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THE INFLUENCE OF TECHNOLOGICAL, ORGANIZATIONAL, AND ENVIRONMENTAL FACTORS ON ORGANIZATIONAL PERFORMANCE AND COMPETITIVE ADVANTAGE THROUGH SUPPLY CHAIN ANALYTICS ADOPTION AT BONDED ZONE

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ABSTRACT

This study aims to analyze the influence of Product Features, Brand Image, Perceived Price, and Social Influence on Purchase Intention of Samsung smartphones in the Greater Jakarta area. Using a quantitative approach with PLS-SEM analysis, the results show that Product Features, Brand Image, and Social Influence have a positive and significant influence on Purchase Intention, while Perceived Price has no significant influence. These findings emphasize the importance of feature innovation, brand image strengthening, and social influence optimization in increasing consumer purchase intention. In addition, the Importance–Performance results identify several priority indicators for improvement, particularly related to brand image, value for money, and social proof. Overall, this study provides strategic implications for Samsung to improve its marketing effectiveness and product appeal in the Indonesian market.

KEYWORDS: Product Features, Brand Image, Perceived Price, Social Influence, Purchase Intention

1. INTRODUCTION

The acceleration of digitalization in the supply chain has transformed Supply Chain Analytics (SCA) into a strategic imperative for modern organizations. SCA encompasses the application of advanced analytical techniques both descriptive, predictive, and prescriptive supported by artificial intelligence (AI), machine learning, and real-time data streams. Implementing this technology promises improved supply chain visibility, accelerated decision-making, optimized inventory management, and enhanced organizational resilience. However, the success of SCA adoption is determined not only by the technology's potential but also by the organization's internal capabilities and the external pressures it faces (Al-Omoush et al., 2025; Kalaitzi & Tsolakis, 2022).

The Technology Organization Environment (TOE) Framework emphasizes that technology attributes, organizational readiness, and environmental factors collectively determine the rate and outcomes of technology adoption. This model has been validated and expanded in recent studies on supply chain analytics, suggesting the integration of sustainability and external policy aspects into the TOE framework, evolving into Technology, Organization, and Environment Sustainability (TOES) to reflect regulatory pressures and contemporary environmental, social, and governance (ESG) issues (Kalaitzi & Tsolakis, 2022).

From a technological perspective, compatibility is a critical aspect determining the extent to which an analytics system can integrate with existing data infrastructure, such as Enterprise Resource Planning (ERP), Warehouse Management Systems (WMS), and Internet of Things (IoT) devices. Good integration reduces implementation barriers and accelerates adoption. High data integrity and a scalable system architecture are also key prerequisites for reliable predictive models and the expansion of analytics applications across an organization. Without consistent, high-quality data streams, analytics results tend to be distrusted by management and provide limited operational value (S. Lee & Kim, 2023).

On the other hand, data security and privacy issues are critical determinants of SCA adoption because analytics processes often involve the integration of commercially sensitive transaction, inventory, and customer data. Cybersecurity risks, data privacy regulations, and cross-border data transfer requirements can undermine organizational confidence and willingness to implement cloud-based analytics unless adequate risk mitigation and governance are in place. Furthermore, cost is a significant limiting factor, especially for organizations with limited resources. The investment and maintenance costs of analytics platforms, the need for data scientists, and integration expenses are often key constraints affecting the speed and scope of SCA adoption (Satyro et al., 2024).

At the organizational level, organizational readiness, encompassing information technology infrastructure, analytics competency, top management support, data governance, and a data-driven culture, is a key determinant driving SCA adoption. This readiness also determines how technological and environmental pressures translate into concrete investments in supply chain analytics. Organizations that build absorptive capacity, implement training programs, and align analytics initiatives with business strategy tend to be more successful in transforming technology's potential into operational performance improvements. Furthermore, company size also influences adoption rates. Larger companies generally have the financial capacity, more structured processes, and larger data volumes to support analytics implementation. However, smaller companies can overcome resource limitations by leveraging cloud-native solutions or analytics-as-a-service models when the organization is sufficiently prepared (Maroufkhani et al., 2020).

From an external perspective, increasing customer expectations for service speed, personalization, and information transparency create competitive pressure for organizations to adopt SCA as a tool for demand sensing and fulfillment optimization. Support from trading partners and ecosystem readiness, where suppliers, logistics providers, and retailers implement shared data standards and integrated systems, can reduce coordination costs and generate network benefits such as collaborative forecasting and synchronized inventory replenishment. Furthermore, government policies and regulations (including incentives, industry standards, and data protection) can act as either accelerators or inhibitors of adoption, depending on the extent to which they encourage digital innovation or restrict cross-border data exchange (Axsal et al., 2025; Chen et al., 2024).

Organizational and environmental factors often have a more significant influence on adoption rates than technology attributes alone. In other words, superior technology will not have a meaningful impact without the support of organizational readiness and conducive external conditions. When SCA is implemented effectively, it can improve various aspects of organizational performance, such as cost efficiency, improved service quality, faster inventory turnover, and increased market responsiveness. These conditions ultimately contribute to achieving sustainable competitive advantage through superior operational capabilities and data-driven decision-making (Khan et al., 2023).

Furthermore, the benefits of SCA are not only operational but also strategic. Strong analytical capabilities can develop into dynamic capabilities that enable organizations to detect and capitalize on opportunities faster than their competitors. Organizations can also reconfigure supply chain resources in the face of external disruptions and embed continuous learning processes across all supply chain functions. These outcomes will provide a competitive advantage when supported by good governance, strong organizational routines, and effective ecosystem collaboration (Aljohani, 2023).

Organizational readiness can act as a mediator or moderator in the relationship between technological factors and SCA adoption. For example, the level of technological compatibility becomes less significant when a company has high internal integration capabilities. On the other hand, environmental pressures will only accelerate adoption if accompanied by adequate management support and funding. The importance of incorporating sustainability and ESG dimensions into the technology adoption model (TOES) is evident, given the increasing social and policy pressures related to green supply chain sustainability. Supply chain analytics are now used not only for operational efficiency but also for tracking carbon emissions and optimizing circularity, which ultimately impacts organizational performance and stakeholder perceptions of the company's competitive position (Harifuddin et al., 2025; Huang & Mao, 2024).

The purpose of this study is to determine the influence of technological factors, organizational factors, and environmental factors on organizational performance and competitive advantage through supply chain analytics adoption.

2. LITERATURE REVIEW

2.1. Organizational Performance

Organizational performance is a multidimensional construct that measures the extent to which an organization achieves its strategic objectives, both financially and non-financially (Gutterman, 2023). Organizational performance encompasses measurable outcomes such as profitability, return on assets or investment, revenue growth, market share, and efficiency, as well as softer metrics such as customer satisfaction, operational reliability, product or service quality, innovation capacity, and internal process effectiveness (Gutterman, 2023; Indawati et al., 2024). Organizational performance also involves how well a company utilizes its internal human, technological, and financial resources and aligns them with strategic objectives, ensuring adaptability in a dynamic environment (Hanifah et al., 2025; Meria et al., 2025).

Academically, strong organizational performance integrates the achievement of predetermined objectives; efficiency and effectiveness in operations; satisfaction of stakeholder expectations (e.g., customers, shareholders, employees); and operational resilience and adaptability in a changing environment (Augusto et al., 2022).

2.2. Competitive Advantage

Competitive advantage is a set of attributes, resources, capabilities, or strategic positions that enable an organization to create value that is difficult for competitors to imitate, thus enabling the organization to achieve superior performance compared to its competitors (Baia et al., 2020). Competitive advantage arises when an entity can offer its customers perceived benefits, whether through lower costs, differentiated features, better quality, or unique services, compared to alternatives, and maintain this position over time despite competitive pressures (Rozhko & Aloshyn, 2024).

The essence of this concept is the notion of value creation, differentiation, uniqueness, and sustainability: value must exceed costs, differentiating features must be meaningful to customers, competitors must find it difficult to imitate or substitute the source of advantage, and the company must maintain its advantage in the face of changing environmental conditions (Climent & Haftor, 2021).

Competitive advantage is not static but dynamic, as it requires a continuous alignment between internal strengths (such as core competencies, innovation capabilities, intellectual and relational capital) and external demands (market expectations, technological change, and the regulatory environment). Competitive advantage serves as a critical determinant of long-term organizational success, influencing market share, profitability, resilience, and the ability to respond to environmental disruptions (Liu & Zhang, 2024).

2.3. Supply Chain Analytics Adoption

Supply Chain Analytics Adoption is the process by which an organization moves beyond awareness of analytical tools and techniques such as descriptive, predictive, and prescriptive analytics to the routine and integrated use of these tools in its supply chain operations (Oyewole et al., 2024). Adoption encompasses the stages of recognizing the value of analytics, acquiring or developing relevant infrastructure and data pipelines, integrating analytics into decision-making, and achieving assimilation so that analytics become part of routine supply chain planning, execution, and monitoring. This requires not only technology implementation but also organizational commitment, workflow changes, data governance, trust in analytical outputs, and coordination with stakeholders along the supply chain (Kalaitzi & Tsolakis, 2022).

Key prerequisites include reliable data sources, scalable computing resources, security and privacy protections, alignment with organizational strategy, and adequate capabilities in terms of skills and resources (Jha et al., 2020). Adoption also involves continuous learning and adaptation, allowing analytics tools to evolve with changing environmental pressures (e.g., customer demand, external regulations) and internal capabilities. When fully adopted, supply chain analytics delivers improved visibility, responsiveness, and optimization across procurement, inventory, logistics, demand forecasting, and order fulfillment (Bendhi, 2025).

2.4. Technological Factors

Technological factors refer to the intrinsic characteristics of a technology that influence the ease, readiness, and security of its adoption within an organization (Malik et al., 2021). Compatibility describes the extent to which a technology aligns with existing systems, processes, work culture, and technological infrastructure, resulting in smoother integration and minimized operational disruptions (Li, 2024).

Data integrity and scalability refer to the ability of data to remain accurate, consistent, and reliable, and to handle increasing data volume, velocity, and complexity as technology grows and expands, without performance degradation (Salamkar, 2021). Security and privacy issues encompass the risk of security threats such as unauthorized access, data breaches, system intrusions, and concerns about the privacy of individuals and entities whose data is processed; these issues require protection mechanisms, encryption, good data governance, and regulatory compliance (Farayola et al., 2024).

Cost encompasses all costs associated with technology adoption: initial costs (hardware, software, licensing), implementation, and integration. human resource training, and long-term operational and maintenance costs. These four subfactors collectively influence an organization's decision to adopt new technology because they determine the relative weight of benefits compared to technical, financial, and security risk barriers (Hadwer et al., 2021).

2.5. Organisational Factors

Organizational factors encompass internal firm-level attributes that determine the capability and readiness to adopt innovation. Two core organizational factors are organizational readiness and firm size (Kalaitzi & Tsolakis, 2022). Organizational readiness refers to the level of ownership of the necessary resources (financial, technological, and human resources), leadership commitment, a culture conducive to change, and the infrastructure for implementing new technologies. This readiness encompasses not only physical assets (e.g., IT capabilities) but also non-physical aspects such as knowledge, skills, policies, and governance mechanisms that facilitate innovation adoption. "Ready" firms are more likely to transition from experimentation to full implementation, manage risks, and integrate change with minimal disruption (Li, 2024).

Meanwhile, firm size reflects structural scale, often measured by number of employees, revenue, asset base, or market reach, and influences the availability of resources and economies of scale in innovation adoption. Larger firms tend to have more diversified capabilities: they can more easily absorb costs, support specialized staff, and maintain training. Conversely, they may also face structural inertia. Conversely, smaller firms may be more agile but are resource-constrained and may rely on external support (Duc & Nguyen, 2023; Maroufkhani et al., 2020).

2.6. Envionmental Factors

External environmental factors, in the context of supply chain technology and analytics adoption, refer to circumstances and pressures outside the organization that influence adoption decisions and speed. These environmental factors include customer expectations, trading partner support, and policy and regulations (Alaskar et al., 2021). Customer expectations include demands for speed of delivery, process transparency, product personalization, and sustainability and ethics. Modern customers expect organizations to respond in real time, provide status information, and consider environmental and social impacts within the supply chain (Asha et al., 2023).

Trading partner support involves the readiness of suppliers, distributors, and logistics to share data, standardize processes, and synchronize operational activities. This collaboration reduces communication barriers, increases visibility, and enables the integration necessary for effective analytics. Policies and regulations encompass legal norms, industry standards, data protection regulations, environmental regulations, fiscal or non-fiscal incentives, and public policy frameworks that guide how technology and analytics can be used, their limits, and how compliance is ensured (Schmidt et al., 2024). These three subfactors generate external pressures that can accelerate or hinder adoption; organizations that respond proactively to this environment tend to gain a competitive advantage due to their ability to adapt their products and processes to market expectations and regulatory requirements (Su et al., 2023).

3. METHOD

This study employed a quantitative approach. The research strategy employed was an associative approach. The population comprised employees at bonded zone that use the facility of Soekarno-Hatta Customs and Excise Office.. The sampling procedure employed was non-probability sampling, employing purposive sampling, a technique based on specific considerations. The sample size was 100 young executives with a minimum position as supervisor, assistant manager or manager. The data collection technique employed was a questionnaire. The measurement scale used was a Likert scale. The data were processed using SmartPLS SEM (Partial Least Squares - Structural Equation Modeling).

Table 1: Operational Definitions

Variable	Definition	Indicator	Scale
Technological Factors	Technological Factors are factors related to the development and application of technology that can influence business activities, consumer behavior, and decision-making processes in an organization or market.	The use of the Supply Chain Analytics system aligns with the company's work style	Likert 1 - 5
		The use of the Supply Chain Analytics system is fully compatible with current business operations	Likert 1 - 5
		The use of the Supply Chain Analytics system is compatible with the company's culture	Likert 1 - 5
		The Supply Chain Analytics system is compatible with the company's existing hardware and software applications	Likert 1 - 5
		The Supply Chain Analytics system is compatible with the company's existing hardware applications	Likert 1 - 5
		Data quality issues are relevant to my organization when implementing the Supply Chain Analytics system	Likert 1 - 5
		Data interoperability issues are relevant to my organization when implementing the Supply Chain Analytics system	Likert 1 - 5
		The Supply Chain Analytics system is supported by data integration	Likert 1 - 5
		Customer data needs to be integrated into the Supply Chain Analytics system	Likert 1 - 5
		My organization is concerned about data security in the Supply Chain Analytics system	Likert 1 - 5
		My organization is concerned about the security of customer data in the Supply Chain Analytics system	Likert 1 - 5
		Organization I implement procedures to protect information shared within the Supply Chain Analytics system, for example, from modification or disclosure.	Likert 1 - 5
		The investment in adopting a Supply Chain Analytics system far outweighs the benefits.	Likert 1 - 5
		The cost of maintaining and supporting the Supply Chain Analytics system is substantial.	Likert 1 - 5
		The amount of money and time required to train employees to use the Supply Chain Analytics system is also substantial.	Likert 1 - 5
Organisational Factors	Organizational factors are internal factors within an organization that influence how the organization operates, makes decisions, and achieves its goals.	My company has sufficient human resource capabilities and capacity to use the Supply Chain Analytics system to support its operations.	Likert 1 - 5
		My company has no difficulty accessing all the necessary resources (e.g., funding, human resources, time) to adopt Supply Chain Analytics technology.	Likert 1 - 5
		My company's employees have sufficient knowledge and skills regarding the Supply Chain Analytics system.	Likert 1 - 5
		My company supports ongoing training programs for personnel related to the Supply Chain Analytics system.	Likert 1 - 5
		Company management considers the Supply Chain Analytics system important and supports its use.	Likert 1 - 5
		Management is willing to communicate with staff during the Supply Chain Analytics system implementation process.	Likert 1 - 5
		Management is willing to participate in the Supply Chain Analytics system implementation process.	Likert 1 - 5
		My company's capitalization is high compared to the industry at large.	Likert 1 - 5
		My company's annual revenue is high compared to the industry at large.	Likert 1 - 5
		My company has a high number of employees compared to the industry at large.	Likert 1 - 5

Envionmental Factors	Environmental factors are external factors that originate from the surrounding environment and can influence the operations, strategy, and sustainability of an organization or consumer behavior.	A business partner recommends that our company adopt a supply chain analytics system.	Likert 1 - 5
		My company's customers require the use of an SCA system to conduct business with them.	Likert 1 - 5
		My company's relationship with customers will suffer if we don't adopt an SCA system.	Likert 1 - 5
		My company's customers may perceive it as a loss if we don't implement an SCA system.	Likert 1 - 5
		Third-party service providers provide technical support for the effective use of the SCA system.	Likert 1 - 5
		There are institutions that provide training on the SCA system.	Likert 1 - 5
		Technology vendors offer incentives for adoption, but they don't guarantee compatibility or interoperability of the IT infrastructure.	Likert 1 - 5
		Technology vendors offer free training sessions but without comprehensive guidance on how to implement the SCA system.	Likert 1 - 5
		Legal protections exist for the use of the SCA system, but the company struggles to comply with policies and regulations due to the large amount of unstructured data.	Likert 1 - 5
		Legal regulations are sufficient to ensure the use of the SCA system.	Likert 1 - 5
		Financial incentives are provided to encourage the adoption of the SCA system.	Likert 1 - 5
Supply Chain Analytics Adoption	Supply Chain Analytics Adoption is the process of implementing data-driven analytics across all supply chain activities to improve efficiency, visibility, and strategic decision-making within an organization.	My company is currently evaluating the use of a supply chain analytics system.	Likert 1 - 5
		My company has evaluated the implementation of a supply chain analytics system.	Likert 1 - 5
		My company has planned to implement a supply chain analytics system.	Likert 1 - 5
		My company has adopted a supply chain analytics system.	Likert 1 - 5
Organisational Performance	Organizational Performance is a measure of the extent to which an organization succeeds in achieving its stated goals, both in financial and non-financial aspects.	Implementing a supply chain analytics system improves on-time product delivery.	Likert 1 - 5
		Implementing a supply chain analytics system improves the efficiency of internal processes (e.g., inventory control, overtime production).	Likert 1 - 5
		Implementing a supply chain analytics system improves the efficiency of external processes (e.g., waste mitigation).	Likert 1 - 5
		Implementing a supply chain analytics system streamlines work processes.	Likert 1 - 5
		Implementing a supply chain analytics system shortens task handling time.	Likert 1 - 5
Competitive Advantage	Competitive Advantage is a competitive advantage that an organization has over its competitors, which enables the company to create greater value for customers and maintain a superior position in the market in the long term.	Implementing a supply chain analytics system differentiates the company from its competitors (e.g., innovation, sustainability).	Likert 1 - 5
		Implementing a supply chain analytics system strengthens buyer-supplier relationships.	Likert 1 - 5
		Implementing a supply chain analytics system improves information sharing, thereby increasing transparency and resilience.	Likert 1 - 5
		Implementing a supply chain analytics system helps our company introduce new products to market quickly.	Likert 1 - 5
		Implementing a supply chain analytics system increases flexibility, namely the ability to adapt effectively to change, such as unexpected events.	Likert 1 - 5

4. RESULTS

The sample size used in this study was 178 respondents, namely young executives with a minimum position as supervisor, assistant manager or manager at employees at bonded zone that use the facility of Soekarno-Hatta Customs and Excise Office. Testing was conducted using SmartPLS version 4.01. In SmartPLS testing, there are two models: an outer model and an inner model. The outer model consisted of two measurements: a reliability test and a validity test.

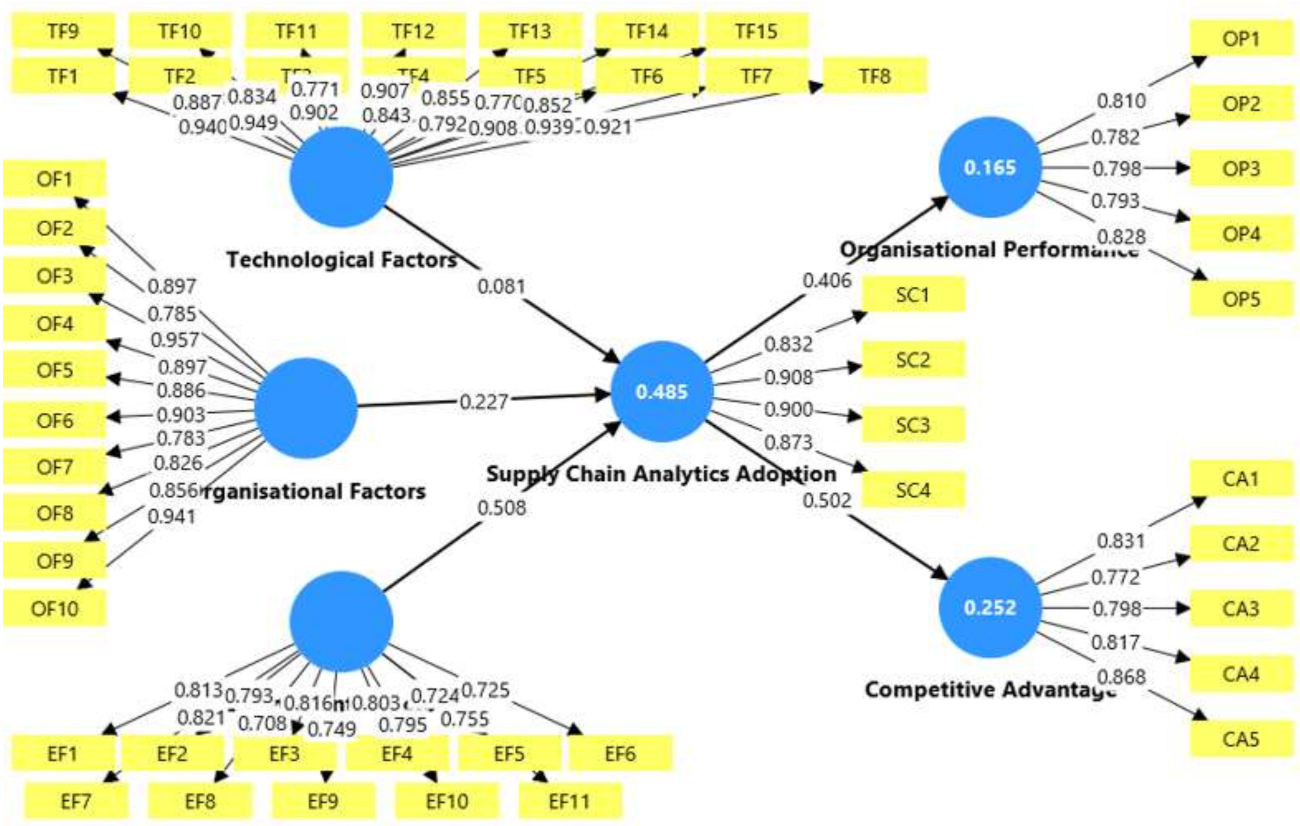

Figure 1: Outer Model

Source: *SmartPLS Data Processing Results version 4 (2025)*

4.1. Validity Test

The convergent validity test is obtained through the correspondence between the indicator values and the construct values (latent variables). To analyze the convergent validity value, the correlation value (loading factor) can be used. According to D. Lee (2019), a correlation can be said to meet convergent validity if it has a correlation value of ≥ 0.7. The output shows that the correlation value (loading factor) provides a value above the recommended value of 0.7, so the indicators used in this study have met convergent validity. However, in the initial research stage of the measurement scale development study, correlation values ≥ 0.7 are still acceptable. The results of the outer loading test in this study can be seen in Table 2 below:

Table 2: Indicator Validity Test Results (Outer Loading Values)

Variables	Code	*Outer Loading*	Status
Competitive Advantage	CA1	0,831	Valid
	CA2	0,772	Valid
	CA3	0,798	Valid
	CA4	0,817	Valid
	CA5	0,868	Valid
Envionmental Factors	EF1	0,813	Valid
	EF2	0,793	Valid
	EF3	0,816	Valid
	EF4	0,803	Valid
	EF5	0,724	Valid
	EF6	0,725	Valid
	EF7	0,821	Valid
	EF8	0,708	Valid
	EF9	0,749	Valid
	EF10	0,795	Valid
	EF11	0,755	Valid
Organisational Factors	OF1	0,897	Valid

	OF2	0,785	Valid
	OF3	0,957	Valid
	OF4	0,897	Valid
	OF5	0,886	Valid
	OF6	0,903	Valid
	OF7	0,783	Valid
	OF8	0,826	Valid
	OF9	0,856	Valid
	OF10	0,941	Valid
Organisational Performance	OP1	0,810	Valid
	OP2	0,782	Valid
	OP3	0,798	Valid
	OP4	0,793	Valid
	OP5	0,828	Valid
Supply Chain Analytics Adoption	SC1	0,832	Valid
	SC2	0,908	Valid
	SC3	0,900	Valid
	SC4	0,873	Valid
Envionmental Factors	TF1	0,940	Valid
	TF2	0,949	Valid
	TF3	0,902	Valid
	TF4	0,843	Valid
	TF5	0,792	Valid
	TF6	0,908	Valid
	TF7	0,939	Valid
	TF8	0,921	Valid
	TF9	0,887	Valid
	TF10	0,834	Valid
	TF11	0,771	Valid
	TF12	0,907	Valid
	TF13	0,855	Valid
	TF14	0,770	Valid
	TF15	0,852	Valid

Source: SmartPLS Processing Results (2025)

Based on Table 2, the results of the outer loading test indicate that all indicators in this study are valid because they have outer loading values greater than 0.7. The next validity measure is the average variance extracted (AVE). The average variance extracted (AVE) test indicates that each construct has the same correlation with other constructs in the model, indicating good discriminant validity. An AVE value of 0.5 or higher indicates that, on average, the construct explains more than half of the variance in its indicators. Conversely, an AVE value of less than 0.5 indicates that, on average, more variance remains in the error side of the items than in the variance explained by the construct. Therefore, the AVE value should reach or exceed 0.5 for optimal Convergent Validity at the construct level (Hair et al., 2022). The results of the Average Variance Extracted (AVE) test in this study can be seen in the table below:

Table 3: Convergent Validity Test Results (AVE Values)

Variable	AVE	Status
Competitive Advantage	0,669	Valid
Envionmental Factors	0,599	Valid
Organisational Factors	0,766	Valid
Organisational Performance	0,644	Valid
Supply Chain Analytics Adoption	0,772	Valid
Technological Factors	0,763	Valid

Source: SmartPLS Processing Results (2025)

Based on Table 3, it is known that all variables in this study can be considered valid because they have an AVE value > 0.5. The next test is discriminant validity. Discriminant validity is intended to assess the extent to which two variables are significantly different from each other. Discriminant validity is considered met when the correlation between a variable and itself is better than the correlation between the variables with other variables. Discriminant validity can also be determined using the HTMT (Heterotrait-Monotrait Ratio) value. If the HTMT value is below 0.9, it can be interpreted as having a good level of discriminant validity (Hair et al., 2022).

Table 4: Heterotrait–Monotrait (HTMT) Ratio Assessment

Variable	Competitive Advantage	Envionmental Factors	Organisational Factors	Organisational Performance	Supply Chain Analytics Adoption	Technological Factors
Competitive Advantage						
Envionmental Factors	0,620					
Organisational Factors	0,582	0,593				
Organisational Performance	0,825	0,463	0,639			
Supply Chain Analytics Adoption	0,557	0,721	0,566	0,430		
Technological Factors	0,288	0,371	0,211	0,332	0,310	

Source: SmartPLS Processing Results (2025)

Based on table 4, it is known that the results of the HTMT test show that the HTMT correlation value of each research variable is not above 0.9, so it can be said that the research model formed from the four variables above is valid.

4.2. Reliability Testing

Reliability testing is conducted using two metrics: Cronbach's alpha and composite reliability. Cronbach's alpha serves as an indicator to evaluate the extent to which items in a set of variables correlate with each other, indicating the internal consistency or reliability of a measuring instrument such as a survey or questionnaire. For a measurement instrument to be considered reliable, Cronbach's alpha must have a value above 0.7.

Table 5: Reliability Test Results

Variable	*Cronbach's Alpha*	*Composite Reliability*	Status
Competitive Advantage	0,876	0,910	Reliable
Envionmental Factors	0,933	0,943	Reliable
Organisational Factors	0,965	0,970	Reliable
Organisational Performance	0,864	0,900	Reliable
Supply Chain Analytics Adoption	0,901	0,931	Reliable
Technological Factors	0,978	0,980	Reliable

Source: SmartPLS Processing Results (2025)

Based on Table 5, the reliability test results show that each variable has a Cronbach's Alpha and Composite Reliability value >0.7, indicating that all variables in this study can be considered reliable.

The next test is multicollinearity analysis to ensure that the construct being measured differs significantly from other constructs. In the PLS-SEM method, multicollinearity testing uses the Variance Inflation Factor (VIF) metric. The expected VIF value is <5.

Table 6: Multicollinearity Analysis Results

Variable	Competitive Advantage	Envionmental Factors	Organisational Factors	Organisational Performance	Supply Chain Analytics Adoption	Technological Factors
Competitive Advantage						
Envionmental Factors					1,627	
Organisational Factors					1,477	
Organisational Performance						
Supply Chain Analytics Adoption	1,000			1,000		
Technological Factors					1,155	

Source: SmartPLS Processing Results (2025)

Based on Table 6, it is known that there is no multicollinearity in this study because each variable in this study has a VIF value <5.

4.3. Structural Model Test Results (Inner Model)

The model structure testing in this study was conducted using the coefficient of determination and hypothesis testing. The coefficient of determination is used to measure the extent to which endogenous variables are influenced by other variables. An R-square result of 0.67 or above for endogenous latent variables in the structural model indicates a good influence of the exogenous (influencing) variable on the endogenous (influenced) variable. A result of 0.33–0.67 is considered moderate, and a result of 0.19–0.33 is considered weak.

Table 7: Coefficient of Determination (R^2) Analysis Results

Variable	Determination Coefficient
Competitive Advantage	0,252
Organisational Performance	0,165
Supply Chain Analytics Adoption	0,485

Source: SmartPLS Processing Results (2025)

Based on Table 7, the coefficient of determination for the Competitive Advantage variable is 0.252, meaning that 25.2% of the Competitive Advantage variable can be explained by the Supply Chain Analytics Adoption variable, with the remaining 74.8% explained by other variables not included in the research model. For the Organizational Performance variable, the coefficient of determination is 0.165, meaning that 16.5% of the Organizational Performance variable can be explained by the Supply Chain Analytics Adoption variable, with the remaining 83.5% explained by other variables not included in the research model. Furthermore, the Supply Chain Analytics Adoption variable has a coefficient of determination of 0.485, meaning that 48.5% of the Supply Chain Analytics Adoption variable can be explained by the Technological Factors, Organizational Factors, and Environmental Factors, with the remaining 51.5% explained by other variables not included in the research model. The next test is the hypothesis test:

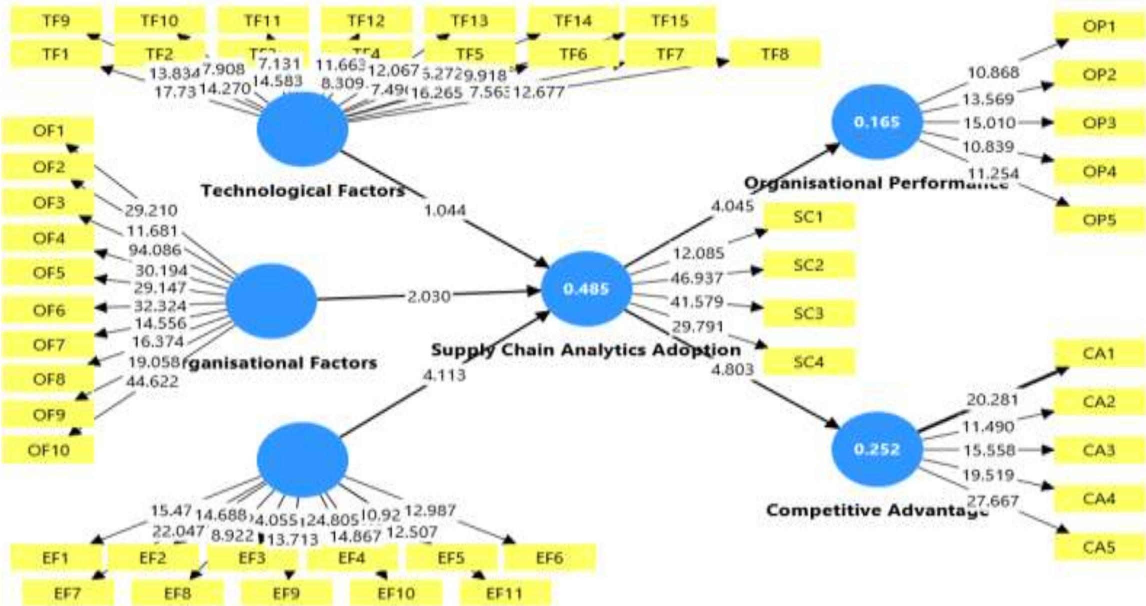

Figure 2: Inner Model
Source: *SmartPLS Processing Results (2025)*

Table 8: Path Coefficient Test Results

Model	*Original Sample*	t-statistics	*P-Values*	Status
H1: Environmental Factors Influence Supply Chain Analytics Adoption	0,508	4,113	0,000	Accepted
H2: Organizational Factors Influence Supply Chain Analytics Adoption	0,227	2,030	0,021	Accepted
H3: Supply Chain Analytics Adoption Influences Competitive Advantage	0,502	4,803	0,000	Accepted
H4: Supply Chain Analytics Adoption Influences Organizational Performance	0,406	4,045	0,000	Accepted
H5: Technological Factors Influence Supply Chain Analytics Adoption	0,081	2,044	0,014	Accepted
H6: Supply Chain Analytics Adoption Mediates the Effect of Organizational Factors on Organizational Performance	0,092	2,460	0,002	Accepted
H7: Supply Chain Analytics Adoption Mediates the Effect of Technological Factors on Competitive Advantage	0,041	2,889	0,018	Accepted
H8: Supply Chain Analytics Adoption Mediates the Effect of Technological Factors on Organizational Performance	0,033	2,833	0,003	Accepted
H9: Supply Chain Analytics Adoption Mediates the Effect of Environmental Factors on Competitive Advantage	0,255	3,413	0,000	Accepted
H10: Supply Chain Analytics Adoption Mediates the Effect of Organizational Factors on Competitive Advantage	0,114	1,657	0,049	Accepted
H11: Supply Chain Analytics Adoption Mediates the Effect of Environmental Factors on Organizational Performance	0,206	3,563	0,000	Accepted

Source: SmartPLS Processing Results (2025)

This research hypothesis was tested using PLS-SEM using the bootstrapping method. The results obtained from bootstrapping included t-statistics, p-values, and the original sample. These results were then compared with existing regulations to determine whether the hypothesis was rejected.

Hypothesis 1: Environmental Factors influence Supply Chain Analytics Adoption, with a path coefficient of 0.508, a t-statistic of 4.113, and a p-value of 0.000. Therefore, it can be concluded that H1 is accepted.

Hypothesis 2: Organizational Factors influence Supply Chain Analytics Adoption, with a path coefficient of 0.227, a t-statistic of 2.030, and a p-value of 0.021. Therefore, it can be concluded that H2 is accepted.

Hypothesis 3: Supply Chain Analytics Adoption influences Competitive Advantage with a path coefficient of 0.502, a t-statistic of 4.803, and a p-value of 0.000. Therefore, it can be concluded that H3 is accepted.

Hypothesis 4: Supply Chain Analytics Adoption influences Organizational Performance with a path coefficient of 0.406, a t-statistic of 4.045, and a p-value of 0.000. Therefore, it can be concluded that H4 is accepted.

Hypothesis 5: Technological Factors influence Supply Chain Analytics Adoption with a path coefficient of 0.081, a t-statistic of 2.044, and a p-value of 0.014. Therefore, it can be concluded that H5 is accepted.

Hypothesis 6: Supply Chain Analytics Adoption mediates the effect of Organizational Factors on Organizational Performance with a path coefficient of 0.092, a t-statistic of 2.460, and a p-value of 0.002. Therefore, it can be concluded that H6 is accepted.

Hypothesis 7: Supply Chain Analytics Adoption mediates the effect of Technological Factors on Competitive Advantage with a path coefficient of 0.041, a t-statistic of 2.889, and a p-value of 0.018. Therefore, it can be concluded that H7 is accepted.

Hypothesis 8: Supply Chain Analytics Adoption mediates the effect of Technological Factors on Organizational Performance with a path coefficient of 0.033, a t-statistic of 2.833, and a p-value of 0.003. Therefore, it can be concluded that H8 is accepted.

Hypothesis 9: Supply Chain Analytics Adoption mediates the effect of Environmental Factors on Competitive Advantage with a path coefficient of 0.255, a t-statistic of 3.413, and a p-value of 0.000. Therefore, it can be concluded that H9 is accepted.

Hypothesis 10: Supply Chain Analytics Adoption mediates the effect of Organizational Factors on Competitive Advantage with a path coefficient of 0.114, a t-statistic of 1.657, and a p-value of 0.049. Therefore, it can be concluded that H10 is accepted.

Hypothesis 11: Supply Chain Analytics Adoption mediates the effect of Environmental Factors on Organizational Performance with a path coefficient of 0.206, a t-statistic of 3.563, and a p-value of 0.000. Therefore, it can be concluded that H11 is accepted.

5. DISCUSSION

The results of the study indicate that environmental, organizational, and technological factors significantly influence the adoption of supply chain analytics within the employees at bonded zone that use the facility of Soekarno-Hatta Customs and Excise Office. Environmental factors have the strongest influence on adoption, with a path coefficient of 0.508 and a p-value of 0.000, indicating that external conditions such as government regulations, market dynamics, and compliance pressures are the primary drivers of supply chain analytics adoption. This finding aligns with Su et al. (2023), who stated that external pressures and the need to reduce inflammation drive companies and public agencies to adopt analytical technology in the supply chain.

Organizational factors also proved significant, with a coefficient of 0.227 and a p-value of 0.021, indicating that internal capabilities, top management support, and human resource readiness play a critical role in successful adoption. This aligns with Kalaitzi & Tsolakis (2022), which showed that organizational readiness and a culture of innovation are dominant predictors of digital transformation, including the implementation of analytics in supply chain management systems.

Technology factors also influence adoption, with a coefficient of 0.081 and a p-value of 0.014. Although the effect is relatively small compared to environmental and organizational factors, these results emphasize the importance of technology readiness, system compatibility, and perceived technology benefits in driving the adoption of supply chain analytics. S. Lee & Kim (2023) support these findings by stating that the adoption of technological innovation in the logistics sector is highly dependent on technological compatibility and IT infrastructure readiness.

Supply Chain Analytics adoption was shown to have a positive effect on competitive advantage (coefficient of 0.502) and organizational performance (coefficient of 0.406). This confirms that the use of analytics in the supply chain can improve decision-making accuracy, operational efficiency, and responsiveness to changes in demand, which in turn strengthens competitive advantage and organizational performance. Khan et al. (2023)

showed that integrating analytics into the supply chain improves error reduction and process optimization, contributing to better performance outcomes.

Furthermore, analytics adoption mediated the effects of organizational, technological, and environmental factors on competitive advantage and organizational performance. This significant mediation confirms that TOE factors cannot directly improve performance without the implementation of analytics technology as a connecting mechanism. This aligns with the arguments of Satyro et al. (2024), who contend that technological, organizational, and environmental drivers influence organizational outcomes primarily through the effective adoption of digital solutions within the Technology–Organization–Environment–Sustainability (TOES) framework. It also corresponds to Al-Omoush et al. (2025), who showed that institutional pressures only translate into improved innovation capability when firms effectively adopt and integrate supply chain analytics.

Overall, this study reinforces recent literature showing that supply chain analytics adoption is a strategic capability that mediates the influence of TOE factors on competitive advantage and organizational performance, in both the public and private sectors. These findings provide empirical evidence that the implementation of analytics in supply chain management is not simply a technological innovation but also a critical mechanism for translating internal and external conditions into tangible performance outcomes.

6. CONCLUSION

This study demonstrates that environmental, organizational, and technological factors significantly influence the adoption of Supply Chain Analytics at employees at bonded zone that use the facility of Soekarno-Hatta Customs and Excise Office. This analytics adoption then positively impacts competitive advantage and organizational performance, and mediates the relationship between TOE factors and organizational outcomes. Thus, the implementation of supply chain analytics not only strengthens internal capabilities but also bridges external and technological influences to achieve optimal performance outcomes.

Theoretically, this study strengthens the literature on the TOE framework, digital supply chain, and the mediating role of analytics adoption in the context of public organizations. Practically, Customs and Excise Office management is recommended to improve organizational readiness, strengthen management support, and facilitate the adoption of analytics technology to optimize competitive advantage and performance. Furthermore, policymakers need to consider regulations that support supply chain digitalization to improve operational efficiency and responsiveness.

Limitations of this study include the relatively small sample size (100 young executives) and the focus on only one government agency. This limits the generalizability of the results to other agencies or the private sector. Furthermore, the study used a cross-sectional design, thus failing to capture the dynamics of analytics adoption over time. Future research is recommended to use a broader sample, including various types of institutions, and to consider a longitudinal design to assess the long-term impact of analytics technology adoption.

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