THE IMPACT OF ARTIFICIAL INTELLIGENCE AND SUSTAINABLE DIGITALISATION ON THE RESILIENCE OF LOGISTICS CHAINS IN ROMANIA

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Abstract

In the context of increasingly frequent disruptive phenomena, the adoption of artificial intelligence (AI) in supply chain logistics holds the promise of strengthening economic resilience. However, the existing literature has not sufficiently investigated the mechanisms through which this consolidation can be effectively achieved. Accordingly, the present study examines the complex relationships between factors associated with sustainable digital transformation and the economic resilience of supply chains, using SmartPLS software to analyse data collected from Romanian companies. The modelling is based on variance-based structural equation modelling (PLS-SEM), grounded in the Diffusion of Innovations theory, the Technology-Organisation-Environment (TOE) framework, and the Dynamic Capabilities Theory.

The results highlight that the adoption of AI and sustainable digitalisation contribute to strengthening SCR, but its positive impact is mainly manifested through competitive advantage, identified as the main predictor. The originality of this study lies in the development and testing of an econometric model centred on AI adoption as a strategic instrument to gain competitive advantage, significantly amplified through the integration of AI techniques into green logistics practices and closely linked to organisational digital maturity. Thus, the study expands the understanding of the complex causal mechanisms that link the adoption of AI and sustainable digitalisation, based on green logistics practices, to the resilience of logistics chains. The results also provide strategic benchmarks

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for companies seeking to strengthen the resilience of their supply and delivery chains in the face of economic and geopolitical disruptions.

Keywords: artificial intelligence, digital maturity, green logistics practices, competitive advantage, PLS-SEM, supply chain resilience.

JEL Classification: M10, C35, C54.

Introduction

The adoption of artificial intelligence (AI) in supply chain logistics (SCL) promises significant operational and environmental gains through faster routes, more accurate demand forecasts, and reduced wasteful miles, leading to lower costs and emissions (Liu and Lin, 2021). The extent to which these promises are fulfilled is ultimately reflected in the resilience of the supply chain (SCR) (Kassa et al., 2023; Sunmola and Baryannis, 2024; Tang, Wu, and Zhou, 2025). In SCL, AI is essentially a technological innovation that uses intelligent systems, mainly consisting of software (Hansen et al., 2024). Adopting AI brings significant benefits (Han et al., 2020; Oliveira et al., 2023; Bigliardi et al., 2025), but also involves certain risks possible to avoid (Fosso Wamba et al., 2024).

Supply chain resilience (SCR) is a complex concept that refers to the ability of the supply chain to return to its normal state after a disruption (Hohenstein, 2015). From a dynamic capability’s perspective, the supply chain can not only recover, but also evolve to a more advanced level than before the disruptive event. Empirical studies suggest that AI supports all phases of SCR, namely pre-event preparation, event response, and post-event recovery (Gupta et al., 2023; Tang et al., 2025; Yang et al., 2025; Balan et al., 2025). AI can also reduce the negative impact of geopolitical risks, but the magnitude of its benefits depends on the company's digital readiness and the quality of implementation (Dong et al., 2025).

The ability of AI to contribute to SCR depends on the existence of well-defined causal connections. At the beginning of this causal chain, there are the factors that determine the adoption of AI within a firm (Tornatzky and Fleischer, 1990; Culot et al., 2024; Mao, 2025). Once adopted, AI generates measurable operational improvements that lead to a competitive advantage (Teece, 2007; Kocabasoglu-Hillmer et al., 2023). More importantly, resilience, at the end of the causal chain triggered by the adoption of AI, depends heavily on green logistics practices (Liu and Lin, 2021; Sharma and Gupta, 2025), which constitutes a strategic factor of competitiveness, with a cross-cutting impact on the other factors (Ponomarov and Holcomb, 2009; Tukamuhabwa et al., 2015).

Within Romanian enterprises, previous studies (Rugiubei and Pînzaru, 2022) have highlighted significant differences in the level of AI integration in SCL, with the sporting goods sector in a leading position (Rugiubei and Stoica, 2025). In the process of transition towards digitalisation and sustainability (Pînzaru et al., 2022), data governance and regulatory alignment appear as essential factors for the effective implementation of AI (Ceptureanu et al., 2025). The case of Romania contrasts sharply with that of China (Bigliardi et al., 2025), the country most frequently analysed in the specialised literature on AI and SCL, but different in its centralised context and substantial resources allocated to SCL (Dong et al., 2025; Ma et al., 2025). Therefore, the Romanian context generates both the need and the opportunity for conducting our research in the broader context of the European Green Deal and the adoption of emerging technologies.

Considering the above-mentioned aspects, through this study we aim to answer the following questions: How does the adoption of artificial intelligence and the implementation of sustainable digitalisation influence the resilience of supply chains? Are there significant differences regarding the impact of these dimensions in generating the resilience of supply chains? To answer these questions, the authors resorted to conducting empirical research, using as a research instrument the questionnaire, administered online to mid-level managers in Romanian companies.

1. Literature Review

1.1 Supply Chain Resilience

Supply chain resilience (SCR) is broadly defined as the ability of a socio-economic system to quickly restore its normal logistics operations following external disruptions or shocks (Tang et al., 2025).

According to the literature, SCL is influenced by a series of internal factors, such as organisational practices, risk management routines, the existence of operational reserves, coordination capacity, and operational flexibility (Ponomarov and Holcomb, 2009; Tukamuhabwa et al., 2015; Riad et al., 2024). Strategies to strengthen resilience are articulated around three fundamental dimensions, consisting of preparation, reaction, and recovery in the context of a disruptive event (Hohenstein et al., 2015; El-Naggar and Ali, 2023). Preparation reflects a proactive approach, oriented towards anticipating risks and developing continuity plans. Reaction designates the set of reactive measures adopted during the disruption, and recovery involves both the restoration of functionality and the initiation of learning and continuous improvement processes (Han et al., 2020).

Although research on SCR in the last decade has advanced considerably and highlighted both the impact of traditional determinants (Ponomarov and Holcomb, 2009; Tukamuhabwa et al., 2015; Riad, Naimi and Okar, 2024) and newer ones (Liu and Lin, 2021; Sharma and Gupta, 2025), as well as the idea of understanding resilience through the lens of adaptive capacity oriented towards obtaining competitive advantage (e.g., Kocabasoglu-Hillmer et al., 2023), empirical studies remain limited and focused mainly on China and India.

1.2 AI as a Strategic Enabler of Supply Chain Resilience

AI strengthens SCR by enhancing the firm’s ability to detect, respond, and adapt to disruptions in innovative ways often turning volatility into competitive advantage (Cannas, 2023; Belhadi et al., 2024; Hansen et al., 2024). Previous research identified several positive effects of AI adoption in SCR, mainly consisting of accurate forecasting, economic and environmental supplier evaluation, effective risk management, optimised distribution, personalised customer interaction, and sustainability-driven competitor practices (Richey et al., 2023; Kassa et al., 2023; Raouf et al., 2025; Ceptureanu et al., 2025). Accordingly, AI does not just shift SCR from a reactive to a proactive framework, but it becomes a key enabler of both incremental and radical resilience. AI can reinforce incremental resilience through early detection of threats financial, technological, reputational, environmental, or social and by estimating their impact on logistics operations (Cohen et al., 2022). Radical resilience, on the other hand, is shaped by AI's contribution to rapid process adaptation, bold decision-making (whether previously tested or not), network reconfiguration, and the development of eco-services, depending on the nature and intensity of the disruption (Shahzadi et al., 2024).

At this point, it is necessary to underline that AI adoption depends on its perceived functional benefits, business model compatibility, and the enterprise's digital maturity (Dubey et al., 2021; Rugiubei and Pînzaru, 2022; Gupta et al., 2023). On the other hand, when modelling the complex relationships between AI adoption and supply chain resilience (SCR) using SEM, most studies have relied on a conceptual framework rooted in the Technology-Organisational-Environment (TOE) model (Dubey et al., 2021), or on hybrid approaches that combine TOE with other theories such as the Resource-Based View (Wang and Pan, 2022) or Dynamic Capabilities Theory (DCT) (Aslam et al., 2025). In the case of the particular study of the adoption of AI in European SMEs, Sánchez et al. (2025) used a TOE-Diffusion of Innovation (DOI) (Rogers, 2003) theory framework. DOI provides insight into how AI, as a technological innovation, is adopted among European SMEs, while the TOE framework helps explain the different levels of AI adoption, depending on internal capabilities and external pressures that influence the success of this process.

Given the exponential adoption of AI, integrating a theoretical foundation based on TDI, TOM, and TCD, with the aim of modelling the complex relationships between AI adoption and SCR could contribute to a better understanding of its strategic role in strengthening the ability of firms to respond adaptively to environmental disruptions.

1.3 The relationship between supply chain resilience, performance and AI

The existing literature highlights the existence of a significant correlation between SCR and organisational performance (e.g., Batista et al., 2022). For example, through its ability to anticipate demand, AI contributes to reducing waste, and by optimising transport routes it reduces fuel consumption; both aspects support the development of both economically and environmentally efficient supply chains (Pournader et al., 2021; Raouf et al., 2025). At the same time, ecological supply chains tend to be more resilient (Liu and Lin, 2021). It can be argued that, within them, routine losses are reduced, and innovative ecological services are developed as tools that can support the company in managing strategic changes and maintaining profitability even after unexpected disruptions. Also, the specialised literature indicates that SCR represents a factor generating superior financial and operational performance, resulting in faster recovery from crises, reduced costs, and increased productivity (Wang and Prajogo, 2024; Yang et al., 2025).

In summary, studies investigating the relationship between SCR, performance, and artificial intelligence exist, but they mainly focus on centralised or developed economies. In emerging economies, such as Romania, the literature indicates an insufficiently developed approach.

2. Research Framework and Hypothesis Development

Several theoretical models have been used in our research. Traditionally, supply chain resilience (SCR) has been explained through organisational practices such as risk management, use of additional resources, and flexibility, which enable firms to anticipate, absorb, and recover from disruptions (Ponomarov and Holcomb, 2009; Tukamuhabwa et al., 2015; Hohenstein et al., 2015; Han et al., 2020). However, recent empirical studies, suggest that green logistics practices including the use of low-emission transport, renewable fuels, and environmentally efficient distribution, also strengthen resilience by reducing exposure to fuel price volatility, regulatory shocks, and environmental risks, while enhancing flexibility and stakeholder legitimacy (Liu and Lin, 2021; Sharma and Gupta, 2025). Given the essential role of logistics in maintaining supply chain continuity, reconfiguring the determinants of resilience to include the ecological dimension provides a more current and contextually relevant perspective. In addition, we considered green logistics practices as fundamental to SCR, thus ensuring that this capability is not only reactive, but proactively integrated into the structuring of supply chains. As a result, we formulated the first research hypothesis as follows:

H1: Green logistics practices positively influence the resilience of supply chains.

AI adoption has been previously described as having a consistent contribution to achieving competitive advantage in supply chains by optimising operational efficiency and increasing organisational agility (Han et al., 2020; Kassa et al., 2023; Culot et al., 2024). As a result, we find that:

H2: Artificial intelligence adoption positively influences competitive advantage in supply chains.

In turn, competitive advantage is a key driver of resilience, as firms with superior competitive positioning are better equipped to respond to disruptions (Teece, 2007; Kocabasoglu-Hillmer et al., 2023). As competitive advantage is enhanced by AI, which supports all stages of supply chain resilience, from pre-emptive planning to post-event response, by improving agility and efficiency (Gupta et al., 2023; Tang et al., 2025), the influence of comparative advantage on supply chain resilience is amplified. Therefore, we postulate that:

H3: Competitive advantage positively influences supply chain resilience

The ability of AI to contribute to SCR is supported by a large body of research, as evidenced by systematic reviews of the specialised literature (Kassa et al., 2023; Shahzadi et al., 2024; Culot et al., 2024; Smyth et al., 2024). The results of these studies highlight that the adoption of AI can influence SCR both directly and indirectly, through competitive advantage. For example, the anticipatory capacity offered by AI directly contributes to the performances associated with resilience, while other effects, such as differentiation and agility, manifest indirectly, through the strengthening of the competitive position (Yang et al., 2025). Based on these considerations, we propose the following hypothesis:

H4: The adoption of artificial intelligence positively influences the resilience of supply chains, both directly and indirectly, through competitive advantage.

Based on these four hypotheses derived from the literature, we propose the model in Figure no. 1.

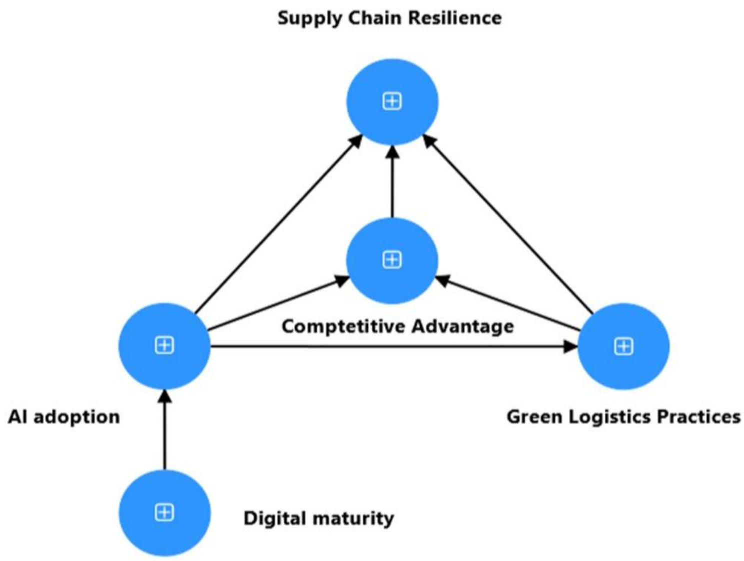

Figure no. 1. The influence of AI adoption and green logistics practices on competitive advantage and supply chain resilience

As illustrated in Figure no. 1, the proposed model captures the pathway from AI adoption and green logistics practices to competitive advantage, and from there to supply chain resilience (SCR). Grounding the model in key determinants of SCR ensures both theoretical and econometric validity, helping to avoid misleading results and maintaining alignment with established literature in the field (Ponomarov and Holcomb, 2009; Tukamuhabwa et al., 2015). By integrating AI adoption, we extend this framework to highlight how digital technologies open new avenues toward incremental resilience (rapid recovery from localised disruptions) and radical resilience (strategic reconfiguration in response to systemic shocks).

3. Data, Operationalisation of Constructs, and Modelling Approach

3.1. Data collection and verification

Data were collected between March and August 2025, through an online questionnaire conducted on the Google Forms platform, addressed to mid-level managers from Romanian companies belonging to various industries, included in a structured database. The questionnaire included questions regarding the following aspects: general information about the company, level of digital maturity, adoption of artificial intelligence, green practices, competitive advantage and resilience of the supply and delivery chain. From the beginning, participants were clearly informed about the objectives of the study, the estimated duration, the procedures involved and all relevant details. The items taken from the specialised literature, presented in section 3.2, were translated using consecutive reverse translation.

In February 2025, prior to the distribution of the questionnaire, it was tested with the help of two economics and IT specialists from the academic environment and three middle-level managers from companies. Based on the feedback received, including on the completion time, the questionnaire was revised, and subsequently 142 responses were collected. First, we analysed early responses (March–April) compared to late responses (July–August). Since we did not find significant differences, we considered that the non-response bias was low. Subsequently, we performed a final check to eliminate any incomplete responses, leaving a number of 114 valid questionnaires. This resulted in a convenience sample, considered appropriate for exploratory research, which includes 114 companies from all economic sectors (Annex 1).

At the same time, our sample can be considered adequate in the context of structural equation modelling (PLS-SEM), according to the recommendations of Hair et al. (2021; 2024), who support the substantiation of the sample on statistical power considerations. Thus, following a power analysis of the test, for a medium-sized effect ($f^2 = 0.15$) and a significance threshold ($\alpha = 0.05$), a sample of $N = 103$ is required to achieve a statistical power of 90%. Therefore, our sample of 114 respondents provides sufficient power to identify medium-sized effects. In addition to the sample size, our analysis focused on standard criteria for evaluating measurement and structural models. This approach is appropriate in the context of the present research because, as the literature points out, variance-based SEM, as implemented in SmartPLS, is considered non-parametric and does not depend on the normality of the data (Hair et al., 2021; 2024).

3.2 Operationalisation of Constructs

To operationalise the constructs in our model, we rely on pre-existing measurement instruments, adapted to the context of the supply-delivery chain and artificial intelligence:

- AI adoption – 4 items assessing the integration of AI into supply chain functions, including planning, forecasting, logistics, and risk management. The items were drawn from Oliveira et al. (2023) and Gupta et al. (2023), and adapted to the specifics of this research.

- Digital maturity – 5 items measuring the level of organisational commitment to AI adoption within the supply-delivery chain. The items, sourced from Rossman (2019) and Van Tonder et al. (2024), were tailored to fit the research context.

- Competitive advantage – 4 items evaluating cost efficiency, differentiation, responsiveness, and service quality as performance outcomes of AI adoption in supply chain management. The items were adapted to the study's focus, based on existing approaches in the literature (Liu and Lin, 2021; Riad et al., 2024; Belhadi et al., 2024).

- Green logistics practices – 4 items measuring the company's commitment to sustainable transportation and distribution, adapted from Rajak et al. (2021).

- Supply chain resilience – 4 items assessing operational and strategic capacity to respond effectively to disruptions, adapted from Pettit, Fiksel and Croxton (2010) and Pournader, Shi and Seuring (2021).

The scales, including all items, are presented in Annex 2.

3.3. Modelling Approach

Our modelling strategy involves the exclusive use of reflective constructs. All five latent constructs are modelled reflectively because the observed indicators represent manifestations of the underlying latent variables. The analysis begins with the assessment of the constructs to ensure indicator reliability, internal consistency, convergent validity, and discriminant validity (Hair et al., 2021; 2024). For this SEM analysis, we adopt a variance-based approach, which is suitable for estimating complex models with reflective and formative constructs, given a relatively modest sample size, as in our case. The measurement model is initially assessed to confirm the reliability and validity of the constructs (Hair et al., 2021), followed by the analysis of structural relationships, including the mediation paths from AI adoption to competitive advantage and supply chain resilience, using a variance-based SEM approach. To estimate the statistical significance of effects, including indirect ones, SmartPLS uses the bootstrap method. In the present study, 5000 iterations were performed, the default value in SmartPLS.

4. Results

Model fit is adequate, as indicated by an SRMR (Standardised Root Mean Square Residual) value of 0.067 and NFI of 0.943.

4.1 Data Testing

The results of the reliability and validity testing of the constructs are presented in Appendix 2. As shown in the appendix, all external loading values exceed the recommended threshold of 0.50 (Hulland, 1999). The Cronbach's Alpha coefficient values (0.825-0.975) exceed the 0.70 benchmark set by Nunnally (1978), while the composite reliability ($\rho c > 0.85$) and AVE (> 0.60) meet the standards suggested by Becker et al. (2023). In addition, all VIF values are below the threshold of 5, indicating the absence of concerns related to multicollinearity.

For the assessment of discriminant validity by the Fornell–Larcker criterion, table no. 1 presents on the main diagonal the square root of the extracted mean value (AVE) for each construct.

Table no. 1. Discriminant validity

	AI Adoption	Competitive Advantage	Digital Maturity	Green Logistics Practices	Supply Chain Resilience
AI Adoption	0.948				
Competitive Advantage	0.625	0.925			
Digital Maturity	0.773	0.54	0.903		
Green Logistics Practices	0.449	0.669	0.48	0.872	
Supply Chain Resilience	0.649	0.834	0.597	0.627	0.972

Table no. 1 shows that the elements on the main diagonal are significantly larger than the off-diagonal elements, which confirms the presence of discriminant validity.

4.2 Structural model

Direct effects are presented in table no. 2.

Table no. 2. Path estimates

Path	Beta (ES)
AI adoption -> Competitive advantage	0.406*** (0.068)
AI adoption -> Supply chain resilience	0.108.(0.058)
AI adoption -> Green logistic practices	0.449***(0.068)
Competitive advantage -> Supply chain resilience	0.869***(0.047)
Digital maturity -> AI adoption	0.773***(0.050)
Green logistic practices -> Competitive advantage	0.487***(0.066)
Green logistic practices -> Supply chain resilience	-0.003(0.046)

*Note: .p<0; ***p<0,001; ES-standard error*

Table no. 2 shows that green logistics practices do not directly influence supply chain resilience. Furthermore, the direct impact of AI adoption on supply chain resilience is only marginally statistically significant. The total effects are presented in table no. 3.

Table no. 3. Total Effects

Path	Beta (ES)
AI adoption -> Competitive advantage	0.625*** (0.061)
AI adoption -> Supply chain resilience	0.649***(0.056)
AI adoption -> Green logistic practices	0.449***(0.068)
Competitive advantage -> Supply chain resilience	0.869*** (0.047)
Digital maturity -> AI adoption	0.773***(0.050)
Digital maturity -> Competitive advantage	0.483***(0.063)
Digital maturity -> Supply chain resilience	0.502***(0.062)
Digital maturity -> Green logistic practices	0.347***(0.064)
Green logistic practices -> Competitive advantage	0.487***(0.066)
Green logistic practices -> Supply chain resilience	0.420***(0.063)

*Note: ***p<0.001; SE-standard error*

All total effects are highly statistically significant.

Additionally, in table no. 4 we present the indirect path' estimates.

Table no. 4. Specific indirect effects

Path	Beta (ES)
AI adoption -> Competitive advantage -> Supply chain resilience	0.353***(0.064)
Digital maturity -> AI adoption -> Green logistics practices-> Supply chain resilience	-0.001(0.016)
Digital maturity -> AI adoption -> Competitive advantage	0.314***(0.059)
Digital maturity -> AI adoption -> Green logistics practices-> Competitive advantage	0.169***(0.038)
Digital maturity -> AI adoption -> Supply chain resilience	0.083.(0.045)
Digital maturity -> AI adoption -> Internal organisational practices	0.347***(0.064)

Path	Beta (ES)
Green logistics practices-> Competitive advantage -> Supply chain resilience	0.423***(0.062)
Digital maturity -> AI adoption -> Green logistics practices-> Competitive advantage -> Supply chain resilience	0.147***(0.035)
AI adoption -> Green logistics practices-> Competitive advantage -> Supply chain resilience	0.190***(0.040)
AI adoption -> Green logistics practices-> Competitive advantage	0.218***(0.044)
AI adoption -> Green logistics practices-> Supply chain resilience	-0.001(0.021)
Digital maturity -> AI adoption -> Competitive advantage -> Supply chain resilience	0.273****(0.055)

*Note: ***p<0.001; SE-standard error*

As shown in table no. 4, most indirect effects are statistically significant, as proof of complex mediation chains being in place in our model.

In summary, the study results are presented in table no. 5.

Table no. 5. Summary of Research Findings

Research Hypothesis	Type of Relationship Tested	Results Obtained	Form of Empirical Support	Remarks
H1: Green logistics practices positively influence supply chain resilience	Direct and mediated	Direct effect not significant; mediated effect significant via competitive advantage	Partial validation: the hypothesised relationship is confirmed only indirectly, through full mediation	Competitive advantage acts as an intermediary mechanism; direct influence is not confirmed
H2: AI adoption positively influences competitive advantage in supply chains	Direct	Significant and positive direct effect between AI adoption and competitive advantage	Full validation: the hypothesised relationship is fully confirmed, without mediation	AI adoption directly contributes to strengthening competitive advantage in the supply chain
H3: Competitive advantage positively influences supply chain resilience	Direct	Significant and positive direct effect between competitive advantage and supply chain resilience	Full validation: the hypothesised relationship is fully confirmed, without mediation	The most substantial and significant path in the model; competitive advantage is a key predictor
H4: AI adoption positively influences supply chain resilience	Direct and mediated	Direct effect not significant; fully mediated effect via competitive advantage	Partial validation: the hypothesised relationship is confirmed only indirectly, through full mediation	AI adoption contributes to resilience exclusively through competitive advantage; direct influence is not confirmed

It can be concluded that the predictive value of the model is validated by the consistency of the results obtained.

5. Discussion

Overall, our findings support the idea that supply chain resilience (SCR) emerges as a consequence of competitive advantage driven by the adoption of AI solutions. Structural Equation Modelling (SEM) results challenge conventional empirical results in the field by demonstrating that green logistic practices do not directly enhance supply chain resilience (e.g., Sheffi, 2005; Christopher and Peck, 2004; Issa et al., 2024). Instead, their impact is fully mediated by the achievement of a competitive advantage.

5.1. The Mediated Path to Supply Chains Resilience

Hypothesis H1, which posited a direct relationship between green logistics practices and supply chain resilience (SCR), is not empirically supported ($\beta = -0.003$, n.s.). By contrast, Hypothesis H2 is fully validated, offering robust empirical evidence for the link between competitive advantage and SCR—this being the strongest and most statistically significant pathway within the proposed model. Notably, the mediated pathway—green logistics practices → competitive advantage → supply chain resilience—yields a positive, substantial, and highly statistically significant effect ($\beta = 0.423$, $p < 0.001$), indicating that the influence of green logistics practices on SCR is fully mediated by competitive advantage. This finding of complete mediation is consistent with and reinforces the existing literature.

Similar results, although focused on traditional internal practices, were reported in the Romanian supply chain context by Balan (2008), who showed that coordination routines reduce costs only when aligned with economic benefits. Moreover, our conclusions are consistent with the recent study by Rese and Tränkner (2024) on German SMEs, which identified an almost identical non-significant direct path. In the same vein, the research conducted by Yang, Huang, and Wang (2025) on listed firms in China highlights that supply chain resilience is closely tied to financial and operational performance, suggesting that environmental practices must also generate economic value to be effective. This effect is more pronounced in private enterprises than in state-owned ones. Therefore, in line with existing empirical studies, our results suggest that green logistics practices, in the absence of financial gains, do not contribute to supply chain resilience.

5.2. AI as a Strategic Enabler

AI adoption significantly enhances competitive advantage ($\beta = 0.406$) and exerts a direct, positive, and statistically significant impact on supply chain resilience ($\beta = 0.649$, $p < 0.001$). Furthermore, the total indirect mediated pathway—AI adoption → competitive advantage → supply chain resilience—is also statistically significant ($\beta = 0.353$, $p < 0.001$). These findings underscore AI's dual role: it not only directly fortifies supply chain resilience but also functions as a strategic enabler by amplifying competitive advantage, which in turn reinforces resilience capabilities. Accordingly, hypothesis H2 is fully validated, while hypothesis H4 receives partial validation, as evidenced in table no. 8.

It is difficult to compare this result with previous studies, as they did not include in the same hypothetical model the indirect path we highlight here, showing how AI acts as a catalyst in the causal chain. AI adoption → Green logistics practices → Competitive advantage → Resilience. However, if we examine separately the findings that AI-based tools contribute to operational efficiency and support competitive positioning, our results align with those reported by Cannas et al. (2023). Similarly, the relationship between competitive advantage and resilience confirms the conclusions of Wang and Prajogo

(2024), who associate competitive advantage with specific resilience outcomes such as rapid recovery capacity, cost efficiency, and adaptability.

5.3. The Foundational Role of Digital Maturity

The total effect of digital maturity on supply chain resilience is strong ($\beta = 0.502$), significantly higher than the values reported in Western European samples (approximately $\beta = 0.30$) (Wieland and Wallenburg, 2013; Scholten and Schilder, 2015). This result suggests that in environments undergoing digital development, each incremental improvement in data quality or analytical capability yields higher marginal returns.

The most explanatory path is also the most extensive: Digital Maturity → AI Adoption → Competitive Advantage → Resilience ($\beta = 0.273$, $p < 0.001$). This relationship highlights that digital maturity alone is not sufficient; it must be effectively transformed into a measurable advantage through AI to meaningfully impact supply chain resilience.

Conclusion

This research focused on a rigorous examination of how sustainable digitalisation influences supply chain resilience (SCR), within the broader context of artificial intelligence (AI) adoption in organisational environments and the objectives of the European Green Deal. The analysis of the results obtained by applying the variation-based structural equation modelling technique (PLS-SEM), using the SmartPLS v4 program, highlights the fact that the adoption of artificial intelligence (AI) and sustainable digitalisation contribute to the consolidation of SCR. However, their positive impact is manifested predominantly through competitive advantage, identified as an essential predictor. Moreover, the favourable effect of AI adoption on SCR is outlined not only as a direct influence on competitive advantage, but also as an effect mediated by green logistics practices. These findings align with the current trends in digital transformation and sustainability orientation, highlighted within Romanian companies (Vătămănescu et al., 2016; Ceptureanu et al., 2025).

The methodological rigour of the PLS-SEM model contributes to the robustness of these conclusions, allowing for the testing of complex mediated relationships and reducing the risk of false results (Hair et al., 2021). Furthermore, the consistency of the identified mediation pattern with findings obtained in distinct contexts (Balan, 2008; Rese and Baier, 2024; Belhadi et al., 2024) enhances external validity and suggests that the model captures a fundamental economic reality, rather than a mere peculiarity of the sample analysed.

The research makes an important theoretical contribution to the literature by integrating three major conceptual frameworks, the Diffusion of Innovation Theory, the Technology-Organisation-Environment Model and the Dynamic Capabilities Theory, thus providing a unified perspective on how the adoption of artificial intelligence (AI) and the development of organisational capabilities influence the resilience of supply chains (RLA-L). The study fills a theoretical gap, as previously these dimensions were analysed separately, and shows that the relationship between AI adoption, green logistics practices and RLA-L is a complex one and mediated by competitive advantage. In addition, the research highlights the relevance of contexts with variable resources, such as Romania, demonstrating that AI can generate both incremental and radical forms of resilience, while supporting the integration of the European Union's sustainability requirements. The results clarify the role of digital maturity and show that green logistics practices cannot increase resilience in isolation, but only as part of a competitive strategy that generates economic value.

From a managerial perspective, the study provides a solid strategic framework for organisations seeking to strengthen the resilience of their supply chains. Adopting AI should be seen as a strategic tool, not just a technological one, as the competitive advantage it generates is the main driver of RLA-L. Managers should integrate AI into decision-making and operational processes so that it supports the agility, efficiency, and adaptability of firms. At the same time, the research shows that green logistics practices contribute to resilience only when they are correlated with economic performance, which implies directing investments towards sustainable initiatives with real added value. Digital maturity proves to be an essential prerequisite, necessary both for the effective adoption of AI and for generating the desired results. Overall, the study suggests that resilience is the result of a deliberate combination of investments, strategies and organisational capabilities, not isolated interventions.

Finally, it is important to emphasise that the present study has certain limitations. Although the use of Smart PLS modelling allows for analysis on small samples and offers increased flexibility in testing complex mediated relationships, the choice of this method restricted access to a more sophisticated approach, namely structural equation modelling based on covariance. Such an approach would have allowed for additional control over covariances among the analysed constructs, providing a more rigorous structural validation of the proposed model. Nonetheless, this limitation opens avenues for future research, where testing the model on larger samples using complementary methods could reinforce and expand the robustness of the findings. In addition, another limitation of the research should be mentioned, namely the fact that the study did not include a comparative approach between different sectors of activity. Consequently, future research should consider the composition of the sample so that the sectoral structure of the companies is adequately reflected and the differences between industries are statistically controlled, thus strengthening the relevance and generalisability of the results.

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Annex no. 1. Organizational characteristics of the sample used in the research

Category	Type	%
Company size	Small firms	53.70%
	Medium -size firms	15.11 8%
	Large firms	31.19%
The company's age on the market	3-5 years	76.31%
	6-10 years	16.74%
	11-20 years	2.95%
	> 20 years	4.00%
Market	National	15.79%
	International	84.21%
Sector	Transportation	56.65%
	Constructions	3.77%
	Food	3.88%
	IT and Electronics	5.79%
	Industry	7.89%
	Services	16.14%
	Others	5.88%

Annex no. 2. Evaluation of internal consistency and convergent validity for the study constructs

Construct	Item	Std. Loadings	Construct reliability and validity
AI Adoption	AIA1: Our company uses AI for demand forecasting.	0.960	Cronbach's alpha (0.962) rho_c (0.973) AVE (0.899)
	AIA2: AI tools support supply chain planning and optimization.	0.961	
	AIA3: AI enhances supply chain traceability and monitoring.	0.955	
	AIA4: AI contributes to early identification of supply risks.	0.916	
Digital Maturity	DM1: Our firm has sufficient digital infrastructure to support AI.	0.866	Cronbach's alpha (0.915) rho_c (0.955) AVE (0.967)
	DM2: Employees possess the necessary digital skills for AI adoption.	0.877	
	DM3: Our organizational culture supports digital innovation.	0.922	
	DM4: We have prior experience implementing advanced digital technologies.	0.931	
	DM5: We are constantly investing in digital technologies, including AI	0.915	
Competitive advantage	CA1: Adopting AI has improved our cost efficiency compared to the competition	0.881	Cronbach's alpha (0.943) rho_c (0.959) AVE (0.855)
	CA2: Adopting AI has increased our ability to differentiate ourselves from competitors	0.939	
	CA3: Adopting artificial intelligence has increased our ability to respond to customer demands	0.949	
	CA4: Adopting artificial intelligence has improved the quality and reliability of our supply chain services	0.928	
Green logistics practices	GLP1: We use low-emission or energy-efficient transport vehicles in our logistics operations	0.899	Cronbach's alpha (0.894) rho_c (0.927) AVE (0.870)
	GLP2: We optimize distribution processes to minimize environmental impact	0.899	
	GLP3: We adopt alternative/renewable fuels (e.g. biofuels, electricity) in logistics operations	0.825	
	GLP4: We continuously monitor and improve the environmental and safety aspects of logistics and transport activities	0.862	
Supply chain resilience	RESI1: Our supply chain can quickly return to normal operations after an interruption	0.965	Cronbach's alpha (0.981) rho_c (0.986) AVE (0.945)
	RESI2: We are able to effectively adapt supply chain processes when unexpected events occur	0.980	
	RESI3: Our supply chain maintains service levels even under disruptive conditions	0.971	
	RESI4: We can quickly reconfigure supply chain resources and relationships in response to disruptions	0.972	