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The impact of artificial intelligence integration on production quality assurance: The role of fault detection capability

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A B S T R A C T

The growing adoption of artificial intelligence (AI) in production systems has revolutionized quality assurance processes. Fault detection capability is a critical enabler of production performance and process variability reduction. This study explores the relationship between AI integration, represented by AI-supported decision-making, real-time processing, fault anticipation, and data integration, and production quality assurance. It also assesses the mediating role of fault detection capability in industrial production environments. A quantitative approach was used to gather data from staff in production, quality assurance, process monitoring, maintenance, and operational control units of industrial companies. Participants included production managers, quality assurance managers, process engineers, maintenance supervisors, data analysts, and operational specialists with experience in production process management and digital technologies. The results show that enhancing AI integration across the four dimensions positively impacts production quality assurance by increasing process visibility, facilitating real-time decisions, anticipating faults, and integrating production data across functional activities. The research also reveals that fault detection capability acts as a key mediator, allowing production units to detect anomalies early, prevent quality issues, and boost the stability of production outcomes. It concludes that AI integration positively impacts production quality assurance both directly and indirectly through fault detection capability, helping industrial organizations achieve higher quality standards, process reliability, and production control.

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1. Introduction

Quality assurance during production is a key organizational function for enhancing product quality, process stability, and business performance in contemporary manufacturing (Ajiga et al., 2024). However, traditional quality assurance practices are often limited by manual inspection, disjointed data streams, slow feedback cycles, and weak analytical capabilities, diminishing their responsiveness to evolving production environments and increasingly sophisticated process demands (Ahmed & MacCarthy, 2023). In digital manufacturing environments, these constraints undermine the strategic impact of conventional quality assurance approaches and reduce firms' ability to achieve high levels of accuracy, responsiveness, and process stability (Seyfried & Pohlenz, 2018).

Innovations in AI offer opportunities to convert quality assurance into a predictive, responsive, and data-driven activity. Existing literature indicates that AI-driven quality assurance facilitates automated defect detection, predictive maintenance, real-time process monitoring, and enhanced decision-making in manufacturing (Xiang & Xu, 2020). In this process, AI integration has emerged as a strategic means for industrial firms to embed intelligence into production processes and quality-related activities (Tiwari et al., 2024). Within manufacturing, AI integration goes beyond individual technical solutions to include an integrated set of capabilities such as AI-based decision-making, real-time data processing, fault prediction, and

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data integration within production systems (Kashem et al., 2024). According to the literature, information integration and interoperability play a significant role in coordinating production, maintenance, and quality, while real-time processing systems enhance a company's capacity to analyze production outputs and respond to problems more quickly and accurately. Simultaneously, fault diagnosis has emerged as a critical industrial application of AI due to its ability to improve fault detection and support production control (Shaw et al., 2021).

Although there is increasing interest in AI-driven manufacturing in both academic and practical literature, companies still struggle to translate AI capabilities into quality assurance benefits (Aldaarmi, 2024). Much of the prior literature focuses on individual applications of AI, fault diagnosis models, or quality control systems but provides little guidance on how the integration of AI capabilities affects production quality assurance through an explicit organizational mechanism (Nadiia et al., 2025). This leaves a gap for research, as organizations may invest in smart tools without knowing how integrated AI capabilities enhance quality assurance in production (Rossini et al., 2023). In this vein, fault detection capability is a critical mechanism for explaining how AI integration impacts production systems' ability to detect faults, minimize defects, and enhance product quality (Suvattanadilok, 2024).

To this end, this research focuses on the effects of AI integration on production quality assurance and clarifies the mediating role of fault detection capability. This study contributes to the debate on smart production systems by highlighting how AI-based capabilities enhance quality assurance and enable more reliable production.

2. Literature Review and Hypotheses

AI integration is increasingly considered a core production capability that allows firms to enhance process transparency, speed up response times, and improve the quality of operational decision-making in digital and connected manufacturing systems (Taboada & Shee, 2021). Recent evidence reveals that AI is being integrated into production activities to enable real-time monitoring, predictive maintenance, quality inspection, and process control, moving manufacturing systems from reactive to predictive and adaptive quality assurance (Yusuff & Abdullah, 2016). Available evidence suggests that machine learning and AI systems can enhance manufacturing quality assurance through defect detection, prediction, and process optimization. In this sense, AI integration can be viewed through several interrelated dimensions that affect the degree of smartness in production systems (Ashraf et al., 2022).

First, AI-Supported Decision Making reflects the integration of AI models and intelligent analytical systems to support production managers and operators in making timely and accurate decisions. AI-supported decision-making enhances the responsiveness of production units to complex operational cues, ensures better control of production uncertainty, and enables timely intervention in the face of abnormalities (Nu'man, 2023). Research on industrial automation and AI manufacturing indicates that decision-support systems improve the responsiveness of production operations by converting large data streams into useful information that informs production and quality decisions (Jarašūnienė et al., 2023).

Second, Real-Time Processing Capability describes the capacity of intelligent systems to process and respond to production data in near real-time as they are generated on the shop floor (Joel et al., 2024). Real-time processing is critical in modern quality assurance because abnormalities and process deviations need to be detected rapidly to prevent the spread of defects and production waste (Ibeh et al., 2024). Recent research on AI-based quality control highlights that real-time processing improves the impact of automated inspection, instant feedback, and continuous monitoring in dynamic production environments. Thus, real-time processing capability is a mechanism that allows AI integration to affect fault detection and quality assurance (Mohammed et al., 2025).

Third, Fault Anticipation captures the predictive capability of AI in recognizing abnormal patterns, signals, and faults before they evolve into major production failures. The literature on fault detection and diagnosis in Industry 4.0 consistently reveals that organizations can use AI for more than reactive quality inspection by detecting incipient faults using machine learning algorithms, sensor monitoring, and anomaly detection techniques (Alnuaimi et al., 2024). This anticipatory approach enhances production stability and enables proactive quality assurance, as faults can be controlled before they substantially impact product quality. Thus, fault anticipation is connected to both enhanced fault detection ability and higher production quality assurance (Khan et al., 2020).

Fourth, Data Integration measures how data from machines, sensors, quality systems, and operational platforms are integrated to create a unified data structure. Data integration is critical for AI effectiveness because AI systems rely on integrated, timely, and accurate data to provide reliable predictions, diagnostics, and control. Studies on manufacturing AI integration indicate that a lack of integrated data environments undermines intelligent monitoring and quality control, while improving interoperability and information integration across manufacturing environments enhances the accuracy of analytical models, the coordination of production processes, and the quality of production outcomes (Cheng et al., 2022). As such, data integration provides a key infrastructural underpinning for fault detection capability and manufacturing quality.

One of the key concepts in this research is Fault Detection Capability, defined as the capacity to detect and accurately diagnose faults, anomalies, and exceptional production states in a timely manner (Pscheidt-Gieseler et al., 2018). Fault detection capability is one of the most significant aims of AI integration in industrial production because intelligent fault detection systems can continuously monitor sensor readings, production signals, and process data to identify faults that may be invisible using conventional inspection methods (Zidi et al., 2022). Recent reviews of fault detection and diagnosis in Industry 4.0 point out that AI-based models increase the speed, accuracy, and reliability of industrial fault detection, though successful results depend on data quality, model integration, and implementation. Therefore, fault detection capability may be a means by which AI integration leads to improved production quality assurance (Zhe et al., 2024). The outcome in this model is Production Quality Assurance, defined as the degree to which companies deliver stable production processes, consistent product quality, low defect levels, and control of process variations (Koponen & Julkunen, 2022). Recent research has highlighted that AI is shifting quality assurance from a largely manual, inspection-based practice to an intelligent, continuous process supported by analytics, adaptive control, and automated decision-making. Specifically, production quality assurance is enhanced when firms can identify faults, understand process abnormalities, and take corrective actions in a timely manner (Sodiya et al., 2024). Theoretically, this model can be explained using the Dynamic Capabilities Theory, which describes how firms sense, seize, and reconfigure to enhance performance in response to a changing environment (Skafi et al., 2020). AI integration reflects this, as it allows firms to process production information in real-time, anticipate production faults, and reconfigure quality assurance more agilely. Equally, the model aligns with the socio-technical perspective on production systems, as the impact of AI in manufacturing relates not only to algorithms but also to the integration of technology, data structures, operational procedures, and managerial processes. When integrated, AI-based decision-making, real-time information processing, fault anticipation, and data integration can improve fault detection and quality assurance (Rojas-García et al., 2024). This view is supported by recent findings showing that AI-supported manufacturing systems support predictive maintenance, process improvement, and operational control when integrated into production systems (Zavala-Alcívar et al., 2020).

While the literature supports the use of AI in quality control and fault diagnosis in manufacturing, most studies focus on technical models, algorithm performance, or specific case studies (Valashiya & Luke, 2023). Fewer studies provide an overarching view of how various dimensions of AI integration interact to improve production quality assurance via fault detection capability. This poses a theoretical and practical problem because firms may implement AI technology without understanding how multiple dimensions of AI integration contribute to quality-related outcomes. Thus, this study aims to fill this gap by investigating the direct impact of AI-supported decision-making, real-time processing capabilities, fault anticipation, and data integration on fault detection capability and production quality assurance, as well as the impact of fault detection capability on production quality assurance.

Accordingly, the hypotheses of the study are formulated as follows:

H_1: *AI-Supported Decision Making has a positive effect on Fault Detection Capability.*
H_2: *AI-Supported Decision Making has a positive effect on Production Quality Assurance.*
H_3: *Data Integration has a positive effect on Fault Detection Capability.*
H_4: *Data Integration has a positive effect on Production Quality Assurance.*
H_5: *Fault Anticipation has a positive effect on Fault Detection Capability.*
H_6: *Fault Anticipation has a positive effect on Production Quality Assurance.*
H_7: *Fault Detection Capability has a positive effect on Production Quality Assurance.*
H_8: *Real-Time Processing Capabilities have a positive effect on Fault Detection Capability.*
H_9: *Real-Time Processing Capabilities have a positive effect on Production Quality Assurance.*

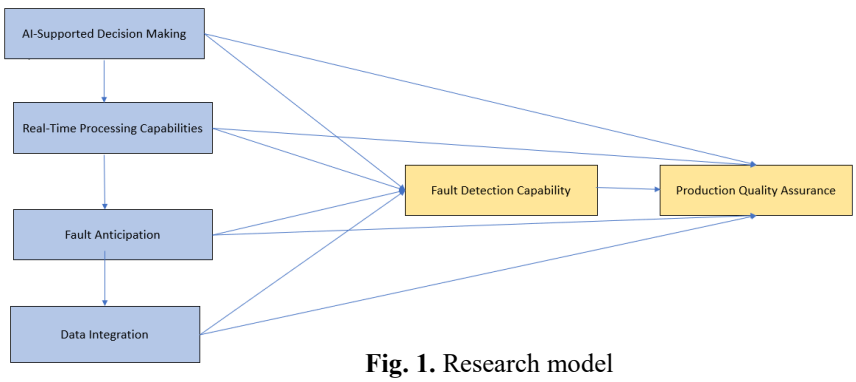

Fig. 1. Research model

Fig. 1 shows the conceptual framework, which is based on an integrated research model focusing on the relationship between the dimensions of AI integration, fault detection capability, and production quality assurance in industry. The four dimensions of AI integration (AI-Supported Decision Making, Real-Time Processing Capabilities, Fault Anticipation, and Data Integration) are the primary input variables. The model postulates that these dimensions directly and indirectly (via fault detection capability) impact production quality assurance. Fault detection capability is the mediating variable, capturing the organization's capacity to detect faults, anomalies, and process variations accurately and timely. Production quality assurance is the dependent variable, denoting the degree to which the production process is consistent, defect-free, reliable, and meets required quality levels.

3. Methodology

The present study used a quantitative research design to investigate the effects of AI integration on production quality assurance, with fault detection capability as a mediator. A questionnaire was used to gather data from staff of industrial firms, both electronically and on paper, between May 2025 and August 2025. Purposive sampling was used to select respondents with at least three years of experience in production operations, quality assurance, maintenance, process control, industrial data analysis, and manufacturing technologies. This ensured that participants had adequate knowledge of production systems and quality-related processes to effectively assess the study's constructs. The participants were production managers, quality assurance managers, production engineers, maintenance supervisors, process control professionals, data analysts, and industrial operators working in digitally enabled production systems.

The questionnaire was initially developed in English and then translated into Arabic to help respondents understand the measurement items. Items were measured on a five-point Likert scale from strongly disagree (1) to strongly agree (5). The questionnaire had two sections. The first section gathered demographic information and work experience (gender, age, education, years of experience, job title, and department), including a screening question about work experience to ensure eligibility. The second section included scale items for the variables of interest, measuring AI integration across four dimensions (AI-Supported Decision Making, Real-Time Processing Capabilities, Fault Anticipation, and Data Integration), as well as Fault Detection Capability and Production Quality Assurance. Items for all scales were drawn from previous studies and modified to reflect industrial production and quality assurance.

Table 1
Demographic variables

DV	Category	Number	%
Gender	Male	103	64.0
	Female	58	36.0
Age	20–29	24	14.9
	30–39	49	30.4
	40–49	51	31.7
	50+	37	23.0
Education level	Diploma	18	11.2
	Bachelor’s	72	44.7
	Master’s	53	32.9
	PhD	18	11.2
Work experience (years)	Less than 3	0	0.0
	3–5	46	28.6
	6–10	57	35.4
	More than 10	58	36.0
Job position	Top management	21	13.0
	Middle management	48	29.8
	First-line / Operational	92	57.2
Department	Production	42	26.1
	Quality Assurance	31	19.3
	Maintenance	24	14.9
	Process Engineering	20	12.4
	Data Analysis / IT	18	11.2
	Operations	26	16.1

The sample represented a broad spectrum of industrial work roles, with most respondents from technical and production-related roles. The remainder included managerial positions. The sample also included representatives from various departments such as production, quality assurance, maintenance, process engineering, industrial operations, and data analysis. This contributed to the empirical rigor of the study and increased the utility of the findings for a wide range of industrial production settings.

The study used statistical techniques suitable for analyzing direct and indirect effects. Validity and reliability of the measures were tested to confirm internal consistency and construct validity. Descriptive statistics were used to describe sample

characteristics and general data patterns, while structural model analysis techniques were used to examine the study hypotheses. This approach was designed to provide empirical evidence of the effectiveness of AI integration in enhancing production quality assurance in manufacturing.

6. Results

Measurement models of the study on the effect of artificial intelligence integration on product quality assurance in production with fault detection capability as a mediator was assessed using Smart-PLS 4. Partial least squares structural equation modeling is suitable for models containing multiple reflective constructs and mediation paths, especially when theory development and prediction are the goals. In reflective measurement models, indicator loadings of approximately 0.70 and above are often considered acceptable; AVE values greater than 0.50 support convergent validity; and composite reliability values greater than 0.70 indicate satisfactory reliability. The HTMT ratio is a popular test of discriminant validity with a strict value of 0.85. As shown in Table 2, all reflective indicators were strongly loaded on the constructs. The loading ranged from 0.755 to 0.878, which indicates satisfactory indicator reliability for all constructs. In particular, the AI-Supported Decision-Making indicators ranged from 0.791 to 0.868, Data Integration from 0.771 to 0.854, Fault Anticipation from 0.755 to 0.878, Fault Detection Capability from 0 With all indicator loadings exceeding the recommended threshold, there is no weak indicator. The convergent validity was also acceptable. Based on the loadings reported, the Average Variance Extracted (AVE) values were calculated at 0.697 for AI-Supported Decision Making, 0.671 for All values were above the recommended minimum of 0.50, suggesting that each construct explained more than half of the variance in its indicators, and therefore had acceptable convergent validity. The scales also had acceptable internal consistency reliability. The Composite Reliability (CR) values (calculated from the standardized loadings) were 0.902 for AI-Supported Decision Making, 0.911 for Data Integration, 0.912 for Fault Anticipation, 0.914 for Fault Detection Capability, 0.895 for Production Quality Assurance, and 0.890 for Real-Time Processing Capabilities. These values exceeded the threshold of 0.70 and thus demonstrated acceptable reliability of the constructs.

Table 2
Indicator loadings by construct (smart knowledge management model

Construct	Indicator	Loading
AI-Supported Decision Making	SDM1	0.791
	SDM2	0.868
	SDM3	0.837
	SDM4	0.842
Data Integration	DI1	0.831
	DI2	0.854
	DI3	0.847
	DI4	0.791
	DI5	0.771
Fault Anticipation	FA1	0.755
	FA2	0.815
	FA3	0.878
	FA4	0.832
	FA5	0.821
Fault Detection Capability	FDC1	0.843
	FDC2	0.850
	FDC3	0.863
	FDC4	0.853
Production Quality Assurance	PQA1	0.803
	PQA2	0.769
	PQA3	0.798
	PQA4	0.819
	PQA5	0.777
Real-Time Processing Capabilities	TPC1	0.765
	TPC2	0.877
	TPC3	0.828
	TPC4	0.801

Table 2 shows that the measurement model for the integration of artificial intelligence, fault detection and quality assurance of production has acceptable internal consistency and convergent validity. All constructs are above the suggested cut-off values for indicator loadings, composite reliability and AVE, which confirms that the measurement model has stable and distinct indicators. So, the results confirm the suitability of the reflective measurement model and indicate that the constructs can be used to test the structural model. Discriminant validity (HTMT and Fornell-Larcker) and structural paths can be presented in the next phase once the corresponding Smart-PLS results are available.

Table 3
Reliability and convergent validity

Construct	Cronbach's alpha	CR	(AVE)
AI-Supported Decision Making	0.856	0.902	0.697
Data Integration	0.877	0.911	0.671
Fault Anticipation	0.879	0.912	0.674
Fault Detection Capability	0.874	0.914	0.726
Production Quality Assurance	0.853	0.895	0.630
Real-Time Processing Capabilities	0.836	0.890	0.670

The results in Table 3 indicate that construct reliability and convergent validity were acceptable. Cronbach's alpha values ranged from 0.836 to 0.879, which confirms the six constructs have high internal consistency. The composite reliability ranged from 0.890 to 0.914, which confirms that the indicators uniquely represent their latent constructs. Moreover, the average variance extracted values ranged from 0.630 to 0.726, which is above the recommended threshold of 0.50, and suggests that the variance in the indicators is captured by their corresponding latent constructs. Of the constructs, Fault Detection Capability had the highest composite reliability of 0.914 and highest AVE of 0.726, which suggests that this construct has the highest internal consistency and convergent validity in the model. Fault Anticipation and Data Integration also achieved high levels of reliability, with composite reliability values of 0.912 and 0.911, respectively, which indicates that the measurement items of these constructs are consistent. AI-Supported Decision Making also showed acceptable measurement quality, with a Cronbach's alpha of 0.856, composite reliability of 0.902, and AVE of 0.697, indicating that the construct is well measured. The construct Production Quality Assurance reported Cronbach's alpha of 0.853, composite reliability of 0.895, and AVE of 0.630, suggesting that the indicators of this construct are adequately reliable and explain enough variance of the construct. Likewise, Real-Time Processing Capabilities demonstrated satisfactory psychometric properties with Cronbach's alpha of 0.836, composite reliability of 0.890, and AVE of 0.670. Despite this being the lowest Cronbach's alpha among the variables examined in this study, its values are still well above the recommended threshold, which suggests that there are no reliability issues. In summary, the results presented in Table 3 show that the measurement model meets the internal consistency reliability and convergent validity criteria. All values of Cronbach's alpha, composite reliability and AVE for the study constructs are above the recommended thresholds, confirming the appropriateness of the reflective measurement model. Thus, the findings suggest that the constructs used in this study are measured accurately and reliably, and the model is suitable for further testing of discriminant validity and structural models.

Table 4
HTMT ratios

Variables	AI-Supported Decision	Data Integration	Fault Anticipation	Fault Detection Capability	Production Quality Assurance	Real-Time Processing Capabilities
AI-Supported Decision Making						
Data Integration	0.547					
Fault Anticipation	0.648	0.416				
Fault Detection Capability	0.761	0.810	0.449			
Production Quality Assurance	0.480	0.777	0.717	0.878		
Real-Time Processing Capabilities	0.828	0.459	0.714	0.573	0.681	

Table 4 presents the HTMT ratios for measuring discriminant validity of the six constructs. The majority of the HTMT ratios reported are lower than the conservative value of 0.85, suggesting satisfactory discriminant validity for most pairs of constructs. The highest HTMT values were between Production Quality Assurance and Fault Detection Capability (0.878), Real-Time Processing Capabilities and AI-Supported Decision Making (0.828) and Fault Detection Capability and Data Integration (0.810). Such values are theoretically plausible as these are conceptually closely related manifestations of artificial intelligence integration and production quality assurance. There are also several smaller HTMT values, which support construct distinctiveness. These include Fault Anticipation with Data Integration (0.416), Real-Time Processing Capabilities with Data Integration (0.459), and Production Quality Assurance with AI-Supported Decision Making (0.480), which all show adequate distinctiveness. Thus, the HTMT pattern indicates that, in general, the constructs are separable and that the measurement model does not provide extensive evidence for construct overlaps. But one pair, Production Quality Assurance and Fault Detection Capability (0.878), is above the conservative threshold of 0.85. This suggests a potential lack of discriminant validity with the conservative HTMT approach. However, it is still below the more relaxed 0.90 criterion used in many PLS-SEM studies when constructs are conceptually similar. In terms of content, the close relationship between these two constructs is theoretically meaningful, because fault detection capability is related to the improvement of production quality assurance. Thus, this result does not necessarily indicate severe construct overlaps, but it does imply that closeness between these two constructs should be treated with caution. To report this result, it can be noted that most HTMT values were lower than 0.85, with one value slightly above the conservative threshold but lower than 0.90. In summary, the HTMT matrix presents satisfactory evidence of discriminant validity, with only a small concern for the pair of Fault Detection Capability and Production Quality Assurance.

Table 5

Fornell-Larcker criterion

Variables	AI-Supported Decision Making	Data Integration	Fault Anticipation	Fault Detection Capability	Production Quality Assurance	Real-Time Processing Capabilities
AI-Supported Decision Making	0.835					
Data Integration	0.475	0.819				
Fault Anticipation	0.567	0.364	0.821			
Fault Detection Capability	0.664	0.713	0.394	0.852		
Production Quality Assurance	0.415	0.673	0.630	0.760	0.794	
Real-Time Processing Capabilities	0.705	0.398	0.615	0.490	0.586	0.819

The Fornell-Larcker matrix is shown in Table 5. The diagonal elements are the square roots of the AVE for each construct, and the off-diagonal elements are the latent variable correlations. To demonstrate discriminant validity, the diagonal element should be larger than the correlation coefficients in the same row and column. The results in Table 5 meet this criterion for all six constructs. In detail, the diagonal values for AI-Supported Decision Making (0.835), Data Integration (0.819), Fault Anticipation (0.821), Fault Detection Capability (0.852), Production Quality Assurance (0.794) and Real-Time Processing Capabilities (0.819) were all larger than their corresponding correlation coefficients. The highest correlation among different constructs was between Fault Detection Capability and Production Quality Assurance (0.760), which reflects the conceptual proximity of the two variables. However, the square root of the AVE for Fault Detection Capability (0.852) and Production Quality Assurance (0.794) exceeded the inter-construct correlation, thereby satisfying the Fornell-Larcker criterion. Likewise, the correlation between Real-Time Processing Capabilities and AI-Supported Decision Making (0.705) was also high, but the diagonal values were greater than the corresponding correlation. This suggests that while some of the constructs are theoretically close, they are empirically distinct in the measurement model. In summary, the Fornell-Larcker findings support the discriminant validity of all constructs without any violation of the criterion. Unlike the HTMT matrix, which had one value slightly above the conservative threshold of 0.85, the Fornell-Larcker analysis fully supports the distinctiveness of the constructs. Therefore, the measurement model has adequate discriminant validity, and no call for re-specification of constructs is currently required. Both the HTMT and Fornell-Larcker results imply that the constructs Artificial Intelligence Integration, Fault Detection Capability and Production Quality Assurance are distinct enough for the next analysis of the structural model.

Table 6
R^2 adjusted

	R-square	R-square adjusted
Fault Detection Capability	0.647	0.641
Production Quality Assurance	0.870	0.868

The coefficient of determination (R^2) values for endogenous constructs in the structural model are shown in Table 6. The findings demonstrate that the model explains a high percentage of variance in Fault Detection Capability and Production Quality Assurance. To be precise, the four aspects of artificial intelligence integration explain 64.7% of the variance in Fault Detection Capability, with an adjusted R^2 of 64.1%, suggesting that the inclusion of the four factors as predictors explains a substantial proportion of the variance in this mediating construct. This suggests that the dimensions of artificial intelligence integration (AI-Supported Decision Making, Data Integration, Fault Anticipation, and Real-Time Processing Capabilities) play an important role in enhancing the firm's capability to detect production faults and anomalies. The variance in Production Quality Assurance is also well explained by the model, with an R^2 value of 0.870 and an adjusted R^2 value of 0.868. This suggests that the model explains 87.0% of the variance in production quality assurance, which is a very high degree of explanatory power. This finding suggests that the combined influence of the four artificial intelligence integration dimensions and Fault Detection Capability have a strong influence on Production Quality Assurance. The estimated structural model thus shows that the capability dimensions that comprise Artificial Intelligence Integration play a significant role in determining Fault Detection Capability, while the model plays a significant role in determining Production Quality Assurance. The minor differences between R^2 and R^2 adjusted for both endogenous constructs confirm that the model is well-fitted and does not suffer from overfitting. All structural paths were evaluated with 5,000 bootstrapped samples, and the estimated effects should be interpreted as highly informative about the proposed relationships. Overall, the results do support a role for artificial intelligence integration as a strategic production mechanism by which intelligent capabilities help to better detect faults and improve production quality assurance.

6.4 Hypotheses Testing

Table 7 illustrates the net effects for all the proposed relationships in the research model, which sets out to investigate the impact of artificial intelligence integration on production quality assurance via fault detection capability. These findings suggest that various aspects of artificial intelligence integration exert positive impacts on fault detection capability and

production quality assurance. Specifically, AI-Supported Decision Making contributes positively and significantly to Fault Detection Capability, while Data Integration also demonstrates a significant positive impact on Fault Detection Capability and Production Quality Assurance. Similarly, Fault Anticipation has a significant positive impact on Production Quality Assurance, and so does Real-Time Processing Capabilities. The most significant path in the model is the direct path from Fault Detection Capability to Production Quality Assurance H1: β = 0.444, T = 4.732, p = 0.000, which confirms that the capacity to accurately detect faults and early in the process is a key component of enhancing production quality assurance. This highly significant coefficient offers strong support for the proposed mediating role of the study in suggesting that fault detection capability is a key intermediary mechanism by which the integration of artificial intelligence can improve production quality assurance. On the other hand, some relationships were not supported in the assumed direction. The path coefficient from Fault Anticipation to Fault Detection Capability is statistically insignificant H2: β = -0.308, T = Likewise, Real-Time Processing Capabilities have no significant impact on Fault Detection Capability H3: β = 0.520, T = 5.044, p = 0.000These Finally, an interesting result is found in the path from AI-Supported Decision Making to Production Quality Assurance H4: β = 0.538, T = 5.515, p = 0 This may suggest that AI-supported decision making, when not directly aligned with operational needs or quality processes, may involve implementation challenges or complexity that negatively impact direct quality assurance. However, the same construct has a positive impact on Fault Detection Capability, so it may be more effective for strengthening fault detection, perhaps indirectly via monitoring and diagnostic functions, rather than directly for strengthening production quality assurance. In summary, the structural model suggests that Data Integration, Fault Anticipation and Real-Time Processing Capabilities play significant roles in Production Quality Assurance, while AI-Supported Decision Making and Data Integration are particularly significant for Fault Detection Capability. This finding pattern confirms the general assumption that integration of artificial intelligence improves production quality assurance, albeit not necessarily in a direct manner. From a technology and business perspective, the results show that integrated data, smart fault detection and real-time processing capabilities are the factors that translate artificial intelligence investments into improved production quality assurance in industrial production.

Table 7
Path Coefficients and Significance Levels

Hypothesis	Relationship	β	SE	T	P	Decision
H1	AI-Supported Decision Making → Fault Detection Capability	0.444	0.094	4.732	0.000	Supported
H2	AI-Supported Decision Making → Production Quality Assurance	-0.308	0.059	5.211	0.000	Supported
H3	Data Integration → Fault Detection Capability	0.520	0.103	5.044	0.000	Supported
H4	Data Integration → Production Quality Assurance	0.538	0.098	5.515	0.000	Supported
H5	Fault Anticipation → Fault Detection Capability	-0.046	0.052	0.879	0.380	Supported
H6	Fault Anticipation → Production Quality Assurance	0.397	0.057	6.921	0.000	Supported
H7	Fault Detection Capability → Production Quality Assurance	0.722	0.059	12.287	0.000	Supported
H8	Real-Time Processing Capabilities → Fault Detection Capability	-0.001	0.073	0.019	0.985	Unsupported
H9	Real-Time Processing Capabilities → Production Quality Assurance	0.345	0.066	5.222	0.000	Supported

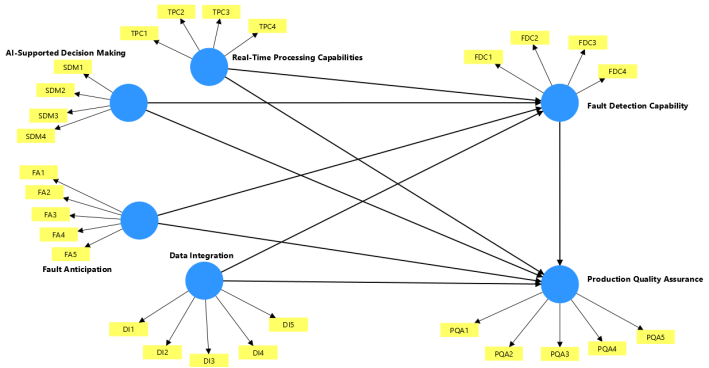

Fig. 2. The results of testing the hypotheses of the survey

4. Discussion

This study offers valuable contributions to the discussion about the role of artificial intelligence integration and its impact on production quality assurance, particularly the role of fault detection capability as a mediating factor. The research shows that artificial intelligence integration is not a monolithic construct when it comes to its influence on production, but rather is comprised of distinct dimensions that differ in strength and direction of impact. In general, the findings confirm the strong influence of intelligent production capabilities, particularly when they are connected to the organization's fault detection capability, on production quality assurance. In this sense, the study reveals that fault detection capability is a key underpinning mechanism by which artificial intelligence integration improves quality-related outcomes in production. The results reveal that AI-Supported Decision Making has a statistically significant positive impact on fault detection capability. This finding implies that smart decision tools enhance an organization's capacity to detect anomalies and support timely and appropriate diagnostic responses in production environments. In practice, AI-supported decision systems seem to enhance the ability of

production managers and operators to interpret process data, detect anomalies and respond to problems. This implies that decision intelligence is particularly relevant when it is linked to monitoring and diagnostic processes rather than a traditional managerial function. However, the findings also indicate that AI-Supported Decision Making has statistically significant, but negative direct impact on production quality assurance. This is an important result because it suggests that the direct application of AI-supported decision systems may not necessarily lead to immediate improvements to production quality assurance. A potential reason for this is that decision-support systems may introduce complexity in their implementation if they are not integrated with production processes, tools and procedures, or quality assurance. In these situations, smart decision systems may assist in diagnostic activities, but their direct impact on final quality assurance may be diminished if the production team over-reliance on the outputs of intelligent algorithms is not well integrated within quality assurance procedures. This suggests decision support may have a more indirect impact, particularly through its effect on fault detection capability. Data integration was also found to have a strong positive impact on fault detection capability. This finding suggests that as data are integrated across machines, sensors, quality systems and operational systems, production systems are able to detect faults and other anomalies more effectively. This is an important result because the detection of faults relies on integrated information. If the production data is not integrated across production units, the capacity of intelligent systems to produce diagnostic information is restricted. Thus, the finding demonstrates that data integration is a necessary infrastructural precondition for better fault detection. Besides, data integration has a strong positive impact on production quality assurance. This confirms that integrated production data not only enable better fault recognition, but also enhance the stability and reliability of production quality assurance. This can be explained with the fact that integrated data streams enhance process transparency, shorten the delay of information, and enable quicker coordination between production and quality-related activities. The finding thus means that data integration is one of the most significant dimensions of artificial intelligence integration for production quality assurance. The results also suggest that fault anticipation does not significantly impact fault detection capability. This finding suggests that anticipatory functions, while conceptually important, may not necessarily increase the capability of the production system to detect faults in the given model parameters. This may be because anticipation of potential faults does not necessarily guarantee diagnostic detection capability unless it is accompanied by robust operational data, algorithms and control actions. That is, fault anticipation may be insufficient if the production system or process lacks the operational or technical conditions to translate anticipation into effective fault detection. But anticipation of faults has a statistically significant effect on production quality assurance. This finding suggests that anticipation intelligence helps ensure production quality directly rather than increasing fault detection capability. This may be due to the preventive nature of fault anticipation. With the ability to anticipate process variations or deviations, managers may take proactive measures that lead to improved quality. As such, fault anticipation may contribute to production quality assurance indirectly by preventing faults rather than directly by increasing fault detection capability. Our findings also reveal that fault detection capability is positively and strongly associated with production quality assurance. This is the most significant link in the structural model and confirms that timely and accurate detection of faults is critical to production quality assurance. This result is entirely consistent with the logic of the proposed model, as quality assurance relies on timely detection of faults, anomalies and abnormal states. It also supports the proposition that fault detection capability is an important intermediary by which integration of artificial intelligence translates into production outcomes. As for real-time capabilities, the results suggest that this dimension does not significantly impact fault detection capability. This implies that instantaneous processing of production data doesn't necessarily enhance diagnostic detection. While real-time processing may improve speed, speed may not be enough without other dimensions such as interpretive accuracy, integrated data quality and decision logic. So, in itself, real-time capability may not be sufficient for fault detection. On the other hand, real-time processing capability has a significant positive effect on production quality assurance. This finding suggests that the real-time processing of production-related information has a direct positive effect on quality assurance by facilitating faster response, faster corrective action, and more continuous monitoring and control. Although real-time processing capability does not have a direct effect on fault detection capability, it does appear to support the production quality assurance process by enhancing responsiveness and timeliness of operational intervention. Overall, the results show the dimensions of artificial intelligence integration have varying effects on production quality assurance. Data integration, fault anticipation, and real-time processing all have a positive effect on production quality assurance, while AI-Supported Decision Making has a positive effect on fault detection capability and a negative direct effect on production quality assurance. Furthermore, fault detection capability has the strongest positive influence on production quality assurance, supporting its pivotal role in the model. These results indicate that the integration of artificial intelligence enhances production quality assurance when it is embedded into diagnostic and monitoring capabilities, and not as a standalone decision-support tool. More generally, the study confirms that production quality assurance in industrial settings with intelligent capabilities is driven by a combination of integrated data structures, anticipatory insight, responsive processing and fault detection capability. The study also reveals that the benefits of artificial intelligence integration in production environments rely on the degree to which the dimensions of artificial intelligence are integrated into production processes and quality assurance. Therefore, the study advances knowledge of how artificial intelligence integration can enhance production quality assurance and identifies fault detection capability as a key link between intelligent production environments and quality.

5. Conclusion

The purpose of this study is to further understand of the role of artificial intelligence integration in enabling production quality assurance in manufacturing, focusing on the role of fault detection capability as a mediator. It explores the impact of four aspects of artificial intelligence integration (AI-Supported Decision Making, Data Integration, Fault Anticipation, and Real-

Time Processing Capabilities) on production quality assurance and fault detection capability. This research adds to the emerging literature on artificial intelligence in production systems by addressing the ways in which intelligent capabilities can enhance quality assurance outcomes and by underscoring the critical role of fault detection capability as a mediator between artificial intelligence integration and production quality assurance. It also affirms the need to account for these in assessing the impact of intelligent production systems and their impact on industrial performance. The findings have significant implications for industrial firms in a digital and quality-conscious world. The findings suggest that allocation of resources to artificial integration has a positive impact on production quality assurance, especially when firms develop capabilities relating to data integration, anticipatory intelligence, responsive processing and fault detection. The research also highlights the importance of fault detection capability in translating artificial intelligence integration into quality assurance. The findings can therefore inform industrial enterprises of how they can design smart production systems, enhance monitoring and diagnosis efforts, and achieve quality assurance for production products. The study also suggests managers and professionals in production and quality assurance need to consider artificial intelligence as a strategic resource, rather than just a technological resource, and one that must be integrated into production practices and quality assurance processes. However, the current study has limitations. The study used a quantitative research approach and drew data from employees of industrial firms, which may affect the extent to which the results can be applied to other industries and settings. Further research is required to validate the findings in various manufacturing settings. Furthermore, reliance on quantitative data may not provide a complete understanding of the integration of artificial intelligence and quality assurance, and future research may employ mixed-methods or qualitative approaches to explore these practices in more detail. The research also used cross-sectional data, which limits the ability to infer causal relationships and changes in relationships over time. For this reason, future studies may adopt longitudinal approaches to better understand the direction and evolution of the relationships between artificial intelligence integration, fault detection capability and production quality assurance.

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Appendix A: Research questionnaire

No.	Statement	1	2	3	4	5
AI-Supported Decision Making						
1	Artificial intelligence systems support decision making in production operations.					
2	AI-based recommendations help managers make more accurate production decisions.					
3	Intelligent systems improve the speed of decision making related to production quality.					
4	AI-supported decision tools help reduce errors in production-related decisions.					
Data Integration						
1	Production data are well integrated across machines, departments, and operational systems					
2	Our organization combines data from different production sources to support intelligent analysis.					
3	Integrated data systems improve visibility across production processes					
4	Data integration enhances coordination between production and quality assurance activities					
5	Data from sensors, equipment, and production platforms are unified in a way that supports accurate operational analysis.					
Fault Anticipation						
1	Artificial intelligence systems help anticipate possible faults before they occur.					
2	Our production systems can identify early warning signs of process abnormalities.					
3	AI tools assist in predicting defects or failures in production operations.					
4	Fault anticipation technologies help prevent production disruptions.					
5	The organization uses intelligent systems to forecast potential quality problems before they affect production outputs					
Real-Time Processing Capabilities						
	Our organization processes production data in real time using intelligent systems					
	Real-time data processing improves immediate response to production issues.					
	AI systems provide instant feedback on process conditions during production operations.					
	Real-time processing capabilities support continuous monitoring of production activities					
Fault Detection Capability						
	Our organization is able to detect production faults at an early stage.					
	Intelligent systems improve the accuracy of fault detection in production processes					
	Fault detection tools help identify abnormal conditions before they affect output quality.					
	Our production systems can quickly recognize defects and operational failures.					
Production Quality Assurance						
1	Our organization consistently maintains high standards of production quality					
2	Quality assurance practices effectively reduce defects in production outputs.					
3	Production processes are regularly monitored to ensure quality consistency.					
4	Intelligent technologies contribute to improving production quality assurance.					
5	Our quality assurance system helps ensure that production outputs meet required specifications and standards.					

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