation and the role of CSR in intelligent transformation, but not tested. Hence, the quantitative approach is appropriate to this study. To identify the intelligent transformation status in Northern Province, the researcher chose urban places and obtained the data from SMEs. A total of 200 SMEs from various industries, such as construction, food and beverage, hotels, health care, financial institutions, education, insurance, handicrafts, supermarkets, printing and media and textile, participated in this survey. The absence of a comprehensive population framework for the SME sector in the Northern Province necessitated the use of a non-probability convenience sampling technique for this study. This methodological approach was deemed appropriate given the lack of reliable data and structured records of SMEs in the region. The study focuses on the application of intelligent technologies within SMEs. Approximately 90% of SMEs in the region operate at the micro-enterprise level, with limited capacity for technological adoption. Only a minority of small and medium-sized enterprises demonstrate readiness to embrace innovative technologies. This disparity underscores significant barriers to intelligent transformation. Sample size affects the generalizability of the results by the ratio of observations to independent variables. A general rule is that the ratio should never fall below 5:1, meaning that five observations are made for each independent variable in the variate; the desired level is between 15 to 20 observations for each independent variable (Hair, et al., 2013). There are two independent variables and one moderator variable in this research. A total of 143 respondents are valid and it reached the adequate level. The results have validated the generalizability of the results. All these participants had more than three years of experience in their business. Data were collected by using questionnaires. The measures for the model were derived from the Wang et al. (2022). There are four variables developed by Wang et al. (2022), namely, CSR, internal factors, external factors, and intelligent technology readiness of SMEs. The measures for these variables were also explored, but these variables were not tested empirically. The research applied a 5-point Likert scale (strongly agree to strongly disagree). Data were analyzed by using confirmatory factor analysis (CFA) and Structure Equation Modeling (SEM).

Findings

Demographic Profile

The data survey was planned for 200 respondents (SMEs), and the response rate was 71.5% (143 respondents). The profile of the sample is given below (Table 1).

Table 1
Demographic Profile of SMEs

	No. of respondents	**%**
Location of the Organization		
Jaffna	97	68
Mullaitivu	12	8
Killinochchi	4	3
Vavuniya	22	15
Mannar	8	6
Ownership		
Individual	22	15
Family	41	29
Institutional ownership	80	56
Education level of managing directors (owners)		
Ordinary level	7	5
Advanced level	24	17
Diploma	18	13
Graduate	52	36
Postgraduate	32	22
Professional qualifications	10	7
Capital investment of your organization		
Below Rs 5 Million	6	4
Rs 6- 10 Million	23	16
Rs 11 - 50 Million	43	30
Rs 51-100 Million	24	17
Rs 101- 250 Million	32	22
Rs 251- 750 Million	12	8
Over Rs 750 Million	3	2

In this survey, 68% of SMEs are from the Jaffna district, 8% from Mullaitivu, 3% from Killinochchi, 15% from Vavuniya, and 6% from Mannar. Further, 15% of SMEs are sole proprietorships, 29% family business and 56% institutional business. In this survey, 36% of SME managers or owners are graduates, 22% are postgraduates, 17% are advanced level, 13% are diploma level, 7% are professional qualifications and only 5 % are with ordinary level. The capital investment of the selected SMEs is 4% which invested below 5 million, 16% is 6-10 million, 30% is 11-50 million, 17% is 51-100%, 22% is 101- 250 million, 8% is 251-750 million and 2% is over 750 million.

Confirmatory Factor Analysis

CFA was performed initially factor-wise on the independent and dependent variables (Hair et al., 2013). Both measurement estimates and structural estimates were examined for overall model fitness as recommended by Hair et al., (2013).

The Results of the Measurement Model

First-order CFA result

There are three variables, namely, external factors, internal factors, and intelligent technology readiness with eighteen items. Low factor loading (<0.5) of three items from internal factor, namely, capacity expansion, capital cost, and loss of talent were deleted, the balance of fifteen items was high factor loading (Table 2).

Table 2
First Order Measurement Model of CFA

Items		SRW	AVE	CR
External factor			0.734	0.917
Product customization	EX1	.882		
Quality control requirements	EX2	.836		
Reduce labor intensity	EX3	.861		
Lean operation	EX4	.906		
Platform construction	EX5	.859		
Policy guidance	EX6	.717		
Financial subsidies	EX7	.711		
Internal Factor			0.685	0.938
Benefit enhancement	IN1	.824		
Labor cost	IN2	.844		
Quality of employees	IN3	.878		
Top management support	IN4	.880		
Intelligent Technology Readiness			0.674	0.892
Piecework scanned into the systems	ITR1	.790		
The work orders	ITR2	.862		
knowledgeable about the system	ITR3	.799		
Employee’s growth and readiness for the system	ITR4	.830		

The above items of external factor, internal factor, and intelligent technology readiness are above 0.5 of standardized regression weight. AVEs of the external factor, internal factor, and intelligent technology are “0.734, 0.685, and 674” respectively which are above 0.5. The value of construct reliability (CR) of all factors is above 0.70 (table II). These measures ensured the validity of the factors which were adopted in the model. The First-order measurement of the model is given below (Figure I). The standardized regression weight (SRW) of items lies between 0.711 and 0.906 (Table 2).

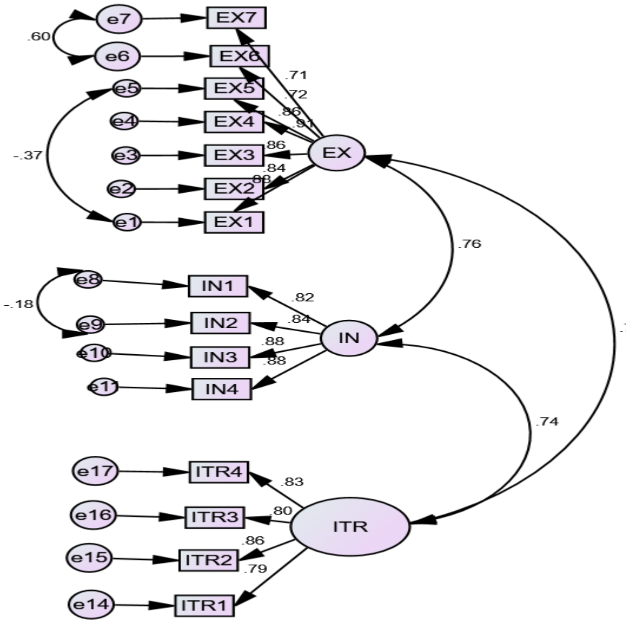

Figure 1: First-order Measurement Model of External and Internal Factors and Intelligent Technology Readiness

Table 3
Discriminant Validity of External and Internal Factors and Intelligent Technology Readiness

	EX	IN	ITR
EX	**.857**		
IN	.760	**.828**	
ITR	.790	.740	**.821**

The discriminant validity for most of the constructs is achieved when a diagonal value, the square root of AVE is higher than the values in its row and column. All the factors have high discriminant validity (Table 3).

Result of the Structural Model and Hypotheses Testing

The CMIN / df, CFI, GFI, RMSEA and NFI values for the external, internal, and intelligent technology readiness of the SME model are 1.432, 0.980, 0.901, 0.055, and 0.9371 respectively, showing high model fit (Table 4).

Table 4
Structural Model Validity of External and Internal Factors and Intelligent Technology Readiness

Name of index	Level of acceptance	Model fit indices
Chi-Square	P-value > 0.05	0.006
RMSEA	RMSEA < 0.08	0.055
GFI	GFI > 0.90	0.901
AGFI	AGFI > 0.90	0.859

CFI	CFI > 0.90	0.980
NFI	NFI > 0.90	0.937
RMR	RMR< 0.08	0.054
Chisq/df	Chi-Square/ df < 5.0	1.432

Result of Hypotheses Testing

The study shows that external factors and internal factors have a significant influence on intelligent technology readiness (SRW= 0.88, P= 0.000). External factor significantly influences intelligent technology readiness (SRW=0.65) and internal factors also affect intelligent technology readiness (SRW=0.37).

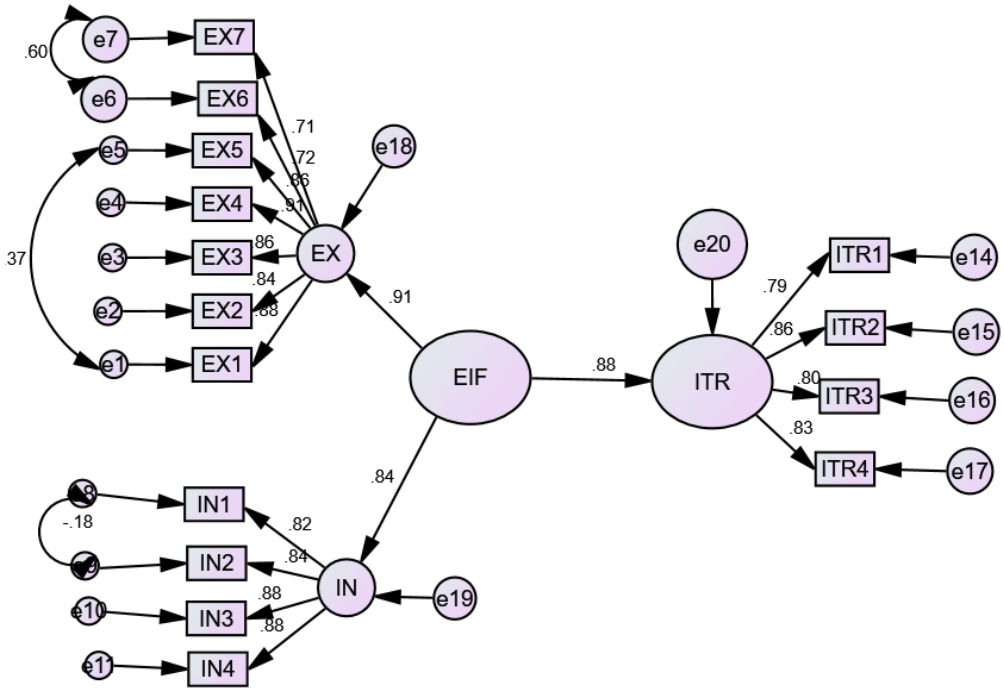

Figure 2: Influence of External and Internal Factor on Intelligent Technology Readiness

CSR moderates the relationship between external factors and intelligent technology readiness

The study examined the moderating role of CSR on the relationship between external factors (TEX) and intelligent technology readiness (TITR). The result revealed a negative significant moderating impact of CSR on the relationship between TEX and TITR (b= -0.142, t= -2.103, p=0.035) supporting H2. The moderating analysis summary is presented in Table V.

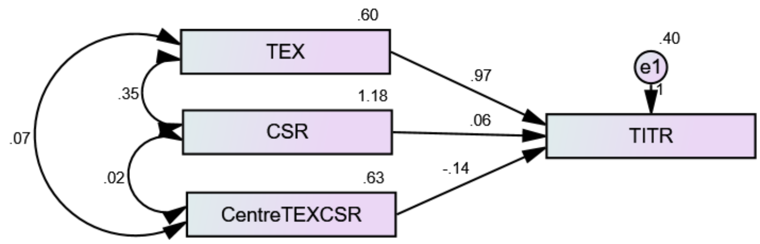

Figure 3: Moderation Analysis of CSR on the Relationship between External Factors and Intelligent Technology Readiness

Relationship	Estimate (Beta)	C.R	P-value
TEX-TITR	.969	12.752	***
CSR-TITR	.057	1.060	.289
TEX*CSR-TITR	-.142	-2.103	.035

Results of a simple slop analysis conducted to better understand the nature of the moderating effects are shown in Figure 4. As can be seen in Figure IV, the line is much sleeper for low CSR, this shows that at the low level of CSR, the impact of TEX on TITR is much stronger in comparison to high CSR. As shown in Figure IV, the level of CSR increased, and the strength of the relationship between TEX and TITR decreased.

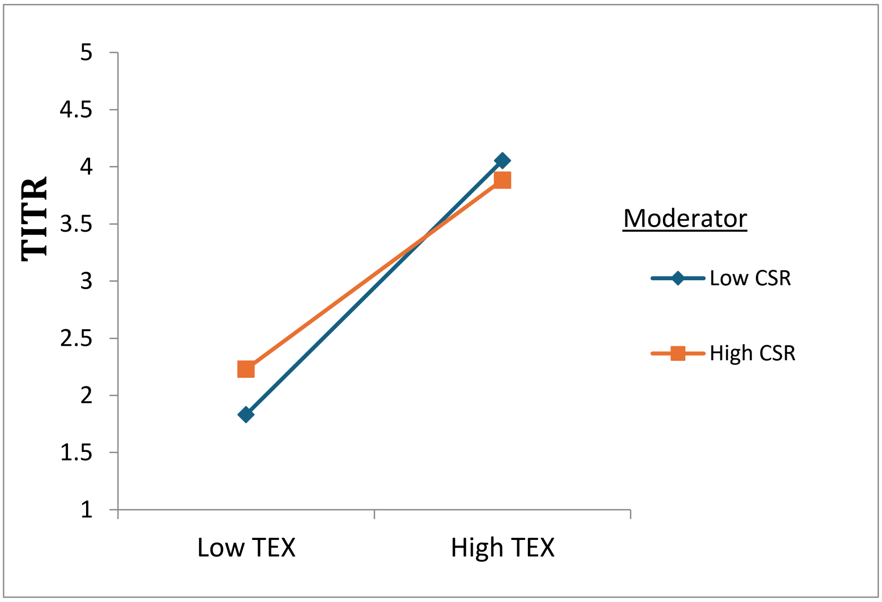

Figure 4: Moderation Analysis of CSR on the Relationship between External Factors and Intelligent Technology Readiness

CSR moderates the relationship between internal factors and intelligent technology readiness

This researcher examines how the interaction between the moderator and independent variable influences the strength of the relationship between the independent variable and the dependent variable. The study assessed the moderating role of CSR on the relationship between internal factors (TIN) and intelligent technology readiness (TITR). The result revealed no impact of CSR on the relationship between TIN and TITR (b= -0.03, t= -0.405, p=0.686), rejecting H3. The moderation analysis summary is presented in Table 6.

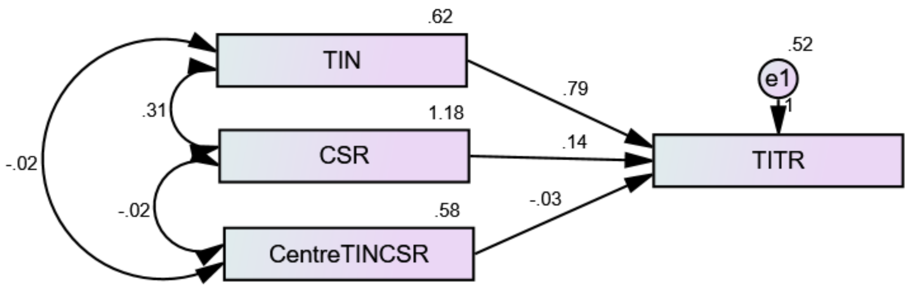

Figure 5: Moderation Analysis of CSR on the Relationship between Internal Factors and Intelligent Technology Readiness

Table 5
Moderation Analysis of CSR on the Relationship between Internal Factors and Intelligent Technology Readiness

Relationship	Estimate (Beta)	C.R	P-value
TIN-TITR	.793	9.598	***
CSR-TITR	.139	2.327	.020
TIN*CSR-TITR	-.032	-.405	.686

Low technological readiness among SMEs, especially at the micro-level, highlights the need for tailored support to enhance their preparedness for intelligent transformation. Practical measures include offering government-policy and financially subsidized technology adoption schemes, providing access to affordable digital tools, and establishing regional innovation hubs that serve as resource centers for SMEs. Such initiatives can bridge the technology gap and create an enabling environment for innovation. Low levels of technological readiness, especially among micro and small enterprises, present significant obstacles to intelligent transformation. SMEs often lack the necessary resources, knowledge, and infrastructure to adopt and integrate advanced technologies. Stakeholders should focus on bridging this readiness gap by providing accessible, low-cost technological solutions, promoting modular technology adoption, and offering tailored training programs that address the specific needs of micro-enterprises in the region.

This study demonstrates that CSR does not moderate the relationship between internal factors and the intelligent technology readiness of SMEs and has a negative moderating effect on the relationship between external factors and the intelligent technology readiness of SMEs. These findings diverge from the theoretical framework proposed by Wang et al. (2022), which emphasizes a positive moderating role of CSR. The results of this study suggest that SMEs face significant resource constraints, limiting their ability to effectively implement CSR activities. In contrast, Çera and Ndou (2024) argue that CSR can serve as a strategic tool for competitive advantage, contributing to the long-term sustainability of SMEs. This discrepancy highlights the context-specific challenges of resource-limited SMEs in aligning CSR activities with technological readiness objectives.

Conclusion and Discussion

The purpose of the research is to find out the impact of internal and external factors on the intelligent technology readiness of SMEs in Northern Province. The finding shows that external factor and internal factors have significant influence on the intelligent technology readiness (0.88) of SMEs (Table VII). Wang et al., (2022) pointed out that both factors profoundly influence intelligent technology readiness. Specifically, external factors push enterprises towards adoption of enterprises and internal factors determine the capacity to integrate and utilize AI technology. Under the diffusion of innovation theory Rogers, Singhal, & Quinlan (2014) and Altayyar & Beaumont-Kerridge, (2016) explained that external factor plays a vital role in the adoption of new technologies. Chen, Li, & Chen (2021) supported that the external factor drives enterprises to adopt intelligent technologies and accelerates the technology readiness of organizations.

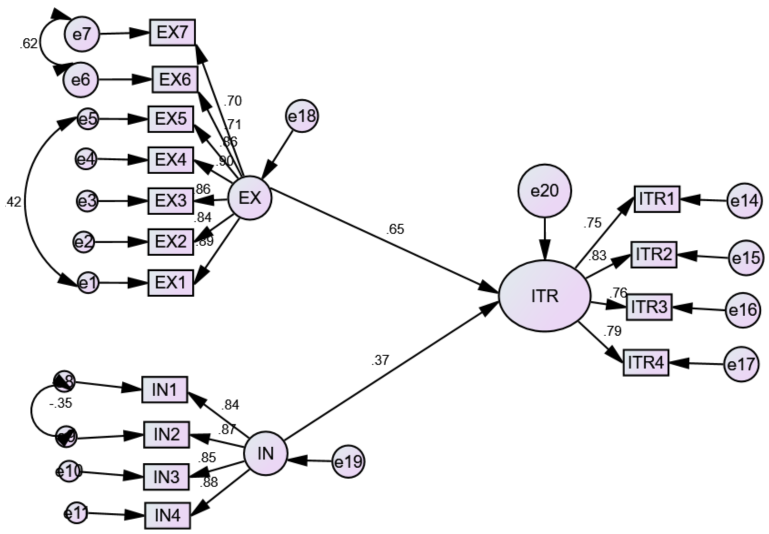

Figure 6: External and Internal Factors and Intelligent Technology Readiness of SMEs

Table 6
Hypothesis Testing

Hypotheses	SRW	Sig.	Conclusion
External and internal factors influence on intelligent technology readiness of SMEs	0.88	0.000	Accepted
External factors influence on intelligent technology readiness of SMEs	0.65	0.000	Accepted
Internal factors influence on intelligent technology readiness of SMEs	0.37	0.000	Accepted
CSR moderates the relationship between external factors and the intelligent technology readiness of SMEs	-0.142	0.035	Accepted
CSR moderates the relationship between internal factors and the intelligent technology readiness of SMEs	-0.032	0.686	Rejected

In particular, the external factor significantly influences intelligent technology readiness is higher than the effect of the internal factor on intelligent technology readiness (0.65) of SMEs (figure VI). The external factors include product customization, quality control requirements, reduced labor intensity, lean operation, platform construction, policy guidance, and financial subsidies. Under external factors, the lean operation which is related to the staff suggestions to streamline the work, is the essential factor. Lins, Zotes, & Caiado (2021) supported that the lean operation with technology adoption creates the greatest value to the customers with the most efficient use of resources. This approach transforms operations with few employees, low capital, few materials, and prompt time. Another important factor under the external factor is product customization which facilitates product to the customer requests standard and quality. Borah (2022) and Pech & Vrchota (2022) mentioned that the unique feature and competitive advantage of the SME sector is customization, and the new AI application makes it possible for customization. Next, external factor is related to optimizing the workflow to labor redundancy and intensity which provide learning opportunities and new ideas. Another factor is platform construction; Harland, Uddin, & Laudien (2020) explained it as providing resource sharing and a common purchase platform. Next, quality control requirements are explained as complex in design and high-quality inspection. The government policy to develop intelligent manufacturing and financial assistances to invest more in businesses. Chwelos et al. (2001) highlighted the influence of regulatory pressures on technology adoption, with regulatory bodies pushing enterprises to upgrade technologies to ensure compliance. Kauffman and Kumar (2008) mentioned that regulatory environments often force firms to adopt intelligent technologies for data-intensive sectors such as healthcare, banking, and government.

Internal factors also significantly influence the intelligent technology readiness (0.37) of SMEs (Figure VI). Internal factors deal with benefit enhancement, labor cost, quality of employees, and top management support. Peretz-Andersson (2024) pointed out that the owners and managers of SMEs need to be interested in implementing AI. The employees need to accept new technology and learn it. AI application facilitates the calculation of labor costs. Improving product quality and efficiency increases the customer value of

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SMEs. Ifinedo (2011) described that the commitment of top management to innovation and technology is one of the most crucial internal factors influencing technology readiness and also mentioned that organizations with a clear strategy vision for technology adoption are ready to implement intelligent technologies.

Intelligent technology readiness is related to employee benefit protection which deals the wages, learning costs, and organizational commitment. IT simply determines the wages of workers based on the piecework (Freeman, 2018). Gkinko & Elbanna (2022) mentioned that when implementing IT, employees' workload will increase and new IT learning creates mental confusion; employees are scared about the system and their job. But later, they are familiar with the IT system. Abrokwah-Larbi & Awuku-Larbi (2024) denoted IT application brings enterprises towards growth and development of institutions.

Another objective of this research is to find out the moderation effect of CSR on the relationship between external factors and intelligent technology readiness. This research proved that CSR moderates negatively the relationship between external factors and the technology readiness of SMEs. The resource allocation required for CSR may reduce the financial and managerial capacity needed to implement new technologies (Jones et al., 2019), reinforcing the negative moderating effect observed in this study. Gadekar, Sarkar & Gadekar (2022) described that considering the external pressures, companies adopt the technologies hastily or reactively, resulting in sustainable and long-term benefits for the companies. Ghobakhloo et al., (2023) explained CSR is an enriching element, it ensures that the adoption of technology readiness is aligned with the external factors.

Another objective of the research is to find out the moderation effect of CSR on the relationship between the internal factor and technology readiness of SMEs. The finding reveals that there is no moderation effect of CSR on the relationship between internal factors and the technology readiness of SMEs. Martinez-Conesa, et al. (2017) mentioned that SMEs consider operational efficiency over CSR-driven technology investments. Dixit & Priya (2023) Mentioned that SMEs have been operating under tight financial and operational constraints; they have limited capacity to engage in extensive CSR activities. The finding that CSR does not moderate the relationship between internal factors and intelligent technology readiness in SMEs provides critical insights into the interplay between organizational resources and CSR initiatives. This result contrasts with theoretical expectations that CSR activities could enhance the effectiveness of internal organizational factors in driving intelligent transformation. SMEs in resource-constrained contexts like Sri Lanka's Northern Province, may prioritize immediate operational needs over strategic CSR initiatives. Given their limited financial and human resources, SMEs often focus on short-term survival and efficiency rather than aligning CSR practices with internal factors to foster technological readiness. This prioritization might reduce the ability of CSR to influence internal factors such as resource allocation, employee training, or leadership involvement in adopting intelligent technologies. Moreover, SMEs in this context may perceive CSR as an external obligation rather than an integral part of their strategic operations. As a result, CSR activities may not sufficiently integrate with internal processes, limiting their impact on intelligent technology readiness. This finding also underscores the unique challenges SMEs face in aligning CSR with technological goals, especially when internal factors are already constrained.

Implication and Future Research Suggestions

The paper addresses a significant gap by empirically testing Wang et al.'s (2022) conceptual model in the SME sector, particularly in a post-conflict, resource-constrained region like Northern Sri Lanka. Highlighting how this research advances existing theories or models (by introducing CSR as a moderator) would emphasize its originality. Previous research focused on developing a conceptual model related to the impact of external and internal factors on the technology readiness of SMEs, this research tested this model and revealed that the external and internal factors have the potential for the technology readiness of SMEs. Under the external factors, lean operation, product customization, reduced labor intensity, platform construction, policy guidance, and financial subsidies are the prominent factors that influence the technology readiness of SMs in Northern Province. This research highlighted that top management support, quality of employees, labor costs, and benefit enhancement are the most important factors in influencing SME technology readiness. These findings encourage SMEs to improve efficiency, productivity, and competitiveness in Northern Province. Policymakers in Northern Province develop or refine policies towards the adoption of intelligent technology. SME owners understand the intelligent technology need and implement internal changes in management practice and upskilling employees and external opportunities to sustain in a competitive and tech-driven market. The intelligent technology application is vital for the economic growth of the region.

This research also proved that CSR moderates negatively the relationship between external factors and the intelligent technology readiness of SMEs. SMEs engaged in CSR need to build relationships with external factors such as policy guidance, financial subsidies, product customization, quality control, lean operation, and platform construction, this offers harder to SMEs. SMEs need to gain grants from the government, strategic alliances, technology partnerships, or community support programs. Otherwise, This CSR cannot create an image and improve the competitiveness of SMEs. This research applied cross-sectional studies; future researchers can apply longitudinal studies to track the SMEs over time to evaluate their intelligent technology readiness. This research focused on intelligent technology readiness broadly, future research could focus on a specific technology such as the Internet of Things (IoT), Artificial intelligence, or data analytics across diverse industries in the SME sector. Future studies could cover the economic conditions and other external macroenvironmental factors that evaluate how resilient SMEs are for digital transformation efforts in global uncertainties.

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