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Smart prosperity through smart supply chain based on using smart and intelligent technologies

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Smart prosperity through smart supply chain based on using smart and intelligent technologies

In modern society, the widespread adoption of Smart and Intelligent Technologies (SIT) significantly impacts traditional supply chains, particularly in an era characterized by heightened risks and rapid market dynamics. To enhance Smart Prosperity (SP), it is essential for supply chains to evolve into Smart Supply Chains (SSC) within an ecosystem comprising Smart Enterprises, Smart Mobility, Smart Energy, Smart Citizens, and an integrated Smart Society. This study, conducted in Serbia as an emerging economy, investigates the role of Information and Communication Technologies (ICTs) and Artificial Intelligence (AI) in advancing Society 5.0. The original model was developed based on an extensive literature review and empirical research in Serbia. The model integrates data collected using the Technique Nominal Group (TNG) method, statistical analysis, Artificial Neural Networks (ANN), and the Smart Prosperity Model (SPM). The research introduces a novel framework incorporating 12 variables linked to Industry 4.0/5.0 concepts, such as Smart Supply Chain Resilience (SSCR), Smart and Intelligent Chain Agility (SASCA), and Smart and Intelligent Prosperity (SIP). Statistical methods and ANN were employed to evaluate the potential improvements in supply chain performance. Initial findings indicate that sustainability and smart technologies profoundly influence prosperity. The originality of this research lies in the development of a comprehensive model that integrates innovative concepts, including SSCR, SASCA, and SIP, alongside statistical and machine learning approaches. The study's results provide an optimistic outlook for future research and practical applications, highlighting the transformative potential of SIT in driving supply chain advancements and fostering smart societal development.

Keywords: Smart and Intelligent Technologies; Smart Prosperity; Smart Supply Chain, Smart Prosperity; Statistical methods; Smart Sustainability; Artificial Neural Network.

1. INTRODUCTION

The concept of Smart Supply Chains (SSC) represents an evolution of traditional supply chain frameworks. Blanchard (2010) identified several core aspects of supply chain

systems that require enhancement: (1) the anatomy of supply chains, (2) supply chain

metrics, (3) traditional core processes of supply chain management, (4) globalization,

(5) supply chain strategies, (6) enterprise collaboration, and (7) green supply chains.

The integration of Information and Communication Technologies (ICTs) within

enterprises and across supply chain participants has been a central focus of numerous

studies.

Collaboration and trust are critical for efficient supply chains. Klein and Rai

(2009) analyzed interfirm strategic information flows in logistics supply chain

relationships, demonstrating a strong correlation among key variables using an original

model and statistical methods.

In the era of globalization, traditional supply chains are being transformed into

Smart Supply Chains through the adoption of advanced technologies, including artificial

intelligence (AI), resilience, agility, and sustainability approaches. These advancements

align with Industry 4.0 and Industry 5.0 paradigms, integrating smart quality, business

excellence, and the necessary social and industrial support. Currently, both traditional

and smart supply chains coexist, varying in the sectors they serve, the technologies they

implement, and the business models they adopt. However, no universal answer exists

regarding the practical outcomes of implementing SSCs, necessitating the development

of new models.

This research introduces the Smart, Intelligent, Agile, Resilient, and Sustainable

Supply Chain (SIARS) model, which incorporates the following variables:

Independent variables: (V1) Level of smart information and AI technologies in SSC

(SIT); (V2) Level of adoption of smart technologies in SSC; (V3) Level of adoption of

AI technologies in SSC; (V4) Level of societal support for SSC; (V5) Level of SSC

agility; (V6) Level of SSC resilience; (V7) Level of SSC sustainability; (V8) Level of

smart prosperity of SSC and society; and (V9) Level of investment in SIT

External variables are: (V10) Level of environmental crisis; (V11) Level of resource crisis, and (V12) Level of political crisis

The proposed model was tested on Serbian supply chains within the industrial sector using the Technique of Nominal Group (TNG), statistical methods, and artificial neural network (ANN)-based software. Preliminary results confirm the hypothesis that SIT significantly impacts smart prosperity. Future research will expand this model by incorporating additional variables such as smart quality, smart business infrastructure, smart enterprise models, and lean and agile strategies.

The paper is organized as follows: Section 2 provides an overview of existing research on smart supply chains and the formulation of hypotheses. Section 3 outlines the applied methodology, presenting both qualitative and quantitative results. Section 4 includes a case study of Serbian supply chains, detailing the state of the industry over the last three years and simulation results based on the ANN method. Section 5 discusses the findings, recommendations, and conclusions.

2. LITERATURE REVIEW & HYPOTHESES

2.1. Literature review

The application of advanced technologies in supply chains has been extensively studied, providing insights into their impact on efficiency, resilience, agility, and organizational performance.

Ovalle and Marques (2003) explored the effectiveness of e-collaboration tools in supply chains using System Dynamics (Sterman, 1989). Their simulation results supported the hypothesis that e-collaboration significantly enhances the effectiveness of

e-supply chains, demonstrating the value of integrating digital tools for supply chain optimization.

Bose, Pal, and Ye (2008) examined the integration of Enterprise Resource Planning (ERP) systems with Supply Chain Management (SCM). Their case study highlighted challenges associated with legacy ERP systems and existing business practices while emphasizing the benefits of integrating ERP with e-SCM. Notable improvements included outbound order fulfillment and inventory management, showcasing the potential for digital transformation in supply chains.

Spiegler et al. (2012) investigated Supply Chain Resilience (SCR) by analyzing disruption sources, performance measures, and mitigation strategies. Their research evaluated supply chain readiness, response time, and recovery through linear and nonlinear models, emphasizing the role of ICT in mitigating delays and feedback issues within the system.

Weber (2002) analyzed supply chain agility within the context of virtual organizations. After defining virtual organizations, the study addressed challenges in measuring variances within supply chains and demonstrated how agility concepts can be applied to respond to market changes effectively.

Yu et al. (2008) focused on the Chinese ICT industry from a supply chain perspective. Their research examined the role of supply chain members within and outside the ICT industry, identifying value-adding opportunities for ICT stakeholders.

Tominc, Oreški, and Rožman (2023) analyzed the impact of AI on supply chain agility. They identified key dimensions, including agile leadership, team skills and capabilities, the adoption of AI technologies in projects and organizations, and the creation of an agile work environment.

Mrugalska and Ahmed (2021) explored the relationship between Industry 4.0 technologies and agility. Their study highlighted the dual role of agility as both a driver and consequence of Industry 4.0 adoption. They examined key technologies such as smart manufacturing, Cyber-Physical Systems, cloud computing, big data analytics, augmented and virtual reality, simulation, IoT platforms, machine-to-machine communication, and sensors. Furthermore, they outlined six agility dimensions: processes, workforce, strategy, information, systems, and facilities.

Kwasek et al. (2024) analyzed the role of AI in organizational management, emphasizing the strategic contributions of AI technologies in enhancing organizational performance and adaptability.

Atienza-Barba et al. (2024) developed a thematic map that placed organizational agility and agility in a quadrant characterized by both high development and high relevance. This work highlights the critical role of agility in modern supply chain management.

Quarshie, Salmi, and Leuschner (2016) analyzed sustainability and corporate social responsibility within supply chains. Their research identified intersections between supply chain management and business ethics, utilizing theoretical frameworks such as stakeholder theory, network/social network theory, resource-based and natural resource-based views, dynamic capabilities, and global value chain models.

Ge et al. (2016) focused on mitigating supply chain complexity and risks through a hybrid optimization-simulation model, providing strategies for addressing uncertainties in supply chain operations.

Boyson et al. (2003) defined the e-supply chain portal as a core business model, comprising three levels: the presentation layer, application layer, and integration layer, illustrating a layered approach to supply chain digitalization.

Additional research themes in SCM include:

(1) Human and IT Interaction: Russell and Hoag (2004) examined the interplay of people and information technology.

(2) Agent-Based ICT for Virtual Enterprises: Aerts et al. (2002) proposed flexible, agent-based ICT infrastructures for virtual enterprises.

(3) Inter-Organizational Relationships: Cheng (2010) investigated how relationships between organizations impact supply chain effectiveness.

(4) Agility and Success Factors: Ismail and Sharifi (2006) proposed balanced approaches to agile supply chains, while Power and Sohal (2001) identified critical success factors based on empirical studies.

(5) IT in Supply Chain Management: Recent studies (e.g., Cuevas-Vargas et al., 2024; Hang et al., 2022) explored the role of IT in SCM, addressing diverse aspects like digital transformation and quality management.

The concept of Smart Supply Chain Management is evolving within the framework of Industry 4.0 and transitioning into Industry 5.0. Smart technologies, including knowledge management and IoT, underpin this transformation. For example, Ivanov (2023) integrated resilience, sustainability, and human-centricity in supply chain design, while Ghobakhloo et al. (2020) emphasized sustainable development.

Sadeghy et al. (2024) explored the intersection of digital resilience, new business models, and international entrepreneurship. Their study focused on themes like SME innovation, technological advancements, and the impact of digital capabilities on organizational performance.

Chan et al. (2021) analyzed critical success factors for enhancing supply chain quality management in manufacturing, adopting a quality-focused approach.

The transition to Industry 5.0 has introduced a focus on human-centered and sustainable AI systems. Martini, Bellisario, and Colleti (2024) emphasized human-centered AI's ethical and transparent applications, exploring intersections with augmented human capabilities. Similarly, Jefrou, Azarian, and Yu (2022) analyzed implications for smart logistics, highlighting human-centricity, resilience, and sustainability as foundational elements of Industry 5.0.

De Giovani (2023) analyzed the emerging concept of the Metaverse, described as "a massive virtual space where users interact through digital avatars." He examined risks and opportunities related to the triple bottom line, emphasizing its economic, environmental, and social performances. The study highlighted how the Metaverse can streamline supply chains by eliminating intermediaries, resulting in shorter and more dynamic chains.

Saniuk, Grabowska, and Straka (2021) identified social and economic expectations in the transformation from Industry 4.0 to Industry 5.0. They emphasized six principles of Industry 4.0: interoperability, virtualization, decentralization, real-time virtualization capability, service orientation, and modularity. Their research underscored the role of Big Data and predictive analytics in understanding and supporting customer needs, along with the economic and social changes brought by Industry 5.0.

Gonzalves-Gallego et al. (2014) investigated SCM using integrated information systems (IS). Their proposed model revealed the role of ICT in external and internal processes, as well as its impact on firm performance related to both customers and suppliers. Statistical regression analyses confirmed hypotheses about the positive influence of ICT on firm performance, particularly through integrated IS for SCM.

Oger et al. (2020) designed a decision support system for strategic supply chain capacity planning under uncertainty. By developing a supply web metamodel, they

visualized what-if scenarios and enhanced decision-making processes, providing

valuable tools for handling uncertainties in SCM.

Thoni and Tioa (2015) explored the role of information technology (IT) in

sustainable SCM. Their findings highlighted both direct effects of IT on environmental

and social sustainability and indirect effects through efficiency improvements. The

research categorized IT/SCM applications into three main areas:

(1) Systems for strategic and tactical management.

(2) Systems for execution and monitoring.

(3) Focus dimensions of sustainable development, particularly environmental and

social aspects.

Agrawal et al. (2024) explored how Industry 5.0 technologies can mitigate

supply chain disruptions caused by global events such as pandemics, wars, and climate

change. Their study answered two critical research questions:

(1) How can Industry 5.0 technologies prevent disruptions in supply chains during

such crises?

(2) What are the future opportunities for adapting and integrating these technologies

within supply chains?

The findings affirmed the potential of Industry 5.0 technologies to address these

challenges effectively.

Cruz and Wakelbinger (2008) analyzed the effects of corporate social

responsibility (CSR) on supply chain networks, transaction costs, and risks. They

emphasized the need to evaluate CSR's impact across diverse social and economic

contexts.

Holmberg (2000) proposed a system perspective on SCM, emphasizing coordination through information exchange to unify diverse measurement systems across supply chain members. Drawing from IKEA's approach, he suggested Balanced Score Card (BSC) metrics, including product range, cost, quality, availability, and service.

Pearson, Masson, and Swain (2010) developed a model of supply chain agility incorporating four decision frontiers related to cost and lead time. They utilized complex adaptive systems (CAS) and agent-based modeling (ABM) and identified three profiles of agility's impact in a case study.

Barakat et al. (2020) examined the integration of supply chains with ICT, identifying five critical factors influencing ICT adaptation: 1) Social influence, 2) Motivation, 3) Behavioral intention, 4) Facilitating conditions, and 5) Values.

Qu and Kim (2024) reviewed the role of AI-integrated technologies in sustainable SCM, identifying ten key topics:

(1) Supplier selection under decision support systems.

(2) Optimizing global SSCM through AI-integrated Big Data.

(3) Food sustainable supply chain optimization.

(4) Smart manufacturing in supply chains.

(5) Renewable energy in supply chains.

(6) Transportation optimization and environmental considerations.

(7) Decision support in SCM.

(8) Sustainable logistics management and system integration.

(9) Data-driven risk management in disruptions.

(10) Environmental management in construction supply chains.

Nitsche et al. (2024) employed a hierarchical approach to map the role of AI in SCM. At the top level, their focus was on AI-inspired supply chain collaboration, with subsequent levels addressing perspectives (technology and supply chain), categories (e.g., AI sub-fields, SCOR process collaboration, SC components), and themes such as artificial intelligence, ANN, decision support systems (DSS), fuzzy logic and sets, machine learning (ML), metaheuristics, and multi-agent systems.

Nazarian and Khan (2002) identified three key dimensions of supply chain performance: visibility, responsiveness, and digital technologies. Their research emphasized the role of enabling technologies such as IoT, AI, blockchain, big data analytics, cobots, 6G, and digital twins in improving these dimensions, confirming their positive impact through tested hypotheses.

Building on this, Jackson et al. (2024) explored the potential of Generative AI (GAI) to enhance traditional AI in SCM and operational management. They proposed a framework that integrates AI and GAI capabilities, which could improve learning, perception, prediction, interaction, adaptation, and reasoning within supply chains. Similarly, Lacinak (2021) defined the resilience of smart transport systems through dimensions such as recovery, absorption, continual functionality, and adaptation. While these concepts were initially applied to smart cities, their relevance extends to SCM by addressing risks and aligning with broader objectives.

Gomez Marton et al. (2022) further advanced the field by updating the Smart Mature Resilience Model (SMR MM), which now incorporates resilience dimensions such as leadership, governance, preparedness, infrastructure, and cooperation, structured across five maturity stages. Their study emphasized the integration of technological, human, and knowledge aspects to improve resilience. Meanwhile, Sanne, Ekholm, and Rahmberg (2018) identified critical features of smart infrastructure, including integrated

systems, intelligent ICT solutions, big/open data technologies, and micro/nano systems. They conceptualized resilience as a union of threat, criticality, and vulnerability, addressing challenges such as cyberattacks, extreme weather, and smart energy supply systems.

Although Canavera-Herrera et al. (2020) analyzed the relationship between resilience and smartness in the context of smart cities, they noted that this connection remains insufficiently explored. Oksuz et al. (2021) proposed a method for Smart Resilience Services (SRS), consisting of six interconnected sub-processes, including specification of current and desired states, narrative development, and requirement specification. Each sub-process aims to answer fundamental questions about goals, methods, and expected results.

Lastly, the Legatum Institute provided a broader societal perspective by defining prosperity through three domains: inclusive society, open economy, and empowered people. These domains are supported by pillars such as safety, personal freedoms, governance, and social capital. Smart supply chains contribute to these areas by fostering advancements in smart industry, agriculture, economy, finance, development, and governance. Collectively, these studies underline the transformative potential of smart technologies and resilience frameworks in creating efficient, adaptive, and sustainable supply chains.

2.2 Hypotheses

Based on the literature review and related topics, the following research questions have been defined:

(1)   Which entities impact smart prosperity?

(2) To what extent do smart AI technologies influence smart prosperity in smart supply chains?

(3) What characteristics do entities in supply chains possess?

(4) To what degree do simulation results validate the initial behavior of these entities' impact on the smart prosperity of smart supply chains?

(5) How do the structures of entities differ within smart supply chains?

(6) Which smart entities have the highest impact on the smart prosperity of smart supply chains?

For this study, the following hypotheses are emphasized:

- H0: The level of smart and intelligent technologies has a significant impact on the smart prosperity of smart supply chains.

- H1: The level of smart sustainability is a positive and highly significant predictor of smart prosperity.

- H2: The level of AI adoption for smart prosperity is a highly significant predictor.

- H3: The level of smart and intelligent technologies is a significant predictor of smart prosperity.

- H4: The level of smart resilience in supply chains is a significant predictor of smart prosperity.

- H5: The level of environmental crises negatively impacts the smart prosperity of supply chains.

Each hypothesis is tested using an original methodology and validated within supply chains in the Republic of Serbia.

3. RESEARCH MODEL

3.1 Model development

The presented model has been developed based on previously described models in the literature review, particularly the model of the Smart Supply Chain for Business Performance (Sharma et al., 2024). In the referenced model, the independent variables include: (1) Industry 4.0, (2) Green Practices, (3) Smart Supply Chain, (4) Supply Chain Agility, (5) Supply Chain Resilience, and (6) Supply Chain Sustainability, while the dependent variable is (7) Sustainable Business Performance. Given the current dominance of Industry 5.0 paradigms, with early influences of Industry 6.0, the authors of this research have developed an expanded model to address a broader scope of variables. Unlike earlier models, agility is not considered a critical characteristic of Smart Supply Chains within this framework. The proposed research model, SITSP (Smart and Intelligent Technologies and Smart Prosperity), includes the following independent variables: Level of Smart and Intelligent Technologies (SIT) and AI Technologies (v1), Level of Adoption of Smart Technologies in Smart Supply Chains (SSC) (v2), Level of Adoption of AI in SSC (v3), Level of Societal Support for SSC (v4), Level of SSC Agility (v5), Level of SSC Resilience (v6), Level of SSC Sustainability (v7), Level of Investment in SIT (v9), Level of Environmental Crisis (v10), Level of Resource Crisis (v11), and Level of Political Crisis (v12). The dependent variable in the model is the Level of Prosperity (v8). This extended model aims to provide a more nuanced understanding of the interplay between smart and intelligent technologies and the factors contributing to the prosperity of smart supply chains.

3.2 Quantitative method

3.2.1. Questionnaire design

The questionnaire design utilized a technique for model testing. It is divided into two

sections: one to gather information about the variables and the other to collect data on

the respondents. Given that there are twelve variables in the proposed SITSP model, we

selected 200 completed responses, which is more than ten times the number of variables

in the model.

3.2.2. Research model

The research model is defined and tested in two parts: (1) using statistical methods with

SPSS 17.0 software and (2) using ANN. The conceptual framework is presented in

Figure 1.

The research model presented in this study is designed to examine the impact of

SITSP. It consists of twelve independent variables, including Industry 4.0, Green

Practices, Smart Supply Chain, Supply Chain Agility, Supply Chain Resilience, and

Supply Chain Sustainability, which contribute to the dependent variable, Sustainable

Business Performance. As the paradigms of Industry 5.0 and partially Industry 6.0 have

gained prominence, the model has been expanded to incorporate these broader concepts.

The model is constructed to reflect the evolving nature of smart technologies and their

integration into supply chain operations.

The model is tested through two distinct approaches. First, statistical methods,

including regression analysis, are used with SPSS 17.0 software to assess the

relationships between the variables. Second, an ANN approach is employed to model

the non-linear relationships and interactions among the variables. This dual approach

provides a robust framework for analyzing the dynamic and interconnected nature of

smart technologies, supply chain resilience, and prosperity in the context of modern
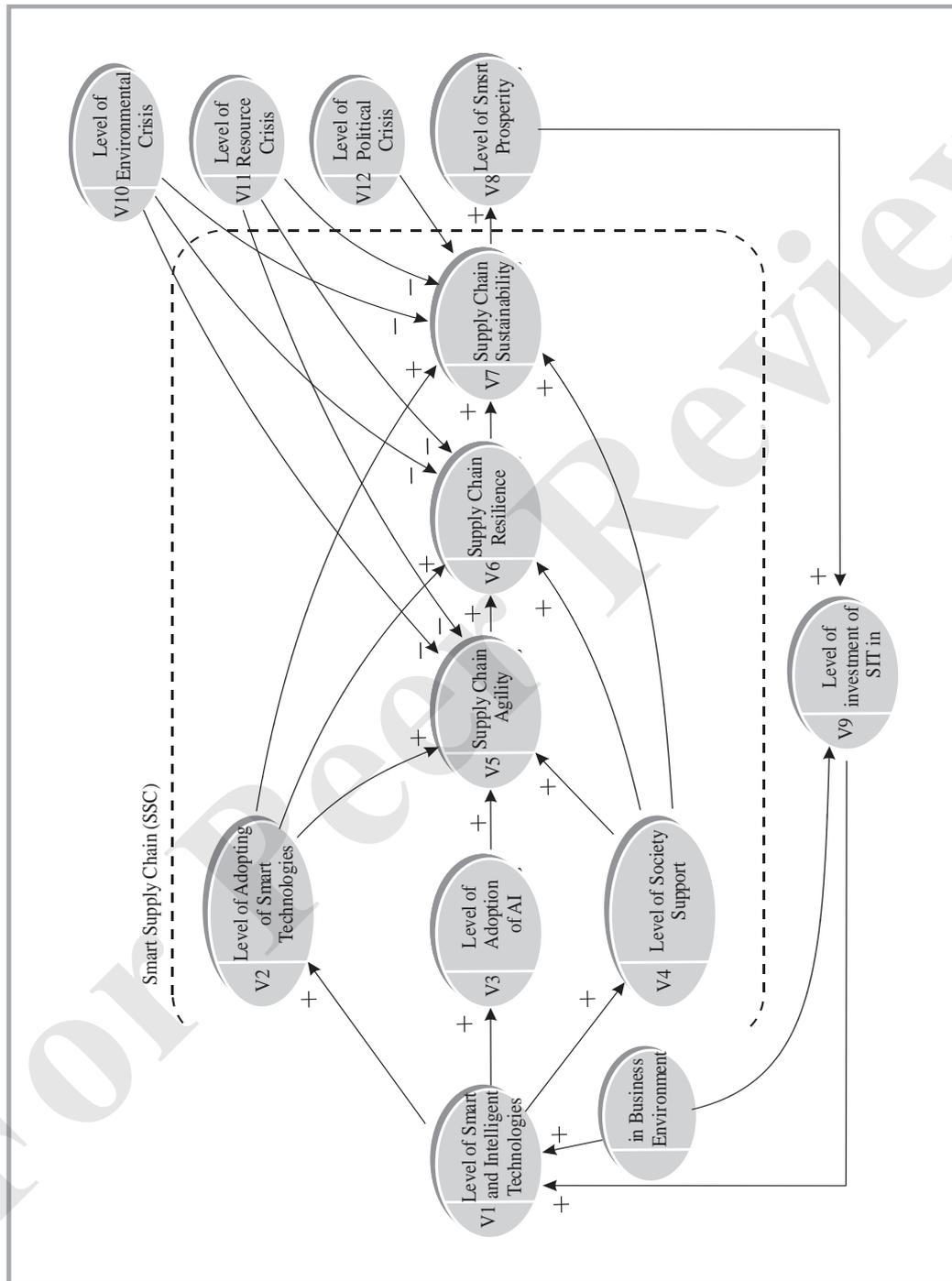
industrial paradigms.

Figure 1. Conceptual framework of SITSP.

In Section Four, the metrics for each variable are presented, along with the quantitative results for both methods (statistical analysis and ANN).

4. RESULTS

4.1 Quantitative method

The qualitative research is based on metrics for each variable. The respondents came from various sectors related to Smart Supply Chains (SSC), including manufacturing (40), quality (32), ICT (20), economics (10), finance (25), the Chamber of Commerce (5), the Association for Quality and Standardization of Serbia (15), professors (20), and master's and PhD students (30). Most of the respondents possess experience and expertise necessary to assess the levels of the variables in the model. They represent countries such as Serbia, Bosnia and Herzegovina, Montenegro, and Croatia. The interviews were conducted in two formats:

(1) During conferences and workshops using an open-ended questionnaire.

(2) Through direct contact with key political representatives, state government officials, and experts in various locations.

The respondents assessed each variable's level on a scale from 1 to 10, where 1 represents dissatisfaction and 10 indicates the highest level.

Table 1. Metrics for variable V1: Level of SIT and AI technologies.

SIT	Percentage of SIT in SSC	Level of ICT in SSC	Level of knowledge and expirience needed for SSC	Level of SIT in communication with on key SSC
	Value:	Value:	Value:	Value:
AI	Percentage using AI in SSC	Level of AI in SSC	Level of knowledge and expirience needed fofSSC	Level of AI needed for communication with key stakeholders
	Value:	Value:	Value:	Value:
Average value:				

In the proposed model, the variable V1: Smart and Intelligent Technologies (SIT) is assessed using the following indicators: the percentage of SIT and Smart Supply Chains (SSC), the level of ICT within SSC, the level of knowledge and experience required for SSC members, and the level of SIT in communication with key SSC members. Additionally, the use of Artificial Intelligence (AI) is considered, including the percentage of AI adoption in SSC, the level of AI integration within SSC, and the level of knowledge and experience required for implementing AI in SSC. For the purposes of this model, the average values of SIT and AI are used (Table 1).

The Level of Adoption of Smart Technologies in SSC is calculated as the average value of several factors: the level of adoption of smart technologies among SSC members, the level of adoption of SIT in communication among SSC members, the level of adoption of SIT with key external stakeholders, and the level of adoption of SIT knowledge within SSC. Similarly, the Level of Adoption of AI in SSC is calculated as the average value of factors such as AI adoption among SSC members, AI adoption in communication among SSC members, AI adoption with external stakeholders, and the adoption of AI knowledge within SSC.

The Level of Society Support for SSC is calculated as the average value of factors such as local government support, state government support for SSC, support from other key external stakeholders, and support from universities and colleges. The Level of SSC Agility is determined by the average value of various technologies and approaches, including smart manufacturing, cyber-physical systems, cloud computing, big data and analytics, augmented and virtual reality, simulations, Internet of Things (IoT), machine-to-machine communication, sensors, and agility dynamics within supply chains, workforce, processes, strategy, and infrastructure.

The Level of SSC Resilience is calculated as the average value of factors such as leadership and governance for smart resilience, preparedness for recovery, the level of infrastructure for resilience, the level of recovery within SSC, the level of costs related to smart resilience, and knowledge on smart resilience. The Level of SSC Sustainability is determined based on dimensions such as environmental sustainability, resource sustainability, financial sustainability, the sustainability of human knowledge and management, and the sustainability of SSC members.

The Level of Smart Prosperity is calculated based on factors such as smart industry, smart agriculture, smart economy, smart finance, smart development, and smart government. This level of prosperity is further linked to the availability of resources such as grants, credits, investment funds, and business angels.

The Level of Environmental Crisis is assessed as the average value of factors such as climate change, soil degradation, resource degradation, and the degradation of protective facilities. The Level of Resource Crisis is calculated as the average value of factors such as human resource crisis, material resource crisis, transportation resource crisis, and resource production crisis. Finally, the Level of Political Crisis is assessed as the average value of factors such as political disturbances, financial crises, legal and migration crises, political system crises, and crises related to diversion and wars.

4.2 Qualitative method

4.2.1 Responded profile

Table 2 presents a detailed breakdown of the respondents' demographics and professional characteristics. The respondents were categorized by age, department, education level, and length of service. In terms of age, the largest group was between 35-45 years old, comprising 45% of the sample, followed by 25-35 years old (35%) and

45-70 years old (20%). The distribution across various departments reveals that the

majority of respondents came from the Manufacturing department (35%), followed by

ICT (20%), Procurement (15%), and others, including Marketing and Technology, with

smaller proportions (10%-15%).

Table 2. Information about respondents.

	Details	Frequency	Percent
Age	25-35 years old	65	35
	35-45 years old	75	45
	45-70 years old	60	20
Department	Manufacturing	70	70/200
	Procurement	30	36/200
	Marketing	20	20/200
	Technology	25	25/200
	ICT	45	35/200
	Others	10	20/200
Education level	High school	110	55%
	Bachelor	70	35%
	Master/PhD	20	10%
Length of Service	5-10 years old	65	22,5%
	10-15 years old	55	27,5%
	15-20 years old	45	22,5%
	More than 20 years	55	22,5%

Regarding educational background, a significant majority of respondents held a

high school diploma (55%), with 35% having a Bachelor's degree and 10% holding a

Master's or PhD degree. In terms of work experience, the respondents were fairly

evenly distributed across different lengths of service. The most notable group had 10-15

years of experience, comprising 27.5% of the respondents, followed by groups with 5-

10 years, 15-20 years, and more than 20 years of experience, each accounting for 22.5%

of the sample.

These demographic details provide valuable context for interpreting the

responses, ensuring a diverse representation of individuals from various backgrounds

and expertise areas within the Smart Supply Chain (SSC) domain.

4.2.2 Descriptive statistics and regression analysis

Based on the analysis of 200 questionnaires, as described in Table 3, the first phase of the study involved conducting descriptive statistics. For each variable, the range, minimum and maximum values, mean values, standard errors, standard deviations, and variances were calculated using the original input data from the 200 validly received questionnaires.

Descriptive statistics provide a comprehensive summary of the data, offering insights into the distribution, variability, and central tendency of the key variables under consideration (Table 3). This statistical summary is essential for understanding the fundamental characteristics of the dataset before delving into more advanced analyses. The results include measures of central tendency (mean), variability (standard deviation and variance), and range, which collectively offer a clear picture of the data's overall structure and variability. This initial examination serves as a foundation for interpreting patterns and relationships within the data, enabling informed decisions in subsequent correlation and regression analyses.

Table 3. Descriptive statistics

	N	Range	Minimum	Maximum	Mean		Std. Deviation	Variance
	Statistic	Statistic	Statistic	Statistic	Statistic	Std. Error	Statistic	Statistic
level_of_smart_and_intelligent_technologies	200	2.64	2.08	4.72	3.4970	.03133	.44310	.196
level_of_adoption_of_smart_technologies	200	2.80	2.08	4.88	3.3367	.03305	.46746	.219
level_of_adoption_of_ai	200	2.51	.66	3.17	1.8904	.03529	.49913	.249
level_of_society_support	200	2.89	1.97	4.86	3.2588	.03520	.49774	.248
supply_chain_agility	200	2.49	3.28	5.77	4.4360	.03313	.46850	.219
supply_chain_resilience	200	2.47	3.86	6.33	5.0340	.03223	.45580	.208
supply_chain_sustainability	200	3.86	3.67	7.53	6.0016	.03347	.47329	.224
prosperity	200	3.13	2.90	6.03	4.6153	.03465	.49004	.240

level_of_investment_in_SIT	200	2.37	2.88	5.25	4.0095	.03073	.43464	.189
environmental_crisis	200	2.26	3.82	6.08	4.9308	.03512	.49672	.247
resource_crisis	200	2.68	2.92	5.60	4.2519	.03129	.44249	.196
politic_crisis	200	2.56	2.69	5.25	3.9184	.03248	.45930	.211
Valid N (listwise)	200						

The descriptive statistics reveal several noteworthy patterns across the analyzed variables. The mean values of key indicators such as "level_of_smart_and_intelligent_technologies" (3.4970) and "level_of_adoption_of_smart_technologies" (3.3367) suggest a moderate level of technological integration among respondents. However, the comparatively low mean for "level_of_adoption_of_ai" (1.8904) indicates a slower uptake of artificial intelligence, potentially highlighting areas for improvement in digital transformation efforts. Supply chain performance variables such as "supply_chain_agility" (mean = 4.4360) and "supply_chain_resilience" (mean = 5.0340) exhibit higher mean values, suggesting that respondents perceive their supply chains as relatively agile and resilient. The highest mean value is observed for "supply_chain_sustainability" (6.0016), indicating strong performance in sustainability practices. This finding underscores the growing emphasis on environmental and sustainable initiatives in supply chain management.

On the other hand, variables related to external disruptions, such as "environmental_crisis" (mean = 4.9308) and "politic_crisis" (mean = 3.9184), show considerable variability, as evidenced by their ranges and standard deviations. These results suggest that respondents experience differing levels of exposure to and perception of crises, which may impact their overall performance and sustainability efforts.

The variance and standard deviation values across all variables indicate diverse responses, reflecting the heterogeneity of the dataset. For instance, "prosperity" (mean =

4.6153) exhibits moderate variability, aligning with its role as a cumulative indicator influenced by multiple factors. Conversely, "resource_crisis" (mean = 4.2519) and "level_of_society_support" (mean = 3.2588) demonstrate tighter clustering of responses, suggesting more uniform perceptions among respondents for these variables.

Overall, the descriptive statistics provide critical insights into the dataset, highlighting strengths in sustainability and resilience while identifying opportunities for improvement in areas such as AI adoption and crisis management. These findings serve as a valuable basis for further exploration through correlation and regression analyses to uncover deeper relationships and drivers of performance.

Figure 2 presents the distribution of data for each variable. Histograms provide a visual representation of the distribution of each attribute, allowing for the identification of columns that exhibit approximately normal distributions, as well as highlighting any potential outliers or asymmetries in the data. By examining these distributions, we can gain insights into the underlying patterns of the dataset, which are crucial for conducting reliable correlation and regression analyses. The normality of distributions is an important assumption in many statistical methods, and any deviations from normality, such as skewness or the presence of extreme values, may impact the results and interpretation of the analysis. Therefore, understanding these characteristics is essential for ensuring the robustness and validity of subsequent correlation and regression models. This chapter will explore the relationships between variables using both correlation and regression techniques, shedding light on how these variables interact and influence one another within the context of the research model.
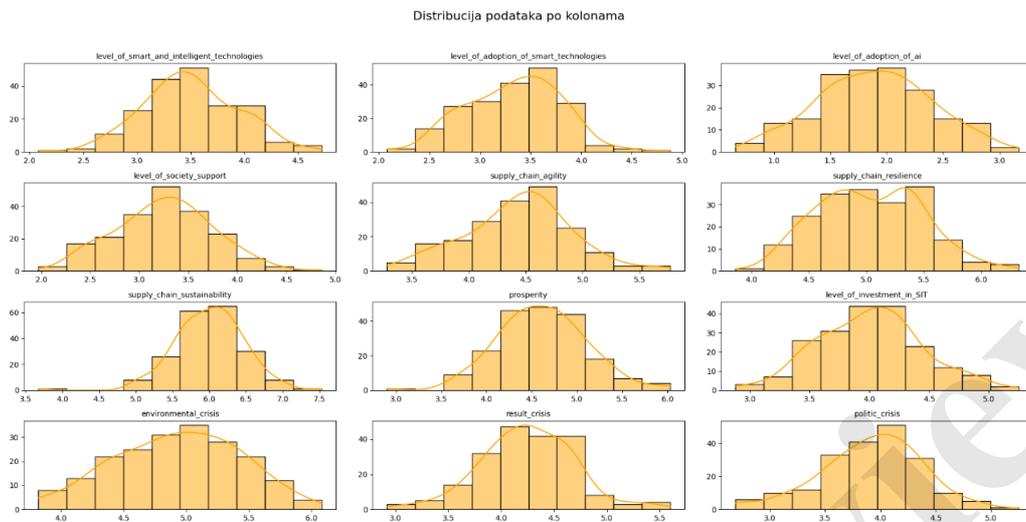
Figure 2. Histograms of the variables under consideration.

Histograms illustrate the distribution of data for all key variables in the analysis,

providing an assessment of their spread and variability. Most of the variables, such as

"level_of_smart_and_intelligent_technologies," "supply_chain_sustainability," and

"prosperity," exhibit approximately normal distributions, which indicates that the values

are evenly distributed around the mean and thus support the reliable application of

statistical methods. On the other hand, variables such as "politic_crisis" and

"resource_crisis" display more limited variability, which may complicate the

identification of significant impacts in the analysis. The visual representation clearly

highlights that critical indicators such as "supply_chain_agility" and

"level_of_adoption_of_ai" are concentrated within a narrow range of values, suggesting

a uniformity in the perception of their impact. These findings suggest that while most of

the data is suitable for regression and correlation analyses, variables with restricted

variability may require further transformation or alternative analytical approaches to

achieve a more accurate interpretation of their significance.

This initial examination of the data distributions through histograms provides a

foundation for understanding the underlying patterns and potential challenges in the

subsequent statistical analysis. By addressing these challenges, the study ensures the

robustness and validity of the correlation and regression models that follow.

Building on this initial analysis of data distributions, the next step is to explore the

relationships between the variables through correlation analysis. The correlation matrix

reveals significant positive correlations among the attributes (Figure 3). For instance,

the variable "level_of_smart_and_intelligent_technologies" shows a strong correlation

with both "level_of_adoption_of_smart_technologies" (0.63) and

"supply_chain_sustainability" (0.62). Additionally, "prosperity" exhibits a high

correlation with "supply_chain_sustainability" (0.79), suggesting a substantial influence

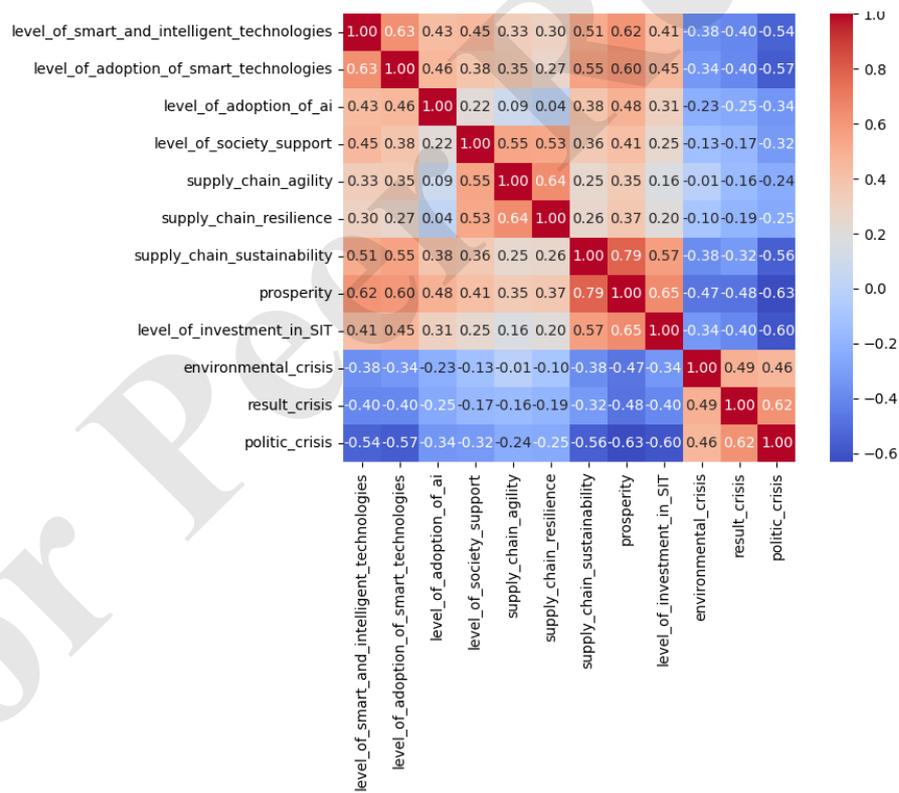of sustainability investments on overall prosperity.

Figure 3. Graphical presentation of correlation analysis.

The correlation matrix indicates significant relationships among the variables,

particularly between "level_of_smart_and_intelligent_technologies" and

"supply_chain_sustainability" (0.62), suggesting that the greater implementation of smart technologies contributes to supply chain sustainability through more efficient processes and waste reduction. Additionally, the positive correlation between "prosperity" and "supply_chain_sustainability" (0.51) indicates that more sustainable practices lead to greater economic and social success. On the other hand, negative correlations, such as between "environmental_crisis" and "supply_chain_sustainability" (-0.38) and between "politic_crisis" and "prosperity" (-0.24), show that crisis factors significantly hinder sustainability and prosperity. Technology-related variables, such as the adoption of artificial intelligence, have a positive impact on supply chain agility (0.33), while weak correlations with "level_of_society_support" and "resource_crisis" suggest their lesser significance in this context. These findings highlight the importance of digital transformation and better crisis management in enhancing sustainability and economic success, with a focus on optimizing key positive factors and mitigating negative impacts.

The summary of the regression model is presented below (Table 4), providing key insights into the relationships between the predictors and the dependent variable prosperity.

Table 4. Model summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics				
					R Square Change	F Change	df1	df2	Sig. F Change
1	.868[a]	.754	.741	.24957	.754	57.823	10	189	.000
a. Predictors: (Constant), politic_crisis, supply_chain_agility, level_of_adoption_of_ai, environmental_crisis, level_of_society_support, supply_chain_sustainability, resource_crisis, level_of_smart_and_intelligent_technologies, supply_chain_resilience, level_of_adoption_of_smart_technologies									

The model shows a high correlation coefficient (R = 0.868), indicating a strong

relationship between the predictors and the outcome variable. The R Square value of

0.754 suggests that 75.4% of the variance in the dependent variable is explained by the

independent variables included in the model. After adjusting for the number of

predictors, the Adjusted R Square remains high at 0.741, further confirming the

robustness of the model.

The standard error of the estimate (0.24957) indicates the average deviation of

observed values from the predicted values, suggesting a reasonably accurate model. The

significance of the model is supported by an F Change value of 57.823 ($p < 0.001$),

demonstrating that the predictors significantly contribute to explaining the variance in

the dependent variable.

This model highlights the critical role of variables such as

"supply_chain_agility," "level_of_smart_and_intelligent_technologies," and

"supply_chain_sustainability" in predicting the outcome, while accounting for potential

impacts of crises and other contextual factors.

The following table (Table 5) presents the coefficients of the regression model,

including unstandardized and standardized coefficients, t-values, significance levels,

and collinearity statistics (Tolerance and VIF). These metrics provide insights into the

contribution and statistical significance of each predictor variable in explaining the

dependent variable, "prosperity," while also verifying the absence of multicollinearity in

the model.

The regression analysis highlights the significant predictors contributing to the

dependent variable, "prosperity". Among them, supply chain sustainability ($\beta = 0.507$, p

< 0.001) emerged as the most impactful factor, indicating that a one-unit increase in

sustainability is associated with a 0.524-unit rise in prosperity. Similarly, the level of

adoption of AI ($\beta = 0.156$, p < 0.001) significantly influences prosperity, showcasing

the positive effect of integrating advanced technologies. The level of smart and

intelligent technologies ($\beta = 0.113$, p = 0.031) and supply chain resilience ($\beta = 0.103$, p

= 0.039) also contribute positively, emphasizing the importance of technological

adoption and robust supply chain processes. Conversely, environmental crisis ($\beta = -$

0.113, p = 0.012) negatively impacts prosperity, highlighting the detrimental effects of

ecological challenges. The model demonstrated no multicollinearity issues, with all

predictors having Tolerance values above 0.2 and VIF values below 10, ensuring the

reliability of the results. These findings underline the critical role of sustainability,

resilience, and technological advancement in enhancing prosperity.

Table 5. Regression model coefficients

Model	Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Statistics	
	B	Std. Error	Beta			Tolerance	VIF
(Constant)	1.192	.514		2.320	.021		
level_of_smart_and_intelligent_technologies	.125	.058	.113	2.174	.031	.481	2.077
level_of_adoption_of_smart_technologies	.000	.056	.000	.008	.994	.459	2.178
level_of_adoption_of_ai	.153	.042	.156	3.673	.000	.723	1.382
level_of_society_support	-.003	.047	-.003	-.058	.954	.563	1.776
supply_chain_agility	.073	.053	.070	1.372	.172	.499	2.004
supply_chain_resilience	.111	.054	.103	2.074	.039	.525	1.905
supply_chain_sustainability	.524	.050	.507	10.455	.000	.555	1.801
environmental_crisis	-.111	.044	-.113	-2.546	.012	.666	1.502
resource_crisis	-.104	.054	-.094	-1.915	.057	.543	1.841
politic_crisis	-.086	.060	-.081	-1.449	.149	.418	2.395
a. Dependent Variable: prosperity							

The regression model demonstrates strong explanatory power, with $R^2 = 0.754$, indicating that the predictors collectively account for 75.4% of the variance in the dependent variable, "prosperity". However, the model is predominantly influenced by supply chain sustainability, which stands out as the most significant predictor. Variables such as the level of adoption of AI and supply chain resilience also play critical roles in explaining the variations in prosperity, emphasizing their importance. In contrast, factors like level of society support and level of adoption of smart technologies do not show a significant contribution to the model.

To further enhance the model, future refinements could involve the removal of non-significant predictors and the exploration of potential non-linear relationships among the variables to better capture the complexity of the underlying phenomena.

The following tables (Tables 6 and 7) present the results of a linear regression model, with level_of_smart_and_intelligent_technologies as the sole predictor for the dependent variable, prosperity.

Table 6. Model summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics				
					R Square Change	F Change	df1	df2	Sig. F Change
1	,629ª	,396	,393	,36434	,396	129,577	1	198	,000
a. Predictors: (Constant), level_of_smart_and_intelligent_technologies									

Table 7. Regression model coefficients

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Statistics	
		B	Std. Error	Beta			Tolerance	VIF
1	(Constant)	1,016	,205		4,947	,000		
	level_of_smart_and_intelligent_technologies	,664	,058	,629	11,383	,000	1,000	1,000

The regression model presented demonstrates a strong relationship between level_of_smart_and_intelligent_technologies and prosperity. The R² value of 0.396 indicates that approximately 39.6% of the variance in prosperity is explained by the level of smart and intelligent technologies, which is a notable contribution for a single predictor. The standardized coefficient (Beta) of 0.629 further highlights the strength of this association, suggesting that for every one-unit increase in the level of smart and intelligent technologies, prosperity increases by approximately 0.664 units. The model's statistical significance (p < 0.001) confirms that this relationship is not due to random chance. The absence of multicollinearity, as indicated by a tolerance value of 1.000 and a variance inflation factor (VIF) of 1.000, further supports the robustness of the model. These results suggest that the implementation of smart technologies plays a significant role in driving prosperity, and that focusing on enhancing this factor could lead to improved outcomes in related sectors.

The following tables (Tables 8 and 9) present the results of a linear regression model, with level_of_smart_and_intelligent_technologies as the sole predictor for the dependent variable, level_of_adoption_of_ai.

Table 8. Model summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics				
					R Square Change	F Change	df1	df2	Sig. F Change
1	.427a	.182	.178	.45253	.182	44.093	1	198	.000

a. Predictors: (Constant), level_of_smart_and_intelligent_technologies

Table 9. Regression model coefficients

Model	Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Statistics	
	B	Std. Error	Beta			Tolerance	VIF
1 (Constant)	.209	.255		.820	.413		

level_of_smart_and_intelligent_technologies	.481	.072	.427	6.640	.000	1.000	1.000
a. Dependent Variable: level_of_adoption_of_ai								

The regression analysis presented in Tables 8 and 9 highlights the relationship

between the level_of_smart_and_intelligent_technologies and level_of_adoption_of_ai.

The R^2 value of 0.182 indicates that approximately 18.2% of the variation in the

adoption of artificial intelligence (AI) can be explained by the level of smart and

intelligent technologies. While this may seem modest, the standardized beta coefficient

of 0.427 suggests a meaningful positive relationship, implying that an increase in the

level of smart technologies is associated with a notable increase in the adoption of AI.

The statistical significance of the predictor ($p < 0.001$) further confirms that this

association is unlikely to be due to chance. Moreover, the tolerance and VIF values of

1.000 indicate that there is no multicollinearity between the variables, suggesting the

model's reliability. Despite the relatively low R^2 value, these results emphasize the

importance of smart technologies as a driving force for AI adoption, which could

inform future strategies for enhancing technological integration within organizations.

The following tables (Table 10 and 11) present the results of a linear regression

model, with level_of_smart_and_intelligent_technologies as the sole predictor for the

dependent variable, level_of_society_support.

Table 10. Model summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics				
					R Square Change	F Change	df1	df2	Sig. F Change
1	.446a	.199	.195	.44653	.199	49.262	1	198	.000
a. Predictors: (Constant), level_of_smart_and_intelligent_technologies									

Table 11. Regression model coefficients

Model	Unstandardized Coefficients	Standardized Coefficients	t	Sig.	Collinearity Statistics

		B	Std. Error	Beta			Tolerance	VIF
1	(Constant)	1.505	.252		5.979	.000		
	level_of_smart_and_intelligent_technologies	.501	.071	.446	7.019	.000	1.000	1.000

a. Dependent Variable: level_of_society_support

The regression analysis presented in Tables 10 and 11 reveals the relationship

between the level_of_smart_and_intelligent_technologies and level_of_society_support.

The R² value of 0.199 indicates that approximately 19.9% of the variation in society

support can be explained by the level of smart and intelligent technologies. Although

this percentage may be considered moderate, the standardized beta coefficient of 0.446

suggests a significant positive relationship between the two variables. This implies that

an increase in the level of smart technologies is associated with an increase in society

support, reinforcing the idea that technological advancements contribute to broader

societal backing. The model's statistical significance (p < 0.001) further supports this

relationship. Additionally, the tolerance and VIF values of 1.000 demonstrate that

multicollinearity is not an issue, ensuring the stability and reliability of the model.

While the R² is relatively modest, these results highlight the role of smart and intelligent

technologies in influencing society's support for technological advancements and can

inform strategies aimed at fostering societal engagement with new technologies.

The following tables (Table 12 and 13) present the results of a linear regression

model, with level_of_society_support, level_of_adoption_of_ai,

level_of_adoption_of_smart_technologies as predictors for the dependent variable,

supply_chain_agility.

Table 12. Model summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics				
					R Square Change	F Change	df1	df2	Sig. F Change
1	.575ᵃ	.331	.321	.38616	.331	32.307	3	196	.000

a. Predictors: (Constant), level_of_society_support, level_of_adoption_of_ai, level_of_adoption_of_smart_technologies

Table 13. Regression model coefficients

Model	Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Statistics	
	B	Std. Error	Beta			Tolerance	VIF
(Constant)	2.424	.228		10.652	.000		
level_of_adoption_of_smart_technologies	.213	.070	.213	3.062	.003	.706	1.417
level_of_adoption_of_ai	-.105	.062	-.111	-1.695	.092	.789	1.267
level_of_society_support	.460	.060	.488	7.707	.000	.851	1.176

a. Dependent Variable: supply_chain_agility

The regression analysis presented in Tables 12 and 13 examines the relationship between level_of_society_support, level_of_adoption_of_ai, level_of_adoption_of_smart_technologies, and supply_chain_agility. The R^2 value of 0.331 indicates that approximately 33.1% of the variation in supply chain agility is explained by the combination of these predictors. The model's statistical significance ($p < 0.001$) demonstrates the relevance of the predictors in explaining supply chain agility.

Looking at the individual coefficients, the level_of_society_support ($\beta = 0.488$, $p < 0.001$) emerges as the most significant predictor, indicating that higher levels of societal support contribute positively to improving supply chain agility. On the other hand, level_of_adoption_of_smart_technologies ($\beta = 0.213$, $p = 0.003$) also positively influences agility, though to a lesser degree. Interestingly, level_of_adoption_of_ai shows a negative relationship ($\beta = -0.111$, $p = 0.092$), but this result is not statistically significant at the 0.05 level, suggesting that its impact may be less pronounced or requires further investigation.

The tolerance and VIF values for all predictors (ranging from 1.176 to 1.417) confirm the absence of multicollinearity, further ensuring the stability and reliability of

the model. Overall, these findings underscore the significant role of societal support in

enhancing supply chain agility, while highlighting the complex interplay between

technology adoption and agility.

The following tables (Table 14 and 15) present the results of a linear regression

model, with politic_crisis, supply_chain_agility, level_of_adoption_of_ai,

environmental_crisis, level_of_society_support, resource_crisis,

level_of_adoption_of_smart_technologies as the predictors for the dependent variable,

supply_chain_resilience.

Table 14. Model summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics				
					R Square Change	F Change	df1	df2	Sig. F Change
1	.688ª	.473	.454	.33691	.473	24.605	7	192	.000
a. Predictors: (Constant), politic_crisis, supply_chain_agility, level_of_adoption_of_ai, environmental_crisis, level_of_society_support, resource_crisis, level_of_adoption_of_smart_technologies									

Table 15. Regression model coefficients

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Statistics	
		B	Std. Error	Beta			Tolerance	VIF
1	(Constant)	2.925	.503		5.815	.000		
	level_of_adoption_of_smart_technologies	-.025	.070	-.026	-.357	.721	.535	1.868
	level_of_adoption_of_ai	-.081	.055	-.089	-1.482	.140	.768	1.302
	level_of_society_support	.242	.060	.264	4.030	.000	.640	1.563
	supply_chain_agility	.483	.063	.496	7.643	.000	.652	1.534
	environmental_crisis	-.041	.058	-.045	-.718	.473	.695	1.438
	resource_crisis	-.055	.073	-.053	-.752	.453	.553	1.807
	politic_crisis	-.038	.077	-.038	-.493	.623	.461	2.169
a. Dependent Variable: supply_chain_resilience								

The regression analysis presented in Tables 14 and 15 explores the relationship between politic_crisis, supply_chain_agility, level_of_adoption_of_ai, environmental_crisis, level_of_society_support, resource_crisis, level_of_adoption_of_smart_technologies, and supply_chain_resilience. The R^2 value of 0.473 indicates that approximately 47.3% of the variation in supply chain resilience can be explained by the selected predictors. The model's statistical significance ($p < 0.001$) suggests that the predictors are meaningful in explaining the variability in supply chain resilience.

Among the predictors, supply_chain_agility ($\beta = 0.496$, $p < 0.001$) and level_of_society_support ($\beta = 0.264$, $p < 0.001$) are the most significant, indicating that greater agility and societal support both positively impact resilience. Conversely, the level_of_adoption_of_smart_technologies ($\beta = -0.026$, $p = 0.721$), level_of_adoption_of_ai ($\beta = -0.089$, $p = 0.140$), environmental_crisis ($\beta = -0.045$, $p = 0.473$), resource_crisis ($\beta = -0.053$, $p = 0.453$), and politic_crisis ($\beta = -0.038$, $p = 0.623$) all show weak or insignificant relationships with resilience, implying that these factors do not have a significant impact in the model at the 0.05 significance level.

The tolerance and VIF values indicate no multicollinearity issues among the predictors, as all values are well within acceptable limits (tolerance > 0.2, VIF < 10). This confirms the stability and reliability of the model. Overall, these results suggest that enhancing supply chain agility and fostering societal support are key to improving resilience, while the roles of crises and technology adoption require further investigation to better understand their influence on supply chain resilience.

The following tables (Table 16 and 17) present the results of a linear regression model, with politic_crisis, supply_chain_agility, level_of_adoption_of_ai, environmental_crisis, level_of_society_support,

level_of_adoption_of_smart_technologies, supply_chain_resilience as the predictors for

the dependent variable, supply_chain_sustainability.

Table 16. Model summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics				
					R Square Change	F Change	df1	df2	Sig. F Change
1	.658ª	.433	.412	.36290	.433	20.928	7	192	.000

a. Predictors: (Constant), politic_crisis, supply_chain_agility, level_of_adoption_of_ai, environmental_crisis, level_of_society_support, level_of_adoption_of_smart_technologies, supply_chain_resilience

Table 17. Regression model coefficients

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Statistics	
		B	Std. Error	Beta			Tolerance	VIF
1	(Constant)	6.031	.574		10.503	.000		
	level_of_adoption_of_smart_technologies	.250	.075	.247	3.323	.001	.535	1.868
	level_of_adoption_of_ai	.119	.059	.125	2.011	.046	.760	1.315
	level_of_society_support	.105	.067	.111	1.571	.118	.594	1.682
	supply_chain_resilience	.057	.078	.055	.730	.466	.529	1.892
	supply_chain_agility	-.012	.078	-.012	-.155	.877	.501	1.998
	environmental_crisis	-.114	.060	-.119	-1.910	.058	.757	1.320
	politic_crisis	-.282	.074	-.273	-3.806	.000	.573	1.744

a. Dependent Variable: supply_chain_sustainability

The regression analysis presented in Tables 16 and 17 investigates the impact of

various predictors, including politic_crisis, supply_chain_agility,

level_of_adoption_of_ai, environmental_crisis, level_of_society_support,

level_of_adoption_of_smart_technologies, and supply_chain_resilience, on

supply_chain_sustainability. The R² value of 0.433 indicates that approximately 43.3%

of the variance in supply chain sustainability is explained by the selected predictors.

The overall model is statistically significant, as evidenced by the F Change of 20.928 (p < 0.001).

Among the predictors, politic_crisis (β = -0.273, p < 0.001) has the strongest negative relationship with supply chain sustainability, suggesting that political crises substantially hinder sustainability efforts. Additionally, level_of_adoption_of_smart_technologies (β = 0.247, p = 0.001) and level_of_adoption_of_ai (β = 0.125, p = 0.046) show positive, significant relationships with sustainability, highlighting the importance of technological adoption in enhancing supply chain sustainability.

Other variables, such as level_of_society_support (β = 0.111, p = 0.118), supply_chain_resilience (β = 0.055, p = 0.466), and supply_chain_agility (β = -0.012, p = 0.877), are not statistically significant at the 0.05 level, indicating that they do not have a meaningful impact on sustainability within the context of this model. Similarly, the environmental_crisis (β = -0.119, p = 0.058) is marginally significant, suggesting that environmental crises may have an influence.

The tolerance and VIF values indicate no multicollinearity concerns, as all values are within acceptable limits (tolerance > 0.2, VIF < 10), ensuring the reliability and stability of the model. These findings emphasize the importance of political stability and technological adoption in promoting sustainable supply chains, while suggesting that further exploration of resilience and crisis impacts is warranted.

The following tables (Table 18 and 19) present the results of a linear regression model, with supply_chain_sustainability as the sole predictor for the dependent variable, prosperity.

Table 18. Model summary

	R			Change Statistics

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	R Square Change	F Change	df1	df2	Sig. F Change
1	.785 a	.616	.615	.30424	.616	318.284	1	198	.000
a. Predictors: (Constant), supply_chain_sustainability									

Table 19. Regression model coefficients

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Statistics	
		B	Std. Error	Beta			Tolerance	VIF
1	(Constant)	-.264	.274		-.961	.338		
	supply_chain_sustainability	.813	.046	.785	17.841	.000	1.000	1.000
a. Dependent Variable: prosperity								

The regression analysis presented in Tables 18 and 19 examines the relationship between supply_chain_sustainability and prosperity. The model demonstrates a high explanatory power, with an R² value of 0.616, indicating that 61.6% of the variance in prosperity is accounted for by supply chain sustainability. The model is highly statistically significant, as evidenced by the F Change value of 318.284 ($p < 0.001$).

The sole predictor, supply_chain_sustainability, has a strong positive and statistically significant impact on prosperity ($\beta = 0.785$, $p < 0.001$). The unstandardized coefficient (B = 0.813) suggests that a one-unit increase in supply chain sustainability is associated with an increase of 0.813 units in prosperity, highlighting the critical role of sustainable practices in driving prosperity.

The model shows no multicollinearity concerns, with tolerance = 1.000 and VIF = 1.000, further confirming the reliability of the results. These findings underscore the importance of focusing on sustainable supply chain practices as a pivotal factor in achieving enhanced prosperity outcomes.

The following tables (Table 20 and 21) present the results of a linear regression model, with prosperity as the sole predictor for the dependent variable, level_of_investment_in_SIT.

Table 20. Model summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics				
					R Square Change	F Change	df1	df2	Sig. F Change
1	.647a	.419	.416	.33220	.419	142.644	1	198	.000

a. Predictors: (Constant), prosperity

Table 21. Regression model coefficients

Model	Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Statistics	
	B	Std. Error	Beta			Tolerance	VIF
1 (Constant)	1.361	.223		6.100	.000		
prosperity	.574	.048	.647	11.943	.000	1.000	1.000

a. Dependent Variable: level_of_investment_in_SIT

The regression analysis detailed in Tables 20 and 21 investigates the impact of

prosperity on the level_of_investment_in_SIT (smart and intelligent technologies). The

model exhibits solid explanatory power, with an R² value of 0.419, indicating that

41.9% of the variance in the level of investment in SIT is explained by prosperity. The

model is statistically significant, with an F Change value of 142.644 ($p < 0.001$).

The predictor, prosperity, has a strong positive and statistically significant effect

on the level of investment in SIT ($\beta = 0.647$, $p < 0.001$). The unstandardized coefficient

(B = 0.574) implies that a one-unit increase in prosperity is associated with a 0.574-unit

increase in investment in SIT. This emphasizes the importance of prosperity as a driving

factor for investments in advanced technologies.

The model shows no multicollinearity concerns, as indicated by tolerance =

1.000 and VIF = 1.000, further affirming the robustness of the findings. These results

highlight the crucial link between economic prosperity and technological investments,

underscoring the role of prosperity in fostering advancements in smart and intelligent

technologies.

The following tables (Table 22 and 23) present the results of a linear regression

model, with prosperity as the sole predictor for the dependent variable,

level_of_investment_in_SIT.

1.   Equation for Prosperity (Dependent Variable)

This model predicts prosperity based on 10 independent variables, which reflect

technological, societal, and supply chain factors, as well as crises:

prosperity=1.192+0.125·level_of_smart_and_intelligent_technologies+0.000·level_of_

adoption_of_smart_technologies+0.153·level_of_adoption_of_ai−0.003·level_of_societ

y_supportprosperity=1.192+0.125·level_of_smart_and_intelligent_technologies+0.000·l

evel_of_adoption_of_smart_technologies+0.153·level_of_adoption_of_ai−0.003·level_

of_society_support+0.073·supply_chain_agility+0.111·supply_chain_resilience+0.524·s

upply_chain_sustainability−0.111·environmental_crisis−0.104·resource_crisis−0.086·p

olitic_crisis+0.073·supply_chain_agility+0.111·supply_chain_resilience+0.524·supply_

chain_sustainability−0.111·environmental_crisis−0.104·resource_crisis−0.086·politic_c

risis   (1)

2. Equation for Level of Adoption of Smart Technologies (Dependent Variable)

This equation models the level of adoption of smart technologies based on the

level of smart and intelligent technologies:

level_of_adoption_of_smart_technologies=1.016+0.664·level_of_smart_and_intelligen

t_technologieslevel_of_adoption_of_smart_technologies=1.016+0.664·level_of_smart_

and_intelligent_technologies   (2)

3. Equation for Level of Adoption of AI (Dependent Variable)

This equation models the level of adoption of AI as a function of the level of smart and intelligent technologies:

$$\text{level\_of\_adoption\_of\_ai} = 0.209 + 0.481 \cdot \text{level\_of\_smart\_and\_intelligent\_technologies} \quad (3)$$

4. Equation for Level of Society Support (Dependent Variable)

The level of society support is modeled as a function of the level of smart and intelligent technologies:

$$\text{level\_of\_society\_support} = 1.505 + 0.501 \cdot \text{level\_of\_smart\_and\_intelligent\_technologies} \quad (4)$$

5. Equation for Supply Chain Agility (Dependent Variable)

This equation describes supply chain agility based on three predictors:

$$\text{supply\_chain\_agility} = 2.424 + 0.213 \cdot \text{level\_of\_adoption\_of\_smart\_technologies} - 0.105 \cdot \text{level\_of\_adoption\_of\_ai} + 0.460 \cdot \text{level\_of\_society\_support} \quad (5)$$

6. Equation for Supply Chain Resilience (Dependent Variable)

This model explains supply chain resilience as a function of seven predictors, including crises, agility, and technology adoption levels:

$$\text{supply\_chain\_resilience} = 2.925 - 0.025 \cdot \text{level\_of\_adoption\_of\_smart\_technologies} - 0.081 \cdot \text{level\_of\_adoption\_of\_ai} + 0.242 \cdot \text{level\_of\_society\_support} + 0.483 \cdot \text{supply\_chain\_agility} -$$

$$0.041 \cdot environmental\_crisis - 0.055 \cdot result\_crisis - 0.038 \cdot politic\_crisis - 0.041 \cdot environmental\_crisis - 0.055 \cdot resource\_crisis - 0.038 \cdot politic\_crisis \quad (6)$$

7. Equation for Supply Chain Sustainability (Dependent Variable)

The model for supply chain sustainability incorporates several factors, including technological adoption, resilience, agility, and crises:

$$supply\_chain\_sustainability = 6.031 + 0.250 \cdot level\_of\_adoption\_of\_smart\_technologies + 0.119 \cdot level\_of\_adoption\_of\_ai + 0.105 \cdot level\_of\_society\_support \; supply\_chain\_sustainability = 6.031 + 0.250 \cdot level\_of\_adoption\_of\_smart\_technologies + 0.119 \cdot level\_of\_adoption\_of\_ai + 0.105 \cdot level\_of\_society\_support + 0.057 \cdot supply\_chain\_resilience - 0.012 \cdot supply\_chain\_agility - 0.114 \cdot environmental\_crisis - 0.282 \cdot politic\_crisis + 0.057 \cdot supply\_chain\_resilience - 0.012 \cdot supply\_chain\_agility - 0.114 \cdot environmental\_crisis - 0.282 \cdot politic\_crisis \quad (7)$$

8. Simplified Equation for Prosperity (Single Predictor)

This simplified model predicts prosperity based solely on supply chain sustainability:

$$prosperity = -0.264 + 0.813 \cdot supply\_chain\_sustainability \quad (8)$$

9. Equation for Level of Investment in SIT (Dependent Variable)

The model for level of investment in smart and intelligent technologies (SIT) depends on prosperity:

$$level\_of\_investment\_in\_SIT = 1.361 + 0.574 \cdot prosperity \; level\_of\_investment\_in\_SIT = 1.361 + 0.574 \cdot prosperity \quad (9)$$

10. Final Simplified Equation for Prosperity

A reduced form of the prosperity equation, derived from key predictors:

prosperity=4.630+0.203·level_of_adoption_of_smart_technologies+0.0968·level_of_a

doption_of_ai+0.0853·level_of_society_support+0.0463·supply_chain_resilience−0.009

8·supply_chain_agility−0.0927·environmental_crisis−0.2293·politic_crisisprosperity=4.

630+0.203·level_of_adoption_of_smart_technologies+0.0968·level_of_adoption_of_ai

+0.0853·level_of_society_support+0.0463·supply_chain_resilience−0.0098·supply_chai

n_agility−0.0927·environmental_crisis−0.2293·politic_crisis   (10)

4.2.2 Artificial neural network

The neural network developed in MATLAB is a multilayer perceptron (MLP) with 12

input features, a single hidden layer containing 10 neurons, and one output neuron,

designed specifically for regression tasks. The input variables in this network are

consistent with those used in the previously described model and include:

level_of_smart_and_intelligent_technologies,

level_of_adoption_of_smart_technologies, level_of_adoption_of_ai,

level_of_society_support, supply_chain_agility, supply_chain_resilience,

supply_chain_sustainability, prosperity, level_of_investment_in_SIT,

environmental_crisis, resource_crisis, and politic_crisis.

The hidden layer employs a tansigmoid activation function (tansig), which

transforms input values into the range of -1 to 1, enabling the modeling of nonlinear

relationships. The output layer uses a linear activation function (purelin), making it

suitable for predicting continuous values.

The network is trained using the backpropagation algorithm, where the weights

are optimized through gradient descent to minimize the error, defined as the mean

squared error (MSE). The network structure requires input data in the form of a matrix

with dimensions $12 \times N12 \times N$ (where N is the number of samples) and outputs as a vector of dimensions $1 \times N$. The train function is utilized for network training.

The tansigmoid function allows the network to learn complex nonlinear relationships, while the linear function ensures accurate regression. This model is well-suited for analyzing the relationships between multiple input variables and the output variable prosperity. Additionally, it offers the potential for further optimization by tuning hyperparameters and refining the architecture (Figure 3).
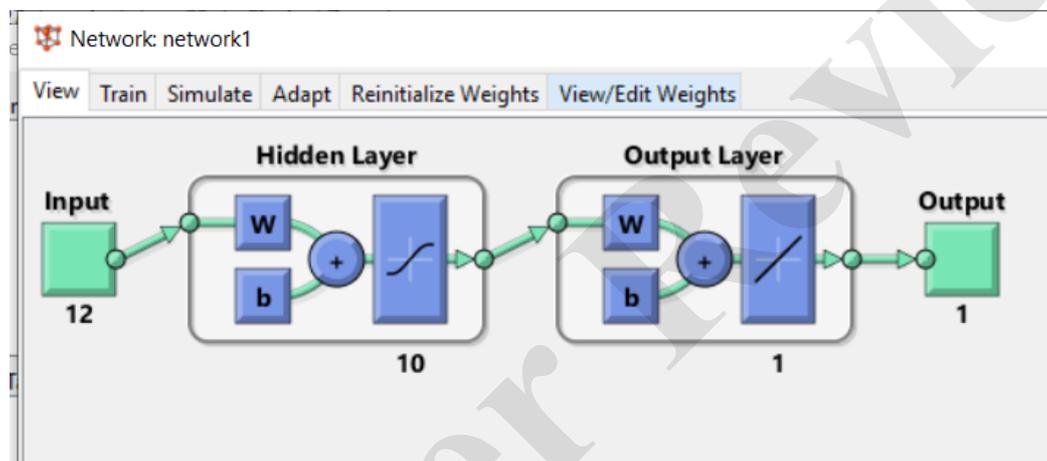
Figure 4. The developed neural network.

After training the neural network, the following results were obtained (Figures 5 and 6), highlighting the quality of training and the network's ability to generalize data:

Data Division: The random method was used for data splitting, meaning the data was randomly divided into training, validation, and testing sets to avoid any bias in data partitioning.

Training Method: The Levenberg-Marquardt algorithm was applied for network training, known as one of the most efficient methods for training neural networks, particularly for regression problems and small datasets. This method combines gradient descent and the Newton method for faster convergence.

Derivative: The default derivative settings were used during the training process.

Epoch: The training was completed in 12 epochs (iterations through the entire dataset), indicating a relatively small number of epochs, which is often characteristic of situations where the model quickly converged to optimal weights.

Performance: The network achieved a performance error of 0.00854, which is an excellent value for a regression model, as a lower error indicates a smaller discrepancy between actual and predicted values.

Gradient: A gradient value of 0.191 suggests that the optimization process is still effectively progressing but has not completely stagnated (as would occur if the gradient were closer to zero), indicating that the network continues to learn and improve.

Mu (Learning Rate): The Mu value of 0.001 reflects a very small learning rate parameter, enabling gradual and precise weight adjustments and reducing the risk of overshooting (excessive adjustments).

Validation Checks: Six validation checks were performed during training to monitor the model's performance on unseen data, reducing the risk of overfitting (over-adjusting the model to the training data).

These results demonstrate the robustness and efficiency of the neural network model in capturing complex relationships within the dataset while maintaining strong generalization capabilities.
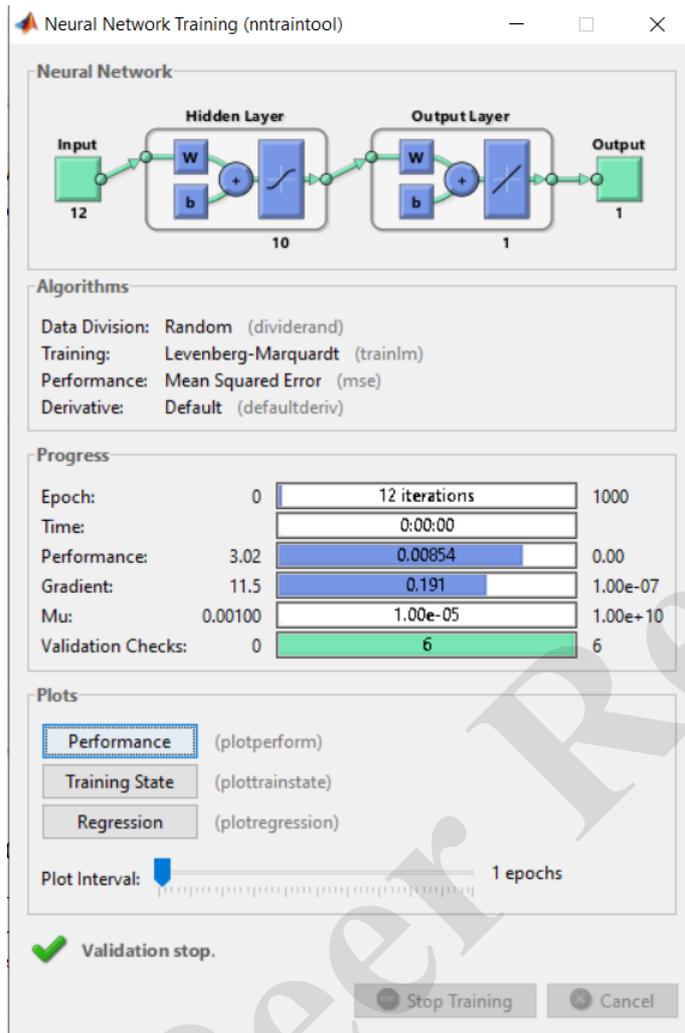
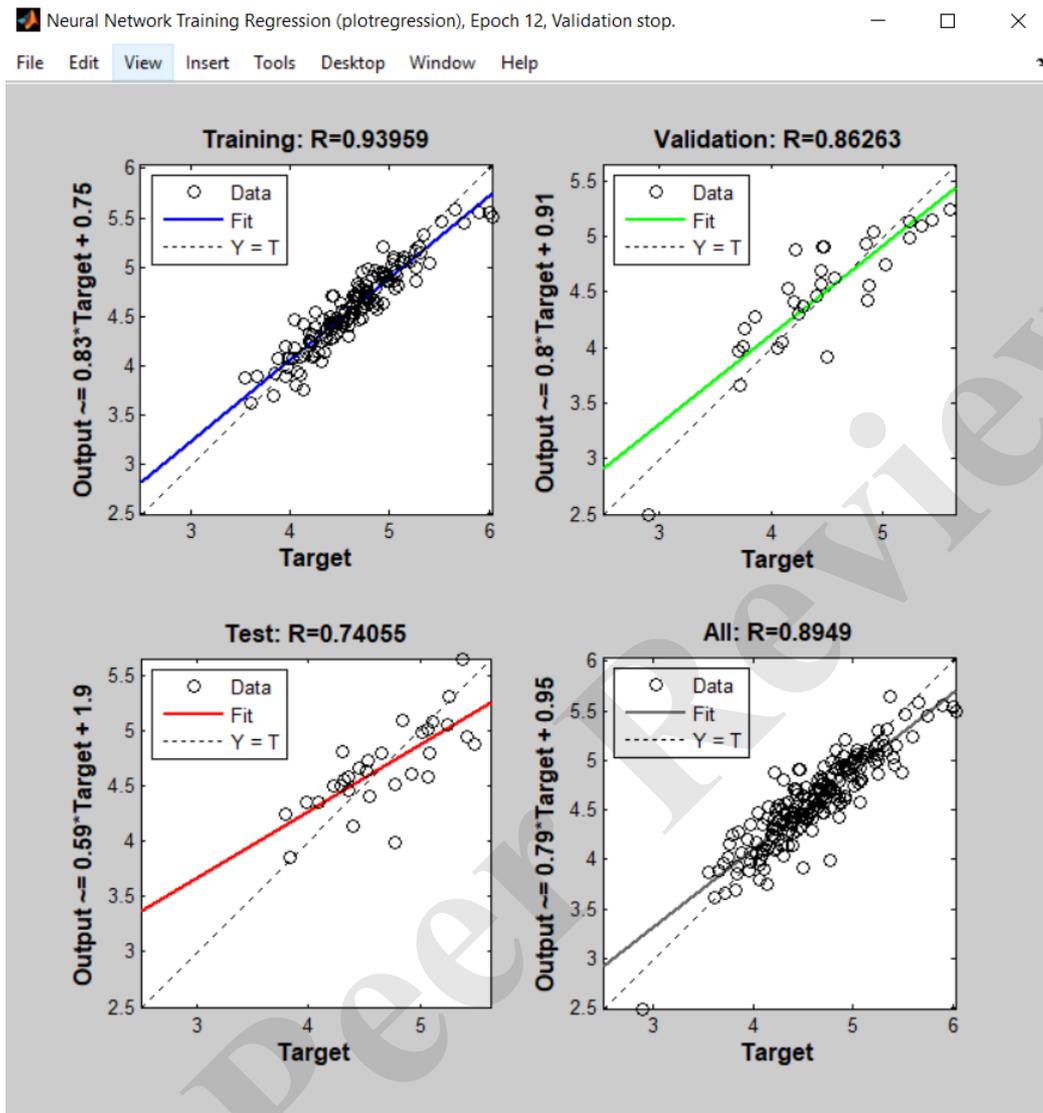Figure5. The developed neural network training

Figure 6. Results of the developed neural network.

When analyzing regression results, the following correlation coefficient (R) values were obtained for different datasets: training, validation, testing, and the overall dataset.

When the "Regression" button is clicked, the regression values indicate the model's performance across these datasets:

Training R = 0.93959: This value represents the correlation coefficient (R) between the actual and predicted values in the training dataset. A high value of 0.93959

suggests that the model fits the training data very well, indicating a strong linear relationship between the predicted and actual values. This is a positive sign, as it demonstrates the model's ability to learn from the training data.

Validation R = 0.86263: This correlation coefficient measures how well the model generalizes to the validation dataset. The value of 0.86263 is still very good, though slightly lower than the training dataset. This indicates that the model might not be fully optimized for unseen data but remains robust enough to handle it.

Test R = 0.74055: This correlation coefficient reflects the model's performance on the test dataset, which was entirely unseen during the training process. The lower R value of 0.74055 compared to the training and validation sets may indicate reduced model performance on unfamiliar data. This could be a result of overfitting, where the model is overly tailored to the training data and fails to generalize sufficiently.

All R = 0.8949: This is the overall correlation coefficient, encompassing all datasets (training, validation, and test). A value of 0.8949 is relatively high, suggesting good overall performance, though the model may not perform equally well on each individual dataset.

The model achieves very good results on the training dataset (high R), but there is a noticeable decline in performance on the validation and test datasets, suggesting limited generalization capabilities. This is a common issue in models that are overly fitted to the training data. Further evaluation and potential fine-tuning of the model are recommended to improve its performance on test data.

The provided plot (Figure 7) compares the actual values of the target variable "Prosperity" with the predicted values obtained from two models: linear regression and an ANN. A detailed analysis of the plot reveals the following key points:
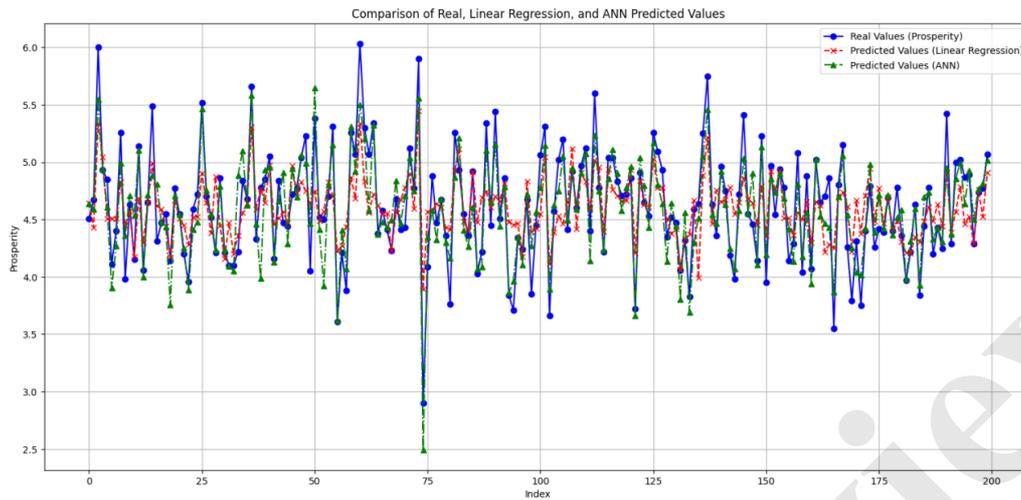
Figure 7. Comparison of the actual values of "Prosperity" with the predicted values obtained from linear regression and ANN.

Real Values (Prosperity): Represented by blue circles and connected by lines, these points depict the actual prosperity values for all data points indexed along the x-axis. The fluctuating pattern of the blue line suggests significant variability in the actual prosperity values, which are subject to fluctuations that reflect real-world complexities.

Predicted Values (Linear Regression): Represented by red crosses connected with dashed lines, these points indicate the predicted values for prosperity generated by the linear regression model. While the linear regression model shows a reasonable ability to track the overall trend of the real values, it exhibits noticeable deviations, particularly at the peaks and troughs of the actual data. This suggests that linear regression is able to capture the general trend but struggles with more intricate fluctuations in the data.

Predicted Values (ANN): Represented by green triangles connected with dashed lines, these points indicate the predictions made by the ANN. The ANN predictions align more closely with the real values than the linear regression model, especially at extreme values and in regions exhibiting higher variability. The ANN's ability to adapt

to complex patterns is more pronounced, demonstrating a better understanding of nonlinear relationships.

Furthermore, the following figure (Figure 8) presents a correlation heatmap between actual values and predictions generated by linear regression and artificial neural network (ANN) models, aimed at evaluating model accuracy.
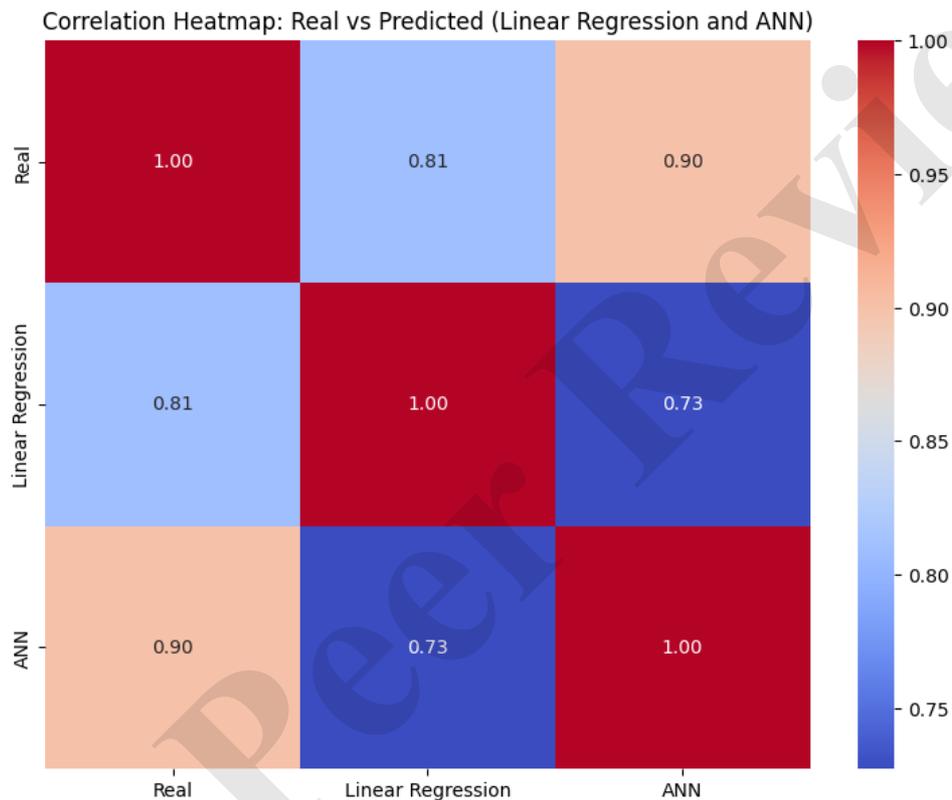

Figure 8. Comparison of the actual values of "Prosperity" with the predicted values obtained from linear regression and ANN.

The heatmap illustrates the correlation coefficients between actual values, linear regression predictions, and ANN predictions. The correlation coefficient between actual values and ANN predictions is 0.90, indicating a high level of agreement, while the correlation with linear regression predictions is slightly lower (0.81). The correlation between linear regression and ANN models is 0.73, suggesting that the two models provide different approaches to estimation, with the ANN showing better alignment

with the actual values. These results highlight the advantage of the ANN model over linear regression in data analysis for this particular case.

The ANN model outperforms the linear regression model in this comparison, as indicated by its closer alignment with the actual prosperity values. However, some deviations persist, highlighting areas where further model optimization could be beneficial, such as through hyperparameter tuning or additional data preprocessing techniques.

5. DISCUSSION AND CONCLUSSION

The proposed model of the Smart and Intelligent Supply Chain (SISC) with twelve variables has been designed to assess the impact of Smart and Intelligent Technologies (SIT) on the prosperity of society. The model incorporates various factors, including: v2 (Level of Adoption of Smart Technologies), v3 (Level of Adoption of AI), v4 (Level of Society Support), v5 (Agility of the Supply Chain), v6 (Resilience of the Supply Chain), v7 (Sustainability of the Supply Chain), v8 (Prosperity), v9 (Level of Investment in SIT), v10 (Level of Environmental Crisis), v11 (Level of Resources Crisis), and v12 (Level of Political Crisis). The initial model was further expanded and renamed as the SIARS (Smart, Intelligent, Agile, Resilient, and Sustainable) Support Chain, making it suitable for new paradigms like Industry 4.0 and Industry 5.0.

The model was constructed to address five research questions, with corresponding hypotheses (H0 – F5). To validate the model, the authors conducted research using the Nominal Group Technique, engaging experts from various fields related to supply chains, particularly manufacturing, universities, supply chain management, professional associations, SIT, quality and standardization bodies, chambers of commerce, and government. A questionnaire was developed and distributed to potential respondents, ultimately receiving the first 200 responses.

To test the stated hypotheses, two methods were employed: (1) statistical analysis, and (2) an ANN approach. The statistical analysis revealed several key relationships in the model. The most significant positive relationship was between "smart and intelligent technologies" and "supply chain sustainability" (0.62), followed by the positive correlation between "supply chain sustainability" and "prosperity" (0.51), and "adoption of AI" and "agility" (0.33). Conversely, the "level of society support" and "resource crisis" showed weaker positive correlations, while a negative weak correlation was found between the "environmental crisis" and "supply chain," as well as between the "political crisis" and "prosperity" (-0.24) and "sustainability" (-0.38).

The model demonstrated strong performance with an R^2 value of 0.754, with the dominant impact of "supply chain sustainability." Other significant predictors included "level of adoption of AI" and "supply chain resilience." However, "level of society support" and "level of adoption of smart technologies" did not have a significant impact on the model. There is potential for improving the model by eliminating non-significant predictors and exploring potential non-linear relationships. The final equation, which links "prosperity" to the independent variables, highlighted the importance of predicting the impact of all significant variables and developing strategies for their improvement.

The model's performance was further validated using an ANN with 12 input variables, one hidden layer consisting of 10 neurons, and one output neuron. The data for the ANN model was sourced from the questionnaire responses. The results demonstrated excellent performance in the training set (R = 0.93959), with slightly lower performance in the validation (R = 0.86263) and test sets (R = 0.74055), leading to an overall performance of R = 0.8949. These results confirm that the model provides reliable predictions.

The authors suggest that further evaluation and adjustments to the model are necessary. Notably, a comparison of the real values with the predicted values from both the linear regression and ANN models revealed minimal differences, with the Correlation Heat Map indicating a very high correlation between the real and predicted values (10.73).

Future research will explore the introduction of additional factors such as "quality," "spirituality," "leadership," "smart infrastructures," "smart economy," and "smart government." Furthermore, the inclusion of more official data and experts with higher levels of expertise is recommended to refine and expand the model.

6. LITERATURE

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