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Article

The Impact of Generative Artificial Intelligence and Lean Practices on Operational Efficiency in Manufacturing Supply Chains: Evidence from Firms

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Abstract: The study focused on how well manufacturing companies are integrating generative AI into their processes and how this integration is affecting them in terms of operational efficiency and supply chain resilience, and the link between these variables. The quantitative approach used in this study was a cross-section, and the data obtained were in the form of questionnaires, which were structured and filled out by 348 manufacturing companies. Automotive companies (28.2%), food processing companies (24.7%) and manufacturing companies related to construction (21.3%) made up the sample. The descriptive statistics, reliability analysis, Pearson correlation analysis and hierarchical multiple regression analysis were applied. The Cronbach's α value of all the measurement scales were in the range of 0.861 to 0.902, which were satisfactory. The results showed that the operational efficiency for generative AI capabilities is significantly and positively related to operational efficiency ($\beta = 0.643$, $t = 8.914$, $p < 0.001$). The operational efficiency for lean manufacturing maturity is significantly and positively related to operational efficiency ($\beta = 0.512$, $t = 7.235$, $p < 0.001$). The operational efficiency was the most important predictor of supply chain resilience ($\beta = 0.588$, $t = 8.102$ and $p < 0.001$). The interaction effect of generative AI capabilities and leadership support was also found to be significant ($\beta = 0.274$, $t = 3.456$, $p = 0.012$), indicating leadership support as another moderating factor. This was done by the direct effects model, which accounted for 62.3% of the operational efficiency.
Keywords: Generative Artificial Intelligence; Lean Manufacturing; Operational Efficiency; Supply Chain Resilience; Quality 4.0; Data-Driven Decision Making

1. Introduction

The manufacturing business is undergoing a paradigm shift from responding to business models that are able to predict and make decisions based on data. Lean Thinking, along with other digital technologies like Artificial Intelligence (AI), plays a major role in this paradigm shift in the scope of Quality 4.0 (Saadouli et al., 2025). In this regard, digital ecosystems are becoming more popular, which can provide organizations with real-time visibility into supply-chain activities, enhancing their decision-making and control over their operations (Nasereddin, 2024). Technologies such as the Internet of Things (IoT) and generative AI can help to detect small inefficiencies and forecast issues, making quality control a more dynamic and self-regulating process (Fatorachian, 2025). This change will make it easier to develop smart production systems based on real-time streams of data that can inspire adaptive and optimized production operations (Lakhouil & Soulhi, 2025) and pave the way towards more profitable financial operations under market volatility (Balouza, 2024).

Although there are advances in this field, there are still large gaps in the literature. Routine quality management processes are frequently inadequate for dealing with dynamic wastes (muda) that occur when unforeseen problems go down the supply chain. Traditional supply chain models are rigid and inefficient, resulting in the build-up of resources when there is uncertainty. Therefore, the need to improve supply chain resiliency by combining with advanced analytical and algorithmic capabilities has increased (Shahin et al., 2024). Despite this, the development of AI-based models for the optimization of manufacturing processes using lean concepts has not been fully developed in operational environments (Mora et al., 2025; Tsai et al., 2025).

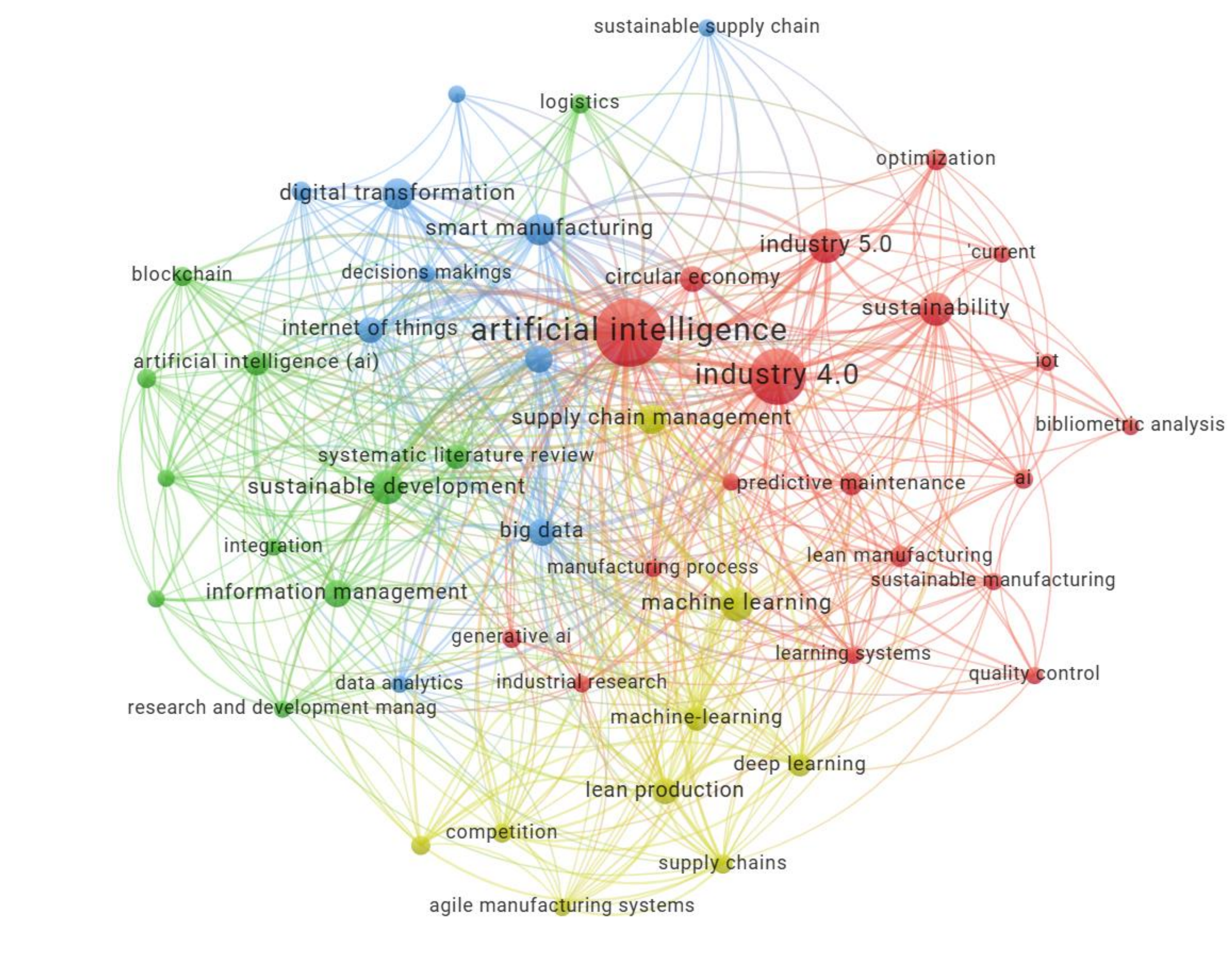
Additionally, the active contribution of generative AI as part of value stream management has not been explored yet, which is the reason why there are some solutions lacking in the scalability aspect to optimize sustainability and efficiency (Mora et al., 2025). As opposed to retrospective analyses, organizations need predictive analytics that help in proactive decision-making and enhance supply chain agility (Atieh, 2025). This is also in line with the whole trend towards Industry 5.0, which merges technological advancement with human-centered and resilient production systems (Nasir et al., 2025).

This study aims to analyze the impacts of the generative AI capabilities and the maturity of lean manufacturing on operational efficiency in a manufacturing supply chain, and the role of operational efficiency as a pathway by which the generative AI capabilities reinforce the supply chain resilience. The contribution has three particularities. First, the study not only examines generative AI as a predictive and adaptive operational capacity but also as a concept of digitalisation in general. Second, it reviews the use of AI in a Quality 4.0 context and demonstrates that one can use AI for prediction in conjunction with lean waste reduction. Third, it looks at leadership support as a moderating factor that enhances the relationship between AI and efficiency. The study, which relies on empirical evidence collected from 348 manufacturing companies, thus offers empirical evidence for the link between generative AI and lean maturity, leadership support, operational efficiency and resilience. In this more focused article, managers will find tips to help them integrate the use of AI into their lean operations, process discipline and leadership-driven implementation in today's manufacturing supply chain.

2. Literature Review

A bibliometric keyword co-occurrence analysis was carried out by the VOSviewer 1.6.20. The bibliometric data were downloaded from Scopus in May 2026. The following keywords were used for the search: “artificial intelligence”, “generative AI”, “lean manufacturing”, “lean production”, “Quality 4.0”, “Industry 4.0”, “operational efficiency” and “supply chain resilience”. The publications that were looked at for the screening period ranged from 2020-2026. The articles used were English language peer-reviewed journal articles, conference articles, and review articles, which included discussion on the concepts of AI, lean practices, operational efficiency, Quality 4.0, or supply chain resilience in the context of manufacturing and supply chain. Duplicate documents were not included, nor were documents that were not published in English, or non-manufacturing studies and conceptual papers. After screening, 126 documents remained. For analysing the co-occurrence of the keywords, full counting, association strength normalisation and a keyword minimum appearance of 3 were used. This analysis shows the results in Figure 1.

Figure 1. Co-occurrence network of the keywords Quality 4.0, Lean Manufacturing and Artificial Intelligence.



Source: Authors' elaboration based on a critical review of the literature using VOSviewer (version 1.6.20).

Well-formed and much interconnected clusters are reflected by the bibliometric map, which corresponds to the evolution of the scientific literature. Central nodes indicate the close connection between Artificial Intelligence (AI) and big data, with optimization of the supply chain and lean manufacturing. Central nodes show an increase in the adoption of AI and big data in the context of supply chain optimisation and lean manufacturing practices beyond a mere study. These connections are tight, friendly and strong, signifying that digitalisation plays a major role in enhancing operability and sustainability. The relations are at a high level of closeness and strength, suggesting digitalization is a key part of enhancing operational efficiency and sustainability. This conceptual framework can be a starting point for contemplation on the importance of technological integration in the elimination of inefficiencies in the supply chain systems. To facilitate systematization, it was decided to present a summary of the most relevant studies, grouped into four thematic clusters, on the basis of the co-occurrence analysis (see Table 1).

Table 1. Summary of the literature grouped by thematic research clusters

Author and year	Context	Method	Key finding	Gap identified	Relevance to present hypotheses
Okuyelu & Adaji (2024)	AI-driven process control in industrial operations	Applied technical study	AI helps to monitor, predict, and take corrective	Lack of direct testing of the generative AI to predict	Supports H1 by connecting the capability of AI with

			action during processes.	the efficiency of operations.	efficiency in operation.
Mora, Tang and Toledo (2025)	AI-based value stream mapping	Conceptual and applied lean analysis	Unlike traditional value stream mapping, AI can detect the waste and inefficiencies in these processes.	Very little empirical data on manufacturing companies.	Helps H1 and H2 in demonstrating the possibility of further reducing waste with the help of AI.
Saadouli et al. (2025)	AI integration in lean systems	Literature-based analytical study	The use of AI enhances the lean systems by enabling evidence-based and adaptive process improvement.	The combination of AI capability and lean maturity is yet to be tested.	Justifies H1 and H2.
Lakhouil and Soulhi (2025)	Lean manufacturing and Industry 4.0 technologies	Review-based study	Lean and digital technologies enhance transparency, coordination and waste reduction.	There is little attention paid to generative AI in Quality 4.0.	Enables H2 by connecting lean maturity and operational efficiency.
Ar (2025)	Lean management and organisational resilience	Bibliometric or review-based mapping	Lean practices help to achieve process discipline and resiliency.	Empirical research is needed to further understand lean as a resilience enabler.	Carries out a lean and resilient efficiency and resilience logic to support H2 and H3.
Nasereddin (2024)	Digital supply chain management	Empirical or analytical supply chain study	Digital technologies enhance information, communication and decision making.	The specific contribution of generative AI to the overall digitalisation process has yet to be clearly distinguished.	Supports H1 by connecting digital skills with process efficiency.

Dhirar & Hamad (2025)	Supply chain resilience in production and logistics	Empirical or review-based analysis	Continuity, flexibility and disruption response are the elements of resilient supply chains.	Efficiency often is not assessed as a route to resilience.	Justifies H3 by making efficiency a means of being resilient.
Atieh (2025)	AI and supply chain resilience	Applied AI and supply chain analysis	AI can enhance resilience by more appropriately responding to disruptions and predicting them.	Some evidence of positive outcomes of operational efficiency in terms of resilience.	Links AI, efficiency and resilience to support H1 and H3.
Sivathanu et al. (2025)	Generative AI in automotive manufacturing	Empirical technology adoption study	There is a need for organisational support to support the successful implementation of generative AI.	Leadership is very rarely used as a moderator variable for the outcomes obtained from the use of AI.	Supports H4 by making a connection between leadership support and the success of the implementation of AI.
Tsai et al. (2025)	AI-based big data analytics in lean manufacturing	Empirical or model-based study	By leveraging AI analytics in conjunction with managerial and process conditions, lean manufacturing can be enhanced.	There are important issues of leadership as a boundary condition that need to be further developed.	Justifies the need for the leader to be a moderator to support H4.
Nasir et al. (2025)	Human-centred Industry 5.0 manufacturing	Conceptual or review-based study	In digital transformation, the approach should be technological but not without taking other aspects into consideration	The human factor isn't always properly represented in operational models of AI adoption.	Provides evidence that supports H4, explaining why it is important for leadership to play a role in efficiency with the use

			: human and organisational.		of artificial intelligence.
Fatorachian (2025)	Industry 5.0 and sustainable production systems	Review-based analysis	To achieve sustainable manufacturing, a synergy between technology, people and environment is needed.	The relationship between efficiency and resilience and Industry 5.0 principles is not well documented, and empirical evidence is lacking.	Ties together the broader context of efficiency and resilience with human-centered transformation.

Source: Authors' elaboration based on a critical review of the literature.

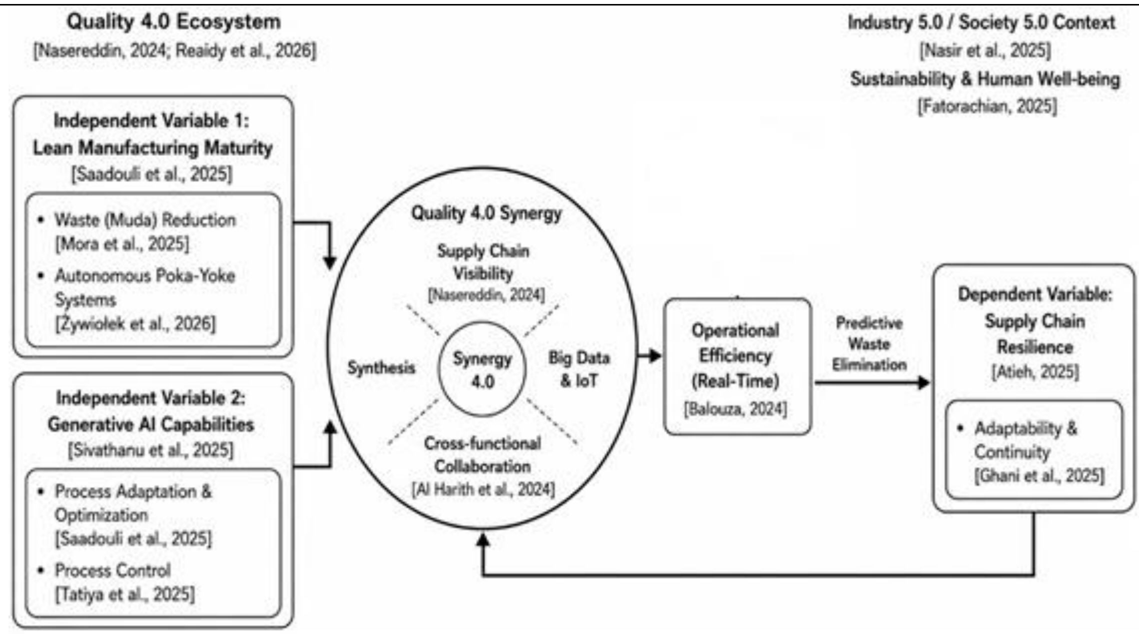
The shift from traditional manufacturing systems to digital ecosystems, Quality 4.0, has become one of the key elements in industrial competitiveness. Not only is the technology to be adopted, but the organizational structures must also be reformed to accommodate massive amounts of data and process it efficiently. Using the Internet of Things (IoT) and big data analysis in the supply chain can improve its visibility and make better, faster decisions (Nasereddin, 2024; Reaidy et al., 2026). This new visibility can enable companies to shift from reactive quality control to proactive and predictive systems that can foresee disruptions before they happen. Therefore, digitalized logistics infrastructures are a source of analytical tools that help in minimizing information asymmetries and systemic waste (Lakhouil & Soulhi, 2025).

The adoption of lean manufacturing with the assistance of Artificial Intelligence is a huge step forward from the traditional way of doing business. The previous studies show that algorithms are able to improve the detection of inefficiencies that are not possible for humans to do in value stream mapping (VSM). This has led to the emergence of lean tools from static to dynamic/adaptive systems. In particular, preventive mechanisms have evolved into independent Poka-Yoke architectures that are able to learn and adapt over time (Sarfaraz et al., 2025). These sophisticated analytics can be implemented at the initial design phase, thus helping companies to avoid waste (muda) and minimize risks of operation. These improvements help to continuously optimize processes and enable the elimination of waste in real time in supply chain processes.

Resilience from a supply chain's point of view has been greatly impacted by the capacity to process and use vast amounts of information. Today's supply chain networks are dynamic and can be put in a position where they have to endure disruption and continue to operate. When facing bottlenecks, the infusion of generative AI has added a new dimension of agility to companies, helping them to reimagine their operations and rethink how they distribute their product or service. This is the ability that can beat the traditional balance of efficiency and flexibility, enabling businesses to have both. Some empirical evidence indicates that data used in the decision-making process results in better financial performance and competitive advantage in an uncertain environment.

Furthermore, Industry 5.0 is a focus on the integration of technological progress, sustainability and people-oriented strategies. This paradigm is not solely based on the automation aspect but also integrates digital systems with environmental and social objectives. In this context, smart supply chain systems are not only meant to make it easier to use resources and workforces sustainably, but to maximise their performance. In the literature, the synergistic partnership between people and technologies to succeed in the process implementation is emphasized, establishing new levels of performance for the Industry. Based on these theoretical foundations, Figure 2 presents the conceptual model of this study, illustrating the relationships between generative AI, lean practices, and supply chain performance.

Figure 2. Conceptual model: Integration of generative artificial intelligence and lean practices for supply chain resilience.



Source: Authors' elaboration based on a critical review of the literature.

The proposed framework integrates lean manufacturing maturity with the capabilities of generative artificial intelligence, forming a Quality 4.0 ecosystem aimed at proactive waste elimination (Alzu'bi et al., 2024; Saadouli et al., 2025). In this system, enhanced Supply Chain visibility and cross-functional integration through the use of IoT and big data technologies are used (Al Harith et al., 2024; Nasereddin, 2024). They can be employed to build control systems that are able to adapt (Okuyelu & Adaji, 2024; Benevides et al., 2026; Alghorayshi et al., 2026) and continuously optimise.

However, systems' success relies on organizational factors that enable the successful implementation of digital solutions, such as technological trust and leadership support (Tsai et al., 2025). If these technological and human aspects are synchronized, a company can move from a cost-based business towards a resilient supply chain that can sustain business continuity in the face of disruption (Alkayed et al., 2025; Atieh, 2025; Dhirar & Hamad, 2025; Kmiecik, 2026). Overall, the combination of lean practices and generative AI paves the way for Industry 5.0, in which operational efficiency, sustainability, and the well-being of people and the environment are realized at the same time (Alghizzawi et al., 2025; Fatorachian, 2025; Nasir et al., 2025).

3. Hypotheses Development

The adoption of Generative Artificial Intelligence (AI) in manufacturing systems has revolutionized the way businesses operate, with the capability to make real-time decisions and predictions. Unlike conventional systems that respond to disruptions, generative AI enables organizations to predict them, optimize workflows and minimize disruptions. Previous research indicates that AI systems can improve process control by uncovering patterns within vast amounts of data, resulting in better performance in production and fewer mistakes (Ali et al., 2024; Mora et al., 2025; Qusef et al., 2025). These capabilities are especially significant in supply chain environments where they can help in responding to variability and uncertainty in a timely manner. Therefore, based on the above arguments, the following hypothesis is proposed:

H1. Generative artificial intelligence has a positive effect on operational efficiency in manufacturing supply chains.

Lean manufacturing has been a well-established method to remove waste (muda) and enhance process efficiency for a long time. The five principles of lean are: continuous improvement, optimizing value streams, and systematically eliminating non-value-added activities. The extension of digital technologies has turned lean processes into more dynamic and adaptive systems, enabling companies to "learn and adapt" better to deal with operational issues. When lean methodologies are combined with digital tools, the visibility, coordination and process standardization of the supply chain activities are boosted (Lakhouil & Soulhi, 2025; Nanjwani et al., 2025; Saadouli et al., 2025; Al Shurideh et al., 2025). Based on this, it is hypothesized that:

H2. The more mature the lean manufacturing, the more beneficial the effect on the efficiency of the manufacturing supply chain.

Moreover, operational efficiency is a key element to establishing a more resilient supply chain, particularly in a setting with high uncertainties and disruptions. The efficient processes allow companies to make better use of the resources, minimize delays and ensure seamless operations in the supply chain. Empirical evidence exists to show that more efficient organisations are more capable of 'bouncing back' from and 'surviving' external shocks and disruptions (Ali et al., 2025; Atieh, 2025). Thus, the hypothesis is put forward that:

H3. An efficient operation is a driver that can positively impact supply chain resilience.

While generative AI has clear technology benefits, it requires organizational conditions, especially leadership support, to be successful. Leaders are essential to drive digital change, enabling access to new resources, a culture of innovation and the development of new technologies. Existing research indicates that managerial support is a crucial element in the success of technological projects and is influential in their impact on the organization's performance (Sivathanu et al., 2025; Tsai et al., 2025). As for generative AI, the role of leadership support can reinforce the link between adopting generative AI and operational results, such as better implementation and integration into processes. Thus, the following hypothesis is advanced:

H4. Leadership support positively moderates the relationship between generative artificial intelligence and operational efficiency, strengthening its impact.

4. Methodology

Research Design and Analytical Strategy

The positivist quantitative research design was used for testing the proposed theoretical model. Because the relationship between generative AI capabilities and lean manufacturing maturity, leadership support, operational efficiency and supply chain resilience could be studied without changing operational conditions in the firms, a cross-sectional, non-experimental survey method was chosen. The questionnaire was designed based on the technology adoption, lean manufacturing, operational performance and supply chain resilience scales developed from validated questionnaires. Items were modified based on earlier research and instruments for AI and digital manufacturing, lean maturity, and supply chain resilience. Examples range from using generative AI for predictive decision making, through to consistently applying lean routines to eliminate waste, to our supply chain reacting quickly when disruptions occur. The items for all constructs were rated on a 5-point Likert scale ranging from 1 = strongly disagree to 5 = strongly agree. The instrument was adapted from three academic and industry experts and was then pilot tested with 20 manufacturing managers. Minor changes in wording were made prior to reliability/regression analysis.

Sampling Procedure and Data Collection

The target population included manufacturing companies serving in selected industrial markets from the Middle East region, identified based on manufacturing directories, chamber of commerce registers and databases of industry associations. The sampling frame was stratified to provide representation in the manufacturing sector, firm size, technological maturity and international activity to ensure representation by different manufacturing contexts. The automotive, food processing, construction-related manufacturing, electronics and machinery, and other manufacturing industries were the main sector strata. The number of cases in each stratum was allocated proportionately, which means that each stratum was given cases based on its proportion in the sampling frame. Between 650 and 680 companies were targeted by e-mail digital questionnaires for senior managers, operations managers, supply chain managers, quality managers and executives, between January and March 2026. There was a total of 382 responses. Of the 348 questionnaires that were collected, 348 were usable and had a usable response rate of 53.5% after discarding incomplete questionnaires and straight line responses. This process enhanced the transparency of samples and minimized selection bias and the credibility and replicability of the final data set.

Data Analysis

The data analysis was conducted in several stages to test the proposed hypotheses (H1–H4). Pearson correlation analysis was performed to examine the initial relationships among key variables, including generative AI, lean practices, operational efficiency, and supply chain resilience. The multiple linear regression analysis was employed to test the direct effects proposed in the model. The technique enables the estimation of the contribution of each independent variable to operational efficiency, holding other factors of potential confounding constant. For the strength of the results, data diagnostics were carried out to cope with the problem of possible multicollinearity that usually arises in studies that deal with technological constructs that are closely related, such as big data and IoT. The model reduces multicollinearity, which makes the estimate of the individual effects of each variable more reliable. The interaction effects were entered into the regression model to check the moderating effect of leadership support between operational efficiency and generative AI (H4). This step allows a measurement of the effect organizational factors have on the effectiveness of the technological adoption in order to improve operational outcomes.

5. Results

The results share the empirical data from a sample of 348 manufacturing companies and explore the interrelationships between generative AI capabilities, lean manufacturing maturity, leadership support, operational efficiency and supply chain resilience. The research method used is quantitative, and the analysis includes descriptive statistics, reliability test, Pearson correlation and assessment of a regression model. These results serve as the statistical foundation for the assessment of the hypotheses and the conceptual model in general.

Table 2. Profile of participating manufacturing firms

Firm characteristic	Category	Frequency	Percentage
Manufacturing sector	Automotive	98	28.2
	Food processing	86	24.7
	Construction-related manufacturing	74	21.3
	Electronics and machinery	51	14.7
	Other manufacturing	39	11.2
Firm size	Small firms	61	17.5
	Medium firms	134	38.5
	Large firms	153	44.0
Technological maturity	Low	69	19.8
	Moderate	121	34.8
	High	158	45.4
International activity	Domestic only	137	39.4
	Regional operations	86	24.7
	International operations	125	35.9
Respondent position	Operations or supply chain manager	128	36.8
	Senior manager	109	31.3
	Executive or director	68	19.5
	Quality or improvement manager	43	12.4
Total		348	100.0

Most of the respondents were automotive firms (28.2%), food processing (24.7%) and construction-related manufacturing (21.3%) as indicated in Table 2. It is appropriate because these areas tend to be more complicated to operate, and where supply chains can be disrupted. The largest size group is of large firms (44.0%), and a high proportion of firms (45.4%) said their technological maturity is high. The importance of studying the adoption of generative AI is also reinforced. The majority (36.8%) of the respondents were operations or supply chain managers. The number of variables included was limited and were used solely to describe the sample profile; they were not used as control variables as the hypotheses were targeted towards theoretical relationships between generative AI capabilities, lean manufacturing maturity, leadership support, operational efficiency and supply chain resilience.

Table 3. Descriptive statistics for the main study variables

Construct	N	Mean	Standard deviation
Generative AI capabilities	348	3.82	0.68
Lean manufacturing maturity	348	3.91	0.62
Leadership support	348	3.76	0.71
Operational efficiency	348	3.88	0.64

Supply chain resilience	348	3.74	0.66

The mean scores for each of the major constructs are greater than the scale's midpoint, as shown in Table 3. The participating firms were relatively well into lean practices, with a mean score of 3.91 for lean manufacturing maturity. The mean score of operational efficiency was also good (3.88), which is an indication that companies believed their procedures were fairly efficient. The average of the AI capabilities of Generative AI was 3.82, which was rated as a moderate to high level of AI adoption. The mean of supply chain resilience was the lowest, with 3.74, which showed that supply chain resilience is relatively low. Firms' overall efficiency is stronger than their resilience.

Table 4. Reliability analysis of constructs

Construct	Number of items	Cronbach's alpha
Generative AI capabilities	5	0.889
Lean manufacturing maturity	5	0.876
Leadership support	4	0.861
Operational efficiency	5	0.902
Supply chain resilience	5	0.884

The results of the internal consistency of all the measurement scales indicated good internal consistency, as can be seen in Table 4. Cronbach's alpha reliability ranged from 0.861 to 0.902 for the various items from leadership support to operational efficiency. The values of all constructs are higher than the recommended value of 0.70, which shows that the constructs are reliable to use in statistical analysis. The highest alpha value was found to be those items used to measure the construct operational efficiency, which means that the items are most consistent in measuring the construct. The generalisation of their use of Generative AI capabilities, lean manufacturing and supply chain risk resilience was also very high. The findings in this regard make the questionnaire more credible and the usage of the measuring tool for measuring the proposed conceptual model more valid.

Table 5. Pearson correlation matrix

Variable	1	2	3	4	5
1. Generative AI capabilities	1.000				
2. Lean manufacturing maturity	0.536**	1.000			
3. Leadership support	0.548**	0.491**	1.000		
4. Operational efficiency	0.681**	0.624**	0.592**	1.000	
5. Supply chain resilience	0.603**	0.557**	0.524**	0.688**	1.000

Note: $p < 0.01$.

Table 5 shows that all the study variables were significantly and positively correlated with each other at $p<0.01$. The operational efficiency was strongly correlated with Generative AI capabilities ($r = 0.681$), indicating that those with higher AI capabilities have higher operational efficiency. In addition, operational efficiency was also highly correlated with the level of maturity of lean manufacturing, with $r = 0.624$. The relationship between operational efficiency and supply chain resilience was the highest ($r = 0.688$), indicating that the more efficient a company is, the more likely they are to be resilient. The correlations are high yet not too high, which means that the constructs are correlated; however, not so related that they cannot be evaluated via regression.

Table 6. Model fit summary

Model	R	R^2	Adjusted R^2	F-value	p-value
Model 1	0.789	0.623	0.620	284.72	< 0.001

The direct effects regression model with operational efficiency as the dependent variable is shown in Table 6. The predictands for testing H1 and H2 were generative AI capabilities and lean manufacturing maturity. Table 2 reports demographic and firm characteristics, which were not included as controls, as they were included only to describe the demographics and composition of the sample. The model accounted for 62.3% of the variance in operational efficiency; it had an adjusted R^2 of 0.620 and a standard error of estimate of 0.394. This model proved to be statistically significant, $F = 284.72$, $p < 0.001$, which suggests a good level of explanatory power for operational efficiency, provided by the predictors as a group. This facilitates the direct effects of generative AI capabilities and lean manufacturing maturity to be tested using the model.

Table 7. Regression coefficients

Predictor/term	Standardised coefficient (β)	SE (β)	t-value	p-value
Generative AI capabilities	0.643	0.072	8.914	< 0.001
Lean manufacturing maturity	0.512	0.071	7.235	< 0.001
Operational efficiency	0.588	0.073	8.102	< 0.001
Generative AI capabilities × leadership support	0.274	0.079	3.456	0.012

Dependent variable: Operational efficiency

Table 7 shows that the generative AI capabilities are significantly positively associated with operational efficiency for H1 ($\beta = 0.643$, $t = 8.914$, $p < 0.001$). This indicates that companies with a higher level of generative AI capabilities are more likely to state that their business operations are more efficient. Furthermore, the operational efficiency is also positively influenced by H2 maturity, with a significant positive value ($\beta = 0.512$, $t = 7.235$, $p < 0.001$). This is a testament to the continued importance of mature lean practices, both for the improvement of process performance and waste reduction. The operational efficiency has a significant positive effect on supply chain resilience for H3, $\beta = 0.588$, $t = 8.102$, $p < 0.001$. This means that efficient companies have a better chance of responding to the disruption and continuing to operate. Leadership support is also important for H4: $\beta = 0.274$, $p = 0.012$, suggesting that the generative AI capabilities enhance the relationship between AI efficiency and leadership support.

6. Discussion

The results are highly empirical evidence to support the argument of enhanced operational efficiency of manufacturing supply chains with generative AI abilities. For the regression result for H1, we found that there is a significant positive relationship between the operational efficiency of companies and their generative AI capabilities, indicating that having the ability to predict, automate, and make data-informed decisions with the aid of AI can help combat delays, process variations, and operational waste. This discovery aligns with Ali et al. (2024), who stated that AI process control boosts production performance by detecting trends in operational information and enabling quicker corrective actions. It also aligns with Mora et al. (2025), who determined that AI value stream mapping could achieve the hard-to-detect inefficiencies in lean tools. Therefore, the present study aligns with the previous studies by saying that AI transforms manufacturing from being reactive to predictive, an operational improvement.

This agrees with the findings of Saadouli et al. (2025), who noted that AI technologies can help enhance lean systems through evidence-based and adaptive process improvement. This paper, however, takes this argument a step further and demonstrates that generative AI is not just a generic digital technology but can be seen as a statistically significant indicator of operational efficiency across a sample of 348 manufacturing companies. This is in contrast to research on AI that focuses primarily on an abstract or technological rather than operational impact. While Hanandeh et al. (2025) predominantly emphasized the accuracy of AI and the time required to obtain inferences in the context of big data, the current study explicitly draws a link between the use of generative AI and measurable operational outcomes. This makes the discovery more sensible as it connects the usage of AI with efficiency, instead of simply capability.

The second key discovery is that there is a positive relationship between the maturity of lean manufacturing and operational efficiency. The results are aligned with the study conducted by Lakhouil and Soulhi (2025), which highlighted the advantages of combining lean manufacturing with Industry 4.0 technologies, in terms of process visibility, process coordination, and waste reduction. It also backs up Ar (2025), who identified that lean management still plays a role in resilience as it enables a disciplined approach to the control of the process. This is relevant since lean continues to be an important principle in digitally advanced manufacturing systems. Rather, the operational basis is lean, which is where the value can be created with digital tools. As a result, the study confirms the prior studies, acknowledging that lean maturity remains beneficial to efficiency even with the use of AI and other digital technologies in the business.

This discovery is not in line with the more technology-oriented views of Quality 4.0, however, which suggest that high-tech digital devices have the ability to revolutionize operations by themselves. Based on the current findings, the best configuration is that of an AI capability in tandem with lean maturity. This is more in line with Tsai et al. (2025), who suggested that there is a need for synergy between digital technology and lean processes when implementing AI-based big data analytics for lean manufacturing. It also forces those who think that lean discipline can be replaced by technology to think again. While the evidence indicates the potential of generative AI to improve prediction and decision making, lean thinking is still required for standardization, elimination of waste and continuous improvement (Alghizzawi et al., 2024; Bataineh et al., 2025). Therefore, digital transformation should be seen as a "plus" on lean thinking, not a replacement.

The third result is that the more efficient the operation, the more resilient the supply chain. This resonates with Dhirar & Hamad (2025), who stressed the need to ensure production and logistics continue without interruption, even during disruptions, as an essential element of resilient supply chains. Atieh's (2025) findings indicate that the AI-powered supply chain system can increase the resilience of the system by reducing its vulnerability and being more responsive in the event of operational shocks. The operational efficiency was found to be strongly related to supply chain resilience in this study, indicating that efficient firms have a high tendency to react fast to disruptions. The discovery echoes not only the importance of managing resilience in a crisis, but also that it can be achieved as a result of a disciplined day-to-day approach to the business.

Meanwhile, the discovery provides a new explanation for previous resilience research. Other research works, for instance by Reaidy et al. (2026), gave a high priority to digital maturity and supply chain performance, and Claran Santhiyagu et al. (2025) concentrated on digitalization of logistics post-disruption. Unlike the current study, however, it demonstrates that the efficiency of operations serves as a viable link between internal capabilities to improve and resilience results. Specifically, companies do not just get resilient simply by using digital systems. They take on resilience when the systems work more efficiently and effectively, waste less, make quicker decisions and sustain processes (Jebril et al., 2024; Masa'deh et al., 2025). It is crucial to distinguish, since it leads to exaggeration of the contribution of technology to resilience, being communicated as an automatic given.

The fourth finding confirms that with high leadership support, the relationship between operational efficiency and generative AI capabilities is significantly moderated. This finding aligns with Sivathanu et al. (2025), who highlighted that the support of management is crucial to the successful use of generative AI in manufacturing. Moreover, it is in line with what Tsai et al. (2025) found in their study, which demonstrated that leadership commitment helps to connect AI-based analytics with lean manufacturing goals. This study has shown how AI can be more beneficial for the operational aspects with the support of leadership in terms of resources, direction and implementation. This is important because it shows that being ready to adopt AI technology is not a luxury; it is a precondition for it to lead to tangible improvements in performance.

This discovery also contrasts with those that focus primarily on the digital adoption as a technical problem. Various studies on AI, big data, and autonomous quality systems emphasize analytical ability, automation, or prediction accuracy (Alqsass et al., 2024). The results differ in the present study, however, in that the extent to which these tools are utilized to achieve operational performance is related to leadership support. This echoes what Nasir et al. (2025) noted – that the core of Industry 5.0 is not just about the technical aspects of automation, but about the human element as well. It also backs Fatorachian (2025), who says that digital transformation has to be sustainable and considers organizational and human aspects. As a result, the study has contributed by demonstrating that leadership is a prerequisite for being efficient with the help of an AI tool.

The findings are in line with the Quality 4.0 perspective, which states that manufacturing improvement requires digital technology to be combined with the lean process discipline and the ability of the organization. These findings align with Nasereddin (2024), who noted that the supply chain system could be better with the use of digital technology, which can improve the visibility and decision-making process, as well as with Mohammad et al. (2024), who discussed the importance of predictive analytics in the optimization process of the supply chain. The study, however, adds to those focused narrowly on digital transformation by demonstrating that the study of AI, lean maturity, operational efficiency, resiliency and leadership must be studied together. The empirical and practical contribution is thus that resiliency can be achieved by having manufacturing companies use generative AI, but also by integrating generative AI into the lean systems and leadership-supported implementation.

Practical Implications

As for managers, the results reveal that the adoption of digital technologies should go hand in hand with changes in the organisation. This is not enough; companies need to build predictive insights and have a solid technological infrastructure (Alzyoud et al., 2024; Nasereddin, 2024). Furthermore, leadership support and organizational trust are important factors that contribute to the successful implementation of generative AI (Tsai et al., 2025; Rejeb et al., 2025). These technologies need to be integrated together, and cross-functional collaboration must be encouraged to fully utilize information across the supply chain and remove the need for information silos (Al Harith et al., 2024). Furthermore, the move towards Industry 5.0 places a significant emphasis on integrating technology with human factors, such as investing in human-centric approaches and ensuring that digital transformation not only improves operational efficiency but also positively impacts human resource development (Nasir et al., 2025).

Limitations and Future Research

Due to the cross-sectional design, it is not possible to determine causal relationships from the results. Self-reported questionnaire information may also result in response bias and common method bias, as it is the same people who rated the independent and dependent variables. No objective measure of perceived operational efficiency and supply chain resilience was included, such as defect rates, lead time, delivery reliability or recovery time. Using one respondent per firm may not be representative of the practices of the organisation. The geographical scope should also be more precisely defined, thus reducing the generalizability. Future study findings should be enhanced with the use of a longitudinal design, multiple respondent data, and objective measures of performance and clearer regional comparisons.

7. Conclusion

The purpose of this research was to determine the relation between the machine learning abilities of generative AI and lean manufacturing maturity level, and their impact on operational efficiency and supply chain resiliency in manufacturing companies. The results showed that using generative AI and lean practices has a significant impact on enhancing operational efficiency. That is, predictive digital tools and process improvement structured practices are complementary to each other as they relate to tackling inefficiency and increasing operational control. The study also identified operational efficiency as a key enabler of a more resilient supply chain, demonstrating that operational resiliency firms do not only need to be responsive on the outside but also need to be efficient on the inside, as well. It was also identified that leadership support had a positive impact on the relationship between generative AI and operational efficiency, further highlighting that leadership commitment is crucial for successful digital adoption. The study concludes that generative AI is not a standalone technology, and it should be used in conjunction with other technologies. It must be an element of lean maturity, leadership support and strategic process improvement. This inclusive solution provides a greater footing towards effective and resilient manufacturing supply chains.

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