PLS-SEM-Based Empirical Modeling of AI Usability Impacts in Supply Chain Optimization

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In an era of evolving market dynamics, Supply Chains (SC) face pandemic disruptions, geopolitical conflicts, and natural disasters. This investigates how Artificial Intelligence (AI) enhances Supply Chain Management (SCM) through efficiency improvement and optimization using empirical analysis. Data were collected from 534 firms using structured surveys, and statistical analyses were conducted using SPSS and Partial Least Squares Structural Equation Modeling (PLS-SEM) to validate constructs, and mediation effects. Reliability and validity tests providing robust insights into AI-driven performance. The framework examines how AI adoption is influenced by environmental uncertainty, supply chain cooperation, and perceived technological benefits, and how this adoption enhances optimization, efficiency, resilience, and overall performance. Results indicate that Environmental Uncertainty (EU) significantly impacts AI System Usability (ASU) ($\beta = 0.74$, $t = 12.36$, $p < 0.001$). ASU positively influences Cost Reduction (CR) ($\beta = 0.68$, $t = 11.10$, $p < 0.001$), Delivery Reliability (DR) ($\beta = 0.63$, $t = 9.85$, $p < 0.001$), and Demand Variability management (DV) ($\beta = 0.59$, $t = 8.92$, $p < 0.001$). Furthermore, ASU mediates the EU–CR relationship ($\beta = 0.41$, $t = 6.33$, $p < 0.001$). CR strongly contributes to Supply Chain Efficiency (SCE) ($\beta = 0.55$, $t = 7.20$) and Supply Chain Resilience (SCR) ($\beta = 0.52$, $t = 6.80$), while DR and DV significantly enhance Supply Chain Performance (SCP) ($\beta = 0.60$, $t = 8.10$; $\beta = 0.58$, $t = 7.50$). Overall, the findings highlight AI's capability in improving forecasting and logistics coordination, thereby strengthening resilience and promoting sustainable SCP.

Povzetek: Empirična študija na 534 podjetjih z uporabo PLS-SEM pokaže, da negotovost okolja spodbuja uporabnost AI sistemov, ta pa prek znižanja stroškov, zanesljivejših dobav in boljšega obvladovanja nihanj povpraševanja izboljša učinkovitost, odpornost in skupno uspešnost oskrbovalnih verig.

1 Introduction

Technological innovation is becoming better applied, and Artificial Intelligence (AI) is improving responsiveness, flexibility, and decision-making across industries [1]. The competitive map is gradually becoming more biased toward organizations that successfully implement AI to streamline Supply Chains (SC). Organizations that can structure intelligent systems gain greater visibility into inefficiencies, growth opportunities, and services more rapidly, reliably and cost-effectively than utilizing conventional methods [2]. The need to adopt innovative SC solutions has been driven by uncertainty in the environment due to various elements like global trade wars, climate change and variations in consumer preference. Organizations are applying AI to achieve agility in their operations, allocate resources appropriately, and leverage participant collaboration with greater efficiency and flexibility in a volatile business environment [3]. The AI applicability in SCM has turned into necessity rather than a competitive advantage. Such tools assist the analysts to have a better understanding of performance, make faster decisions and enhance the accuracy of forecasts, which ultimately reduces the cost and increases level of services across value chain [4]. The capability to foresee threats and adapt swiftly in response to emerging circumstances and market trends provides a strategic advantage [5]. AI also positively influences the SC to perform effectively under uncertainty by enabling the accurate prediction of demand, better inventory management, and optimization of routes in response to unpredictable conditions to achieve higher purchasing satisfaction and competitiveness in the market [6]. The modification of AI to SCM is explained by its ability to integrate speed, scale, and precision. This integration allows organizations to react more quickly to change, identify new paths to grow, and achieve operational perfection in the evolving and competitive global market

[7]. AI helps organizations to create effective and sustainable SC that enhance expansion in rapidly changing settings. It also delivers predictive information to improve overall SCP [8]. AI-based systems distribute the level of analytical detail and speed of response required to manage such conditions, all while remaining stable and efficient [9]. Through predicting shifts and simulating potential outcomes, organizations improve understanding and generate a more synchronized connection and transparency around the mitigation of goods and services [10].

1.1 Problem statement

Earlier research often lacked large-scale empirical validation and focused narrowly on either efficiency or resilience, without integrating both dimensions. Many researches has shown unnoticed contextual variables, such as environmental uncertainty and cooperation, shape AI adoption results. This research aims to explore how Environmental Uncertainty (EU) influences AI System Usability (ASU) and, in turn, how ASU impacts Cost Reduction (CR), Delivery Reliability (DR), and Demand Variability (DV) to enhance Supply Chain Efficiency (SCE), Resilience (SCR), and overall Supply Chain Performance (SCP), using empirical data from 534 firms analyzed through SPSS and PLS-SEM.

1.2 Key contribution

- ❖ Research created an integrated framework connecting contextual drivers' relative advantage, collaboration, and environmental uncertainty with AI adoption in SC.
- ❖ Empirical analysis uses survey data composed of 534 firms across diverse industries, allowing statistically strong evaluation.
- ❖ AI's contribution to improving logistics coordination, inventory control, and forecasting accuracy might be measured to provide clear influences on efficacy and optimization.
- ❖ Dependability and rationality of the constructs are measured, while EFA, correlation analysis, and PLS-SEM are used to test the model.
- ❖ Results provide actionable guidance for organizations to strengthen flexibility and accomplish sustainable performance in volatile market environments.

1.3 Research questions

How does EU influence the AI adoption and usability in SCM? To what extent does ASU mediate the connection between EU and key SCP outcomes such as CR, DR, and DV? What is AI adoption impact on SC optimization, operational efficacy, and resilience under varying levels of external market uncertainty? How can AI-enabled SC collaboration enhance forecasting accuracy, inventory management, and logistics coordination to improve overall performance and sustainability?

1.4 Paper organization

The paper is organized as Section 1 introduces, while Section 2 examines pertinent research on AI applications in SC optimization. Section 3 explains the conceptual framework and hypothesized relationships, AI adoption, and SC outcomes. Section 4 details the empirical analysis, including reliability and validity testing, correlation analysis, and PLS-SEM modeling. Section 5 and 6 discuss the results, interpreting the findings in light of theory and practice. Section 7 provides the conclusion, emphasizing key contributions, and future research.

2 Related works

The investigators examined how suppliers were affected by the commitment of buying firms towards environmental management initiatives through a contingent causal process framework by Qiao et al. [11]. The data for survey were attained from 237 Chinese suppliers and were analyzed by regression analysis using bootstrapping. The results showed that environmental collaboration has a greater influence on improving the environmental commitment of the suppliers as compared to environmental assessment. Limitations include the focus on Chinese suppliers, which restricted the generalizability of the discoveries to other countries. The investigation examined the determinants influencing firms' readiness to implement AI in SC, guided by the specified framework by Wang & Pan [12]. Data from the survey of 318 Chinese firms were evaluated using PLS-SEM. The overall results indicated that SC cooperation, and relative advantages of AI have the greatest effects on AI adoption. Limitations include focusing primarily on Chinese firms and cultural or regional restrictions to generalizability. Table 1 provides the related works summary.

Table 1: Related works on AI in SC and sustainability

Ref	Dataset	Purpose	Suggested Model	Result	Limitation
Wong et al. [13]	Survey data from Small and Medium Enterprises (SME) executives	Examine how AI improves SCM risk management and agility	PLS-SEM and ANN	Re-engineering mediates the risk-agility link, while AI improves risk management capacities by enhancing SC re-engineering and agility.	Focused only on SMEs; limits generalizability to other industries and company sizes.
Hasan et al. [14]	Historical emission factor data	Predict high-emission areas for targeted sustainability interventions	Random Forest	AI accurately identifies emission hotspots for effective carbon footprint reduction interventions.	Based on data, limits worldwide applicability
Olan et al. [15]	Literature-based conceptual framework for the Food and Drink Industry (FDI)	Explore AI applications in financing mechanisms in complex SCM networks	Meta-framework developed from theoretical contributions	AI-enabled SCM networks create sustainable financing streams for FDIs	Lack of empirical validation; requires real-world testing
Lim et al. [16]	Survey data from 177 manufacturing firms	Investigate the combined effect of SCM and QM	ANN with sensitivity analysis	Customer focus (CF) had impact on sustainability performance	Small sample size and focus on manufacturing firms limit generalizability to other regions or industries
Benzidia et al. [17]	Data from 168 French hospitals	Analyze the impact of AI on green SC integration	PLS-SEM under Organizational Information Processing Theory	AI promotes environmental process integration and green SC collaboration	Restricted to French hospitals; findings may not apply to other sectors or countries
Alabdali & Salam [18]	Survey of 221 SC professionals via LinkedIn	Investigate the effect of Digital Transformation (DT) on SC	PLS-SEM using SmartPLS	DT significantly improves SC, and SC mediates the effect of DT	Sample limited to LinkedIn users; cross-sectional design limits understanding of long-term effects

2.1 Research gap

While prior researches have explored AI applications in SCM and sustainability, most focus on single-dimensional outcomes, such as risk mitigation, emission reduction, or green integration [11-15]. Existing models often lack multivariate analysis, failing to jointly consider constructs like EU, AI System Usability (ASU), and performance outcomes (Cost Reduction, Delivery Reliability, Demand Variability). Additionally, many researches are limited to specific industries, regions, or survey-based datasets, restricting generalizability [16-18]. The present research addresses these gaps by developing an integrated, multi-objective framework that empirically evaluates how AI adoption simultaneously enhances SCM efficiency, resilience, and optimization across diverse contexts.

2.2 Variable definition

The following variables are selected based on their applicability to the adoption of AI and how they enhance SCR, efficiency, and optimization in various industries.

- **Environmental Uncertainty (EU):** It reflects the uncertainty in market conditions, supply, and external factors impacting SC. It influences the organizations' implementation of AI to enhance SC flexibility and operational stability.
- **Cost Reduction (CR):** It entails reducing costs across SC operations using enhanced efficiency and better resource utilization. Precise forecasting and improved logistics through integration of AI add up directly to these cost savings.
- **Delivery Reliability (DR):** It denotes the ability to satisfy delivery dates and orders accurately on a regular basis. The use of AI applications enhances this reliability in SC processes by improving coordination and planning.
- **AI System Usability (ASU):** It describes the ease and success with which users utilize AI adoption in SC. Increased usability supports easier adoption and implementation of AI in the SC processes.
- **Demand Variability (DV):** It is characterized as changes in customer demand over time. DV awareness guides the establishments to apply AI that allows making predictions and modifying operations of SC accordingly.
- **Supply Chain Efficiency (SCE):** It is the capability for SC to perform with a minimum of time, cost, and resources with quality. Knowledge in SCE firms to automate operations and enhance productivity in the processes.
- **Supply Chain Resilience (SCR):** It signifies the capacity of SC to adapt, restore, and operate in case of disruption. SCR knowledge assists firms to enhance flexibility, risk-management, and continuity in the event of uncertainty.
- **Supply Chain Performance (SCP):** It encompasses total efficiency of the SC in meeting its target objectives like cost efficiency, reliability, and customer satisfaction. Knowledge of SCP enables firms to evaluate outcomes, enhance competitiveness, and drive sustainable operational improvements.

2.3 Hypotheses development

The hypotheses examine the relation between EU and ASU, and also provide insight into key SC performance factors, including CR, DR, SCE, SCR, SCP and DV management. The framework highlights the contextual and technological forces being examined as direct influences on operational performance, as demonstrated in Figure 1.

EU increases the necessity of adaptive and usable AI systems. As uncertainty increases organizations are more likely to view artificial system use and adaptability (ASU) as critical for efficient SCM.

H1: EU positively impacts ASU.

Greater ASU enables organizations to effectively utilize AI tools, which reduces costs and makes operations more efficient. Thus, an increase in usability directly impacts the attainment of CR in SC.

H2: ASU significantly influences CR.

Improved ASU makes SC operations more accurate and efficient; it is leading to more reliable deliveries. The resulting improved usability aids in on-time deliveries that will improve DR.

H3: ASU positively influences DR.

Improved ASU allows firms to better utilize AI tools for forecasting and demand planning. This facilitates stronger management of DV and fewer SC disruptions.

H4: ASU significantly influences DV management.

EU drives firms to adopt AI systems that are user-friendly and adaptable ASU. In turn, this increased usability mediates the effect of uncertainty on achieving CR in SC.

H5: ASU mediates the relationship between EU and CR.

ASU explains how the EU influences CR. High EU drives firms to adopt AI effectively.

H6: CR positively influences SCE.

Effective CR practices, such as sustainability and ethical operations, streamline processes, reduce waste, and optimize resources, thereby improving SCE.

H7: CR positively influences SCR

Responsible CR practices strengthen supplier relationships, risk management, and proactive planning, enabling the SCR to anticipate, absorb, and recover from disruptions.

H8: DR positively influences SCP

High DR allows firms to respond swiftly to market variations, minimizing delays and stockouts and enhancing overall SCP.

H9: DV positively influences SCP

Managing DV through timely and accurate data improves forecasting, inventory control, and partner coordination, resulting in a stronger SCP.

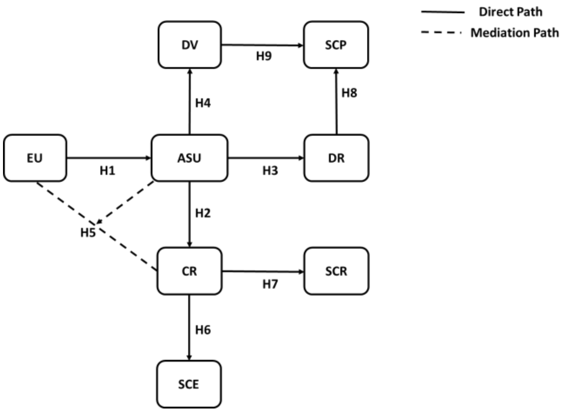

Figure 1: Conceptual framework of the proposed hypothesis

Figure 1 illustrates the hypothesized relationships framework among key constructs influencing SCP. EU, CR, DR, SCR, SCP, SCE and DV represent the external and operational drivers affecting supply chain dynamics. ASU acts as a facilitating factor, enhancing the effectiveness of these drivers. SCE and SCR function as mediating variables that channel the effects of the drivers toward overall SCP. The framework proposes that effective AI adoption improves operational efficiency, strengthens resilience against disruptions, and ultimately enhances performance outcomes across the SC.

3 Methodology

The research aims to examine how AI adoption enhances SC optimization, efficiency, and resilience, using data from 534 firms across multiple industries. Exploratory factor analyses, PLS-SEM analysis and correlation are conducted to validate measurement constructs. Figure 2 shows the methodological flow in which survey data were collected from 534 firms to examine the influence of EU, ASU, CR, DR, DV SCE, SCR, and SCP. SPSS and PLS-SEM analyses validate constructs and mediation effects, showing AI adoption enhances optimization, efficiency, and resilience. Assessments of validity and reliability guarantee the outcome's accuracy and robustness.

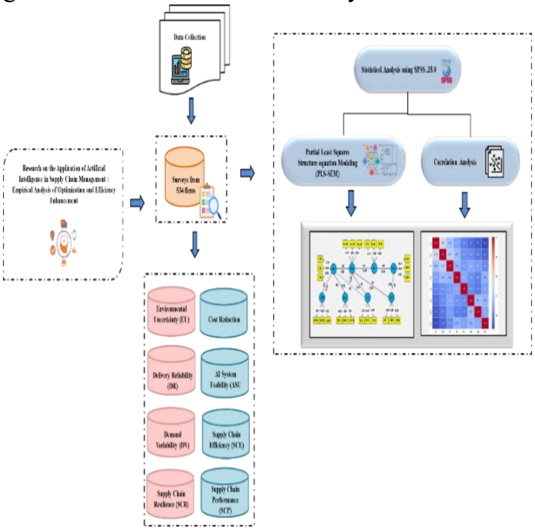

Figure 2: Analytical framework of empirical analysis

3.1 Data collection

Structured survey data were gathered from 534 firms across diverse industry sectors. Respondents included SC managers, operations directors, and executives with direct knowledge of AI implementation. The demographic distribution of participating firms by respondent role, company size, industrial sector, and experience is displayed in Table 2, demonstrating the representative and varied sample that was used for the empirical analysis.

Table 2: Demographic profile of participating firms' overview

Demographic Variable	Category	Frequency (n)	Percentage (%)
Industry Sector	Manufacturing	180	33.7
	Retail	120	22.5
	Logistics	95	17.8
	Technology	75	14.0
	Others	64	12.0
Firm Size (Employees)	Small (1–99)	210	39.3
	Medium (100–499)	185	34.6
	Large (500+)	139	26.1
Respondent Role	SC Manager	250	46.8
	Operations Director	160	30.0
	Executive/Top Management	90	16.9

	Other	34	6.3
AI Implementation Experience (Years)	Less than 1 year	160	30.0
	1 to 3 years	200	37.5
	4 to 6 years	120	22.5
	More than 6 years	54	10.0

Table 2 shows that the survey captured a diverse sample of 534 firms, with the largest representation from manufacturing (33.7%) and small-sized firms (39.3%). Most respondents were SC managers (46.8%) with 1–3 years of AI implementation experience (37.5%), ensuring broad and relevant insights for the analysis.

3.2 Questionnaire

The survey used a structured approach with closed-ended questions to evaluate variables affecting AI adoption in SCM. Table 3 presents the dimensions and corresponding questions, which evaluate user perceptions and actual use of AI technologies within SC operations.

Table 3: Participants' Questionnaires

Variable	Questions	Measurement Scale (Likert Scale)
EU	1. How often do unexpected market changes affect your SC decisions?	1 = Never, 2 = Rarely, 3 = Sometimes, 4 = Often, 5 = Always
	2. What external factors create challenges in planning your SC operations?	1 = Not at all challenging, 2 = Slightly challenging, 3 = Moderately challenging, 4 = Very challenging, 5 = Extremely challenging
	3. Why is adapting to regulatory changes important for your SCM?	1 = Insignificant, 2 = Slightly significant, 3 = Moderately significant, 4 = Significant, 5 = Highly significant
CR	1. What benefits have you observed in reducing costs after adopting AI in your SC?	1 = No benefit, 2 = Minor benefit, 3 = Moderate benefit, 4 = Significant benefit, 5 = Very high benefit
	2. How has AI helped your company minimize operational expenses?	1 = Not at all, 2 = Slightly, 3 = Moderately, 4 = Considerably, 5 = Greatly
	3. Why is cost reduction a key goal in your SC strategy?	1 = Not important, 2 = Slightly important, 3 = Moderately important, 4 = Important, 5 = Very important
DR	1. How reliable are your deliveries in meeting scheduled deadlines consistently?	1 = Very unreliable, 2 = Unreliable, 3 = Neutral, 4 = Reliable, 5 = Very reliable
	2. What improvements has AI brought to your order fulfillment accuracy?	1 = No improvement, 2 = Slight improvement, 3 = Moderate improvement, 4 = High improvement, 5 = Significant improvement
	3. Why is maintaining delivery reliability critical for customer satisfaction?	1 = Not critical, 2 = Slightly critical, 3 = Moderately critical, 4 = Critical, 5 = Very critical
ASU	1. How easy is it for your team to learn and use AI tools in SC tasks?	1 = Very difficult, 2 = Difficult, 3 = Neutral, 4 = Easy, 5 = Very easy
	2. What kind of training or support helps users interact effectively with AI systems?	1 = Not effective, 2 = Slightly effective, 3 = Moderately effective, 4 = Effective, 5 = Very effective
	3. Why does user-friendly AI technology matter for successful adoption?	1 = Insignificant, 2 = Of little value, 3 = Moderately valuable, 4 = Valuable, 5 = Extremely valuable

DV	1. How frequently does customer demand fluctuate in your SC?	1 = Never, 2 = Rarely, 3 = Sometimes, 4 = Often, 5 = Very often
	2. What challenges arise from demand variability in forecasting and planning?	1 = No challenge, 2 = Minor challenge, 3 = Moderate challenge, 4 = Major challenge, 5 = Severe challenge
	3. Why is managing demand variability crucial for SC efficiency?	1 = Not crucial, 2 = Slightly crucial, 3 = Moderately crucial, 4 = Crucial, 5 = Very crucial
SCE	1. How effectively does your SC use resources to minimize costs and time?	1 = Very ineffective, 2 = Ineffective, 3 = Neutral, 4 = Effective, 5 = Very effective
	2. How has AI improved process efficiency and operational productivity in your SC?	1 = Not at all, 2 = Slightly, 3 = Moderately, 4 = Considerably, 5 = Greatly
	3. Why is SC efficiency important for overall organizational performance?	1 = Not significant, 2 = Slightly significant, 3 = Moderately significant, 4 = Significant, 5 = Extremely significant
SCR	1. How quickly can your SC recover from unexpected disruptions?	1 = Very slowly, 2 = Slowly, 3 = Neutral, 4 = Quickly, 5 = Very quickly
	2. How effective are your risk mitigation strategies in maintaining SC continuity?	1 = Not effective, 2 = Slightly effective, 3 = Moderately effective, 4 = Effective, 5 = Very effective
	3. Why resilience is critical for sustaining SC operations during disruptions?	1 = Not critical, 2 = Slightly critical, 3 = Moderately critical, 4 = Critical, 5 = Very critical
SCP	1. How satisfied are you with your SC's ability to meet organizational objectives?	1 = Very dissatisfied, 2 = Dissatisfied, 3 = Neutral, 4 = Satisfied, 5 = Very satisfied
	2. How has AI adoption enhanced the overall performance of your SC?	1 = Not at all, 2 = Slightly, 3 = Moderately, 4 = Considerably, 5 = Greatly
	3. Why is monitoring SCP important for long-term competitiveness?	1 = Not important, 2 = Slightly important, 3 = Moderately important, 4 = Important, 5 = Very important

4 Statistical analysis

This analysis assessed how AI adoption increases SC efficiency and resilience by utilizing SPSS software. Exploratory Factor Analysis (EFA) identifies underlying dimensions among survey items, reliability and validity are confirmed using CA, CR, and AVE. Correlation analysis and PLS-SEM examine relationships, including direct, indirect, and mediating effects, ensuring robust model evaluation.

5 Result

The analysis revealed that environmental uncertainty, SC cooperation, and relative advantage positively influence AI adoption in SCM. AI adoption was found to improve SC optimization, and resilience, permitting more accurate forecasting, improved inventory control, and better logistics coordination.

➢ **Reliability analysis**

It evaluates the internal steadiness of survey items in measuring constructs linked to AI adoption and its effects on SCP. High reliability indicates that the survey items reliably measure usability, responsiveness, and digitalization outcomes. Table 4 presents reliability outcomes for the constructs.

Table 4: Reliability assessment of AI-driven SC constructs

Construct	Items	CA	CR	AVE	IL
EU	Frequency of Market Changes	0.87	0.91	0.72	0.81
	External Planning Challenges	0.88	0.91	0.72	0.83
	Regulatory Adaptability Importance	0.85	0.91	0.72	0.80
ASU	Ease of Learning AI Tools	0.88	0.91	0.73	0.82
	Training and Support Effectiveness	0.86	0.91	0.73	0.81
	Importance of User-Friendly AI	0.87	0.91	0.73	0.82
CR	Benefits from AI Cost Savings	0.87	0.90	0.71	0.80
	Reduction in Operational Expenses	0.85	0.90	0.71	0.79
	Strategic Importance of Cost Reduction	0.82	0.90	0.71	0.78
DR	On-Time Delivery Performance	0.88	0.91	0.72	0.81
	Delivery Consistency	0.86	0.91	0.72	0.80
	Order Fulfillment Accuracy	0.83	0.91	0.72	0.79
DV	Frequency of Demand Fluctuations	0.87	0.90	0.71	0.80
	Forecasting and Planning Challenges	0.84	0.90	0.71	0.79
	Importance of Managing Demand Variability	0.81	0.90	0.71	0.78
SCE	Resource Utilization Effectiveness	0.86	0.90	0.71	0.80
	AI-Enhanced Process Productivity	0.86	0.90	0.71	0.81
	Importance of SC Efficiency for Performance	0.86	0.90	0.71	0.79
SCR	Recovery Speed from Disruptions	0.87	0.91	0.72	0.81
	Effectiveness of Risk Mitigation	0.87	0.91	0.72	0.80
	Importance of SC Resilience	0.87	0.91	0.72	0.79
SCP	Satisfaction with SC Objectives Achievement	0.88	0.92	0.73	0.82
	AI-Driven SC Performance Improvement	0.88	0.92	0.73	0.81
	Importance of Monitoring SC Performance	0.88	0.92	0.73	0.80

Table 4 presents the measurement model outcomes for all constructs: EU, ASU, CR, DR, DV, SCE, SCR, and SCP. CA ranges (0.81 to 0.88), and CR ranges from 0.90 to 0.92, showing strong uniformity. AVE shows a 0.71 to 0.73 range, confirming good convergent validity. IL for all items falls between 0.78 and 0.83, demonstrating that each item reliably measures its respective construct. Overall, it indicates reliability and validity of model, suitable for PLS-SEM structural analysis.

➢ **Exploratory Factor Analysis**

EFA identifies underlying dimensions of the survey items to show how the AI usage affects SC. It permits the ability to verify that dimensions for usability, responsiveness, and digitalization are distinct and accurately represented. Table 5 reports the EFA results.

Table 5: EFA of AI-driven SC constructs

Factor	Variable	Factor Loading	Eigenvalue	Variance Explained	Cumulative Variance
EU	EU1	0.85	4.60	34%	34%
	EU2	0.81	1.05	8%	42%
	EU3	0.83	0.95	7%	49%
ASU	ASU1	0.84	4.20	32%	32%
	ASU2	0.79	1.10	8%	40%
	ASU3	0.81	0.95	7%	47%
CR	CR1	0.82	3.50	27%	27%
	CR2	0.78	1.10	8%	35%
	CR3	0.80	0.90	7%	42%
DR	DR1	0.83	3.20	25%	25%
	DR2	0.80	1.05	8%	33%
	DR3	0.79	0.90	7%	40%
DV	DV1	0.84	3.00	24%	24%
	DV2	0.80	1.00	8%	32%
	DV3	0.78	0.85	6%	38%
SCE	SCE1	0.83	3.40	26%	26%
	SCE2	0.81	1.05	8%	34%
	SCE3	0.80	0.90	7%	41%
SCR	SCR1	0.84	3.50	27%	27%
	SCR2	0.82	1.10	8%	35%
	SCR3	0.81	0.95	7%	42%
SCP	SCP1	0.85	3.60	28%	28%
	SCP2	0.83	1.05	8%	36%
	SCP3	0.82	0.95	7%	43%

Table 5 presents EFA outcomes of all key constructs, including EU, ASU, CR, DR, DV, SCE, SCR, and SCP. Factor loadings range (0.78 to 0.85) providing strong item-construct relationships. Eigenvalues for the first factor of each construct range from 3.00 to 4.60, while the variance explained by individual items ranges from 6% to 34%. Cumulative variance across items within each construct ranges from 38% to 49%, demonstrating adequate representation of the underlying latent variables. These confirm that all are reliable and valid for subsequent structural analysis.

- **PLS-SEM**

PLS-SEM is utilized to discover complex relationships among latent constructs and observed measures. Internal consistency is assessed using CR, while convergent validity is confirmed through AVE and CA (α). Table 6 and Figure 3 present the validity and reliability data that allow the assessment of SC performance driven by AI.

Table 6: Reliability and validity assessment in key measurement constructs

Construct	Item Code	Factor Loading	SE	t-value	CR	AVE	α	R²	Validity Satisfied
EU	EU1	0.81	0.35	23.14	0.912	0.722	0.887	0.00	Yes
	EU2	0.87	0.30	28.96					
	EU3	0.85	0.32	26.56					
ASU	ASU1	0.79	0.34	21.94	0.908	0.735	0.881	0.68	Yes
	ASU2	0.88	0.28	30.20					
	ASU3	0.86	0.30	28.66					
CR	CR1	0.78	0.36	22.33	0.900	0.710	0.875	0.57	Yes
	CR2	0.85	0.31	27.42					
	CR3	0.82	0.33	25.68					
DR	DR1	0.80	0.35	23.11	0.906	0.720	0.879	0.53	Yes
	DR2	0.87	0.29	29.78					
	DR3	0.83	0.31	27.22					
DV	DV1	0.77	0.37	20.81	0.895	0.705	0.870	0.49	Yes
	DV2	0.84	0.33	25.45					
	DV3	0.81	0.34	24.30					
SCE	SCE1	0.82	0.32	25.63	0.900	0.710	0.875	0.55	Yes
	SCE2	0.84	0.30	27.88					
	SCE3	0.81	0.33	24.55					
SCR	SCR1	0.83	0.31	26.77	0.905	0.720	0.878	0.58	Yes
	SCR2	0.85	0.29	29.31					
	SCR3	0.82	0.32	25.63					
SCP	SCP1	0.84	0.30	28.00	0.910	0.730	0.882	0.60	Yes
	SCP2	0.86	0.28	30.71					
	SCP3	0.83	0.31	26.77					

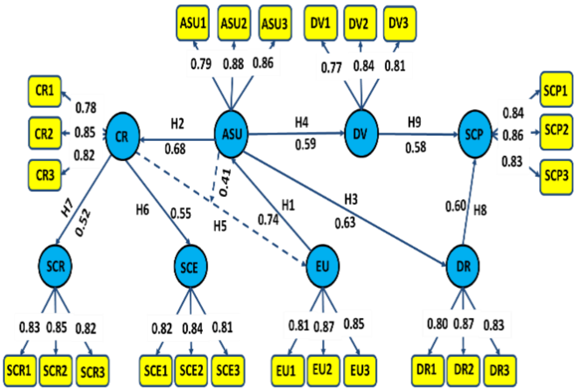

Figure 3: PLS-SEM measurement and structural model with loadings

Figure 3 presents the factor loadings and reliability analysis for all constructs, including EU, ASU, CR, DR, DV, SCE, SCR, and SCP. Factor loadings from 0.77 to 0.87 with standard errors (SE) between 0.28 and 0.37 and t-values from 20.81 to 30.71 indicate a significant load on respective constructs. CR ranges from 0.895 to 0.912, AVE (0.705 to 0.735), and CA (α) ranges from 0.870 to 0.887 demonstrating robust and convergent validity. The R^2 values range from 0.00 to 0.68, reflecting predictive power.

➢ **Structural model**

The model explores both direct and mediating relationships among key factors, emphasizing their collective influence on AI usability and overall SC performance. Table 7 presents the structural model assessment of hypothesized paths.

Table 7: Structural model results showing supported hypothesized relationships

Path Direction	**β Coefficient**	**t-value**	**p-value**	**Supported**
H1: EU → ASU	0.74	12.36	0.000	Supported
H2: ASU → CR	0.68	11.10	0.000	Supported
H3: ASU → DR	0.63	9.85	0.000	Supported
H4: ASU → DV	0.59	8.92	0.000	Supported
H5: EU → CR (mediated by ASU)	0.41	6.33	0.000	Supported
H6: CR → SCE	0.55	7.20	0.000	Supported
H7: CR → SCR	0.52	6.80	0.000	Supported
H8: DR → SCP	0.60	8.10	0.000	Supported
H9: DV → SCP	0.58	7.50	0.000	Supported

Table 7 presents the hypothesized relationships among the key constructs. The (β) range from 0.41 to 0.74, representing moderate to strong effects. The t-values range from 6.33 to 12.36, and all p-values are 0.000, showing that all hypothesized paths are significant at the 0.001 level. Specifically, H1 (EU → ASU) has the strongest effect with β = 0.74 and t = 12.36, while the mediation effect in H5 (EU → CR via ASU) shows β = 0.41 and t = 6.33. Other significant effects include CR → SCE (β = 0.55, t = 7.20), CR → SCR (β = 0.52, t = 6.80), DR → SCP (β = 0.60, t = 8.10), and DV → SCP (β = 0.58, t = 7.50).

➢ **Correlation analysis**

It is conducted to determine the movement and power of correlations among the critical factors influencing AI usability and SC performance and to assess interrelationships, which contribute to improved reliability and resilience in SC processes. Table 8 and Figure 4 show the correlation between critical constructs in the model.

Table 8: Correlation matrix of key constructs

Constructs	**EU**	**ASU**	**CR**	**DR**	**DV**	**SCE**	**SCR**	**SCP**
EU	1.000	0.74	0.68	0.63	0.59	0.57	0.55	0.53
ASU	0.74	1.000	0.71	0.67	0.61	0.60	0.58	0.56
CR	0.68	0.71	1.000	0.66	0.62	0.64	0.62	0.60
DR	0.63	0.67	0.66	1.000	0.64	0.61	0.59	0.65
DV	0.59	0.61	0.62	0.64	1.000	0.60	0.58	0.63
SCE	0.57	0.60	0.64	0.61	0.60	1.000	0.67	0.66
SCR	0.55	0.58	0.62	0.59	0.58	0.67	1.000	0.64
SCP	0.53	0.56	0.60	0.65	0.63	0.66	0.64	1.000

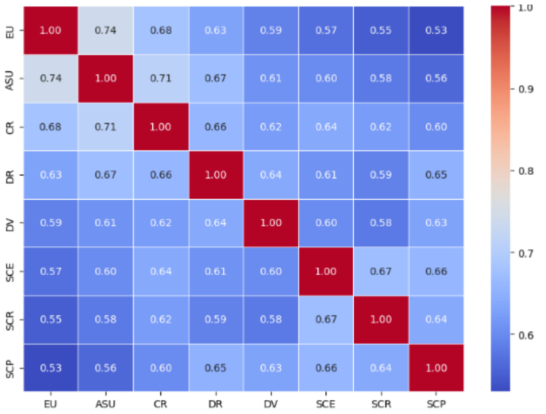

Figure 4: Outcome of correlation analysis

Figure 4 presents the correlation matrix for all constructs, including EU, ASU, CR, DR, DV, SCE, SCR, and SCP. Correlation coefficients range from 0.53 to 0.74, demonstrating moderate to strong positive relationships among all constructs. EU shows its highest correlation with ASU ($r = 0.74$) and lowest with SCP ($r = 0.53$). SCE is most powerfully associated with SCR ($r = 0.67$) and SCP ($r = 0.66$). SCP displays robust correlations in DR ($r = 0.65$), SCE ($r = 0.66$), and DV ($r = 0.63$), reflecting its dependence on efficiency, resilience, and responsiveness.

6 Discussion

Research analyzed the effectiveness and usability of AI applications on SC performance through intermediary variables. Previous researches on AI adoption in SC exhibit several key limitations. Most investigations were conducted within specific regional, which restricts the generalizability of findings [13]. Many relied on limited or cross-sectional survey data, constraining long-term performance evaluation [18]. Prior models often overlooked critical contextual factors, leading to incomplete assessments of AI-driven SC outcomes [17]. Several researches lacked an integrated view of efficiency, resilience, and performance dimensions, focusing narrowly on isolated outcomes [16]. This research addressed these shortcomings, using a dataset of 534 multi-industry firms, by combining EU and ASU in the analytical model, and using PLS-SEM to determine the direct and mediating effects. This holistic approach increases the generalizability, creates stronger causal relationships, and gives a comprehensive sense of AI-enabled SC. Results showed that EU significantly affects ASU ($\beta = 0.74$, $t = 12.36$, $p < 0.001$), which positively influences CR ($\beta = 0.68$, $t = 11.10$), DR ($\beta = 0.63$, $t = 9.85$), and DV ($\beta = 0.59$, $t = 8.92$). ASU also mediates the effect of EU on CR ($\beta = 0.41$, $t = 6.33$). Furthermore, CR contributes to SCE ($\beta = 0.55$, $t = 7.20$) and SCR ($\beta = 0.52$, $t = 6.80$), while DR and DV drive overall SCP ($\beta = 0.60$, $t = 8.10$; $\beta = 0.58$, $t = 7.50$). The research provides actionable insights for managers to leverage AI for enhancing performance. By integrating AI usability with contextual factors like environmental uncertainty, firms optimize forecasting, reduces costs, and strengthens responsiveness, enabling data-driven decisions and sustainable competitiveness across diverse industries and regions.

7 Conclusion

The research focused on AI's role in improving the performance of SC through optimization of operations, enhancement of efficiency, and further resilience during times of global uncertainty. A sample of 534 firms was used to collect data, which was supported by strong analyses, such as EFA, correlation analysis, and PLS-SEM, to confirm the measurement model and contributing hypothesized relationships. Results indicated that EU strongly improves ASU with $\beta = 0.74$, $t = 12.36$, which improves CR with $\beta = 0.68$, $t = 11.10$, DR with $\beta = 0.63$, $t = 9.85$, and DV with $\beta = 0.59$, $t = 8.92$. ASU also intermediates EU's effect on CR with $\beta = 0.41$, $t = 6.33$. Furthermore, CR drives SCE with $\beta = 0.55$, $t = 7.20$ and SCR with $\beta = 0.52$, $t = 6.80$, while DR and DV enhance overall SCP with $\beta = 0.60$, $t = 8.10$; $\beta = 0.58$, $t = 7.50$. These results confirm that AI adoption under environmental uncertainty significantly strengthens SC. The usage of survey-based, and a relatively small number of firms restricts the generalizability to industries and regions. Future research may include longitudinal data and cross-industrial research to confirm the SCP driven by AI in different operational settings.

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Declaration:

Ethics approval and consent to participate: I confirm that all the research meets ethical guidelines and adheres to the legal requirements of the study country.

Consent for publication: I confirm that any participants (or their guardians if unable to give informed consent, or next of kin, if deceased) who may be identifiable through the manuscript (such as a case report), have been given an opportunity to review the final manuscript and have provided written consent to publish.

Availability of data and materials: The data used to support the findings of this study are available from the corresponding author upon request.

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