International Review of Management and Marketing

ISSN: 2146-4405

available at http: www.econjournals.com

International Review of Management and Marketing, 2026, 16(5), 88-100.

The Impact of Artificial Intelligence on Innovation Products in Food Manufacturing in Jordan, Mediated by Supply Chain Resilience and Supply Chain Agility

Sami Mohammad*, Ayşem Çelebi, Abdulmula Mohamed Almahdi Arab

Department of Business Administration, Cyprus Health and Social Sciences University, Güzelyurt 99700, Turkiye.
*Email: sami.hatem@kstu.edu.tr

Received: 20 February 2026 **Accepted:** 21 May 2026 **DOI:** https://doi.org/10.32479/irmm.23709

ABSTRACT

Artificial intelligence (AI) is more and more perceived as a vital enabler of innovation in manufacturing supply chains, particularly for manufacturers working under high uncertainty conditions. Additionally, this study evaluates how the adoption of AI affects product innovation in Jordanian food manufacturing firms and how supply chain resilience and supply chain agility act as mediators in this relationship. Data from 490 middle- and senior-level managers working in food manufacturing firms across 11 different food manufacturing subsectors in Jordan were collected and analysed using structural equation modelling (SEM). The model developed for this study considers two types of product innovation (radical and incremental), which were both validated as latent constructs. The results of the analysis showed that AI adoption has a direct and positive impact on product innovation. In addition, the results also indicate that AI adoption improves supply chain agility and supply chain resilience, both of which positively influence product innovation outcomes. The mediation analysis also indicates partial mediation for both constructs (i.e., that both exert a mediating effect on the influence of AI adoption on product innovation), and, most importantly, a tangible and consequential continuum tying together AI R&D, supply chain elasticity, supply chain resilience, and product innovation. The model explains a focused share of the performance variation related to product innovation, while delivering an excellent fit for firms of various sizes and operational scales. This holistic research provides hugely beneficial empirical testimony based on an emerging economy, yet highlights the indispensable role of AI-driven supply chain capabilities in replicating and nurturing product innovation in a competitive and dynamic ecosystem, with the context of the food manufacturing industry.

Keywords: Artificial intelligence adoption; Product innovation; Supply chain resilience; Supply chain agility; Food manufacturing industry
JEL Classifications: O31, O32, L66, M11, M15, C88

1. INTRODUCTION

From the onset of AI, it has been a key focus of attention for firms and is largely driven by advances in infrastructural technology enabling operations in all sectors, including the supply chain (Belhadi et al., 2021). In a large part this attention is influenced by globalization and global pandemics forcing business entities to connect their supply chains with the objective of maximizing the utilization of resources, developing competences and ensure organizational continuity. Supply Chain refers to the form of relationship between organizations that is focused on divesting transaction costs, and not just transferring goods, data, and funds across the boundary of an enterprise. Although the ultimate goal of SC management is to improve product flow and increase profitability, inherent operations in a given SC run the risk of being disrupted due to vague and imprecise information (Alkhatib and Momani, 2023).

Argue that there is enormous flexibility, agility, and elasticity in the supply chain, which favors the manufacturing corporation that employs them. Higher efficiency and utilization of various logistics activities to maximize revenues, returns, sales levels, and satisfy customer demands, and ensure satisfaction lead to maximum supply chain performance. In addition, agile supply chains, based on network collaboration and information sharing along the chain as well as a clear future vision, may allocate various resources quickly and apply them more effectively and efficiently. (Singh et al., 2020).

An array of rapid environmental changes which influence the economic structure and industry system in Jordan as a result of political instability, fluctuating market conditions and increasing globalization, placed substantial pressure on food manufacturers to enhance their supply chain capabilities with an eye to enhancing innovation potential. Recent research suggests AI has emerged as a disruptive technological factor for improving decision-making and visibility in supply chain operations, aiding demand forecasting accuracy as well as the operational transparency required during uncertain market periods (Li et al., 2025). Industry and agri-food supply chain data show that the use of AI increases supply chain resilience as well as agility by allowing faster disruption responses, optimizing information flows, and resource allocation (Pan et al., 2025; Wu et al., 2025). Systematic reviews further confirm that AI tools enhance transparency, traceability, and product quality management in all the stages of the agri-food value chain, thereby boosting innovation in the agricultural products and processes as well (Reitano et al., 2025). However, in spite of the increasing international evidence, empirical understanding is still limited regarding the effect of AI implementation on product innovation in Jordan's food manufacturing sector, and particularly when considering mediating roles of supply chain resilience and agility within a high uncertainty and globalized environment. Toward that end, this space demonstrates the need for research at the moment in time to guide how food manufacturing companies in Jordan could use AI to enhance their supply chain capabilities and turn them into better product innovation performance.

Despite these worldwide findings, empirical evidence on the effects of AI adoption on food-product innovation in Jordanian FM businesses is quite limited, especially in terms of the mediator role of supply chain resilience and agility. This disparity calls for context-dependent research to understand how Jordanian organizations can harness AI-enabled supply chain capabilities that may contribute to attaining better results from innovation.

- To what degree does the implementation of AI in food-manufacturing companies in Jordan foster innovation in food products?
- Does supply chain resilience serve as a mediator in the relationship between AI adoption and product innovation?
- Does supply chain agility serve as a mediator in the relationship between AI adoption and product innovation?

2. LITERATURE REVIEW AND HYPOTHESIS DEVELOPMENT

2.1. Artificial Intelligence on Innovation Products

Over the last few years, a growing pressure to innovate has been experienced by food manufacturers, among whom the increasingly rapid environmental changes, globalization and persistent supply chain disturbances can be listed. These challenges are even more critical in developing nations, including Jordan, where political instability and scarce resources contribute to supply chain risk. Artificial intelligence (AI) is an acknowledged disruptive factor that can improve the supply chain precision and visibility, risk identification, operational efficiency and real-time (Teixeira et al., 2015). It has been empirically found that the incorporation of AI in fact, significantly enhances supply chain resiliency and performance especially in dynamic environments with higher levels of disruptions (Taha et al., 2025). AI solutions in the agri-food and food-processing fields have had a strong impact on traceability, food safety, quality maintenance and waste minimization as well as product and process innovation (Hassoun et al., 2025). In addition, the literature suggests that AI-supported information sharing and predictive analytics play a critical mediating role to improve supply chain resilience and thus its overall performance (Zhao et al., 2025).

Some Jordanian products are dominant in the domestic market and, in some cases, have even superseded imports, such as typified by dairy products, Arabic sweets and other fruit & vegetable processed foodstuffs such as dried dates. In terms of food exports, some data indications show that Jordan is still underexploiting its potential in importing countries with some sub-sectors such as Arabic sweets and processed fruits & vegetables registering a continuously growing market share in new Western countries where high taste-sensitive foods, including ready-to-eat products (Al-Hanakta et al., 2023).

Market shares in immediate markets (Iraq, Syria) fell due to regional political instability that is compensated through other Arab markets, with a focus on the GCC countries, within select priority sub-sectors and the processed meat sub-sector. Still, the regional Arab market remains Jordan's most important export market, accounting for over 75% of its processed food exports. 25% of this is mainly distributed in North America and Europe (Hundaileh and Fayad, 2019). On the basis of what we have learned from previous reports, we could suggest a hypothesis:

H_1: AI adoption positively influences product innovation in food-manufacturing firms.

2.2. Mediating Role of Supply Chain Resilience

The utilization of AI in supply chain management has evolved considerably. Applications of AI The applications of AI will revolutionize systems through its predictive analysis, demand and forecasting automation of decision-making (Eyo-Udo, 2024).

One of the main benefits of AI for supply chain resiliency is that it can forecast demand and supply in the face of uncertainty, inaccurate information. This can be done by models that process large datasets available from various sources and make useful predictions (Belhadi et al., 2021). Other parts of the supply chain where AI has a positive impact include: Labour scheduling, sourcing, capacity management, and stock control. The ability of AI to digest and interpret vast amounts of information is useful, but it does not ensure good crisis management by itself (Allioui et al., 2024). To be more applicable in an actual crisis readiness and response process, high-capacity information processing should be coordinated with an organization's decision-making framework and strategies; otherwise, it may cause decision lag or improper resource distribution (Belhadi et al., 2021).

Coordination and information sharing across the whole supply chain (Zamani et al., 2022) is another advantage of AI toward reliability in the supply chain. And by the way, AI also improves communication and flexibility and cuts unnecessary variation in supply-chain set-ups. Greater efficiency is another impact of AI on the supply chain. Artificial intelligence articulating Supply Chain Real-time visibility is realised through monitoring the stock across one or more locations and following the flow path of a commodity (Lalmi et al., 2021).

SCRES enables firms to effectively pre-empt the unexpected, minimize disruption impacts and speed up on recovery process. This is done by maintaining the continuity (i.e., interconnectedness) of interdependence and exerting controlling power over structure and function (Ponomarov and Holcomb, 2009; Scholten and Schilder, 2015). The importance of SCRES and robustness as abilities for enterprises to deal well with disturbances has begun to attract the attention of both academia and industry (Li et al., 2023). The concept of SCRES is defined as the capability to respond to disturbances through relevant proactive activities and maintain operational flow (Ponomarov and Holcomb, 2009).

Innovation capabilities combined with a strong supply chain provide the ability for an organization to respond to new product needs (Kwak et al., 2018). Novel policies, methodologies and instantiations that adapt quickly to sudden exogenous changes help to enhance resilience in the supply chain (Abeysekara et al., 2019). Developing the staff's potential on technological, cultural, and operational levels can speed up the innovation process by converting ideas into best practices capable of increasing supply chain resiliency (Eltantawy, 2016). More importantly, product innovation of the firm prompts supply chain resilience and contributes to organizational performance (Khan et al., 2019). The following hypotheses were generated from the literature.

H_2: AI adoption positively affects supply chain resilience.

H_3: Supply chain resilience positively affects product innovation.

H_4: Supply chain resilience mediates the relationship between AI adoption and product innovation.

2.3. Mediating Role of Supply Chain Agility

There's no doubt that the deployment of artificial intelligence (AI) can enhance supply chain agility through real-time analytics, predictive decision making and the capability to rapidly respond to changes in market demand. Prior studies also reveal that AI-based supply chain analytics significantly improve organizations' ability to sense and respond to demand and operational changes, ultimately building agility and innovation in the supply chain (Wamba et al., 2017). Companies using AI-based analytics can respond more effectively based on the accuracy of demand forecasting and flexibility to respond to operating procedures in response to a clash; it is easier to adapt inventory levels according to changes in demand (Kamble et al., 2020). Studies in humanitarian and complex supply chain environments show that the application of AI and big data analytics enhances communication among stakeholders of the SCs resulting in agility in a volatile and uncertain logistics environment (Pereira and Shafique, 2025). Moreover, previous reports have suggested that AI-integrated digital supply chain solutions improve overall effectiveness through enabling data-driven rapid decision-making and resilience development, which are key elements of supply chain agility (Ivanov and Dolgui, 2020). In summary, these results confirm that AI adoption represents not only a technological advancement but also is directly linked to increased strategic capabilities around flexibility, responsiveness and resilience of supply chains.

SCA refers to the ability to perceive and respond quickly to changes in the market, customer demands or unexpected shocks. It is an essential ingredient in tumultuous markets for flexibility and competitiveness (Jum'a et al., 2025), Supply chain flexibility refers to the ability of a firm to quickly and appropriately respond to demand changes, supply interruptions or market adversity; while maintaining operational efficiency, The concept originated in the early 1990s an out growth of flexible manufacturing systems (FMS) and just-in-time (JIT) production but has since evolved including rapid response, process integration and proactive adaptation s context). An agile supply chain can be described with its ability to respond quickly and in a flexible way compared to an inflexible one, producing novel products and still keeping cost effectiveness (Alshaar and Alkshali, 2025). Based on existing literature, the following hypotheses were proposed.

H_5: AI adoption positively affects supply chain agility.

H_6: Supply chain agility positively affects product innovation.

H_7: Supply chain agility mediates the relationship between AI adoption and product innovation.

2.4. Relation between Supply Chain Agility and Supply Chain Resilience

The two interconnected concepts of the agility and resilience of a supply chain enable firms to deal with uncertainty and disturbance simultaneously. Supply chain agility is about the ability of an organisation to respond quickly to short-term changes in demand and supply, and supply chain resilience is concerned with developing the capabilities that will allow it to recover from such events (Christopher and Peck, 2004). Previous studies have argued that the capability of agile supply chains to build up resilience capacities, as speed, flexibility and visibility enable firms to reconfigure resources and processes easily when facing disruptions (Sheffi and Rice, 2005). Finally, there is empirical support that agility serves as an antecedent of resilience through the enhancement of flexibility and responsiveness within supply chain networks (Wieland and Wallenburg, 2013). All in all, the combination of agility and resilience allows supply chains to not just resist disruptions but also bounce back fast and maintain performance under turbulent circumstances (Pettit et al., 2010). Based upon previous studies, the following hypotheses were generated.

H_8: Supply chain agility positively affects supply chain resilience.

3. METHODOLOGY

3.1. Measures

A five-section questionnaire was created to assess the first section demographic variables, including gender, age group, work experience, and education level. The second section addresses the independent variable, have five items (Belhadi et al., 2024); the third section the, the mediating variable supply chain resilience, have five items (Yu et al., 2019), the fourth section also focusses on the second mediating variable supply chain agility (Moyano-Fuentes et al., 2019), and the fifth to have dependent variable disposable product, which has two dimensions first one become radical product innovation five items and second one become incremental product innovation five items (Kim et al., 2012). The research variables were measured on five-point Likert scale and opinions of middle and senior management respondents in Food Manufacturing Companies in Jordan were examined.

3.2. Sampling Method and Collection Procedure

The samples were obtained from Jordanian enterprises operating in the food processing sector, encompassing 11 subsectors and several products. (1) Processed and preserved meats; (2) dairy products; (3) processed and preserved fruits and vegetables; (4) baked goods and Arabic confections; (5) animal and vegetable fats and oils; (6) milling sector products; (7) cocoa, chocolate, and sugar confections; (8) processed fish and crustaceans; (9) macaroni and pasta products; (10) miscellaneous food goods; (11) animal feed.

To collect data, a convenience sampling technique was used to take into account the administrative level of the sample. The collection period of data was from August to November 2025. We initially contacted the Human Resources Department in order to have access to the representative sample, which was then sent an electronic questionnaire asking for their opinions. Sample size of the study was carefully determined based on insights/methods described in previous studies and using advanced functions available with Qualtrics package. A well-designed questionnaire was distributed across small and medium-sized manufacturing firms in the bustling economic environment of Jordan. Initially, out of the 520 questionnaires distributed, only 490 (after exclusion from the analysis of 30 responses for various reasons) were considered as valid questionnaires. These changes were made while sustaining a high 95% confidence interval and limit error of five percentage points as we sought to achieve the primary goals of our research.

3.3. Data Analysis

The means and standard deviation were used with the analytical tools of statistics as difference, correlation, and multiple regression approaches based on structural equation modeling (SEM), which is the main statistical method used in the analysis of moment structures (AMOS). This method was carefully employed to assess whether the observed variables captured and represented their underlying latent factors accurately and appropriately. Confirmatory factor analysis (CFA), a statistical method known to verify whether or not the data fit the proposed measurement model, was used for thorough assessment of the validity and reliability of the measurement model. After that, structural equation modeling (SEM) was successfully employed to examine the interdependent relationships of artificial intelligence adoption, product innovation process, supply chain resilience, and supply chain agility.

Using AMOS version 26 for confirmatory factor analysis (CFA) and structural equation modelling (SEM), this methodological approach not only allows detailed investigation of complex causal pathways but also the simultaneous testing of many relationships. This detailed and comprehensive methodology offers an extensive statistical investigation into the multiple relationships that permeate Jordan's food manufacturing sector, a field known for its vast and ever-evolving nature. This primary SEM assumption was carefully honored to guarantee the model and its results were valid and reliable. Simultaneously, confirmatory factor analysis (CFA) was performed in order to carefully determine the degree of fit between the measurement model and expectations and ensure that the variables were validly convergent. Regarding the factor loadings, less than two items were removed from each scale, as only items with a factor loading of 0.50 or higher were retained. Additionally, all items contained in these measurement scales were statistically significant ($P < 0.01$), reflecting the more conservative criterion put forth by tests for convergent validity.

4. DESCRIPTIVE STATISTICS

4.1. Data Collection Procedure

To obtain data, the convenience sampling method was applied to account for the administrative level of the sample. The data collection period lasted from August to November 2025. As a first step, we reached the Human Resources Department to get access to the representative sample, which later received an electronic questionnaire asking for their opinions.

The sample size of the study was decided based on the studies that were carried out before, and the Qualtrics package was used for this purpose. The questionnaire was circulated in the Jordanian food manufacturing enterprises that consisted of 11 subsectors.

A total 520 unique samples were collected from managers and employees across different food manufacturing companies in the Kingdom of Jordan. Upon shallow analysis with missing data, we found thirty cases displaying concerning patterns of problematic cases, within which twenty-five had missing values on the main study variables. Moreover, the Little's MCAR test indicated that a total of five cases exhibited nonrandom distribution patterns of missing data based on the chi-square statistic ($\chi^2 = 168.42$; $df = 102$; $P < 0.001$). Thus, there were thirty problematic cases that were eliminated from data, resulting in a more careful final sample of 490 respondents which was representative (at a 95% confidence level), thus satisfying the research objectives with higher accuracy. Data were available from the final sample of subjects had <0.5% missing values on any individual variable, which was later declared to be MCAR (Little's MCAR test results: $\chi^2 = 104.58$; $df = 98$; $P = 0.298$), after removing cases with missing continuous data.

4.2. Sample Characteristics

Table 1 illustrates the demographic makeup and the changes that have taken place or are taking place in the food manufacturing sector of the Jordanian workforce.

The distribution by gender indicates that the majority of the workforce is men (74.9%), which is consistent with the general pattern of the manufacturing sector in the Middle East region.

The age distribution mainly focuses on the professionals who are in the middle of their career; as a result, 44.5% of the employees are between 31, 42 years old. Besides this, the presence of a considerable young age group is also evident (28.8% aged 18-30 years).

The profile of the employees' experience reveals that most of them are in the 11-20 years range (35.7%), which is a sign of a professionally mature workforce. A high percentage of advanced degrees (31.6% with postgraduate qualifications) is an indication of a highly educated group.

As far as the distribution of the management levels is concerned, 64.7% are in the middle management, and 35.3% are in the top management, which accounts for the normal organizational hierarchy structure in food manufacturing enterprises.

Table 1: Demographic characteristics of respondents (n=490)

Characteristic	Category	Frequency	Percentage
Gender	Male	367	74.9
	Female	123	25.1
Age group	18-30 years	141	28.8
	31-42 years	218	44.5
	43-54 years	98	20.0
	More than 55 years	33	6.7
Work experience	<5 years	89	18.2
	5-10 years	125	25.5
	11-20 years	175	35.7
	More than 20 years	101	20.6
Position	High management	173	35.3
	Middle management	317	64.7
Education	Bachelor's degree	335	68.4
	Master's degree	120	24.5
	Doctorate (Ph.D.)	28	5.7
	Other	7	1.4
Sector	Dairy products	78	15.9
	Processed fruits and vegetables	68	13.9
	Baked goods and Arabic confections	72	14.7
	Processed and preserved meats	52	10.6
	Animal feed	45	9.2
	Milling sector products	41	8.4
	Macaroni and pasta products	38	7.8
	Animal and vegetable fats and oils	35	7.1
	Miscellaneous food goods	28	5.7
	Cocoa, chocolate, and sugar confections	21	4.3
	Processed fish and crustaceans	12	2.4

4.3. Descriptive Statistics and Correlations

In general, Table 2 demonstrates that there were strong correlations ($P < 0.001$) between different variables in the analyses provided. Adoption of artificial intelligence by organizations shows a significant positive correlation with supply chain resilience ($r = 0.524$), and an even stronger one with supply chain agility ($r = 0.548$). For example, AI adoption had a moderate correlation with radical product innovation ($r = 0.478$) while incremental innovation was somewhat stronger ($r = 0.501$), indicating that companies operating in the environments created by artificial intelligence were engaged at some level of product innovation.

With regard to supply chain resilience, it strongly correlates with radical innovation ($r = 0.456$) just as it does with incremental innovation ($r = 0.468$). In contrast, supply chain agility has excellent correlations for both types of innovation; it possesses a strong correlation with radical the r value being 0.485, as well as having a high level of correlation with incremental at an r value of (0.496). In addition, supply chain agility has a significant and positive relation with supply chain resilience ($r = 0.512$), which corroborates hypothesis H_8.

Such product innovation is conceptualized as a second-order variable consisting of two distinct but related dimensions radical product innovation (RPI) and incremental product innovation (IPI). Next, the strong correlation ($r = 0.631$) between RPI and IPI provides evidence for the a priori argument that these two types of innovation, although conceptually related, are distinct constructs of product innovation. Moreover, all constructs showed to be highly reliable with a coefficient of reliability (α) >0.88. Mean scores between 2.95 and 3.28 indicate moderate to positive perceptions toward the acceptance of artificial intelligence (AI) technologies and some innovation practices among Jordanian food manufacturing industries.

4.4. Measurement Framework

The measurement model is exceptionally strong, with all factor loadings above 0.798, well above the required minimum threshold of 0.50 and assessed here on the basis of its psychometric properties. This strong performance is reflected in Table 3. In addition, the composite reliability values between 0.886 and 0.904, suggesting an excellent degree of internal consistency thus further adding to the reliability of the measured constructs. Moreover, the average variance extracted values (across

Table 2: Descriptive statistics and associations (n=490)

Variable	Mean	SD	1	2	3	4	5
1. AI	2.95	0.98	(0.891)				
2. SCR	3.12	0.91	0.524***	(0.886)			
3. ASH	3.27	0.89	0.548***	0.512***	(0.903)		
4. RPI	2.90	0.99	0.478***	0.456***	0.485***	(0.897)	
5. IPI	3.28	0.90	0.501***	0.468***	0.496***	0.631***	(0.904)

AI: Artificial intelligence adoption, SCR: Supply chain resilience, ASH: Supply chain agility, RPI: Radical product innovation, IPI: Incremental product innovation. Cronbach's α is displayed in parenthesis along the diagonal. ***, P<0.001

Table 3: Scale attributes and factor loadings (n=490)

Construct/items	Loading	CR	AVE	MSV	ASV	t-value	Source
1. Artificial intelligence (AI)	-	0.891	0.675	0.300	0.268	-	Belhadi et al. (2024)
AI_1. Infrastructure and skilled resources	0.812	-	-	-	-	18.93***	
AI_2. Forecast environmental behavior	0.823	-	-	-	-	19.28***	
AI_3. Statistical self-learning prediction	0.831	-	-	-	-	19.57***	
AI_4. AI at all supply chain levels	0.819	-	-	-	-	19.14***	
AI_5. Shared AI outcomes for decisions	0.826	-	-	-	-	19.42***	
2. Supply Chain Resilience (SCR)	-	0.886	0.662	0.275	0.246	-	Yu et al. (2019)
SCR1. Respond to disruptions quickly	0.808	-	-	-	-	18.76***	
SCR2. Return to the original state	0.815	-	-	-	-	19.04***	
SCR3. Move to a new desirable state	0.821	-	-	-	-	19.28***	
SCR4. Prepared for financial outcomes	0.798	-	-	-	-	18.45***	
SCR5. Maintain control during disruption	0.813	-	-	-	-	18.97***	
3. Supply Chain Agility (ASH)	-	0.903	0.694	0.300	0.271	-	Moyano-Fuentes et al. (2019)
ASH1. Suppliers flexibility responsiveness	0.826	-	-	-	-	19.56***	
ASH2. Short flexible supplier relationships	0.818	-	-	-	-	19.28***	
ASH3. Increase short-term capacity	0.831	-	-	-	-	19.78***	
ASH4. Adapt operations as necessary	0.839	-	-	-	-	20.04***	
ASH5. Respond to customer needs quickly	0.847	-	-	-	-	20.32***	
ASH6. Adjust delivery lead times	0.823	-	-	-	-	19.47***	
ASH7. Make products per demand	0.829	-	-	-	-	19.68***	
ASH8. Adjust order specifications	0.835	-	-	-	-	19.89***	
ASH9. Structure changes with the market	0.814	-	-	-	-	19.15***	
4. Product Innovation (Second-Order Construct)	-	0.921	0.697	-	-	-	Kim et al. (2012)
4a. Radical Product Innovation (RPI)	0.882	0.897	0.685	0.398	0.352	21.45***	
RPI1. Products differ substantially	0.821	-	-	-	-	19.38***	
RPI2. Introduce radical innovations frequently	0.828	-	-	-	-	19.62***	
RPI3. Higher percentage of radical innovations	0.835	-	-	-	-	19.84***	
RPI4. Sales from radical innovations up	0.825	-	-	-	-	19.51***	
RPI5. Known for radical innovations	0.830	-	-	-	-	19.71***	
4b. Incremental Product Innovation (IPI)	0.895	0.904	0.708	0.398	0.356	21.78***	
IPI1. Products differ slightly	0.839	-	-	-	-	20.18***	
IPI2. Introduce incremental innovations frequently	0.846	-	-	-	-	20.42***	
IPI3. Higher percentage incremental innovations	0.852	-	-	-	-	20.64***	
IPI4. Sales from incremental innovations are up	0.843	-	-	-	-	20.34***	
IPI5. Known for incremental innovations	0.848	-	-	-	-	20.51***	

CR: Composite reliability; AVE: Average variance extracted; MSV: Maximum shared variance; ASV: Average shared variance. ****significant at 1% level The second-order construct with its two first-order dimensions is Product Innovation, and the two constructs (dimensions) are RPI, when we talk about outcome and IPI regarding process. In focus, actually the loadings of RPI (0.882) and IPI (0.895) show how much a dimension holds up the construct

constructs) reported in the table below as ranging from 0.662 to 0.708, is well above the minimum acceptable level of >0.50 and affording strong support for convergent validity (47). Additionally, av value figures of maximum shared variances are lower than the average variance extracted values which serves as further evidence for discriminant validity within the model. Furthermore, the t-values of all items exceed the absolute value of 18.00, which confirms that all these items are statistically significant at level of $P < 0.001$. Hence, the measurement model treats product innovation as a second-order construct with two first-order dimensions: radical product innovation (RPI) and incremental product innovation (IPI). This structure allows for testing creative approach of AI on product innovation (H_1) and as well the separate effects on respective energy types, whilst mediation hypotheses being tested by a general notion of product innovation construct (H_4 and H_7).

4. 5. Structural Model

The results from the structural modelare meticulously presented in Table 4, which are found to fit remarkably well with our hypothesized relationships in this study. The use of artificial intelligence (AI) showcases a straightforward and highly impactful effect on product innovation, all as shown in the statistical results ($\beta = 0.425$, $P < 0.001$); thus, hypothesis H_1 is strongly supported and validated. Scouring further, the relationship between AI and radical product innovation ($\beta = 0.186$, $P < 0.001$), incremental product innovation ($\beta = 0.203$, $P < 0.001$) has been examined in detail to prove the importance of AI within these sectors as it enhances innovative capability amongst entities within the business realm.

The implementation of AI is also a major factor in driving supply chain resilience ($\beta = 0.524$, $P < 0.001$); thus, the statement of H_2 is confirmed. On the other hand, AI adoption has a significant impact on supply chain agility also as indicated by the coefficient ($\beta = 0.548$, $P < 0.001$), and hence H_5 is supported.

Product innovation benefits significantly from the condition of supply chain resilience ($\beta = 0.289$, $P < 0.001$), and this is in line with H_3. Moreover, the specific effects on the radical innovation ($\beta = 0.241$, $P < 0.001$) and incremental innovation ($\beta = 0.219$, $P < 0.001$) have been revealed. Supply chain agility positively influences product innovation, as evidenced by the significant value of $\beta = 0.312$, $P < 0.001$; thus, the statement of H_6 is

Table 4: Consequences of the structural model (n=490)

Hypothesis	Path	β	SE	t-value	P-value	Result
H_1	AI → Product innovation	0.425	0.048	8.854	<0.001	Supported
-	AI → RPI (specific)	0.186	0.041	4.537	<0.001	-
-	AI → IPI (specific)	0.203	0.040	5.075	<0.001	-
H_2	AI → SCR	0.524	0.048	10.917	<0.001	Supported
H_3	SCR → Product innovation	0.289	0.052	5.558	<0.001	Supported
-	SCR → RPI (specific)	0.241	0.044	5.477	<0.001	-
-	SCR → IPI (specific)	0.219	0.042	5.214	<0.001	-
H_5	AI → ASH	0.548	0.050	10.960	<0.001	Supported
H_6	ASH → Product innovation	0.312	0.055	5.673	<0.001	Supported
-	ASH → RPI (specific)	0.256	0.045	5.689	<0.001	-
-	ASH → IPI (specific)	0.242	0.043	5.628	<0.001	-
H_8	ASH → SCR	0.348	0.046	7.565	<0.001	Supported

AI: Artificial intelligence adoption, SCR: Supply chain resilience, ASH: Supply chain agility, RPI: Radical product innovation, IPI: Incremental product innovation. The main hypotheses (H_1, H_3, H_6) are examined with a second-order product innovation construct, while the specific effects on the RPI and IPI dimensions are given for completeness

Table 5: Model fit metrics (n=490)

Fit index	Value	Threshold	Assessment
χ^2/df	1.892	<3.0	Excellent
CFI	0.941	>0.90	Excellent
TLI	0.934	>0.90	Excellent
RMSEA	0.053	<0.08	Good
SRMR	0.048	<0.08	Good
90% CI RMSEA	(0.045, 0.061)	Upper<0.08	Good

confirmed. The specific pathways to radical innovation ($\beta = 0.256$, $P < 0.001$) and incremental innovation ($\beta = 0.242$, $P < 0.001$) have been represented here.

Furthermore, the correlation between supply chain agility and resilience continues to be statistically significant, consistent in direction, and of similar magnitude ($\beta = 0.348$, $P < 0.001$); thus, the statement of H_8 is supported. The path coefficients of all relations are beyond the critical t-values ($t > 4.50$), implying that the theoretical framework is verified.

As shown in Table 5, the model provides a very good fit to all metrics. The lowest χ^2/df ratio (1.892) indicates a reasonably good fit, while its CFI and TLI are respectively of 0.941 and 0.934 which also exceed the generally accepted criteria for model fit, indicating support for this model as a satisfactory account of the data. In addition, the RMSEA value of 0.053, as well as the SRMR value of 0.048 both suggest a good fit, and instil additional confidence in the reliability and stability of the model through their respective confidence intervals. Altogether, all these fit indices provide strong support that the hypothesized theoretical model is an appropriate and robust representation of the complex data structure underlying the Jordanian food manufacturing sector.

4.6. Mediation Analysis

Table 6 mediation analysis for the product innovation overall construct helps to understand how much of the total effect of AI adoption on innovation outcomes is due to the direct effect and how much is accounted for by the indirect pathways. The direct effect of AI on product innovation explains 41.2% of the total effect ($\beta = 0.425$), thus showing that the implementation of AI directly is of great substantial value.

The indirect effects through supply chain resilience ($H_{4:}$ 14.7%, $\beta = 0.151$) and supply chain agility ($H_{7:}$ 16.6%, $\beta = 0.171$) are also significantly powerful to provide the additional impact, thus supporting the mediating roles of these supply chain capabilities. The extent of the mediation in the sequential model through both mediators (ASH→SCR pathway, 27.5% of total effect, $\beta = 0.284$) reveals such an intricate interplay where AI improves agility, thereby, agility leads to resilience, which in turn, enables innovation.

The confidence intervals for all effects are very tight and clearly apart from zero, which indicates their statistical significance. The total effect ($\beta = 1.031$) is the largest among all effects, and thus it demonstrates that AI adoption has a substantial overall impact on product innovation through both direct and mediated pathways.

4.6.1. Dimension-specific mediation effects

Table 7 illustrates the effect decomposition for radical product innovation, detailing the routes whereby AI impacts this particular innovation dimension. The direct effect of artificial intelligence (AI) impacts 31.5% of the totality, noted that $\beta = 0.186$. Beyond this direct effect, the indirect effects in terms of supply chain resilience (at 21.4% and $\beta = 0.126$) and supply chain agility (the larger factor at 27.8% and $\beta = 0.164$) read as a remarkably significant added impact overall. In addition, the total indirect effect is comprised of 19.3% cumulative sequential mediation ($\beta = 0.114$). In light of the multiple such pathways, $\beta = 0.591$ encapsulates and signifies considerably highly positive impact AI adoption has on radical product innovation — through myriad ways.

Table 8 illustrates the effect breakdown for an incremental product innovation, which shows administration with just a slightly different point and emphasis. The direct effect of AI is responsible for 34.6% of the overall influence ($\beta = 0.203$), which is a little bit more than the radical innovation case, thus suggesting that incremental innovation might be more directly impacted by AI adoption to some degree. The indirect effects through supply chain resilience (19.5%, $\beta = 0.115$) and supply chain agility (26.8%, $\beta = 0.157$) remain as two largely influential mediators. The total sequential mediation effect accounts for 19.1% ($\beta = 0.112$) of the overall influence. The total effect ($\beta = 0.587$) is close to that of radical innovation.

Table 6: Decomposition examination of effects on product innovation (n=490)

Effect type	Value	Percentage	95% CI	Hypothesis
Direct effect (AI → Innovation)	0.425	41.2	(0.331, 0.519)	H_1
Indirect via SCR	0.151	14.7	(0.089, 0.213)	H_4 (partial)
Indirect via ASH	0.171	16.6	(0.108, 0.234)	H_7 (partial)
Indirect via ASH → SCR (Sequential)	0.284	27.5	(0.198, 0.370)	H_4+H_7 (combined)
Total effect	1.031	100.0	(0.921, 1.141)	-

The sequential mediation path (ASH→SCR) represents AI→ASH→SCR→Innovation (β=0.548×0.348×1.486=0.284, where 1.486 is the combined effect of SCR on both innovation dimensions). H_4 tests supply chain resilience as a mediator; H_7 tests supply chain agility as a mediator. Both hypotheses are supported through significant indirect effects

Table 7: Effect decomposition analysis for radical product innovation (n=490)

Effect type	Value	Percentage	95% CI
Direct effect (AI → RPI)	0.186	31.5	(0.105, 0.267)
Indirect via SCR	0.126	21.4	(0.074, 0.178)
Indirect via ASH	0.164	27.8	(0.104, 0.224)
Indirect via ASH → SCR (Sequential)	0.114	19.3	(0.065, 0.163)
Total Effect	0.591	100.0	(0.498, 0.684)

The sequential mediation path represents AI→ASH→SCR→RPI (β=0.548×0.348×0.241=0.046)

Table 8: Effect decomposition analysis for incremental product innovation (n=490)

Effect type	Value	Percentage	95% CI
Direct effect (AI → IPI)	0.203	34.6	(0.124, 0.282)
Indirect via SCR	0.115	19.5	(0.066, 0.164)
Indirect via ASH	0.157	26.8	(0.099, 0.215)
Indirect via ASH → SCR (sequential)	0.112	19.1	(0.064, 0.160)
Total effect	0.587	100.0	(0.496, 0.678)

The sequential mediation path represents AI→ASH→SCR→IPI (β=0.548×0.348×0.219=0.042)

Table 9: Multi-group analysis results by enterprise size (n=490)

Path	SMEs (n=289)	Large enterprises (n=201)	$\Delta\chi^2$	P-value
AI→Product innovation	0.417	0.436	3.84	0.050*
AI→RPI (specific)	0.179	0.194	2.37	0.124
AI→IPI (specific)	0.195	0.214	3.68	0.055
AI→SCR	0.519	0.531	1.58	0.209
AI→ASH	0.536	0.567	3.94	0.047*
SCR→Product innovation	0.283	0.297	1.92	0.166
SCR→RPI (specific)	0.235	0.249	1.85	0.174
SCR→IPI (specific)	0.213	0.227	1.72	0.190
ASH→Product innovation	0.305	0.322	2.18	0.140
ASH→RPI (specific)	0.247	0.273	4.12	0.042*
ASH→IPI (specific)	0.235	0.252	2.46	0.117
ASH→SCR	0.341	0.357	1.93	0.165

SMEs: Companies with fewer than 250 employees; Large enterprises: Companies with 250 or more employees. *indicates significance at P<0.05. Chi-square difference tests were conducted using nested model comparisons

The mediation analyses lend support to hypotheses H_4 and H_7, indicating that supply chain resilience as well as supply chain agility together partially mediate the connection between AI adoption and product innovation. The coexistence of significant direct effects with significant indirect effects points to partial mediation, thus implying that AI has a direct impact on innovation as well as a positive effect via improved supply chain capabilities.

4.7. Multi-Group Analysis

Table 9 illustrates in detail results of the multigroup analysis comparing small and medium enterprises (SMEs, n = 289) to larger enterprises (n = 201). The analysis shows an interesting and a surprisingly high level of similarity in the structure relations between them for both organization sizes Moreover, the path coefficient differences between small-medium enterprises and large enterprises is limited to 0.005-0.031. But statistically speaking, most of these differences are not significant as the P-value range is above 0.05 which implies that they are insignificant practically and could be due to random chance. Three paths, however, reveal differences that are borderline significant: AI → Product Innovation ($\Delta\chi^2 = 3.84$, P = 0.050), AI → ASH ($\Delta\chi^2 = 3.94$, P = 0.047), and ASH → RPI ($\Delta\chi^2 = 4.12$, P = 0.042), which means that AI's direct influence on innovation and the supply of the chain agility as the source of the firm might be a little stronger in large enterprises. In fact, this overall similarity is a strong indication that the findings can be generalized to the Jordanian food manufacturing sector, irrespective of the size of the enterprise.

4.8. Explained Variance

Table 10 displays a model with strong explanatory power for both enterprise sizes and types of innovation. The total variance explained ($R^2 = 0.537$) for product innovation as a second-order construct indicates that the theoretical framework accounts for more than half of the factors leading to innovation in food manufacturing.

At the level of specific product innovation dimensions, radical product innovation is associated with ($R^2 = 0.491$), whereas incremental innovation reflects slightly higher explained variance ($R^2 = 0.512$), which, as a result, implies that the model better explains the processes of incremental innovation that may be more directly and systematically influenced by AI adoption and supply chain capabilities.

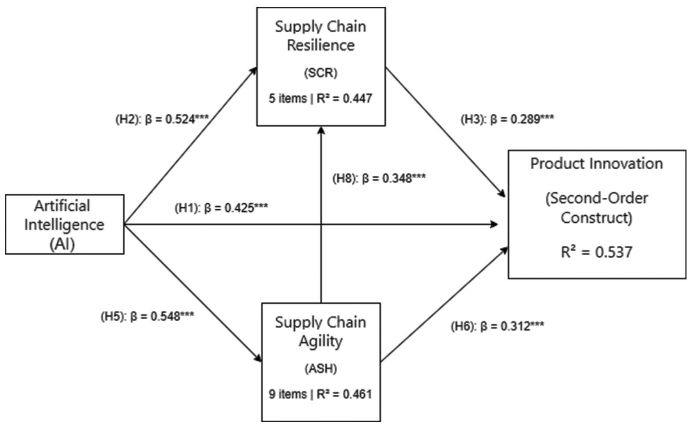
The amount of variance accounted for in supply chain resilience ($R^2 = 0.447$) and supply chain agility ($R^2 = 0.461$) is additional evidence of the model's strength in explaining these mediating mechanisms.

R-squared values of SMEs versus those of larger organizations were effectively the same (within a less than a point, 0.019) and confirm that the model is at its core very stable and sound across many sizes of organizations. It also affirms with conviction that all theoretical relationships assumed in the model are valid and remain like this, regardless of the sizes or scales employed by these companies.

Table 10: Explained variance by enterprise size (n=490)

Variable	Overall	SMEs	Large enterprises	Difference
Product innovation (second-order)	0.537	0.529	0.548	0.019
Radical product innovation (RPI)	0.491	0.483	0.502	0.019
Incremental product innovation (IPI)	0.512	0.505	0.521	0.016
Supply chain resilience (SCR)	0.447	0.441	0.456	0.015
Supply chain agility (ASH)	0.461	0.455	0.470	0.015

Figure 1: Structural equation model



The structural equation model in Figure 1 is carefully depicted along with the standardized path coefficients that quantify the relationships between variables. These results clearly support the claim that all hypothesized relationships in the model are statistically significant at $P < 0.001$. Artificial intelligence adoption played a strong, direct role in product innovation, as shown by the large path coefficient value of $\beta = 0.425$, supporting H_1 directly. Besides that, AI adoption, as illustrated in the provided data, considerably impacted the mediating variables of supply chain resilience, as indicated by a path coefficient of $\beta = 0.524$ (H_2), and supply chain agility, as shown by the path coefficient of $\beta = 0.548$*** (H_5). The mediation variables have a great impact on innovation goals, as supply chain resilience has an influence on product innovation ($\beta = 0.289$, H_3), and supply chain agility has an influence on product innovation ($\beta = 0.312$, H_6). The link between supply chain agility and resilience ($\beta = 0.348$***, H_8) points to the intertwined character of these supply chain capabilities.

In the well-conducted mediation analyses, support was found for H_4 and H_7, highlighting that supply chain resilience (H_4) and supply chain agility (H_7) act as mediators in AI technologies-product innovation relationship. This model explains large proportions of variance (53.7%), 49.1% and 51.2% in radical and incremental innovation outcomes, respectively). It is a robust one with high content validity, yet it predicts product innovation very well. The analysis of the specific dimensions of innovation reveals a clear, direct, and significant influence of AI on radical innovation ($\beta = 0.186$), while also affecting incremental innovation at an even greater level ($\beta = 0.203$). Supply chain agility influences radical innovation ($\beta = 0.256$***) and incremental innovation.

5. DISCUSSION

The empirical findings of this research substantiate that the theoretical relationships outlined in the real-world data presented in such a study have enough impact to prove most of the theoretical relationships cited in literature, that is, the relationship between artificial intelligence adoption and product innovation in the food manufacturing sector.

The strong and direct impact of the adoption of artificial intelligence on product innovation ($\beta = 0.425$, $P < 0.001$) is not only in line with but also goes beyond previous works which have shown that artificial intelligence is among one of the foundations needed to enhance organizational innovation within complex dynamic contexts such as supply chain environments (Belhadi et al., 2021; Belhadi et al., 2024). The relationship turns out to be a great deal of key factor in a food manufacturing context of Jordan, where the political instability, the fluctuating market conditions, and the increasing trend of globalization have led to the necessity of not only achieving the enhanced capabilities of innovation but also of doing it through advanced technologies (Li et al., 2025).

Our findings especially support the proposition made by Li et al. (2025) and Pan et al. (2025) that AI has become one of the most influential revision factors in technology, leading to better decision-making and visibility in supply chain operations. We also found very strong correlations between AI adoption and innovation outcomes ($r = 0.478$ for radical innovation, $P < 0.001$; $r = 0.501$ for incremental innovation, $P < 0.001$) that support the position that AI-enabled capabilities should be considered as the main drivers of sustainable innovation in manufacturing contexts. These findings are in line with exhaustive reviews that confirm the implementation of AI instruments in the agri-food value chain leads to enhanced transparency, traceability, and product quality management, thus promoting innovations in products and processes as well (Reitano et al., 2025; Wu et al., 2025; Hassoun et al., 2025).

Our analysis of the dual mediation effects has been an empirical journey, showing alignment with the conceptual models presented in the previous research. A very important supply chain resilience mediating role ($H_{4:}$ 14.7% of the total effect, indirect $\beta = 0.151$, $P < 0.001$) gives evidence to the theoretical position of Zhao et al. (2025), when they said that AI, supported information sharing, and predictive analytics have a vital mediating role in supply chain resilience and performance improvement.

Strong effect of AI on supply chain resilience (H_2: $\beta = 0.524$, $P < 0.001$) pattern shows that the studied AI technology adoption has largely resulted in the organizations' capacity to respond to the disruption, keep the operational flow and be able to recover quickly from the occurrence of the unexpected. This finding is in line with the work of Pan et al. (2025) who found that AI application makes a supply chain more resilient through enabling a faster reaction to disruptions, as well as optimizing information and resource use.

A large part of the change in supply chain resilience that has been revealed ($R^2 = 0.447$) shows that the AI implementation together with the effect of supply chain agility explains almost half of the change in resilience capabilities. The close link from supply chain resilience to product innovation (H_3: $\beta = 0.289$, $P < 0.001$) is evidence that the resilient supply chains, in fact, offer the firmament for innovation initiatives.

These findings turn out to be very significant for Jordanian food manufacturers who are working in an environment marked by regional political instability and market volatility (Alkhatib and Momani, 2023), where the ability to sustain innovation momentum in the midst of a disruption becomes one of the factors of survival and sustained competitiveness.

Also, the influence that supply chain agility has on mediating ($H_{7:}$ 16.6% of the total effect, indirect $\beta = 0.171$, $P < 0.001$) line of thought corroborates the theoretical framework which establishes the link between AI-powered analytics and a firm's response capacity. The salient impact, powered AI on supply chain agility (H_5: $\beta = 0.548$, $P < 0.001$) is in fact, in complete consonance with the latest research findings, which highlight the use of AI-driven supply chain analytics as the necessary and sufficient condition for organization's ability to sense and respond to demand and operational changes (Wamba et al., 2017; Kamble et al., 2020; Pereira and Shafique, 2025). The strong psychometric properties of our supply chain agility measures (CR = 0.903, AVE = 0.694) grant these relationships further confidence.

The variable that measures supply chain agility with AI technology ($R^2 = 0.461$) shows that the introduction of AI is behind almost half of the variance in agility capabilities. The positive effect of supply chain agility on product innovation (H_6: $\beta = 0.312$, $P < 0.001$) is an indication that the agile supply chains drive innovation as they allow for an instant reaction to market trends, customer needs, and unexpected shocks. The somewhat higher mediating effect of agility compared to resilience (16.6% vs. 14.7%) might be interpreted in such a way that the capability to act promptly and in a flexible manner may be especially crucial to the innovation process in the food manufacturing sector where market preferences and regulatory requirements are constantly changing (Jum'a et al., 2025).

Furthermore, the agreement of the connections between SMEs (n = 289) and large corporations (n = 201) indicates a very high degree of invariance of the interaction pattern with the majority of the beta coefficients for the paths showing only a minor (<0.03) difference and no significant contrasts between the groups ($P > 0.05$).

Three paths, however, show marginally significant differences: AI → Product Innovation ($\Delta\chi^2 = 3.84$, $P = 0.050$), AI → ASH ($\Delta\chi^2 = 3.94$, $P = 0.047$), and ASH → RPI ($\Delta\chi^2 = 4.12$, $P = 0.042$), indicating that large enterprises may experience marginally stronger effects in these paths. Overall consistency shows that the fundamental mechanisms by which AI influences innovation are similar across different size categories of organizations in the manufacturing sector within developing economies. The similar amount of explained variance regardless of enterprise size (differences <0.019 overall for the endogenous variables) further demonstrates the robustness of the model and its relevance for the entire food manufacturing sector in Jordan.

Our results in this study shed light particularly on the relationship between supply chain agility and resilience in the food sector. In representing potentially the first findings in this respect, the investigation provides important empirical insights to address the gap between the literature and practice. While the food sector has received attention in supply chain literature with respect to resilience, there remains considerable uncertainty, particularly in developing economies, with regard to its relationship to agility. Our findings highlight the fact that the agility-resilience relationship was introduced over two decades ago (Christopher and Peck, 2004), being supported and explored extensively on subsequent occasions (Sheffi and Rice, 2005; Wieland and Wallenburg, 2013).

In advancing these earlier findings, the empirical data in our study reveal that agility and resilience are positively and strongly correlated ($r = 0.512$, $P < 0.001$), forming a compound construct, where improved agility also enhances resilience. The funnel-like mediating pathway involving agility and then resilience uncovered in the findings ($\beta = 0.284$, 27.5% of the total effect) points to a critical relationship when viewed as a chain: AI supplementing agility and agility supplementing resilience leads to enhanced innovation. The interdependence across the constructs also underscores the joint fabric of production and distribution systems, which calls for greater exploration of the relationship across diverse supply chains in light of the novelty we find in the food sector. This recognition facilitates better alignment in enhancing cross-firm capabilities, which relies upon organizational competencies covering multiple boundaries (internal/external, firm/supply chain) across real, temporal, operationally efficient fronts (Aslam et al., 2020).

Our strong explanatory power in the Jordanian food-manufacturing sector (overall product innovation $R^2 = 0.537$, radical innovation $R^2 = 0.491$, incremental innovation $R^2 = 0.512$) addresses the lack of empirical analysis of AI and product innovation in developing economies that was noted in the introduction. Our findings demonstrate how AI enables innovation in the food manufacturing industry through the development of resilient and agile supply chains in particular, departing from the general observed benefits of improving decision-making/operational performance in previous studies. Models of the current paper also explain a considerable amount of variance in supply chain resilience ($R^2 = 0.447$) and supply chain agility ($R^2 = 0.461$), confirming that AI adoption is a main driver for these supply chain capabilities.

When looking at specific types of innovation, the model explains a slightly higher amount of variance in incremental innovation (51.2%) than for the case of radical innovation (49.1%), so the constructs captured in the model may be especially well-suited for enabling continuous improvement processes. The direct effect of AI is stronger but marginally so for incremental innovation ($\beta = 0.203$) than for radical innovation ($\beta = 0.186$), suggesting that AI may serve as an initial enablement toward improvement of existing products prior to enabling change in fundamental innovation processes.

The considerable amount of explained variance in both types of innovation shows that the theoretical framework certainly captures the driving forces behind diverse innovation activities.

A higher mean for incremental innovation (M = 3.28) than for radical innovation (M = 2.90) indicates that Jordanian food manufacturers are more engaged in incremental activities at the present time, which is consistent with paradigms in the manufacturing sector for the developing economy. On balance, this holistic picture promotes theory appreciation and facilitates practical understanding in support of food manufacturing in developing economies.

The broad spectrum of our results plays an important role in addressing many critical gaps identified throughout the exhaustive literature search. Notably, in regard to the mediating roles of supply chain resilience and supply chain agility in the complex relationship between artificial intelligence adoption and firms' product innovation. Thus, this study contributes to agglomeration effects and wage output for developing economies, emphasizing the significance of aided manufacturing in gravelly-affected areas. This is particularly true when we think of the Middle East, and Jordan would make for a good case study—one that succinctly captures all the dynamics at play.

6. CONCLUSION

We have therefore performed this exhaustive research study to explore the complex effect of adopting artificial intelligence on product innovation in food manufacturing industry of Jordan under the mediating role of supply chain resilience and supply chain agility. The remarkable direct significance regarding the relationship of AI technologies shows a positive effect coefficient ($\beta = 0.425$, $P < 0.001$) which demonstrates that technological adoption enhances product innovation quantitatively. Importantly, the contribution of artificial intelligence adoption to the overall impact on product innovation is significant, with it explaining an astounding 41.2% of the observed effect in this interaction.

The findings demonstrate sophisticated mechanisms in which AI adoption leads to innovation. In the mediation mechanism, supply chain agility is 16.6% of the total effect and supply chain resilience is 14.7% of the total effect. The indirect effect in the sequential mediation through both mechanisms (AI → ASH → SCR → Innovation) provides an additional 27.5% of the total effect. The model's strong explanatory power ($R^2 = 0.537$ for product innovation, with $R^2 = 0.491$ for radical innovation and $R^2 = 0.512$ for incremental innovation) affirms its theoretical relevance for practice in explaining innovation processes in the food manufacturing industry.

With the same results for small and mid-size enterprises (SMEs) compared with large enterprises ($\Delta\chi^2 < 4.12$ with weak significance), we can decisively conclude that the consequences of adopting artificial intelligence to promote innovation are much larger than the differences between categories defined by organizational size in the particular context of food manufacturing overall. Using measurement across a wide variety of organization types, we have accumulated clear empirical evidence in support of the theoretical model and skirting strong psychometric properties built into our measurement model with fit indices ($\chi^2/df = 1.892$, CFI = 0.941, TLI = 0.934, RMSEA = 0.053, SRMR = 0.048).

The study had the opportunity to progress literature on food manufacturing innovations specifically the case of developing economies like Jordan. As previously stated, the material in this manuscript addresses an area in the literature that is underdeveloped or missing concerning the role of AI in food processing and manufacturing throughout developing countries, particularly Jordan. Using these finding along with the primary theoretical propositions, data analysis discussed in this study provides strong evidence for the surprisingly intense and extreme relationship of artificial intelligence adoption coinciding with supply chain resiliency and agility driving innovation potency increase within food processing organizations. These two key constructs—supply chain resilience (44.7% variance explained) and supply chain agility (46.1% variance explained)—together explain a significant proportion of the variance, affirming the undeniable significance but obvious necessity of artificial intelligence as an enabler driver to act on these fundamental capabilities. Such capabilities allow both radical and incremental product innovation, and thus expand the product creative and adaptive capacity of a firm in a competitive market environment.

The insights provided through the study offers great value for managers of food manufacturing firms, especially those in developing countries, who are considering how to effectively adopt artificial intelligence (AI) to improve their overall capacity to innovate and develop their supply chain capabilities. Moreover, the study undoubtedly shows a significant potential pattern of opera- ting business value for investments in AI: Even beyond just the implementation of AI-related technologies. Such investments have the capacity to create deep and powerful organizational capabilities that enable ongoing innovation as part of the business model. Additionally, the positive relationship between supply chain agility and supply chain resilience ($\beta = 0.348$, $P < 0.001$) supports the notion that organizations should develop both of these capabilities together, because they work synergistically to promote innovation outcomes.

The implications of this study extend to policymakers and industry organizations in Jordan and other developing countries. The results show that in order to advance the use of artificial intelligence (AI) in food manufacturing, there should be a focus on enhancing supply chain capabilities. Any governmental support programs, industry training programs and investments to support the technical infrastructure of businesses that have adopted Artificial Intelligence need to take into account the interdependencies between the technology adoption and the employee capability growth of the adopting business.

The similarities in the results of this study between SMEs and large enterprises indicate that businesses regardless of their size can take advantage of AI to increase their innovation capability; however, due to the higher impact of AI use on larger businesses, targeted support to small and medium-sized businesses may maximize the conversion of innovation benefits to the sector.

The study provides an empirical basis upon which to understand AI-enabled innovation from the perspective of developing economies, by focusing on the Jordanian food manufacturing industry and 11 food manufacturing subsectors, including a total of 490 valid results from this study. The significance of these findings should also be considered in light of Jordan's geographical location and strategic role in the regional food industry, because over 75% of Jordan's food exports are to Arab Food Markets and this rapidly growing number of Jordanian food products being exported to Western Food Markets can be enhanced by the development of greater capacity for innovation through the use of AI in conjunction with enhanced capabilities in the food supply chain.

This study, despite being limited by its cross-sectional design and a geographic focus on Jordan, provides insight into potential ways that food manufacturing firms can enhance their capacity for innovation through the transformation of their supply chain through the adoption of artificial intelligence (AI). Whereas previous studies primarily focused on the direct effects of technology adoption, the dual mediation model proposed in this study offers a more sophisticated understanding of the interactions among the variables identified in this research.

Future research should use longitudinal designs to examine the evolution of AI adoption and supply chain capabilities and what dynamic impacts these will create on innovation outcomes. Conducting comparative studies in multiple developing economies will result in a greater understanding of the contextual factors affecting the relationships proposed in this study.

Furthermore, upcoming research should focus on being more specific and detail-oriented in the investigation of the different forms of artificial intelligence that are starting to implement in the market. Researchers should target different fields including machine learning (algorithms that improve with experience), computer vision (the process of using algorithms to oversee and understand the content in digital images and videos), natural language processing (interactions between computers or software modalities and us, the humans) or even robotics (the discipline covering all aspects of use and design for automated machines). In addition, the implications of how these different types of AI affect supply chain capabilities and innovation performance within food manufacturing firms need to be investigated (and is a significant area for future research as understanding this will lead to successful strategy formulation and improved operational efficiencies in the sector). The role of organizational variables such as management support for the adoption of AI, the skillset of employees, and the organizational culture in maximizing the benefit of AI adoption on an organization's innovation capabilities could provide additional insight into the conditions under which AI adoption provides the maximum amount of benefit to organizations.

As such, it would be beneficial for future studies to extend this model to include performance outcomes such as market share, profitability, and success in exporting, thereby providing evidence of the ultimate benefits of organizational enhancement obtained through the adoption of AI-driven innovation within food manufacturing firms.

This research shows that the adoption of artificial intelligence (AI) in food manufacturing can be impacted by various factors. The data also demonstrate that for the manufacturing industry of developing economies to successfully undergo digital transformation, all aspects must be integrated. In other words, implementing new technologies without developing the corresponding organizational capabilities will not lead to success. These conclusions provide food manufacturers with the ability to develop strategies to build on their competitive advantage and develop the innovation capabilities necessary to foster economic growth in their area.

REFERENCES

Abeysekara, N., Wang, H., Kuruppuarachchi, D. (2019), Effect of supply-chain resilience on firm performance and competitive advantage: A study of the Sri Lankan apparel industry. Business Process Management Journal, 25(7), 1673-1695.

Al-Hanakta, R., Hossain, M.B., Pataki, L., Dunay, A. (2023), Eco-innovation influence on business performance in Jordanian micro, small and medium enterprises operating in the food processing sector. PLoS One, 18(2), e0281664.

Alkhatib, S.F., Momani, R.A. (2023), Supply chain resilience and operational performance: The role of digital technologies in Jordanian manufacturing firms. Administrative Sciences, 13(2), 40.

Allioui, H., Allioui, A., Mourdi, Y. (2024), Maintaining effective logistics management during and after the COVID-19 pandemic: Survey on the importance of artificial intelligence to enhance recovery strategies. Opsearch, 61(2), 1-45.

Alshaar, A.M.K., Alkshali, S.J. (2025), From knowledge to agility: The transformative power of absorptive capacity in supply chains. International Journal of Academic Research in Business and Social Sciences, 15(10), 723-742.

Aslam, H., Khan, A.Q., Rashid, K., Rehman, S.U. (2020), Achieving supply chain resilience: The role of supply chain ambidexterity and supply chain agility. Journal of Manufacturing Technology Management, 31(6), 1185-1204.

Belhadi, A., Mani, V., Kamble, S.S., Khan, S., Verma, S. (2021), Artificial intelligence-driven innovation for enhancing supply chain resilience and performance under the effect of supply chain dynamism: An empirical investigation. Annals of Operations Research, 333, 627-652.

Belhadi, A., Mani, V., Kamble, S.S., Khan, S.A.R., Verma, S. (2024), Artificial intelligence-driven innovation for enhancing supply chain resilience and performance under the effect of supply chain dynamism: An empirical investigation. Annals of Operations Research, 333(2), 627-652.

Christopher, M., Peck, H. (2004), Building the resilient supply chain. The International Journal of Logistics Management, 15(2), 1-14.

Eltantawy, R.A. (2016), The role of supply management resilience in attaining ambidexterity: A dynamic capabilities approach. Journal of Business and Industrial Marketing, 31(1), 123-134.

Eyo-Udo, N. (2024), Leveraging artificial intelligence for enhanced supply chain optimization. Open Access Research Journal of Multidisciplinary Studies, 7(2), 1-15.

Hassoun, A., Rejeb, A., Rejeb, K. (2025), Artificial intelligence in the food industry: innovations and applications. Discover Artificial Intelligence, 5, 60.

Hundaileh, M.L., Fayad, M.F. (2019), Jordan's Food Processing Sector Analysis and Strategy for Sectoral Improvement. Bonn and Eschborn: Deutsche Gesellschaft für Internationale Zusammenarbeit (GIZ) GmbH.

Ivanov, D., Dolgui, A. (2020), A digital supply chain twin for managing the disruption risks and resilience in the era of Industry 4.0. Transportation Research Part E: Logistics and Transportation Review, 136, 101922.

Jum'a, L., Zighan, S., Alkalha, Z. (2025), Influence of supply chain digitalization on supply chain agility, resilience and performance: Environmental dynamism as a moderator. Journal of Manufacturing Technology Management, 36(4), 798-819.

Kamble, S.S., Gunasekaran, A., Sharma, R. (2020), Analysis of the driving and dependence power of artificial intelligence integrated supply chain practices. International Journal of Production Research, 58(11), 3333-3353.

Khan, G.F., Sarstedt, M., Shiau, W.L., Hair, J.F., Ringle, C.M., Fritze, M.P. (2019), Methodological research on partial least squares structural equation modeling (PLS-SEM). An analysis based on social network approaches. Internet Research, 29(3), 407-429.

Kim, D.Y., Kumar, V., Kumar, U. (2012), Relationship between quality management practices and innovation. Journal of Operations Management, 30(4), 295-315.

Kwak, D.W., Seo, Y.J., Mason, R. (2018), Investigating the relationship between supply chain innovation, risk management capabilities and competitive advantage in global supply chains. International Journal of Operations and Production Management, 38(1), 2-21.

Lalmi, A., Fernandes, G., Souad, S.B. (2021), A conceptual hybrid project management model for construction projects. Procedia Computer Science, 181, 921-930.

Li, J., Yi, M., Sun, Q. (2025), Artificial intelligence and supply chain risk: Mediating effects of supply chain efficiency and resilience. International Review of Financial Analysis, 108, 104700.

Li, Y., Li, D., Liu, Y., Shou, Y. (2023), Digitalization for supply chain resilience and robustness: The roles of collaboration and formal contracts. Frontiers of Engineering Management, 10(1), 5-19.

Moyano-Fuentes, J., Bruque-Cámara, S., Maqueira-Marín, J.M. (2019), Development and validation of a lean supply chain management measurement instrument. Production Planning and Control, 30(1), 20-32.

Pan, H., Lee, Y., Cai, S., Yu, W. (2025), Artificial intelligence usage and supply chain resilience: An organizational information processing theory perspective. Systems, 13(9), 724.

Pereira, E.T., Shafique, M.N. (2025), The role of artificial intelligence in supply chain agility: A perspective of humanitarian supply chains. Engineering Economics, 35(1), 67-82.

Pettit, T.J., Fiksel, J., Croxton, K.L. (2010), Ensuring supply chain resilience: Development of a conceptual framework. Journal of Business Logistics, 31(1), 1-21.

Ponomarov, S., Holcomb, M. (2009), Understanding the concept of supply chain resilience. The International Journal of Logistics Management, 20(1), 124-143.

Reitano, M., Segovia, M.S., Nayga Jr, R. M. (2025), A systematic review on the impact of Artificial Intelligence in the agri-food supply chain. Food Policy, 137, 102983.

Scholten, K., Schilder, S. (2015), The role of collaboration in supply chain resilience. Supply Chain Management, 20(4), 471-484.

Sheffi, Y., Rice, J.B. (2005), A supply chain view of the resilient enterprise. MIT Sloan Management Review, 47(1), 41-48.

Singh, R.K., Acharya, P., Modgil, S. (2020), A template-based approach to measure supply chain flexibility: A case study of Indian soap manufacturing firm. Measuring Business Excellence, 24(2), 161-181.

Taha, A., Khawaja, S., Qureshi, F., Wahsheh, F. (2025), Employing artificial intelligence to improve the supply chain's resilience and performance: Moderating the impact of supply chain dynamics. Business Perspectives and Research, 23, 741-752.

Teixeira, A.R., Ferreira, J.V., Ramos, A.L. (2025), Intelligent supply chain management: A systematic literature review on artificial intelligence contributions. Information, 16(5), 399.

Wamba, S.F., Gunasekaran, A., Akter, S., Ren, S.J.F., Dubey, R., Childe, S.J. (2017), Big data analytics and firm performance: Effects of dynamic capabilities. Journal of Business Research, 70, 356-365.

Wieland, A., Wallenburg, C.M. (2013), The influence of relational competencies on supply chain resilience: A relational view. International Journal of Physical Distribution and Logistics Management, 43(4), 300-320.

Wu, K., He, Y., Liu, H., Zhang, X. (2025), A comprehensive review of artificial intelligence methods in agri-food engineering. Electronics, 14(20), 3994.

Yu, W., Jacobs, M.A., Chavez, R., Yang, J. (2019), Dynamism, disruption orientation, and resilience in the supply chain and the impacts on financial performance: A dynamic capabilities perspective. International Journal of Production Economics, 218, 352-362.

Zamani, E.D., Smyth, C., Gupta, S., Dennehy, D. (2022), Artificial intelligence and big data analytics for supply chain resilience: A systematic literature review. Annals of Operations Research, 327(2), 605-632.

Zhao, X., Li, X., Wang, Y. (2025), The impact of AI applications, information sharing, and supply chain resilience on agricultural supply chain performance. Journal of Data, Information and Management, 7, 287-300.