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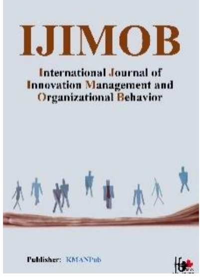

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Investigating the Effect of Artificial Intelligence Capabilities on Operational Performance with the Mediating Role of Production System Resilience and the Moderating Role of Human–Organization–Technology Fit in the Abadan Oil Industry

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ABSTRACT

Objective: The present study investigated the effect of artificial intelligence capabilities on operational performance, with the mediating role of production system resilience and the moderating role of human–organization–technology fit in the Abadan oil industry.

Methods and Materials: In terms of purpose, this study was applied and quantitative, and in terms of nature, it was descriptive-survey and correlational. The statistical population included 420 managers and experts working in the Abadan oil industry. Based on Cochran's formula, the sample size was calculated as 201. The questionnaires were distributed randomly among the participants, and 200 completed questionnaires were returned. To examine the research questions, structural equation modeling (SEM) was used through the structural equation modeling approach with the assistance of SmartPLS 3 software.

Findings: The findings showed that the path coefficient between artificial intelligence capability and production system resilience was 0.794, with a t-statistic of 9.053. The path coefficient between production system resilience and operational performance was 0.880, with a t-statistic of 10.574. The path coefficient for the moderating role of human–organization–technology fit was 0.602, with a t-statistic of 8.029. This means that fit positively moderates the effect of artificial intelligence capability on production system resilience. Therefore, artificial intelligence capability positively improves operational performance through production system resilience.

Conclusion: The findings indicate that artificial intelligence capabilities indirectly improve the refinery's operational performance by strengthening production system resilience. Moreover, human–organization–technology fit plays a positive moderating role in the relationship between artificial intelligence and resilience. These results emphasize the necessity of simultaneous attention to technological infrastructure, personnel training, and the preparation of organizational structures in order to achieve sustainable and resilient operations in the Abadan oil industry.

Keywords: *Artificial intelligence capabilities, operational performance, production system resilience, human–organization–technology fit*

1 Introduction

Artificial intelligence has become one of the most influential technological forces reshaping contemporary operations management, particularly in industries characterized by asset intensity, process complexity, environmental uncertainty, and high reliability requirements. The increasing volatility of global markets, disruptions generated by pandemics and geopolitical tensions, and the reconfiguration of supply chains have intensified the need for intelligent, adaptive, and resilient production systems. Recent studies on supply chain transformation after the COVID-19 crisis show that firms can no longer rely solely on conventional efficiency-centered operating models, because crisis conditions require flexibility, visibility, rapid decision-making, and the capacity to reconfigure resources under uncertainty (Min, 2023; Qrunfleh et al., 2023). At the macro level, economic rivalry and reshoring tendencies have further highlighted the strategic importance of technological autonomy, digital intelligence, and operational resilience in industrial sectors that are deeply embedded in national economic security (Gur & Dilek, 2023). In this context, digital and AI-enabled capabilities are no longer peripheral tools but core organizational resources that can influence operational performance by enhancing sensing, prediction, coordination, and response capabilities across production systems (Venkatesh et al., 2023).

The oil and gas industry represents a particularly relevant context for examining the operational value of artificial intelligence capabilities. This industry is marked by complex production processes, high capital intensity, hazardous operating environments, strict safety requirements, fluctuating demand, and exposure to technological, environmental, and geopolitical risks. Studies in the oil and gas sector have emphasized that AI can support performance improvement through predictive maintenance, process optimization, risk assessment, equipment monitoring, production planning, and decision-support systems; however, these benefits depend on the organizational ability to integrate AI into existing operational routines and managerial processes (AlAbdouli & Al-Shihabi, 2025). In the upstream oil sector, readiness for AI adoption is shaped by infrastructure, data quality, managerial support, workforce capabilities, and strategic alignment, suggesting that technological adoption cannot be separated from organizational preparedness (Toghraei et al., 2024). Evidence from the Norwegian petroleum industry also shows that digitalization changes work organization, managerial control, and coordination patterns, meaning that advanced technologies influence not only technical operations but also the social and organizational architecture of production (Melberg & Gressgård, 2023).

Artificial intelligence capability refers to an organization's ability to acquire, deploy, integrate, and leverage AI-related resources for value creation. This capability is multidimensional and includes data resources, technological infrastructure, human expertise, managerial skills, and organizational routines that allow AI tools to be used effectively in decision-making and operational processes. Research on AI capabilities in organizations indicates that AI contributes to performance not merely through automation but through the creation of analytical, predictive, and adaptive capacities that support better decisions and more effective service or production outcomes (Mikalef et al., 2023). In production systems, AI can be linked to sustainable business model innovation by improving resource utilization, enabling intelligent process redesign, and facilitating more responsive production configurations (Wang & Zhang, 2025). Similarly, AI capacities have been positioned as dynamic capabilities that support business model innovation, digital servitization, and circular value creation, especially when firms are able to transform technological potential into strategic and operational renewal (Sjodin et al., 2023). However, the governance of AI is also essential, because responsible AI use requires accountability, transparency, risk management, and organizational mechanisms that ensure alignment between technological innovation and broader strategic objectives (Papagiannidis et al., 2025).

The relationship between AI capability and operational performance is not automatic. Organizations may invest in AI technologies yet fail to realize meaningful performance gains if their data infrastructure is fragmented, employees do not trust AI outputs, managerial processes remain rigid, or technology is misaligned with operational tasks. Empirical evidence on AI adoption in European small and medium-sized enterprises suggests that digital capabilities, innovation orientation, and the external environment jointly influence AI adoption and its organizational outcomes (Arroyabe et al., 2024). In Iranian industrial contexts, studies on digital transformation components have shown that technological development must be evaluated in relation to organizational priorities, implementation readiness, and performance importance, rather than treated as an isolated technical investment (Bakhtiari et al., 2025). In the petrochemical industry, the alignment between digital capabilities and innovation strategy has been identified as a key issue, indicating that digital resources generate value when they are strategically coordinated with innovation goals and sector-specific requirements (Ghazi-Nouri et al., 2024). At the same time, research on Industry 4.0 technologies has emphasized that sustainable operations face challenges related to costs, skills, infrastructure, organizational resistance, and integration complexity (Dabbagh et al., 2025).

Operational performance in the oil industry includes efficiency, productivity, quality, reliability, responsiveness, cost control, safety-related continuity, and the ability to maintain stable outputs under changing conditions. AI can improve these dimensions through real-time monitoring, predictive analytics, intelligent control systems, anomaly detection, and enhanced coordination across departments. Research on AI-driven innovation and supply chain performance has shown that AI can strengthen organizational performance when it enhances resilience and enables firms to operate effectively under dynamic conditions (Belhadi et al., 2024). In emerging markets, AI-based supply chain resilience has also been linked to firm performance, suggesting that AI improves outcomes when it supports the capacity to absorb, respond to, and recover from disruptions (Mukherjee et al., 2024). In the oil and gas sector, AI and knowledge management have been found to support interactive green innovation in traditional industries, showing that AI capabilities may also contribute to sustainability-oriented operational transformation (Abdulmuhsin et al., 2026). Beyond industrial production, studies of AI-powered digital platforms show that algorithmic recommendation and intelligent decision systems can influence competitive outcomes, which further demonstrates the broad performance relevance of AI-enabled analytical capability (Zhou et al., 2023).

Despite the direct performance potential of AI, one of the most important mechanisms through which AI capability may affect operational performance is production system resilience. Production system resilience refers to the capacity of a production system to anticipate disruptions, absorb shocks, adapt to changing conditions, recover from disturbances, and continue functioning effectively. In complex industrial settings, resilience is not simply the ability to return to a previous state; rather, it includes cognitive, behavioral, and contextual capacities that enable organizations to interpret signals, coordinate responses, improvise solutions, and redesign routines. Studies on resilient supply management systems during crisis conditions show that resilience depends on visibility, flexibility, collaboration, and the ability to adjust supply and production arrangements under pressure (Vega et al., 2023). Similarly, research on digital technologies in manufacturing during the COVID-19 pandemic shows that digital tools can enhance supply chain resilience by improving information processing, coordination, and response speed (Ning et al., 2023). Therefore, AI capability may improve operational performance because it strengthens the resilience mechanisms that allow production systems to remain stable and adaptive in uncertain environments.

The mediating role of resilience is particularly important in industrial sectors where disruptions are frequent and consequences are costly. AI can support resilience by improving early warning systems, identifying weak signals, enabling predictive maintenance, optimizing resource allocation, and supporting rapid scenario analysis. Research on artificial intelligence and information system resilience indicates that AI can help organizations cope with supply chain disruption by strengthening information processing and response mechanisms (Gupta et al., 2024). Intelligent digital twins have also been proposed as tools for stress-testing, resilience, and viability because they enable organizations to simulate disruption scenarios and evaluate system behavior before failures occur (Ivanov, 2023). In addition, systematic research on AI and prescriptive analytics for supply chain resilience shows that AI can move organizations beyond descriptive monitoring toward recommended actions that improve preparedness and adaptive response (Smyth et al., 2024). Explainable AI has also been associated with agile decision-making and cyber resilience, suggesting that AI-enabled resilience requires not only algorithmic sophistication but also interpretability and managerial usability (Sadeghi et al., 2024).

Production system resilience can be understood through cognitive, behavioral, and contextual dimensions. Cognitive resilience involves the ability to perceive risks, interpret data, learn from events, and understand changing operational conditions. Behavioral resilience refers to the capacity to act flexibly, improvise, coordinate, and implement adaptive responses. Contextual resilience reflects the broader organizational and environmental conditions that support resilient action, including culture, resources, communication patterns, and managerial support. Research on transactive memory systems and entrepreneurial team performance suggests that team knowledge structures and the ability to improvise can influence performance under competitive conditions, which is relevant to understanding the human and collective dimensions of resilience (Hu et al., 2023). In oil and gas production systems, resilience is also linked to safety and hazard management. The assessment of chemical industrial areas under Natech-related cascading multi-hazards demonstrates that industrial resilience requires integrated attention to technological, environmental, and systemic risk factors (Zeng et al., 2023). Accordingly, AI capability may contribute to operational performance when it enhances the cognitive recognition of risks, the behavioral capacity to respond, and the contextual readiness of the production system.

However, the effect of AI capability on resilience may depend on the degree of fit among humans, the organization, and technology. Human–organization–technology fit reflects the alignment between technological tools, user capabilities, organizational processes, and task requirements. When this fit is high, employees are more likely to understand AI outputs, trust intelligent systems, integrate AI recommendations into decisions, and adapt work routines accordingly. When fit is low, AI systems may create resistance, confusion, fragmented workflows, or underutilized technological capacity. Research on employees' cognitive trust in AI emphasizes that trust development is a critical condition for effective AI use, because employees must perceive AI systems as understandable, reliable, and relevant to their work (Rostamzadeh Ganji & Jayeravandi, 2025). This is consistent with broader AI governance arguments that responsible and effective AI implementation requires social, managerial, and technical alignment rather than technology-centered deployment alone (Papagiannidis et al., 2025). Therefore, human–organization–technology fit can be expected to strengthen the positive effect of AI capability on production system resilience.

The moderating role of fit is especially meaningful in the oil industry because AI implementation often requires changes in routines, decision rights, technical skills, interdepartmental coordination, and managerial interpretation of data-driven outputs. If AI tools are compatible with operational tasks and employees have the necessary competencies to use them, AI capability is more likely to generate resilient production behaviors. If organizational structures support data sharing, learning, and cross-functional coordination, AI-enabled insights can be translated into timely operational responses. Conversely, even advanced AI systems may fail to improve resilience if they are disconnected from users' needs, misaligned with work processes, or unsupported by organizational culture. Evidence from digitalization in petroleum operations indicates that technological transformation changes work organization and management practices, confirming that human and organizational factors are central to the operational consequences of digital technologies (Melberg & Gressgård, 2023). Likewise, challenges of Industry 4.0 implementation show that sustainable operations require attention to skills, acceptance, organizational readiness, and technology integration (Dabbagh et al., 2025). Thus, the performance value of AI depends on a sociotechnical configuration in which people, structures, tasks, and technological systems are mutually aligned.

The Abadan oil industry provides an important context for examining these relationships because oil refining and related industrial activities require continuous operations, reliable production systems, high safety standards, and coordinated responses to operational disturbances. In such a context, AI capabilities may offer substantial opportunities for improving operational performance, but these opportunities are likely to be realized through the strengthening of production system resilience and under conditions of adequate human–organization–technology fit. Existing research has separately examined AI adoption, digital transformation, supply chain resilience, Industry 4.0 challenges, and oil-sector AI readiness; however, fewer studies have integrated these elements into a single explanatory model that connects AI capabilities to operational performance through production system resilience while also considering the moderating role of sociotechnical fit (AlAbdouli & Al-Shihabi, 2025; Belhadi et al., 2024; Ghazi-Nouri et al., 2024; Mukherjee et al., 2024; Toghraei et al., 2024). Addressing this gap is important because it can clarify whether AI capability functions as a direct technological resource, an indirect resilience-building mechanism, or a capability whose effectiveness depends on the alignment of human, organizational, and technological elements.

The aim of this study is to investigate the effect of artificial intelligence capabilities on operational performance with the mediating role of production system resilience and the moderating role of human–organization–technology fit in the Abadan oil industry.

2 Methods and Materials

In terms of purpose, this research was applied and quantitative, and in terms of nature, it was descriptive-survey and correlational. In terms of the method of data collection and analysis, the study was considered a correlational study based on structural equation modeling. The statistical population of this study included managers and experts in the Abadan oil industry, including individuals holding positions such as manager, deputy manager, supervisor, officer-in-charge, expert, and senior expert, with a total population of 420 individuals. The sample size was calculated as 201 based on Cochran's formula. The questionnaires were randomly distributed among the individuals, and 200 questionnaires were completed. After the questionnaires were collected, they were subjected to statistical analysis. To examine the research questions, structural equation modeling (SEM) was used with the assistance of SmartPLS 3 software.

To collect the data, a questionnaire was used. To examine artificial intelligence capability, the 46-item scale developed by Mikalef and Gupta (2021) was employed across eight dimensions, including data, technology, and basic resources. Organizational performance was assessed through leading and lagging indicators: operational performance was measured using four items, and financial performance using three items. Based on the underlying logic, production system resilience was measured in three dimensions: cognitive resilience with two items, behavioral resilience with four items, and contextual resilience with four items. Fit was measured through data–tool fit, human–tool fit, and task–tool fit, each with three items. Given the multidimensional nature of the constructs in the model, partial least squares structural equation modeling (PLS-SEM) was used to test the hierarchical model.

To determine the validity of the questionnaires, the content validity ratio (CVR) and content validity index (CVI) were used. Finally, Cronbach's alpha coefficient was used to determine the reliability of the questionnaires.

Table 1

Reliability of the Research Constructs

Construct	Number of Items	Cronbach's Alpha	Composite Reliability (CR)	AVE > 0.5
Artificial intelligence capabilities	45 items	0.957	0.958	0.660
Production system resilience	10 items	0.788	0.789	0.604
Human–organization–technology fit	9 items	0.738	0.739	0.587
Operational performance of the oil industry	7 items	0.754	0.755	0.551
Reliability of all items	71 items in total	0.932	—	—

As shown in Table 1, the coefficients are higher than the minimum value of 0.60, indicating appropriate reliability of the indicators. In addition, the average variance extracted for the variables of this study ranged from 0.551 to 0.660, which is higher than the minimum value of 0.50, indicating appropriate convergent validity of the constructs.

3 Findings and Results

The Kolmogorov–Smirnov test was used to determine whether the data were normally or non-normally distributed.

Table 2

Results of the Kolmogorov–Smirnov Test for Examining the Assumption of Normality or Non-Normality

Variables	Sample Size	Test Statistic	p-value	Result
Artificial intelligence capabilities	200	0.156	0.000	Non-normal
Production system resilience	200	0.119	0.000	Non-normal
Human–organization–technology fit	200	0.113	0.000	Non-normal
Operational performance of the oil industry	200	0.110	0.000	Non-normal

The significance level was lower than 0.05; therefore, the distribution of the data was non-normal. Accordingly, SmartPLS 3 software was used.

Table 3

Fornell–Larcker Criterion

Variable	1	2	3	4
Artificial intelligence capabilities	0.908			
Production system resilience	0.899	0.901		
Human–organization–technology fit	0.892	0.890	0.888	
Operational performance of the oil industry	0.891	0.887	0.876	0.872

The square root of the average variance extracted (AVE) is presented on the diagonal elements, and the correlations among the constructs are shown below them. The square root of AVE for all reflective constructs was greater than the correlation of each construct with the other latent variables in the path model. Overall, the Fornell–Larcker criterion provides evidence for the discriminant validity of the constructs. Figures 1 and 2 were then drawn. Before presenting the research model, it was necessary to ensure the adequacy of the subcomponents related to the research variables. Therefore, confirmatory factor analysis was used at this stage.

Figure 1

Standardized Values of the Research Items

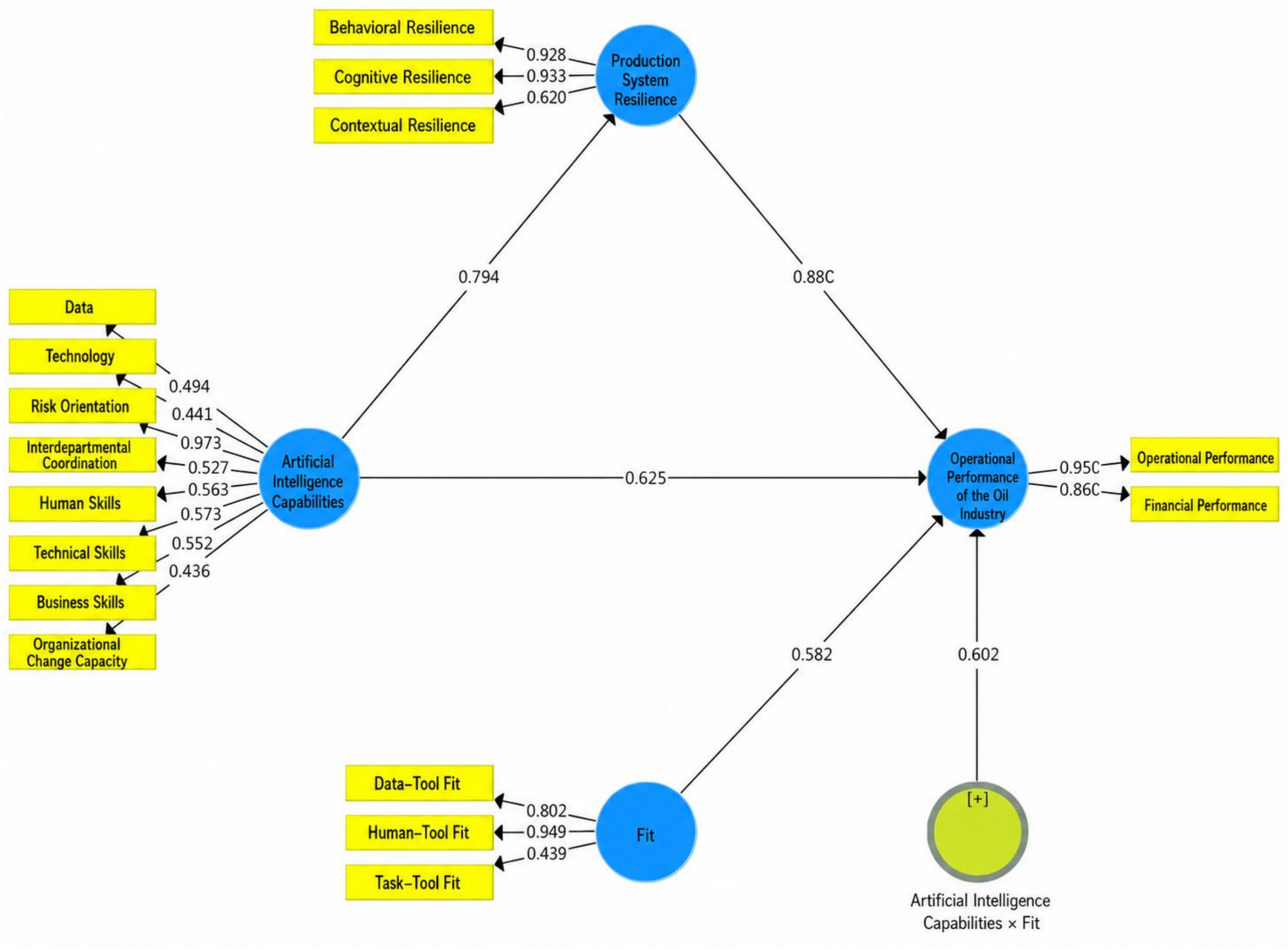
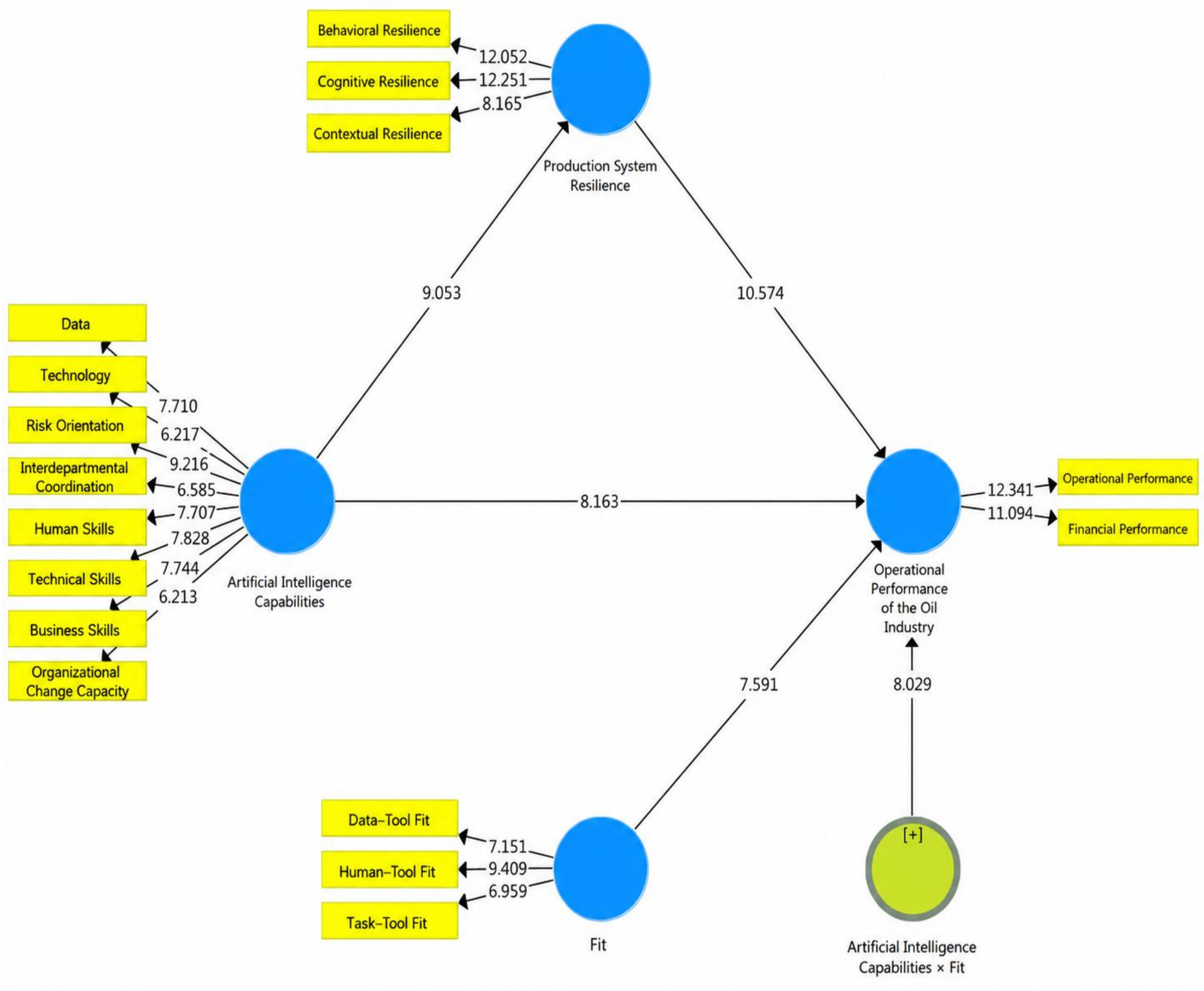


Figure 2

Significance Values of the Research Items



Items with factor loadings lower than 0.30 do not have sufficient adequacy to remain in the model and should be removed. As observed in the model, all values are above 0.30; therefore, no item was removed. If the t-value falls between +1.96 and −1.96, the relationships between the variables are not significant at the 95% confidence level. If the t-value is greater than +1.96 or lower than −1.96, the relationships between the variables are significant at the 95% confidence level. Therefore, if the t-statistic exceeds 1.96, it indicates the validity of the relationship between the constructs and, consequently, the confirmation of the research hypotheses at the 95% confidence level. Based on this criterion, all relationships in the model were significant. Since the mediating role of variables was also examined in this study, it should be noted that, when examining relationships among variables in the presence of a mediating variable, both direct and indirect effects must be assessed. If the indirect effect is greater than the direct effect, the mediating role of the mediator is accepted. If the significance value obtained through this method is greater than the absolute value of 1.96, the null hypothesis is rejected and the alternative hypothesis is confirmed. A summary of the results is presented in Table 4.

Table 4

Results of the Sobel Test

Hypothesis	Unstandardized Estimate of the First Path	Standardized Estimate of the Second Path	Standard Error of the First Path	Standard Error of the Second Path	Z	Result
The effect of artificial intelligence capability on operational performance through production system resilience	0.65	0.64	0.065	0.064	6.02	Confirmed

To determine the indirect paths, namely the effect of artificial intelligence capability on operational performance through production system resilience, the bootstrapping method was used through the Preacher and Hayes (2008) macro in SPSS 23 software.

Table 5 presents the bootstrapping results for the indirect paths of the model. According to the table, the upper and lower limits of the confidence interval for the mediating role of production system resilience in the relationship between artificial intelligence capability and operational performance did not include zero. The confidence level of this interval was 95%, and the number of bootstrap resamples was 1,000. Since zero was outside this interval, the indirect relationship among the variables was significant.

Table 5

Bootstrapping Results for the Indirect Paths

Path	Data	Boot	Bias	Standard Error	Lower Limit	Upper Limit
Artificial intelligence capability on operational performance through production system resilience	0.2014	0.2016	0.0002	0.04144	0.1897	0.3102

The coefficient of determination, R^2, indicates the extent to which an exogenous variable affects an endogenous variable. The R^2 value is calculated only for the dependent, or endogenous, constructs of the model; for exogenous constructs, the value of this criterion is zero. The higher the R^2 value of the endogenous constructs in a model, the better the model fit. Chin (1998) proposed three values of 0.19, 0.33, and 0.67 as criteria for weak, moderate, and strong fit of the structural part of the model based on R^2. The predictive relevance criterion, Q^2, indicates the predictive power of the model. Models with acceptable structural fit should have the ability to predict the indicators related to the endogenous constructs of the model. Henseler et al. (2009) defined three values of 0.02, 0.15, and 0.35 to indicate weak, moderate, and strong predictive power of the related exogenous construct or constructs. It should be noted that this value is calculated only for endogenous constructs in the model whose indicators are reflective.

Table 6

Coefficient of Determination and Predictive Relevance

Dependent Variable	Coefficient of Determination, R^2	Predictive Relevance, Q^2	Strength
Operational performance	0.810	0.324	Strong
Mean	0.810	0.324	Strong

Three values of 0.01, 0.25, and 0.36 have been introduced as weak, moderate, and strong values for this criterion.

GOF = 0.51

The goodness-of-fit index (GOF) was used to assess the overall model fit. The GOF criterion for the overall model fit was calculated as 0.51, indicating a strong model fit.

Table 7

Research Results

Result	t-Value	Path Coefficient	Relationships Between Variables
Confirmed	9.053	0.794	Artificial intelligence capability → production system resilience
Confirmed	10.574	0.880	Production system resilience → operational performance
Confirmed	—	0.794 × 0.880 = 0.698	Artificial intelligence capability → production system resilience → operational performance
Confirmed	8.029	0.602	Moderating role of human–organization–technology fit in the industry

4 Discussion

The findings of the present study showed that artificial intelligence capabilities had a strong, positive, and significant effect on production system resilience in the Abadan oil industry. The path coefficient between artificial intelligence capabilities and production system resilience was 0.794, and the t-value was 9.053, indicating that the development of AI-related resources, including data capacity, technological infrastructure, technical skills, human skills, business skills, risk orientation, interdepartmental coordination, and organizational change capacity, can substantially strengthen the resilience of the production system. This result suggests that AI capabilities improve the ability of industrial systems to identify operational risks, process complex information, detect weak signals, support predictive decision-making, and respond more effectively to disruptions. This finding is consistent with studies emphasizing that AI enables organizations to enhance resilience by improving information processing, prediction, coordination, and adaptive decision-making in uncertain environments (Gupta et al., 2024; Ning et al., 2023; Smyth et al., 2024). It also aligns with evidence from the oil and gas sector showing that AI can support performance and operational continuity when it is integrated into technical and managerial processes (AlAbdouli & Al-Shihabi, 2025; Toghraei et al., 2024).

This finding can be explained by the fact that production system resilience depends not only on physical assets or emergency routines but also on the system's cognitive and analytical capacity. In complex oil-industry operations, the ability to anticipate failures, interpret operational data, evaluate alternative responses, and coordinate decisions across units is central to resilience. AI capabilities provide the analytical foundation for these functions by enabling predictive maintenance, real-time monitoring, anomaly detection, and data-driven planning. The result is also consistent with research on intelligent digital twins, which highlights the role of intelligent simulation and stress testing in strengthening resilience and viability in production and supply systems (Ivanov, 2023). Similarly, studies on resilient supply management systems during crises indicate that resilience is strengthened when organizations are able to improve visibility, flexibility, and response coordination (Vega et al., 2023). Therefore, in the Abadan oil industry, AI capabilities appear to operate as a strategic resource that enhances the cognitive, behavioral, and contextual foundations of production system resilience.

The results also showed that production system resilience had a strong and significant positive effect on operational performance. The path coefficient between production system resilience and operational performance was 0.880, with a t-value of 10.574. This means that higher resilience in the production system is associated with improved operational performance in the oil industry. In practical terms, resilient production systems are better able to maintain continuity, reduce downtime, respond to disturbances, stabilize processes, and sustain productivity under changing conditions. This finding is in line with prior studies indicating that resilience contributes to firm and supply chain performance by improving the ability to absorb shocks, recover from disruptions, and maintain operational effectiveness (Belhadi et al., 2024; Mukherjee et al., 2024). It also supports the argument that post-crisis operational environments require organizations to move from efficiency-only models toward resilience-oriented systems capable of continuity and adaptation (Min, 2023; Qrunfleh et al., 2023).

The strong effect of production system resilience on operational performance is theoretically meaningful because operational performance in the oil industry is highly sensitive to disruptions, process instability, equipment failure, coordination problems, and environmental uncertainty. When a production system is resilient, it can protect output quality, maintain process reliability, reduce delays, and improve decision speed. This is especially important in oil refining and related industrial activities, where even small operational disturbances may have significant financial, safety, and environmental consequences. Previous studies on chemical and industrial systems have similarly emphasized the importance of resilience assessment in environments exposed to cascading hazards and complex technological risks (Zeng et al., 2023). Therefore, the present finding confirms that resilience is not only a defensive capability but also a performance-enhancing mechanism. In other words, resilience enables the organization to transform uncertainty management into operational advantage.

The study further found that artificial intelligence capabilities indirectly improved operational performance through production system resilience. The indirect effect was confirmed through the Sobel test and bootstrapping results. The Sobel test showed a significant mediation effect, with a Z-value of 6.02, and the bootstrapping confidence interval did not include zero. In addition, the indirect path coefficient calculated through production system resilience was 0.698. This finding indicates that AI capabilities improve operational performance largely by strengthening the resilience of the production system. Therefore, the value of AI in the Abadan oil industry should not be understood only as a direct technological effect; rather, AI appears to enhance operational outcomes by improving the system's ability to anticipate, adapt, recover, and sustain performance. This result is consistent with studies showing that AI-based resilience mechanisms can improve organizational and operational performance, particularly in dynamic and disruption-prone environments (Belhadi et al., 2024; Mukherjee et al., 2024; Smyth et al., 2024).

This mediating effect can be explained through the logic of capability transformation. AI capability is an input-level strategic capability, but operational performance is an outcome-level construct. Between these two levels, organizations need mechanisms that convert technological potential into operational value. Production system resilience functions as such a mechanism. AI resources, data infrastructure, technical expertise, and intelligent systems create value when they are used to strengthen the organization's capacity to sense disturbances, interpret operational signals, coordinate responses, and maintain continuity. Studies on AI-enabled organizational performance similarly suggest that AI capabilities foster performance when they are embedded in organizational routines and decision processes (Mikalef et al., 2023). Research on generative AI and sustainable business model innovation also supports the view that AI creates operational value when it contributes to redesigning production systems and improving adaptability (Wang & Zhang, 2025). Accordingly, the present results show that AI capability becomes operationally valuable when it is translated into resilience.

Another important finding was that human–organization–technology fit had a significant positive role in the model. The results showed that fit had a positive effect on operational performance, with a path coefficient of 0.582 and a t-value of 7.591. More importantly, the moderating role of human–organization–technology fit was confirmed, with a path coefficient of 0.602 and a t-value of 8.029. This indicates that the effect of AI capabilities becomes stronger when there is alignment among employees, organizational structures, technological tools, data systems, and operational tasks. In other words, the positive impact of AI capabilities depends on whether personnel have the skills and trust required to use AI, whether the organization supports AI-based decision-making, and whether technological tools are compatible with actual work processes. This result is consistent with research emphasizing that employees' cognitive trust in AI is essential for effective AI implementation (Rostamzadeh Ganji & Jayeravandi, 2025). It also aligns with responsible AI governance literature, which argues that AI effectiveness requires organizational accountability, appropriate governance mechanisms, and alignment between AI systems and human decision-making (Papagiannidis et al., 2025).

The moderating role of human–organization–technology fit is especially important in the oil industry because AI implementation is not merely a software or hardware issue. AI adoption changes how employees interpret data, how decisions are made, how departments coordinate, and how operational risks are managed. If AI systems are technically advanced but employees lack the required skills, or if organizational procedures do not support AI-based decisions, the effect of AI on resilience and performance may be weakened. This interpretation is consistent with research on digitalization in the petroleum industry, which shows that digital technologies transform work organization and management practices, not only technical processes (Melberg & Gressgård, 2023). It also supports studies on Industry 4.0 challenges showing that sustainable operations require attention to skills, infrastructure, organizational readiness, and technology integration (Dabbagh et al., 2025). Therefore, the present finding confirms the sociotechnical nature of AI implementation: AI capabilities generate value when humans, organizational systems, and technologies are mutually compatible.

The results also support the broader digital transformation literature, which emphasizes the importance of aligning digital capabilities with strategic and operational priorities. In the Iranian industrial context, studies have shown that digital transformation components should be evaluated based on their importance and performance contribution in specific industries (Bakhtiari et al., 2025). In the petrochemical sector, alignment between digital capabilities and innovation strategy has been identified as a critical dimension of digital transformation (Ghazi-Nouri et al., 2024). The present study extends this line of evidence by showing that, in the Abadan oil industry, alignment must be examined not only at the strategic level but also at the operational and sociotechnical levels. AI capabilities, production system resilience, and human–organization–technology fit must be considered together because their combined effect determines whether digital transformation leads to stronger operational performance.

The findings are also consistent with studies suggesting that AI and digital technologies support innovation and adaptive transformation when they are embedded within organizational capabilities. AI adoption in small and medium-sized enterprises has been shown to depend on digital capabilities, innovation orientation, and the external environment (Arroyabe et al., 2024). AI capacities have also been conceptualized as dynamic capabilities that enable circular business model innovation and digital servitization (Sjodin et al., 2023). In addition, research on AI and knowledge management in the oil and gas sector indicates that AI can promote interactive green innovation in traditional industries (Abdulmuhsin et al., 2026). Taken together, these studies support the interpretation that AI capabilities should be understood as part of a broader organizational transformation process. In the present study, this transformation process is reflected in the strengthening of production system resilience and the improvement of operational performance.

The predictive and explanatory indices of the model also support the strength of the proposed framework. The coefficient of determination for operational performance was 0.810, indicating that a substantial proportion of the variance in operational performance was explained by the model. The predictive relevance value was also strong, suggesting that the model had acceptable predictive power. These results indicate that AI capabilities, production system resilience, and human–organization–technology fit together provide a robust explanation of operational performance in the Abadan oil industry. The findings are also compatible with research agendas in operations management that call for deeper investigation of AI and emerging technology adoption in operational contexts (Venkatesh et al., 2023). They also complement evidence from different technological settings, such as AI-powered platforms and digital business models, which shows that AI affects performance through its capacity to enhance decision quality, responsiveness, and competitive positioning (Kumar et al., 2023; Zhou et al., 2023).

5 Conclusion

Overall, the results of this study show that artificial intelligence capabilities are a strategic driver of operational performance, but their effect is mainly realized through the resilience of the production system and strengthened by human–organization–technology fit. This means that oil-industry organizations should not evaluate AI investments only in terms of technological acquisition. Instead, they should examine whether AI improves resilience-related capabilities such as anticipation, monitoring, adaptation, learning, and recovery. They should also assess whether employees, organizational processes, data systems, and technological tools are sufficiently aligned to support AI-enabled decision-making. The findings therefore contribute to the literature by integrating AI capability, production system resilience, operational performance, and sociotechnical fit into a single empirical model in the oil industry. They also provide practical evidence that AI-enabled performance improvement requires simultaneous investment in technology, resilience-building routines, workforce capabilities, and organizational alignment.

The present study had several limitations that should be considered when interpreting the findings. First, the study was conducted in the Abadan oil industry, and although this context is highly relevant for examining AI capabilities and operational performance, the findings may not be directly generalizable to other industries or regions with different technological infrastructures, organizational cultures, and regulatory conditions. Second, the study used a cross-sectional survey design, which limits the ability to make strong causal claims about the relationships among AI capabilities, production system resilience, human–organization–technology fit, and operational performance. Third, the data were collected through questionnaires, and therefore the findings may be affected by self-report bias, respondents' subjective perceptions, and common method variance. Fourth, although the model explained a high proportion of variance in operational performance, other factors such as organizational culture, leadership style, safety climate, investment intensity, environmental uncertainty, and regulatory pressure were not included in the model.

Future research should examine the proposed model in other oil, gas, petrochemical, energy, manufacturing, and process-industry settings to determine whether the relationships identified in this study remain stable across different operational environments. Longitudinal research designs are recommended to examine how AI capabilities evolve over time and how their effects on resilience and performance emerge across different stages of implementation. Future studies may also compare upstream, midstream, and downstream oil-industry operations to identify whether the role of AI capabilities differs across production contexts. In addition, future research should include other mediating and moderating variables, such as organizational learning, digital culture, safety climate, employee trust in AI, leadership support, environmental dynamism, and technological turbulence. Mixed-method research could also provide richer insights by combining survey-based modeling with interviews, case studies, and operational performance records.

From a practical perspective, managers in the Abadan oil industry should treat AI implementation as an integrated sociotechnical transformation rather than a purely technological project. Investment in AI infrastructure should be accompanied by systematic workforce training, improvement of data quality, redesign of operational routines, and development of cross-functional coordination mechanisms. Managers should focus on using AI to strengthen resilience capabilities, including early warning, predictive maintenance, scenario analysis, rapid response, and post-disruption learning. Organizations should also assess the fit between AI tools and actual operational tasks before full implementation, because misalignment can reduce the effectiveness of AI investments. Finally, decision-makers should create a supportive organizational environment in which employees trust AI outputs, understand their role in AI-enabled processes, and are encouraged to combine human expertise with intelligent technologies for more stable, adaptive, and high-performing operations.

Authors' Contributions

All authors have contributed significantly to the research process and the development of the manuscript.

Declaration

In order to correct and improve the academic writing of our paper, we have used the language model ChatGPT.

Transparency Statement

Data are available for research purposes upon reasonable request to the corresponding author.

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Declaration of Interest

The authors report no conflict of interest.

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Ethical Considerations

In this research, ethical standards including obtaining informed consent, ensuring privacy and confidentiality were observed.

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