Research Square

Preprints are preliminary reports that have not undergone peer review.
They should not be considered conclusive, used to inform clinical practice,
or referenced by the media as validated information.

Organizational Deep Learning Capability and Manufacturing Quality Intelligence in Integrated Circuit Manufacturing

RongHao Zhang

mirpdq9818@outlook.com

Beijing University of Posts and Telecommunications

Article

Keywords:

Posted Date: November 12th, 2026

DOI: https://doi.org/10.21203/rs.3.rs-11184758/v1

License: This work is licensed under a Creative Commons Attribution 4.0 International License.
Read Full License

Additional Declarations: No competing interests reported.

Organizational Deep Learning Capability and Manufacturing Quality Intelligence in Integrated Circuit Manufacturing

RongHao Zhang[1,*]

[1]Beijing University of Posts and Telecommunications, Beijing 100876, China
[*]mirpdq9818@outlook.com

ABSTRACT

Deep learning is increasingly used in integrated circuit manufacturing, but its contribution to quality management depends on how organizations turn analytical outputs into usable information. This study examines the associations among deep learning application capability (DLAC), quality inspection effectiveness (QIE), quality risk identification capability (QRIC), and manufacturing quality performance (MQP). Drawing on organizational information processing theory and a dynamic capability perspective, we propose that DLAC is associated with MQP through the generation of reliable inspection information and its interpretation as quality risk knowledge. A cross-sectional survey of professionals in integrated circuit and related semiconductor manufacturing in mainland China yielded 384 valid responses. Confirmatory factor analysis supported the four-construct measurement model. Covariance-based structural equation modeling showed positive associations between DLAC and QIE ($\beta = 0.54$, $p < 0.001$), DLAC and QRIC ($\beta = 0.25$, $p < 0.001$), QIE and QRIC ($\beta = 0.45$, $p < 0.001$), and QRIC and MQP ($\beta = 0.47$, $p < 0.001$). The sequential indirect association from DLAC to MQP through QIE and QRIC was 0.114 (95% bootstrap confidence interval, 0.073–0.164). These findings suggest that organizational use of deep learning is associated with perceived manufacturing quality performance through two connected information-processing capabilities. The cross-sectional, self-reported data do not establish causal effects or changes in objectively measured production quality.

1 Introduction

Integrated circuit manufacturing generates substantial amounts of information across wafer fabrication, lithography, deposition, etching, packaging, and testing. Small deviations in process conditions, equipment status, or inspection practices can affect product consistency, making the timely interpretation of quality information important for manufacturing operations. Deep learning has expanded the range of patterns that can be identified in semiconductor production data. Applications include fault classification and diagnosis[1], wafer map defect classification[2], defect pattern identification using deep autoencoders[3], and anomaly detection and segmentation[4]. Similar developments have been reported in industrial surface inspection[5] and reviews of wafer defect detection[6]. These studies establish the technical relevance of deep learning to inspection tasks. For an organization, however, identifying a pattern is only one part of quality management. Analytical outputs must also be incorporated into inspection routines, interpreted in relation to production risks, and made available for operational decisions.

This organizational challenge is particularly relevant when manufacturing data and defect patterns vary across production settings. Technical research has addressed imbalanced defect categories[7], changes in defect appearance through transfer learning[8], limited labeled data through semi-supervised learning[9], and the joint localization and classification of defects[10]. These advances can improve the information available to manufacturers, while their contribution to routine quality management depends on how analytical tools are deployed and used. Research on predictive quality describes the conversion of process data into information that can support quality prediction and control[11]. Quality 4.0 research likewise emphasizes the organizational processing and use of manufacturing data[12]. Studies of artificial intelligence and data analytics capabilities suggest that technological resources need to be combined with relevant skills, data, and operational processes to support organizational outcomes[13,14]. Accordingly, the present study defines Deep Learning Application Capability (DLAC) as an organization's capacity to deploy deep learning in manufacturing activities, integrate its outputs with existing information systems and quality routines, and adapt its applications as new data become available[15]. DLAC is an organizational construct rather than a measure of the accuracy of a particular neural network.

The relationship between DLAC and manufacturing quality may depend on how organizations process the information produced by analytical systems. Semiconductor research has extensively examined defect classification, anomaly recognition, and inspection accuracy, while providing less direct evidence about the organizational interpretation and use of these outputs[16]. We distinguish two related capabilities within this process. Quality Inspection Effectiveness (QIE) concerns the generation

of timely and reliable information about defects and abnormalities. Detection alone does not establish the significance of an abnormality for subsequent production stages[17]. Quality Risk Identification Capability (QRIC) concerns the interpretation of inspection and other manufacturing information in terms of risk severity, priority, and potential downstream consequences[18]. Contextualizing and prioritizing quality signals can help connect inspection with operational decisions[19]. Research on Industry 4.0 and manufacturing analytics similarly links digital capabilities to operational outcomes through the integration of information into manufacturing activities and decision processes[20–22]. This distinction between generating quality information and interpreting quality risks provides a basis for examining how DLAC relates to perceived manufacturing quality performance.

We therefore propose an organizational quality intelligence framework comprising DLAC, QIE, QRIC, and Manufacturing Quality Performance (MQP). The framework specifies an expected sequence of associations from DLAC to QIE, from QIE to QRIC, and from QRIC to MQP. It also considers an association between DLAC and QRIC because analytical applications may draw on process, equipment, and historical quality data beyond formal inspection outputs. Organizational Information Processing Theory explains why the capacity to generate and interpret information matters when manufacturing activities are complex and interdependent. A complementary dynamic capability perspective explains why organizations may need to integrate and adapt analytical resources as production conditions change. Prior research has associated the organizational value of AI with the combination of technological resources and adaptive capabilities[23,24], and has examined analytics capability as a resource that can be continually reconfigured[25]. The two perspectives have also been considered together in research on analytics-enabled organizational processes[26]. Using a cross-sectional survey of professionals in integrated circuit and related semiconductor manufacturing, this study tests the proposed associations and the corresponding indirect pathway. The design assesses respondents' reports of organizational capabilities and manufacturing quality performance; it does not evaluate a specific deep learning model or establish changes in objective production outcomes.

2 Literature Review and Hypothesis Development

2.1 Theoretical Foundations of Deep Learning-Enabled Quality Intelligence

The growing use of artificial intelligence in manufacturing has created a need to distinguish the possession of advanced analytical technologies from the organizational capability to use those technologies effectively. Deep learning algorithms can process complex data structures and learn representations that are difficult to specify through fixed rules, but the existence of such algorithms does not guarantee that their outputs will become embedded in manufacturing routines or quality decisions. Research on analytics capability shows that organizational value depends on the ability to combine data, analytical resources, technical expertise, and operational processes rather than on the isolated presence of a particular analytical tool[14]. A similar argument appears in research on artificial intelligence capability, where AI capability is conceptualized as an organizational capacity that combines technological and organizational resources to support broader organizational outcomes[13]. This distinction is particularly relevant to integrated circuit manufacturing because production environments generate information from equipment status, process parameters, wafer inspection, testing, defect records, and quality control activities. These information sources vary in structure, scale, and operational significance. A deep learning application may produce useful analytical results, yet those results have limited organizational value when the system is poorly connected with manufacturing information systems, quality routines, or engineering decisions. Deep Learning Application Capability (DLAC) is thus defined as the organizational ability to apply deep learning technologies to complex manufacturing information, extract useful patterns, deploy analytical models in relevant manufacturing activities, integrate analytical results with existing operational systems, and improve analytical applications as new data become available. This definition treats DLAC as a capability that converts technological resources into an ongoing information processing function. It differs from simple AI adoption because adoption indicates whether a technology is present, while capability reflects whether that technology can be repeatedly and effectively used within manufacturing operations. It also differs from algorithm performance because a model may achieve strong technical accuracy in a controlled data set without being integrated into routine production decisions. Organizational Information Processing Theory provides a suitable theoretical lens for this distinction. The theory views organizations as systems that must develop sufficient information processing capacity to deal with uncertainty, complexity, and interdependence in their operating environments. Integrated circuit manufacturing places substantial demands on information processing because quality outcomes depend on the interpretation of many signals generated across connected production stages. When manufacturing complexity increases, organizations require stronger mechanisms for collecting, filtering, interpreting, and distributing relevant information. Deep learning can contribute to this capacity by identifying complex patterns within large manufacturing data sets and converting raw signals into information that can be used by engineers and quality managers. Research on big data analytics and manufacturing performance supports the broader proposition that advanced analytical resources become valuable when they are embedded in organizational processes and linked with operational use[27]. Evidence concerning the use of big data analytics and artificial intelligence in manufacturing also indicates that operational performance is connected with the capability to deploy analytical technologies within organizational decision processes[21]. Industry 4.0 research reaches a related conclusion by showing that manufacturing benefits depend on how digital technologies are incorporated into production systems rather than on technology

availability alone[28]. From an information processing perspective, DLAC can consequently be viewed as a mechanism that expands the capacity of an integrated circuit manufacturer to interpret complex quality information. This capacity provides the theoretical starting point for examining whether deep learning application capability is associated with more effective inspection and stronger quality risk identification.

Dynamic Capability Theory provides a complementary theoretical explanation for the adaptive nature of deep learning-enabled analytical capability. The dynamic capability perspective emphasizes an organization's ability to integrate, renew, and reconfigure technological and organizational resources as operating conditions change. This perspective has become increasingly relevant to artificial intelligence because the value generated by AI depends not simply on acquiring analytical technologies, but on an organization's ability to combine them with complementary resources and adapt their use over time. Recent evidence shows that AI-enabled dynamic capability can influence organizational outcomes by enabling firms to mobilize and coordinate AI-related resources[23]. Research on the coupling of AI capability and strategic agility similarly indicates that organizations obtain greater value from AI when technological capability is combined with the flexibility to reorganize resources and respond to changing conditions[24]. Research on big data analytics reaches a related conclusion by conceptualizing analytics capability from a dynamic capability perspective in which sensing, resource mobilization, and reconfiguration enable analytical resources to support organizational adaptation and innovation[25]. This perspective is particularly relevant to integrated circuit manufacturing because manufacturing conditions are not static. Product configurations, equipment states, process parameters, defect distributions, inspection requirements, and available data can change as production technologies and operating conditions evolve. Under these circumstances, the quality-related value of deep learning depends not only on the initial deployment of an analytical model but also on the ability to incorporate new manufacturing information, update analytical applications, integrate model outputs with evolving manufacturing systems, and realign analytical processes with changing quality requirements. DLAC can therefore be interpreted as providing an adaptive analytical foundation for the proposed quality intelligence framework. This interpretation does not imply that DLAC is measured as a complete dynamic capability construct in the present study; rather, Dynamic Capability Theory helps explain why the integration, updating, and continued adaptation of AI-enabled analytical resources are important for manufacturing quality intelligence[29]. Recent manufacturing studies provide related evidence that AI adoption and AI-enabled organizational capabilities can be associated with stronger operational and manufacturing performance when AI resources are effectively embedded in organizational and production processes[30].

As illustrated in Figure 1, the proposed architecture consists of three connected stages. The first stage is analytical enablement, in which Deep Learning Application Capability (DLAC) provides the analytical foundation for processing complex manufacturing data, extracting relevant patterns, integrating analytical applications with existing systems, and adapting these applications as new manufacturing information becomes available. This stage reflects the adaptive role of AI-enabled analytical resources emphasized by the dynamic capability perspective. The second stage is quality intelligence processing and contains two distinct information transformations. Quality Inspection Effectiveness (QIE) represents the generation of reliable quality signals through accurate, timely, and consistent identification of manufacturing defects and abnormalities. Quality Risk Identification Capability (QRIC) represents a subsequent interpretive process in which these signals are evaluated in terms of severity, priority, potential downstream effects, and decision relevance. Quality intelligence is thus conceptualized not as a single analytical output, but as a process through which manufacturing data are converted first into reliable quality information and then into actionable risk knowledge. The third stage is the manufacturing outcome represented by Manufacturing Quality Performance (MQP). Risk knowledge provides a stronger informational basis for defect control, process stability, product consistency, abnormality response, and the reduction of quality-related rework and scrap. The architecture also recognizes that deep learning applications may provide direct analytical support for quality risk identification through process, equipment, and historical quality data without relying exclusively on formal inspection outputs. A residual direct association between DLAC and MQP is retained because AI-enabled analytical capability may also contribute to manufacturing quality through other operational mechanisms. The architecture consequently provides a broader theoretical representation of the quality intelligence process, while the subsequent conceptual model specifies the structural relationships examined empirically.

2.2 Deep Learning Application Capability and Quality Inspection Effectiveness

Quality inspection is a fundamental information generating activity in integrated circuit manufacturing because decisions about abnormal products, process adjustment, rework, and further investigation depend on the reliability of inspection results. Quality Inspection Effectiveness (QIE) refers to the extent to which manufacturing defects and abnormalities are detected accurately, promptly, sensitively, and consistently[31]. The construct concerns the performance of the inspection process as an organizational activity rather than the accuracy of one specific algorithm. Traditional semiconductor inspection can combine statistical control, engineering rules, image inspection, manual review, and automated measurement. These methods remain important, but complex defect patterns may be difficult to represent through predefined features or fixed thresholds[32]. Deep learning provides a different analytical mechanism because relevant patterns can be learned directly from manufacturing data. Early research

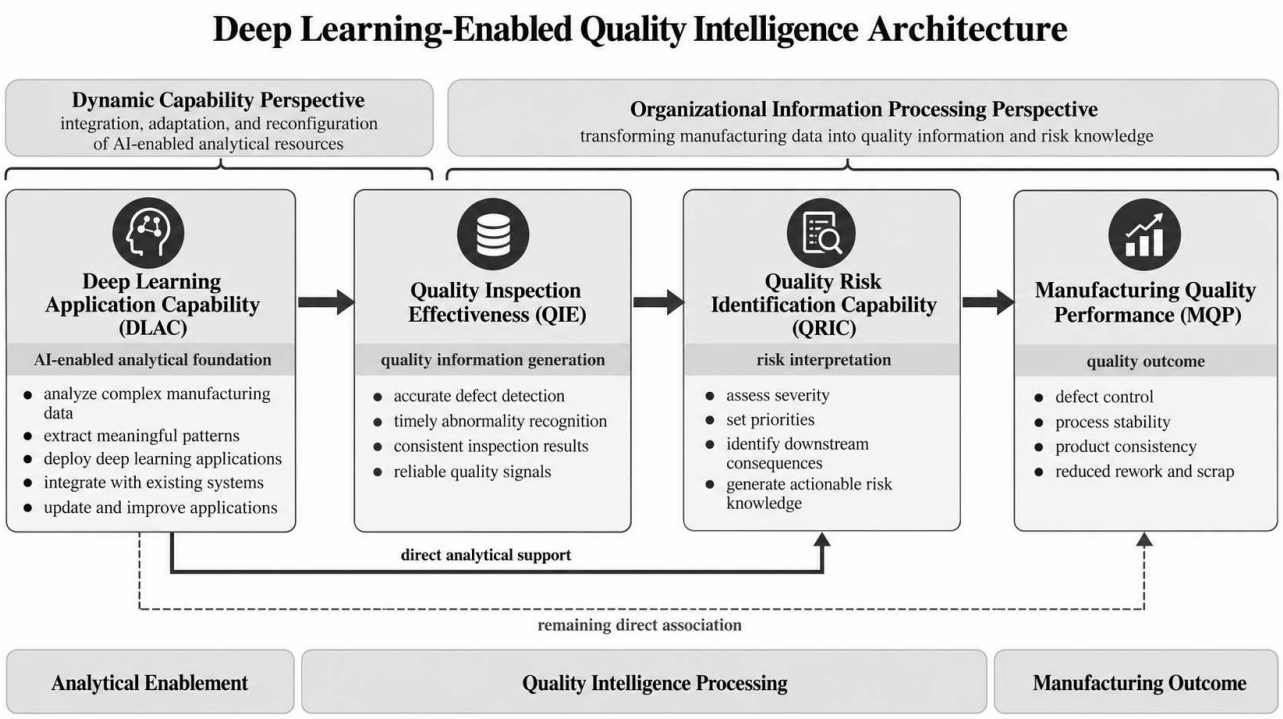


Figure 1. Deep Learning-Enabled Quality Intelligence Architecture. The architecture integrates the Dynamic Capability perspective with the Organizational Information Processing perspective. DLAC provides the AI-enabled analytical foundation through which manufacturing data and analytical resources are integrated, adapted, and renewed. QIE represents the generation of reliable quality information from manufacturing defects and abnormalities, while QRIC represents the interpretation of quality information into risk knowledge concerning severity, priority, and downstream consequences. MQP represents the resulting manufacturing quality outcome. The architecture distinguishes analytical enablement, quality intelligence processing, and manufacturing outcome as related stages of AI-enabled quality intelligence in integrated circuit manufacturing.

on semiconductor fault classification showed that convolutional neural networks could extract process related representations and support automated diagnosis of manufacturing faults[1]. Wafer map studies provide further evidence that convolutional models can recognize spatial defect patterns without depending entirely on manually constructed descriptors[2]. Deep encoder and decoder architectures have also been used for anomaly detection and defect segmentation, illustrating the capacity of deep models to identify unusual patterns that differ from expected wafer structures[4]. These capabilities are relevant to QIE because effective inspection requires more than identifying highly visible defects. Manufacturing environments often contain rare defects, subtle abnormal signals, mixed patterns, and substantial variation in defect frequency. Research on imbalanced semiconductor data demonstrates that defect recognition performance can be affected when some defect categories occur much less frequently than others[7]. The use of transfer learning provides another route for strengthening recognition when the available manufacturing data are limited or when learned representations must be adapted to new inspection conditions[8]. Semi supervised methods also indicate that useful inspection knowledge can be developed when only part of a large manufacturing data set has been labeled by experts[9]. The relevance of these findings at the organizational level lies in the capacity to convert such analytical methods into a stable inspection process. A manufacturer with stronger DLAC is more capable of analyzing complex inspection information, learning useful representations from historical quality data, integrating model outputs with existing inspection systems, and adapting analytical applications when new production conditions emerge. These capabilities can reduce excessive dependence on fixed inspection rules and support more consistent analysis across repeated production activities. Reviews of industrial defect detection show that deep learning has become an important method for identifying complex surface defects and improving automated inspection across a range of manufacturing settings[33]. Research focused on industrial surface inspection also indicates that learned visual features can support defect recognition under conditions in which defect appearance varies substantially[5]. The relationship proposed here does not imply that any deep learning system automatically creates effective quality inspection. The theoretical expectation concerns organizational capability. When an integrated circuit manufacturer has stronger DLAC, the organization has greater capacity to select, deploy, integrate, and improve deep learning applications that support inspection tasks. This greater information processing capacity should be

reflected in more accurate defect identification, faster recognition of abnormalities, stronger sensitivity to complex defects, and more consistent inspection results. These arguments lead to the first hypothesis. H1: Deep learning application capability is positively associated with quality inspection effectiveness in integrated circuit manufacturing.

2.3 Deep Learning, Quality Inspection, and Quality Risk Identification

Detecting an abnormality and identifying the quality risk associated with that abnormality represent two related but distinct stages of manufacturing information processing. QIE concerns the detection of current manufacturing conditions, while Quality Risk Identification Capability (QRIC) concerns the interpretation of what those conditions may imply for manufacturing quality[34]. QRIC is defined as the organizational ability to identify potential quality risks, distinguish different levels of risk, recognize issues that require priority attention, evaluate possible effects on subsequent manufacturing processes, and generate risk information that supports quality decisions. The distinction is important because not every detected abnormality has the same operational significance[35]. Some abnormalities may remain localized, while others may indicate unstable process conditions, repeated defects, downstream quality problems, or a need for rapid engineering intervention. Deep learning application capability can contribute directly to QRIC because the analytical scope of deep learning is not limited to visual defect classification. Manufacturing data can contain relationships among process parameters, equipment signals, historical defect records, inspection results, and quality outcomes[36]. Deep learning applications can support the identification of complex patterns across these information sources when the necessary data and organizational integration are available. Predictive quality research shows that machine learning and deep learning methods are increasingly used to connect manufacturing process information with expected quality outcomes[11]. Such applications move analytical activity beyond the identification of existing defects toward the recognition of patterns that may contain information about future or downstream quality states. Quality 4.0 research similarly emphasizes that data intensive quality management requires analytical capabilities that can transform large manufacturing data sets into useful information for quality decisions[12]. These studies do not define QRIC in the same organizational terms adopted here, but they support the broader idea that advanced analytics can contribute to the interpretation of manufacturing information before quality problems become more difficult to manage. An organization with stronger DLAC should be better able to identify weak risk signals, connect information from different manufacturing activities, and interpret patterns that may not be visible through a single quality indicator[37]. This reasoning supports a direct association between DLAC and QRIC. The relationship between QIE and QRIC represents a second and conceptually different pathway. Inspection systems generate information about current defects and abnormalities. When this information is accurate, timely, and consistent, it creates a stronger basis for evaluating the potential significance of the detected condition. Defect localization and classification research demonstrates that richer inspection outputs can provide information not only about whether a defect is present but also about its type and location[38]. Methods that combine segmentation and classification provide an even more detailed representation of defect characteristics by identifying both defect regions and their categories[10]. Attention based wafer defect methods also show that analytical models can focus on informative regions or features within complex wafer patterns[39]. At the organizational level, richer and more reliable inspection information can improve the evidence available for risk interpretation. A defect that is detected inconsistently or too late provides a weak basis for priority setting, while a defect that is detected accurately and linked to relevant process information can be assessed more effectively in terms of severity and potential downstream impact[40]. QIE can consequently be understood as an information quality condition for QRIC. Strong inspection effectiveness supplies reliable signals, while risk identification transforms those signals into judgments about importance, priority, and possible manufacturing consequences[41]. This distinction also reduces conceptual overlap between the two constructs. QIE concerns the effectiveness of recognizing what abnormality is present. QRIC concerns the capability to interpret what risk that abnormality may represent. The proposed relationships lead to two hypotheses. H2: Deep learning application capability is positively associated with quality risk identification capability in integrated circuit manufacturing. H3: Quality inspection effectiveness is positively associated with quality risk identification capability.

2.4 Quality Risk Identification and Manufacturing Quality Performance

Manufacturing Quality Performance (MQP) reflects the quality outcomes associated with the ability of an organization to maintain stable production, control defects, preserve product consistency, respond effectively to abnormalities, and limit quality related rework and scrap. In integrated circuit manufacturing, such outcomes depend not only on detecting defects but also on deciding which detected conditions require attention and how quality information should be incorporated into operational action[42]. QRIC is relevant to this process because risk identification converts observations about defects and process abnormalities into information about their potential importance. When quality risks can be recognized early and differentiated by severity, engineering and quality resources can be directed toward issues with greater potential consequences[43]. Risk identification can also support the prioritization of process investigation, additional inspection, equipment review, or corrective action before a quality problem becomes more widespread. This logic is consistent with predictive quality research, where manufacturing information is used to anticipate quality related outcomes and support earlier operational responses[11]. The broader Quality 4.0 literature also describes quality management as an increasingly data intensive activity in which

analytical information supports faster and more informed quality decisions[12]. The relationship between digital capability and operational outcomes has been examined from several complementary perspectives. Research on Industry 4.0 technologies suggests that digital manufacturing technologies can contribute to industrial performance when they are integrated with operational processes[20]. Studies of big data analytics and manufacturing performance provide related evidence that analytical capabilities can be associated with improvements in operational outcomes[27]. The combination of big data analytics and artificial intelligence has also been linked with operational performance in manufacturing organizations, particularly when analytical resources are supported by suitable organizational conditions[21]. Evidence from digital transformation research in manufacturing indicates that stronger digital development can be associated with improved firm performance, including evidence from Chinese manufacturing settings[44]. Research focused more directly on digital capability reaches a similar conclusion by linking manufacturing capability development with stronger organizational performance[22]. These findings support the broader relationship between information related capability and manufacturing outcomes, while the present framework identifies QRIC as a more specific quality management mechanism. QRIC should be especially relevant to MQP because it addresses the interpretation and prioritization of quality related information before operational responses are selected[45]. An organization that can distinguish low priority abnormalities from high risk quality conditions can allocate engineering attention more efficiently and reduce the possibility that important warning signals remain untreated. Stronger QRIC can also improve communication between inspection functions, process engineers, quality managers, and production personnel by translating technical observations into risk information that is easier to incorporate into quality decisions[46]. This mechanism does not imply that risk identification alone determines manufacturing performance, since quality outcomes also depend on process capability, equipment conditions, workforce expertise, supplier quality, and other operational factors. The theoretical expectation is narrower: organizations with stronger QRIC should be better positioned to use quality information in ways that support defect control, production stability, product consistency, abnormality response, and the control of rework and scrap. This reasoning leads to the fourth hypothesis. H4: Quality risk identification capability is positively associated with manufacturing quality performance.

2.5 Sequential Mediation Mechanism and Conceptual Model

The relationships developed above suggest that the organizational value of deep learning in integrated circuit manufacturing can be understood as a sequence of information processing capabilities rather than as a single direct link between technology and performance. DLAC represents the capacity to transform complex manufacturing data into useful analytical information. QIE represents the effectiveness with which information about current defects and abnormalities is generated. QRIC represents the capability to interpret that information in terms of potential quality significance, priority, and downstream consequences. MQP represents the quality related outcomes associated with the broader manufacturing management process. This sequence is consistent with the central reasoning of Organizational Information Processing Theory because each stage converts available information into a form that is more directly useful for subsequent organizational action. Strong DLAC expands the ability to process complex manufacturing data, but its operational value is more likely to emerge when analytical capacity becomes embedded in specific quality activities. Research on artificial intelligence capability suggests that AI related resources contribute to organizational outcomes through the capabilities that allow those resources to be deployed and coordinated within organizational processes[13]. Studies of analytics capability similarly indicate that analytical resources create value when they are aligned with operational and strategic activities[14]. In the proposed model, QIE represents the first transformation of DLAC into a quality specific operational capability. Deep learning applications support the recognition of patterns in manufacturing information, while effective inspection converts those analytical functions into reliable evidence about current abnormalities. The second transformation occurs when inspection information is interpreted as quality risk. QRIC gives operational meaning to the detected abnormality by evaluating its potential seriousness, priority, and influence on later production stages. This stage is conceptually important because detecting a defect does not automatically specify the managerial response that the defect requires. Predictive quality research supports the value of moving from current process information toward forward looking interpretations of manufacturing quality[11]. The third stage connects risk information with manufacturing quality performance. Once quality risks are recognized and prioritized, the organization has a stronger informational basis for allocating attention, initiating investigation, adjusting quality control activities, and responding to abnormalities. The proposed sequence can thus be represented as DLAC $\rightarrow$ QIE $\rightarrow$ QRIC $\rightarrow$ MQP. A direct path from DLAC to QRIC is retained because risk related information may also be extracted from process, equipment, and historical quality data without passing entirely through the formal inspection process. A direct path from DLAC to MQP can be estimated in the structural model to distinguish the proposed sequential indirect association from any residual direct association, but this path is not specified as a separate hypothesis. The theoretical contribution of the sequential model lies in explaining how a broad technological capability may become connected with quality performance through two distinct organizational information processes. It also prevents quality inspection and quality risk identification from being treated as interchangeable outcomes. The first concerns the generation of reliable information about present abnormalities, while the second concerns the interpretation of that information in terms of

possible manufacturing consequences. This ordered mechanism links technological capability, inspection information, risk knowledge, and quality performance within one framework. Since the empirical design measures the constructs at a single point in time, the proposed sequence represents a theoretically ordered statistical model rather than direct evidence that the variables occur in a confirmed temporal sequence. Bootstrap analysis can assess whether the indirect association linking DLAC with MQP through QIE and QRIC is statistically supported, while longitudinal research would be required to establish temporal ordering more directly. The conceptual model summarizes these proposed relationships and provides the basis for the structural analysis. H5: Quality inspection effectiveness and quality risk identification capability sequentially mediate the association between deep learning application capability and manufacturing quality performance.

The complete conceptual framework is presented in Figure 2. The model distinguishes the four focal constructs and specifies the relationships examined in the empirical analysis. H1 represents the association between Deep Learning Application Capability (DLAC) and Quality Inspection Effectiveness (QIE), while H2 represents the association between DLAC and Quality Risk Identification Capability (QRIC). H3 connects QIE with QRIC, reflecting the proposition that reliable information about current quality abnormalities provides an important basis for evaluating their potential manufacturing significance. H4 links QRIC with Manufacturing Quality Performance (MQP), representing the expected association between stronger risk identification and better quality related manufacturing outcomes. H5 concerns the sequential indirect association in which DLAC is linked with MQP through QIE and QRIC. The structural model also estimates a direct path from DLAC to MQP so that the sequential indirect association can be assessed while accounting for any remaining direct relationship. This additional path is included for model estimation and is not specified as a separate hypothesis.

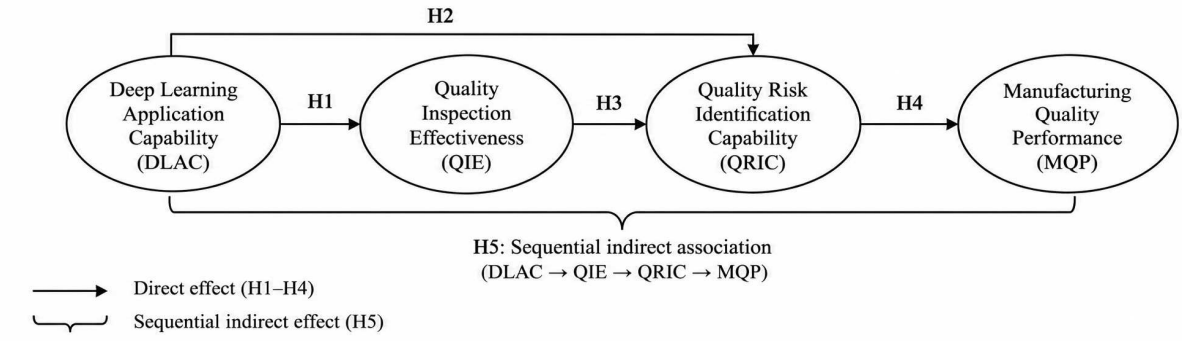


Figure 2. Conceptual model and hypothesized relationships. The model presents the proposed relationships among Deep Learning Application Capability (DLAC), Quality Inspection Effectiveness (QIE), Quality Risk Identification Capability (QRIC), and Manufacturing Quality Performance (MQP). H1–H4 represent the hypothesized structural associations, while H5 represents the sequential indirect association from DLAC to MQP through QIE and QRIC. The direct DLAC to MQP path is estimated in the structural model but is not specified as a separate hypothesis.

3 Methodology

3.1 Research Design and Participants

The study employed a cross sectional questionnaire design to examine the relationships among Deep Learning Application Capability (DLAC), Quality Inspection Effectiveness (QIE), Quality Risk Identification Capability (QRIC), and Manufacturing Quality Performance (MQP) in the context of integrated circuit manufacturing in China. The unit of analysis was the organizational manufacturing context as perceived by professionals who had sufficient knowledge of production, quality, process, equipment, automation, data analysis, or related management activities. This design was selected because the proposed model focuses on organizational capabilities and quality management outcomes that require information from employees who are directly familiar with manufacturing operations and the use of digital technologies. Questionnaire based measurement also allowed the four latent constructs to be assessed through multiple indicators and provided a consistent basis for the subsequent confirmatory factor analysis and structural equation modeling. The study focused on organizations engaged in integrated circuit manufacturing, wafer fabrication, semiconductor packaging, testing, and closely related manufacturing services. Restricting the research setting to China maintained consistency in the institutional and industrial environment and reduced the additional variation that could arise from combining respondents operating under substantially different national manufacturing systems.

Eligible participants were professionals employed in semiconductor or integrated circuit related organizations in mainland China. Participation was limited to respondents whose work was associated with production, process engineering, quality management, equipment engineering, manufacturing engineering, automation, digitalization, data analysis, artificial intelligence

applications, or relevant technical and managerial functions. Respondents were required to have at least six months of work experience in the semiconductor or integrated circuit industry so that their evaluations were based on sufficient exposure to the manufacturing environment. They were also required to possess at least a moderate level of knowledge concerning the use of artificial intelligence or deep learning in their organization. Individuals who reported little or no knowledge of such applications were screened out because reliable assessment of DLAC depends on familiarity with the organization's technological practices. This screening criterion was especially important because DLAC was measured as an organizational capability rather than as a respondent's personal technical skill. The survey did not require participants to be deep learning specialists. Process engineers, quality engineers, production personnel, equipment engineers, automation specialists, digital technology personnel, and managers were considered suitable respondents when their roles provided sufficient exposure to manufacturing quality activities and the organization's use of intelligent analytical systems.

Participation was voluntary, and respondents received an introductory statement explaining the academic purpose of the survey, the general content of the research, the expected completion time, and the confidential treatment of responses. No personal names, identity numbers, or specific company names were required. Participants were instructed to evaluate each statement according to the actual conditions of their current organization rather than according to general opinions about artificial intelligence or semiconductor technology. Five screening questions were presented before the main questionnaire. These questions confirmed that the respondent worked in mainland China, that the organization was involved in integrated circuit manufacturing or related manufacturing activities, that the respondent's role was connected with relevant operational or technical functions, that the respondent had sufficient industry experience, and that the respondent had adequate knowledge of artificial intelligence or deep learning applications within the organization. Responses that did not satisfy the eligibility criteria were excluded before the main analysis. This procedure was intended to increase the relevance of the collected information and to ensure that the four focal constructs reflected informed assessments of manufacturing practices rather than general perceptions of digital technology.

3.2 Questionnaire Development and Measures

The questionnaire was developed to operationalize the four organizational constructs that constitute the proposed deep learning enabled quality intelligence framework: Deep Learning Application Capability (DLAC), Quality Inspection Effectiveness (QIE), Quality Risk Identification Capability (QRIC), and Manufacturing Quality Performance (MQP). The measurement design followed the theoretical roles assigned to the four constructs in the framework. DLAC captures the analytical foundation that enables organizations to apply deep learning to complex manufacturing information. QIE captures the generation of reliable information about current defects and abnormalities. QRIC captures the interpretation of quality information into risk knowledge concerning severity, priority, and possible downstream consequences. MQP captures the manufacturing quality outcomes associated with defect control, process stability, product consistency, abnormality response, and the control of rework and scrap. All core items were measured using a five point Likert scale ranging from 1 for strongly disagree to 5 for strongly agree. Respondents were instructed to evaluate the statements according to the actual practices and conditions of their current organization rather than their personal technical ability or general attitudes toward artificial intelligence. This organizational reference point was maintained throughout the questionnaire because the proposed framework concerns organizational analytical capability, quality information processing, and manufacturing quality outcomes. The operationalization of DLAC was informed by research that conceptualizes artificial intelligence capability as the organizational ability to combine technological resources with organizational processes[13]. Research on analytics capability similarly indicates that the value of advanced analytical technologies depends on the organizational capacity to transform data and analytical resources into information that can support operational activities[14]. Consistent with this reasoning, the DLAC items assess the ability to analyze complex manufacturing data, extract meaningful patterns, deploy deep learning applications, integrate analytical outputs with existing manufacturing and quality systems, and update analytical applications as new data become available. The QIE and QRIC measures were designed to represent two distinct stages of quality intelligence processing. QIE focuses on the effectiveness of generating reliable information about current manufacturing defects and abnormalities through accurate, timely, sensitive, and consistent inspection. QRIC focuses on the subsequent interpretation of manufacturing and inspection information in terms of potential risk, priority, and downstream consequences. This distinction is consistent with predictive quality research, which emphasizes that manufacturing data must not only support defect recognition but also provide information that can guide quality prediction and decision support[11]. MQP was operationalized as the perceived quality performance of the manufacturing organization, including defect control, process quality stability, product consistency, effective response to abnormalities, and control of quality related rework and scrap. Table 1 presents the operational content and complete set of 20 measurement items used to assess the four constructs.

The wording of the measurement items was structured to preserve the conceptual boundaries among the four latent constructs. DLAC measures organizational analytical enablement rather than the technical accuracy of an individual deep learning model. QIE measures the quality of information generated through inspection, including accuracy, timeliness, sensitivity, consistency,

Table 1. Measurement constructs and questionnaire items for the deep learning enabled quality intelligence framework. The four latent constructs represent analytical enablement, quality information generation, quality risk interpretation, and manufacturing quality outcomes. All items were measured using a five point Likert scale ranging from 1 for strongly disagree to 5 for strongly agree.

Construct	Code	Measurement item
Deep Learning Application Capability	DLAC1	Our organization can use deep learning technologies to analyze complex data generated during integrated circuit manufacturing.
	DLAC2	Our organization can use deep learning technologies to automatically extract meaningful patterns and features from manufacturing data.
	DLAC3	Deep learning models have been effectively incorporated into relevant manufacturing or quality management activities in our organization.
	DLAC4	Our organization can integrate deep learning analysis with existing manufacturing and quality management information systems.
	DLAC5	Our organization can update and improve deep learning based analytical applications as new manufacturing data become available.
Quality Inspection Effectiveness	QIE1	Our quality inspection processes can accurately identify manufacturing defects and abnormalities.
	QIE2	Quality abnormalities can be detected in a timely manner during the manufacturing process.
	QIE3	Our inspection processes are effective in detecting small, subtle, or complex manufacturing defects.
	QIE4	Quality inspection results remain consistent across similar production conditions and inspection tasks.
	QIE5	Our quality inspection processes are effective at minimizing missed defects and incorrect defect identifications.
Quality Risk Identification Capability	QRIC1	Our organization can identify potential quality risks before they develop into serious manufacturing problems.
	QRIC2	Our organization can distinguish quality problems with different levels of manufacturing risk.
	QRIC3	Our organization can identify quality risks that require priority attention or intervention.
	QRIC4	Our organization can assess whether detected abnormalities may affect subsequent manufacturing processes or product quality.
	QRIC5	The quality risk information generated in our organization provides useful support for manufacturing quality decisions.
Manufacturing Quality Performance	MQP1	Our organization performs well in controlling manufacturing defects and nonconforming products.
	MQP2	Our manufacturing processes maintain a high level of quality stability.
	MQP3	Our organization maintains consistent product quality across manufacturing operations.
	MQP4	Our organization responds effectively to manufacturing quality abnormalities when they occur.
	MQP5	Our organization performs well in controlling quality related rework and scrap.

and the control of missed or incorrect defect identification. QRIC measures the interpretation of detected abnormalities and other manufacturing information as quality risk knowledge, including risk recognition, differentiation, prioritization, downstream assessment, and decision usefulness. MQP measures manufacturing quality outcomes and does not reproduce the inspection or risk interpretation content represented by QIE and QRIC. This distinction is particularly important to the proposed quality intelligence framework because QIE and QRIC represent consecutive but conceptually different information processing stages. QIE concerns whether manufacturing abnormalities are identified reliably, whereas QRIC concerns what those abnormalities imply for manufacturing risk and subsequent quality decisions. The separation of these constructs allows the empirical model to distinguish quality information generation from quality risk interpretation rather than treating them as a single quality management capability. All 20 substantive items were positively worded and maintained an organizational reference point through expressions such as "our organization" and "our quality inspection processes." For descriptive analysis, each construct score was calculated as the mean of its five corresponding items. In the confirmatory factor analysis, the 20 individual items were treated as observed indicators of their respective latent constructs. Reliability, convergent validity, and discriminant validity were evaluated before estimation of the structural relationships. The principal measurement criteria are summarized in Table 2.

Table 2. Criteria used for assessment of the measurement model. The criteria were applied to evaluate indicator representation, internal consistency, convergent validity, and discriminant validity before estimation of the structural model.

Assessment	Criterion	Interpretation
Standardized factor loading	Preferably ≥ 0.70	Values of approximately 0.70 or above indicate strong representation of the latent construct, while substantially lower values require closer examination.
Cronbach's alpha	≥ 0.70	Indicates acceptable internal consistency among the indicators of a latent construct.
Composite reliability	≥ 0.70	Indicates acceptable construct reliability and consistency among the corresponding indicators.
Average variance extracted	≥ 0.50	Indicates that the latent construct explains at least half of the variance in its observed indicators.
HTMT ratio	< 0.85	Indicates adequate discriminant validity between pairs of latent constructs.

3.3 Sampling, Data Collection, and Quality Control

A purposive sampling strategy was used because valid assessment of the proposed constructs required respondents with direct knowledge of semiconductor manufacturing and organizational quality practices. Recruitment was restricted to professionals working in mainland China in organizations involved in integrated circuit manufacturing, wafer fabrication, semiconductor packaging, testing, or closely related manufacturing services. Participants were approached through professional contacts in semiconductor enterprises, industry oriented technical communities, manufacturing and quality management networks, and referrals from eligible respondents. Snowball recruitment was used as a supplementary approach to reach professionals whose work involved process engineering, quality engineering, manufacturing, equipment, automation, digital technology, artificial intelligence, or related managerial functions. The recruitment process was not intended to produce a probability sample of the entire Chinese semiconductor workforce. Its purpose was to obtain informed organizational assessments from respondents who possessed sufficient knowledge of the manufacturing environment examined in the conceptual model. A target of at least 350 valid questionnaires was established before structural analysis, with recruitment continuing toward approximately 400 valid responses when access permitted. This range was selected to provide a sufficiently large analytic sample for estimation of the four latent constructs, 20 observed indicators, structural paths, control variables, and bootstrap indirect effects. The questionnaire was administered electronically, and each participant first reviewed the study information and eligibility conditions before entering the core survey. No company name or directly identifying personal information was requested.

Data collection incorporated screening procedures before the 20 core measurement items were displayed. Respondents were required to confirm that they currently worked in mainland China, that their organization participated in integrated circuit manufacturing or a directly related manufacturing activity, and that their professional role involved a relevant technical, operational, quality, digital, or managerial function. At least six months of semiconductor or integrated circuit industry experience was required. Participants also indicated their level of familiarity with artificial intelligence or deep learning applications in their organization. Responses from individuals reporting little or no familiarity were not included because DLAC requires an informed evaluation of organizational technological capability. After the eligibility stage, the questionnaire

presented the DLAC, QIE, QRIC, and MQP measures, followed by professional and organizational background questions. An attention item was embedded between the principal measurement blocks and instructed respondents to select a specified response category. The item was used as one component of data quality assessment rather than as an automatic exclusion rule in isolation. Table 3 summarizes the eligibility and quality screening criteria applied during preparation of the analytic data set.

Table 3. Eligibility and data quality criteria used for questionnaire screening. The table summarizes the predefined criteria used to determine whether a response provided sufficiently relevant and reliable information for the subsequent measurement and structural analyses. Exclusion decisions were based on eligibility requirements and multiple indicators of response quality rather than on statistical results obtained from the hypothesis tests.

Assessment area	Criterion	Treatment in data preparation
Geographic eligibility	Current employment located in mainland China	Responses from participants working outside mainland China were excluded.
Industry eligibility	Organization involved in integrated circuit manufacturing, wafer fabrication, packaging, testing, or directly related manufacturing activities	Responses outside the defined semiconductor manufacturing context were excluded.
Professional relevance	Role related to production, process, quality, equipment, automation, digital technology, data analysis, artificial intelligence, or relevant management	Responses without sufficient connection to manufacturing or quality activities were excluded.
Industry experience	At least six months of semiconductor or integrated circuit industry experience	Responses below the minimum experience requirement were excluded.
Knowledge of AI applications	At least a moderate level of familiarity with organizational AI or deep learning applications	Respondents reporting little or no familiarity were screened out before the core questionnaire.
Questionnaire completeness	Core DLAC, QIE, QRIC, and MQP items completed	Responses with substantial missing information in the core measurement section were excluded.
Completion time	Completion duration consistent with careful reading of the questionnaire	Extremely short completion times were flagged and evaluated together with other response quality indicators.
Attention item	Correct response to the embedded attention instruction	An incorrect response triggered further quality review and was not used as the sole basis for automatic exclusion.
Response pattern	Sufficient variation across the 20 substantive items	Near uniform response patterns were examined for straight line responding and retained only when other response characteristics indicated credible participation.
Duplicate submission	No clear evidence of repeated submission from the same respondent	Duplicate records identified through available technical and response pattern information were removed before analysis.

The quality control process was completed before confirmatory factor analysis and hypothesis testing so that decisions about case retention were not influenced by the direction or significance of the structural relationships. Questionnaire completeness, completion duration, attention performance, repeated response patterns, and potential duplicate submissions were examined jointly. Extremely rapid responses were treated as warning signals rather than automatic evidence of invalid participation because completion speed may differ across respondents with different levels of familiarity with the topic. Straight line patterns were evaluated in the same manner, since consistent responses can be legitimate when they reflect a respondent's actual assessment of organizational practices. Cases were removed when multiple indicators suggested insufficient engagement, unreliable completion, or failure to meet the eligibility criteria. The resulting analytic data set was then used for descriptive statistics, measurement model assessment, and structural equation modeling. Because purposive and referral based recruitment was used, sample characteristics are interpreted as the composition of the analytic respondent group rather than as evidence that the sample statistically represents every professional or enterprise in the Chinese integrated circuit industry. This sampling boundary is retained when interpreting the structural associations and their broader applicability.

3.4 Control Variables and Common Method Bias

Four control variables were included in the structural analysis to reduce the possibility that the principal relationships among DLAC, QIE, QRIC, and MQP reflected differences in respondent experience or organizational context. Work experience was included because professionals with longer exposure to semiconductor manufacturing may have greater familiarity with

production processes, quality problems, and digital systems. Position level was controlled because respondents with greater managerial responsibility may have broader access to information concerning organizational technology use and quality performance. Enterprise size was included because larger organizations may possess more extensive digital infrastructure, analytical resources, and formal quality management systems than smaller organizations. Enterprise type was also controlled because wafer fabrication, integrated device manufacturing, packaging, testing, and related manufacturing services can differ in process structure, inspection requirements, and patterns of technology adoption. Work experience, position level, and enterprise size were represented as ordered observed variables based on the questionnaire categories. Enterprise type was treated as a nominal variable and represented through indicator variables in the structural analysis, with one category used as the reference group. The control variables were entered as covariates of MQP in the principal model, while supplementary models also examined their relationships with QIE and QRIC to evaluate whether the estimated H1 to H5 relationships remained stable after accounting for respondent and organizational characteristics.

Common method bias was considered because DLAC, QIE, QRIC, and MQP were measured through the same questionnaire and reported by the same respondent at one point in time. Several procedural measures were incorporated into the survey design before statistical analysis. Participation was anonymous, no company name or directly identifying information was requested, and respondents were informed that the questionnaire had no correct or preferred responses. The wording of the four constructs was kept conceptually distinct so that items measuring technological capability, current quality inspection, risk interpretation, and manufacturing performance did not repeat the same content. Respondents were instructed to evaluate organizational practices according to their work knowledge rather than provide general opinions about artificial intelligence. Statistical assessment of common method bias was conducted after data screening and before evaluation of the structural hypotheses. An unrotated exploratory factor analysis was first used to determine whether a single factor accounted for a dominant proportion of the variance. A confirmatory one factor model in which all 20 measurement items loaded on a single latent factor was then compared with the proposed four factor measurement model. Substantially poorer fit of the one factor model was treated as evidence against the proposition that a single common source factor adequately explained the observed covariance structure. A supplementary common latent factor analysis was also used as a sensitivity assessment, and the substantive structural paths were reexamined to determine whether their direction and magnitude remained stable after consideration of common method variance.

3.5 Data Analysis Strategy

Data analysis was conducted in a sequence that separated preliminary data assessment, measurement model evaluation, and structural hypothesis testing. After completion of the eligibility and response quality screening procedures, the retained data were examined for missing values, response distributions, and potential extreme observations. Descriptive statistics were calculated for the demographic variables and the four principal constructs, including means, standard deviations, and bivariate correlations. The distributions of the measurement items were also examined before structural equation modeling to identify substantial departures from normality. Covariance based structural equation modeling was used because the proposed framework specifies theoretically defined latent constructs and directional relationships among DLAC, QIE, QRIC, and MQP. Confirmatory factor analysis was conducted before estimation of the structural model. The proposed four factor measurement model contained 20 observed indicators, with five indicators assigned to each latent construct. Model fit was evaluated using the chi square to degrees of freedom ratio, Comparative Fit Index, Tucker Lewis Index, Root Mean Square Error of Approximation, and Standardized Root Mean Square Residual. A chi square to degrees of freedom ratio below 5 was considered acceptable and a value below 3 was considered preferable. CFI and TLI values of at least 0.90 indicated acceptable fit, while values approaching or exceeding 0.95 indicated stronger fit. RMSEA values of 0.08 or lower and SRMR values of 0.08 or lower were treated as acceptable, while values near or below 0.06 for RMSEA and 0.05 for SRMR indicated stronger model fit.

Measurement quality was evaluated before testing the hypothesized structural relationships. Standardized factor loadings were examined to determine whether the observed items adequately represented their intended latent constructs, with values of approximately 0.70 or higher regarded as desirable. Cronbach's alpha and composite reliability were used to evaluate internal consistency, and values of at least 0.70 were considered acceptable. Average variance extracted was calculated for each construct, with values of at least 0.50 indicating adequate convergent validity. Discriminant validity was evaluated primarily through the heterotrait monotrait ratio, using a value below 0.85 as the principal criterion for distinguishing the four latent constructs. Particular attention was given to the distinction between QIE and QRIC because these constructs represent consecutive but conceptually different stages of quality information processing. The proposed four factor solution was also compared with more restrictive alternative measurement models, including a one factor model in which all measurement items were assigned to a single latent construct. Measurement model adequacy was established before interpretation of the structural relationships.

The structural model was estimated according to the conceptual relationships presented in Figure 2. H1 was evaluated through the association between DLAC and QIE, H2 through the association between DLAC and QRIC, H3 through the

association between QIE and QRIC, and H4 through the association between QRIC and MQP. Standardized path coefficients, standard errors, confidence intervals, and significance levels were reported for the principal structural relationships. Work experience, position level, enterprise size, and enterprise type were incorporated as control variables. H5 was evaluated by estimating the sequential indirect association from DLAC to MQP through QIE and QRIC. Bootstrap estimation based on 5,000 resamples was used to obtain bias corrected 95 percent confidence intervals for the indirect effects. The sequential indirect association was considered statistically supported when its bootstrap confidence interval did not include zero. The model also estimated the direct association between DLAC and MQP to assess the sequential indirect pathway while accounting for any remaining direct relationship, but this path was not specified as an additional hypothesis. Specific indirect associations through QIE and QRIC were examined alongside the complete sequential pathway. Statistical significance was evaluated at the 0.05 level. Robustness analyses examined whether the direction and substantive magnitude of the principal relationships remained stable after inclusion of the control variables and consideration of common method variance. Since all focal variables were collected through a cross sectional questionnaire at a single point in time, the structural coefficients and bootstrap indirect effects were interpreted as statistical associations rather than evidence of established temporal or causal mechanisms.

3.6 Ethics approval and informed consent

Under the institutional research ethics requirements applicable at Beijing University of Posts and Telecommunications, formal ethics review was not required for the present study because it involved voluntary, anonymous, and non-interventional questionnaire-based data collection from adults, collected no directly identifying information or sensitive personal data, and posed no more than minimal risk to participants. All methods were carried out in accordance with applicable institutional guidelines and regulations and the principles of the Declaration of Helsinki. Before participation, all participants received information about the purpose and procedures of the study, the intended use and handling of the data, their right to withdraw, and the measures adopted to protect privacy and confidentiality. Participation was voluntary, and electronic informed consent was obtained from all participants before data collection. All data were anonymized before analysis, and no personally identifiable information was included in the manuscript.

4 Results

4.1 Sample Characteristics and Descriptive Statistics

A total of 412 survey submissions were recorded during the data collection period. After application of the predefined eligibility and response quality criteria, 28 responses were excluded, leaving 384 questionnaires for analysis and corresponding to a retention rate of 93.2%. Exclusions reflected failure to satisfy the eligibility requirements, substantial missing information in the core measurement items, combinations of attention-check failure and unusually short completion time, response patterns indicating insufficient engagement, or duplicate submissions. No response was removed solely because of an incorrect response to the attention item. The final analytic sample consisted entirely of professionals working in mainland China in integrated circuit manufacturing or closely related semiconductor manufacturing activities. Table 4 presents the demographic, professional, and organizational characteristics of the 384 respondents.

The sample included substantial representation from respondents with direct technical and manufacturing experience. Male respondents accounted for 66.1% of the analytic sample and female respondents for 32.8%. Respondents aged 26–35 years represented 57.3% of the sample, while 88.8% held at least a bachelor's degree. Process or manufacturing engineers formed the largest professional group at 25.3%, followed by quality or inspection personnel at 21.6%. Engineers and specialists accounted for 41.9% of respondents, while supervisors, middle managers, and senior managers collectively represented 38.0% of the sample. Nearly two thirds of respondents (65.6%) had at least four years of semiconductor industry experience. The organizational profile also indicated substantial exposure to technologically intensive manufacturing environments. Respondents from wafer foundries and integrated device manufacturers together accounted for 39.9% of the sample, while those from semiconductor packaging, semiconductor testing, and integrated packaging and testing organizations accounted for 36.7%. In addition, 61.2% of respondents worked in organizations with at least 1,000 employees. More than half of the respondents (51.5%) reported that their organizations had used artificial intelligence or deep learning applications for at least three years, and 45.3% reported contact with such applications several times per week or daily or almost daily. Overall, these characteristics indicate that the analytic sample included respondents with substantial semiconductor manufacturing experience and meaningful exposure to organizational applications of artificial intelligence and deep learning.

Descriptive statistics and bivariate correlations for the four focal constructs are reported in Table 5. Mean scores ranged from 3.61 for QRIC to 3.76 for QIE on the five-point scale, indicating moderately high evaluations across the four organizational constructs. Standard deviations ranged from 0.62 to 0.68, indicating sufficient variation for subsequent multivariate analysis. Skewness values ranged from -0.38 to -0.24, while kurtosis values ranged from -0.18 to 0.09, suggesting no substantial univariate distributional irregularities at the construct level. All six bivariate correlations were positive and statistically significant at $p < 0.001$. DLAC was positively correlated with QIE ($r = 0.54$), QRIC ($r = 0.49$), and MQP ($r = 0.42$). QIE was

Table 4. Characteristics of the analytic sample. The table reports the demographic, professional, and organizational composition of the 384 respondents retained after eligibility and data quality screening. Percentages are calculated using the final analytic sample as the denominator.

Variable	Category	*n*	%	Variable	Category	*n*	%
Gender	Male	254	66.1	Industry Experience	6 months to less than 1 year	31	8.1
	Female	126	32.8		1–3 years	101	26.3
	Prefer not to disclose	4	1.0		4–6 years	108	28.1
					7–10 years	78	20.3
					More than 10 years	66	17.2
Age	25 years or younger	38	9.9	Enterprise Type	Wafer foundry	79	20.6
	26–30 years	104	27.1		Integrated device manufacturer	74	19.3
	31–35 years	116	30.2		Semiconductor packaging	45	11.7
	36–40 years	69	18.0		Semiconductor testing	35	9.1
	41–45 years	36	9.4		Integrated packaging and testing	61	15.9
	46 years or older	21	5.5		Equipment or manufacturing services	62	16.1
					Other related manufacturing organization	28	7.3
Education	College diploma or below	38	9.9	Enterprise Size	Fewer than 100 employees	29	7.6
	Bachelor's degree	232	60.4		100–499 employees	67	17.4
	Master's degree	109	28.4		500–999 employees	53	13.8
	Doctoral degree	5	1.3		1,000–4,999 employees	121	31.5
					5,000 employees or more	114	29.7
Professional Function	Production or manufacturing	61	15.9	Organizational AI or DL Use	Less than 1 year	54	14.1
	Process or manufacturing engineering	97	25.3		1–2 years	132	34.4
	Quality or inspection	83	21.6		3–5 years	136	35.4
	Equipment engineering	47	12.2		More than 5 years	62	16.1
	Automation, digital technology, data, or AI	59	15.4				
	Management or other relevant function	37	9.6				
Position Level	General staff or technician	77	20.1	Contact with AI or DL Applications	Occasionally	52	13.5
	Engineer or specialist	161	41.9		Monthly	60	15.6
	Supervisor or team leader	65	16.9		Weekly	98	25.5
	Middle management	61	15.9		Several times per week	108	28.1
	Senior management	20	5.2		Daily or almost daily	66	17.2
Total	Analytic sample	384	100.0	Total	Analytic sample	384	100.0

positively correlated with QRIC ($r = 0.58$) and MQP ($r = 0.47$), while QRIC was positively correlated with MQP ($r = 0.56$). These correlations are consistent with the directions proposed in the conceptual framework. At the same time, none of the correlations was sufficiently high to suggest, on the basis of bivariate association alone, that the four constructs represented the same underlying concept. Their empirical distinctiveness was therefore examined more directly through confirmatory factor analysis and discriminant validity assessment.

Table 5. Descriptive statistics and correlations among the focal constructs. Means and standard deviations are based on the five-point measurement scale. Pearson correlations summarize the bivariate associations among the four construct scores. All reported off-diagonal correlations are statistically significant at $p < 0.001$.

Construct	Mean	SD	Skewness	Kurtosis	1	2	3	4
1. Deep Learning Application Capability	3.68	0.66	−0.31	−0.12	1.000			
2. Quality Inspection Effectiveness	3.76	0.62	−0.38	0.09	0.54	1.000		
3. Quality Risk Identification Capability	3.61	0.68	−0.24	−0.18	0.49	0.58	1.000	
4. Manufacturing Quality Performance	3.72	0.64	−0.33	0.04	0.42	0.47	0.56	1.000

4.2 Measurement Model, Reliability, and Validity

Confirmatory factor analysis was conducted before estimation of the structural model to evaluate whether the 20 observed indicators adequately represented the four proposed latent constructs. The four factor measurement model demonstrated a satisfactory fit to the data, with $\chi^2 = 283.46$, $df = 164$, $\chi^2/df = 1.73$, CFI = 0.966, TLI = 0.961, RMSEA = 0.044, and SRMR = 0.037. The 90% confidence interval for RMSEA ranged from 0.035 to 0.052. These values satisfied the predefined criteria for acceptable model fit and were generally within the ranges associated with strong fit. A more restrictive three factor model that combined QIE and QRIC produced substantially weaker fit, with $\chi^2 = 533.72$, $df = 167$, CFI = 0.896, TLI = 0.882, RMSEA = 0.076, and SRMR = 0.061. The one factor model also performed poorly, with $\chi^2 = 1014.29$, $df = 170$, CFI = 0.760, TLI = 0.732, RMSEA = 0.114, and SRMR = 0.096. The superior fit of the proposed four factor structure supports the treatment of DLAC, QIE, QRIC, and MQP as empirically distinct latent constructs. This distinction is particularly important for QIE and QRIC because the theoretical model treats them as consecutive stages of manufacturing quality information processing rather than as a single quality management construct.

All standardized factor loadings were positive, statistically significant at $p < 0.001$, and ranged from 0.76 to 0.86, as reported in Table 6. The loadings for DLAC ranged from 0.76 to 0.84, QIE from 0.78 to 0.86, QRIC from 0.77 to 0.85, and MQP from 0.76 to 0.84. Cronbach's alpha values ranged from 0.899 to 0.910, while composite reliability values ranged from 0.900 to 0.911. Each value exceeded the minimum criterion of 0.70 and remained below levels that would suggest substantial item redundancy. Average variance extracted values ranged from 0.644 to 0.673, exceeding the 0.50 criterion for convergent validity. The combination of consistently strong standardized loadings, internal consistency estimates, composite reliability, and average variance extracted provides support for the reliability and convergent validity of the four measurement scales.

Discriminant validity was evaluated by considering both the Fornell Larcker criterion and the heterotrait monotrait ratio. Table 7 reports the square root of AVE on the diagonal, Pearson correlations below the diagonal, and HTMT values above the diagonal. The square root of AVE was 0.802 for DLAC, 0.820 for QIE, 0.817 for QRIC, and 0.804 for MQP. Each diagonal value exceeded the correlations between the corresponding construct and the other latent variables. HTMT values ranged from 0.49 to 0.69 and remained below the predefined threshold of 0.85. The highest HTMT value was observed between QIE and QRIC at 0.69. This value remained sufficiently below the threshold and supports the empirical distinction between inspection effectiveness and quality risk identification capability. The measurement results consequently provide an adequate basis for estimating the hypothesized structural relationships.

4.3 Structural Model and H1–H4 Testing

After the measurement model demonstrated satisfactory reliability and validity, the hypothesized structural model was estimated to examine the relationships among DLAC, QIE, QRIC, and MQP. The structural model showed a satisfactory fit to the data, with $\chi^2 = 296.84$, $df = 169$, $\chi^2/df = 1.76$, CFI = 0.963, TLI = 0.957, RMSEA = 0.044, and SRMR = 0.041. These values were within the predefined acceptable ranges and indicated that the proposed structural relationships provided an adequate representation of the observed covariance structure. The control variables were included in the estimation of manufacturing quality performance, while the principal hypothesis tests focused on the standardized relationships among the four latent constructs. The model explained 29.2% of the variance in QIE, 38.4% of the variance in QRIC, and 36.1% of the variance in MQP. These values indicate that the proposed organizational capability and quality information processing variables accounted for a meaningful proportion of variation in the three endogenous constructs.

Table 6. Standardized factor loadings, reliability, and convergent validity of the measurement model. Standardized loadings were estimated using confirmatory factor analysis. Alpha represents Cronbach's alpha, CR represents composite reliability, and AVE represents average variance extracted. All standardized factor loadings were significant at $p < 0.001$.

Construct	Item	Measurement content	Loading	Alpha	CR	AVE
DLAC	DLAC1	Analysis of complex integrated circuit manufacturing data	0.79	0.899	0.900	0.644
	DLAC2	Automatic extraction of meaningful manufacturing patterns and features	0.84			
	DLAC3	Incorporation of deep learning models into manufacturing or quality activities	0.82			
	DLAC4	Integration of deep learning analysis with existing information systems	0.76			
	DLAC5	Updating and improvement of deep learning applications using new data	0.80			
QIE	QIE1	Accurate identification of manufacturing defects and abnormalities	0.82	0.910	0.911	0.673
	QIE2	Timely detection of quality abnormalities	0.86			
	QIE3	Detection of small, subtle, or complex manufacturing defects	0.83			
	QIE4	Consistency of inspection results across similar production conditions	0.78			
	QIE5	Control of missed defects and incorrect defect identifications	0.81			
QRIC	QRIC1	Identification of potential quality risks before serious problems develop	0.80	0.908	0.909	0.667
	QRIC2	Differentiation of quality problems according to manufacturing risk	0.85			
	QRIC3	Identification of quality risks requiring priority attention	0.82			
	QRIC4	Assessment of possible downstream effects of detected abnormalities	0.77			
	QRIC5	Usefulness of quality risk information for manufacturing decisions	0.84			
MQP	MQP1	Control of manufacturing defects and nonconforming products	0.81	0.901	0.902	0.647
	MQP2	Maintenance of manufacturing process quality stability	0.84			
	MQP3	Consistency of product quality across manufacturing operations	0.79			
	MQP4	Effective response to manufacturing quality abnormalities	0.82			
	MQP5	Control of quality related rework and scrap	0.76			

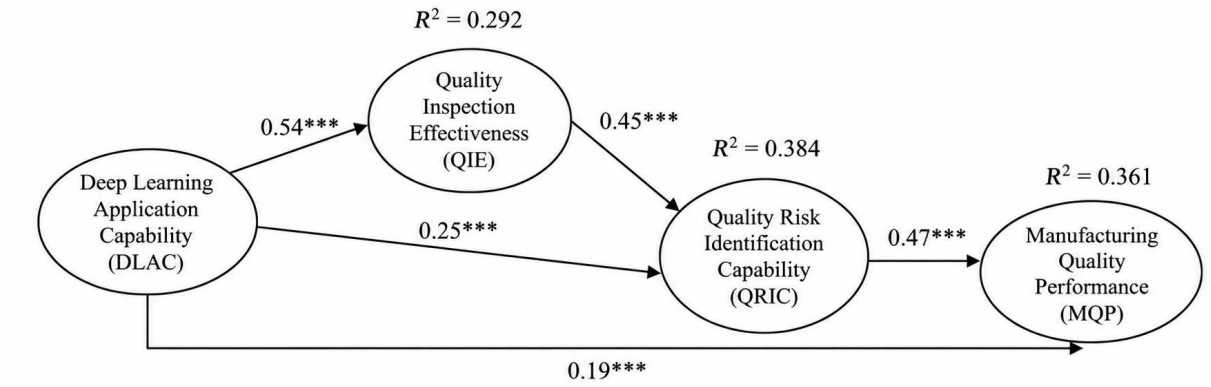
Table 7. Discriminant validity among the four latent constructs. Diagonal values represent the square root of AVE, values below the diagonal represent Pearson correlations, and values above the diagonal represent HTMT ratios.

Construct	1	2	3	4
1. Deep Learning Application Capability	0.802	0.63	0.57	0.49
2. Quality Inspection Effectiveness	0.54	0.820	0.69	0.55
3. Quality Risk Identification Capability	0.49	0.58	0.817	0.66
4. Manufacturing Quality Performance	0.42	0.47	0.56	0.804

The standardized structural estimates are summarized in Table 8 and visualized in Figure 3. The estimated paths were positive and statistically significant, while the magnitude of the coefficients differed across the proposed relationships. DLAC was positively associated with QIE ($\beta = 0.54$, $p < 0.001$), with a 95% confidence interval from 0.45 to 0.63. This result supports H1 and indicates that stronger organizational capability to apply deep learning was associated with more effective identification of manufacturing defects and abnormalities. DLAC also showed a positive association with QRIC ($\beta = 0.25$, $p < 0.001$), supporting H2. The magnitude of this relationship was smaller than the DLAC to QIE association, which is consistent with the proposition that part of the relationship between deep learning application capability and quality risk identification operates through the quality inspection process. QIE was positively associated with QRIC ($\beta = 0.45$, $p < 0.001$), providing support for H3. This relationship indicates that organizations reporting more accurate, timely, and consistent quality inspection also tended to report a stronger capability to distinguish, prioritize, and interpret manufacturing quality risks. QRIC showed a positive association with MQP ($\beta = 0.47$, $p < 0.001$), supporting H4. Among the paths entering manufacturing quality performance, QRIC represented a substantial quality related association, consistent with the theoretical expectation that the interpretation and prioritization of manufacturing risks are closely related to defect control, process stability, product consistency, and effective response to quality abnormalities.

Table 8. Structural path estimates for H1–H4. Standardized coefficients represent the estimated associations among the four latent constructs. CI denotes the 95% confidence interval for the standardized path estimate.

Hypothesis	Structural relationship	β	SE	z	95% CI	p	Result
H1	DLAC → QIE	0.54	0.047	11.49	[0.45, 0.63]	< 0.001	Supported
H2	DLAC → QRIC	0.25	0.057	4.39	[0.14, 0.36]	< 0.001	Supported
H3	QIE → QRIC	0.45	0.052	8.65	[0.35, 0.55]	< 0.001	Supported
H4	QRIC → MQP	0.47	0.049	9.59	[0.37, 0.56]	< 0.001	Supported



Note: Values are standardized path coefficients. R^2 represents the proportion of variance explained for endogenous constructs.
***$p < 0.001$.

Figure 3. Standardized structural model results. The figure presents the standardized associations among Deep Learning Application Capability (DLAC), Quality Inspection Effectiveness (QIE), Quality Risk Identification Capability (QRIC), and Manufacturing Quality Performance (MQP). Values beside the structural paths represent standardized coefficients, while R^2 values indicate the explained variance of the endogenous constructs.

The structural model also estimated the direct association between DLAC and MQP because this path is required to distinguish the sequential indirect association from any remaining direct relationship. The standardized direct estimate was positive and statistically significant ($\beta = 0.19$, SE = 0.052, $z = 3.65$, $p < 0.001$, 95% CI [0.09, 0.29]). This path was not specified as an additional hypothesis and does not alter the H1–H4 hypothesis structure. Its inclusion indicates that DLAC retained a modest association with manufacturing quality performance after accounting for QRIC and the preceding quality inspection pathway. The pattern of coefficients also provides an appropriate basis for examination of H5 because DLAC was associated with QIE, QIE was associated with QRIC, and QRIC was associated with MQP, while the direct DLAC to QRIC path remained statistically significant. The complete sequential indirect association is examined through bootstrap estimation in the following analysis.

4.4 Sequential Mediation Analysis

Bootstrap analysis based on 5,000 resamples was conducted to evaluate the indirect associations between DLAC and MQP. The bootstrap results are reported in Table 9, while the estimated effects and their confidence intervals are visualized in Figure 4. The indirect association from DLAC to MQP through QRIC was positive and statistically significant, with a standardized indirect effect of 0.118 and a bias corrected 95% confidence interval from 0.071 to 0.173. This result indicates that part of the association between deep learning application capability and manufacturing quality performance was statistically transmitted through quality risk identification capability. The sequential indirect association specified in H5 was also statistically significant. The standardized effect for the DLAC $\rightarrow$ QIE $\rightarrow$ QRIC $\rightarrow$ MQP pathway was 0.114, with a bootstrap standard error of 0.023 and a bias corrected 95% confidence interval from 0.073 to 0.164. Since the confidence interval did not include zero, H5 was supported. The result is consistent with the proposed information processing sequence in which stronger deep learning application capability is associated with more effective quality inspection, more effective inspection is associated with stronger quality risk identification capability, and stronger risk identification is associated with better manufacturing quality performance.

Table 9. Bootstrap estimates of direct, indirect, and total associations between Deep Learning Application Capability and Manufacturing Quality Performance. Indirect effects were estimated using 5,000 bootstrap resamples. Bootstrap confidence intervals that do not include zero indicate statistically significant indirect associations.

Effect	Estimate	Boot SE	95% Boot CI	p	Result
DLAC $\rightarrow$ QRIC $\rightarrow$ MQP	0.118	0.026	[0.071, 0.173]	< 0.001	Significant
DLAC $\rightarrow$ QIE $\rightarrow$ QRIC $\rightarrow$ MQP	0.114	0.023	[0.073, 0.164]	< 0.001	H5 supported
Total indirect association	0.232	0.033	[0.171, 0.302]	< 0.001	Significant
Direct DLAC $\rightarrow$ MQP association	0.190	0.052	[0.090, 0.290]	< 0.001	Significant
Total DLAC $\rightarrow$ MQP association	0.422	0.044	[0.336, 0.507]	< 0.001	Significant

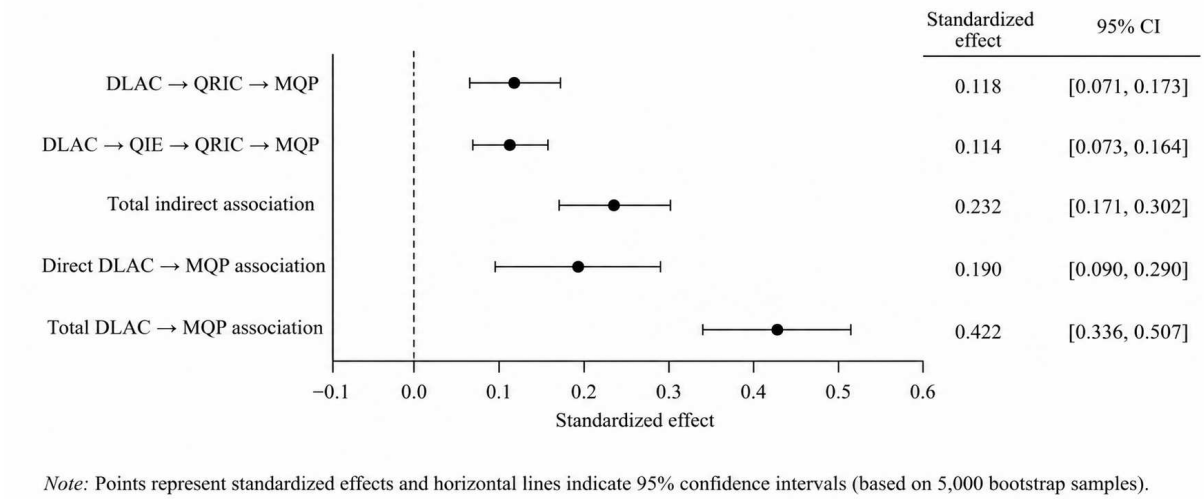
The two statistically significant indirect pathways produced a total indirect association of 0.232, with a bias corrected 95% confidence interval from 0.171 to 0.302. The direct association between DLAC and MQP remained positive and statistically significant after inclusion of QIE and QRIC ($\beta = 0.190$, $p < 0.001$). The resulting total association was 0.422, which is consistent with the positive bivariate relationship reported in the descriptive analysis. Approximately 55.0% of the total association between DLAC and MQP was represented by the combined indirect pathways. The sequential pathway alone accounted for approximately 27.0% of the total association. The persistence of the direct DLAC to MQP relationship indicates that the proposed mediators account for a substantial but not complete portion of the statistical association between deep learning application capability and manufacturing quality performance.

The pattern of indirect effects also clarifies the distinct roles of QIE and QRIC in the conceptual model. The DLAC $\rightarrow$ QRIC $\rightarrow$ MQP pathway indicates that deep learning application capability may be associated with manufacturing quality performance through risk identification even after the quality inspection pathway is considered. The sequential pathway provides separate support for the theoretical ordering proposed in H5 because DLAC is associated with QIE, QIE is associated with QRIC, and QRIC is associated with MQP. The bootstrap evidence supports the statistical indirect association represented by this sequence, but the cross sectional design does not establish that the constructs occur in the proposed temporal order or that changes in one construct cause subsequent changes in another.

4.5 Common Method Bias, Control Variables, and Robustness

Common method bias was assessed using complementary statistical procedures because the four focal constructs were measured from the same respondents through a single questionnaire. An unrotated single factor analysis showed that the first factor accounted for 34.8% of the total variance, which was well below a level suggesting that one general factor dominated the measurement items. The confirmatory one factor model also provided a substantially poorer representation of the data than the proposed four factor structure, with $\chi^2 = 1014.29$, $df = 170$, $\chi^2/df = 5.97$, CFI $= 0.760$, TLI $= 0.732$, RMSEA $= 0.114$, and SRMR $= 0.096$. A supplementary common latent factor model was then estimated to assess whether shared response tendencies materially altered the substantive relationships. After inclusion of the common method factor, the standardized estimates for the principal structural paths changed by no more than 0.03 in absolute magnitude. The DLAC to QIE association remained positive at 0.52, the DLAC to QRIC association remained positive at 0.23, the QIE to QRIC association remained positive at 0.43, and the QRIC to MQP association remained positive at 0.45. The sequential indirect association remained statistically significant at 0.101, with its bootstrap confidence interval excluding zero. The consistency of these results across the different assessments indicates that a single common response source did not provide a sufficient explanation for the observed pattern of relationships.

The four predefined control variables were also examined in relation to MQP. Work experience showed a small positive association with MQP that was not statistically significant ($\beta = 0.07$, $p = 0.128$). Position level showed a modest positive



Note: Points represent standardized effects and horizontal lines indicate 95% confidence intervals (based on 5,000 bootstrap samples).

Figure 4. Bootstrap analysis of direct and indirect associations. The figure presents the standardized direct, indirect, and total associations between Deep Learning Application Capability and Manufacturing Quality Performance. Points represent standardized effect estimates, while horizontal intervals represent bias corrected 95% confidence intervals obtained from 5,000 bootstrap resamples.

association ($\beta = 0.09$, $p = 0.049$), while enterprise size was also positively associated with MQP ($\beta = 0.11$, $p = 0.021$). The set of indicator variables representing enterprise type did not show a statistically significant joint association with MQP ($p = 0.223$). The magnitudes of these control effects were smaller than the focal association between QRIC and MQP. Alternative structural specifications were subsequently estimated to examine whether the substantive findings depended on the treatment of the control variables or common method variance. The principal coefficients across these specifications are reported in Table 10 and visualized in Figure 5. The estimate for DLAC to QIE remained comparatively strong across the tested models, while the coefficients for DLAC to QRIC, QIE to QRIC, QRIC to MQP, and the direct DLAC to MQP association also showed only limited variation across model specifications. The alternative specifications produced the same substantive pattern of findings. H1–H4 remained positive and statistically significant across the tested models, while the sequential indirect association ranged from 0.101 to 0.114 and retained a bootstrap confidence interval that excluded zero in every specification. Removal of the control variables produced almost no change in the focal coefficients, and extending the controls to the mediator constructs resulted in only small reductions in magnitude. Adjustment for the common latent factor produced the largest changes, but these differences remained modest and did not alter the direction or statistical interpretation of the hypothesized relationships. The robustness evidence consequently supports the stability of the H1–H5 results across alternative analytical treatments. Since the underlying data were collected at a single point in time, this stability strengthens confidence in the observed statistical associations but does not establish temporal ordering or causal effects.

Table 10. Robustness of the principal structural associations across alternative model specifications. Standardized coefficients are reported for the focal structural paths and the direct DLAC to MQP association. The sequential indirect effect represents the DLAC to QIE to QRIC to MQP pathway and is accompanied by its bootstrap 95% confidence interval.

Model specification	DLAC → QIE	DLAC → QRIC	QIE → QRIC	QRIC → MQP	DLAC → MQP	Sequential indirect	95% Boot CI
Principal model with controls	0.54	0.25	0.45	0.47	0.19	0.114	[0.073, 0.164]
Model without controls	0.55	0.26	0.44	0.48	0.18	0.114	[0.074, 0.165]
Controls extended to QIE and QRIC	0.53	0.24	0.44	0.46	0.18	0.107	[0.068, 0.156]
Common latent factor adjusted model	0.52	0.23	0.43	0.45	0.17	0.101	[0.062, 0.150]

The marker variable analysis provided an additional assessment of common method variance using the confirmatory factor analytic procedure. The marker construct showed only weak correlations with the four focal constructs. Its correlations with DLAC, QIE, QRIC, and MQP were 0.04, 0.03, 0.05, and 0.06, respectively, indicating limited substantive overlap between the marker and the variables included in the quality intelligence framework. The marker construct was then incorporated into the structural model to estimate the focal relationships after accounting for variance associated with the common response method.

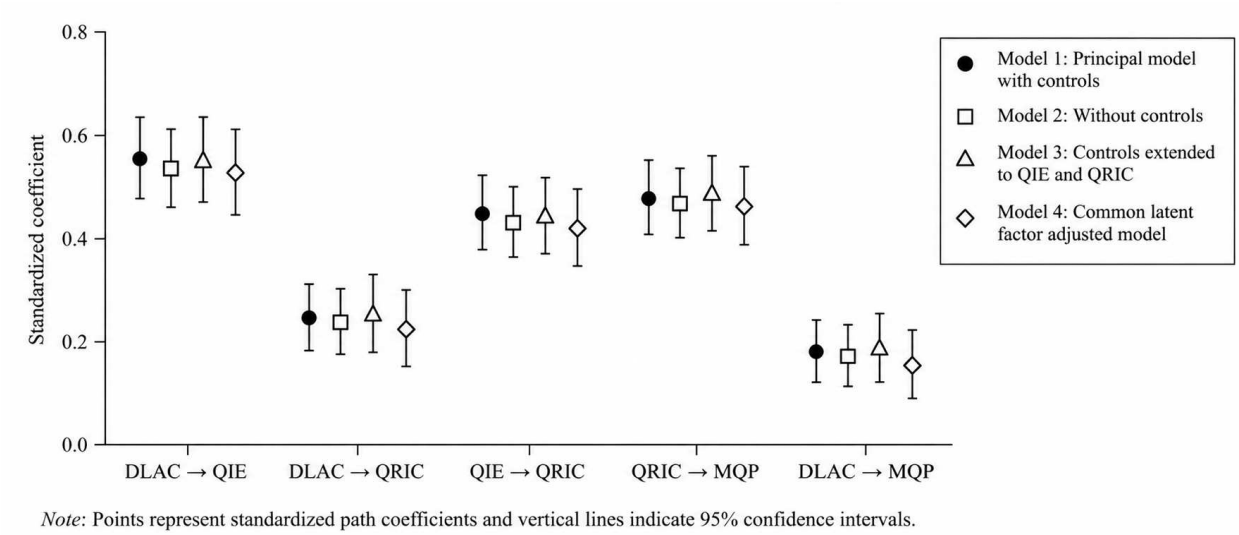


Figure 5. Robustness of structural coefficients across alternative model specifications. The figure compares the standardized structural coefficients obtained from the principal model with controls, the model without controls, the model extending controls to QIE and QRIC, and the common latent factor adjusted model. The close correspondence of the estimates across the four specifications indicates that the principal structural relationships remain substantively stable under alternative analytical treatments.

Table 11. Marker variable assessment of the principal structural relationships. The table compares standardized estimates from the principal structural model with estimates obtained after inclusion of the marker construct. Absolute change represents the difference in coefficient magnitude between the two specifications. The confidence interval for the sequential indirect association was obtained from 5,000 bootstrap resamples.

Relationship	Principal estimate	Marker adjusted estimate	Absolute change	95% CI	p
DLAC → QIE	0.540	0.531	0.009	[0.442, 0.620]	< 0.001
DLAC → QRIC	0.250	0.241	0.009	[0.132, 0.350]	< 0.001
QIE → QRIC	0.450	0.439	0.011	[0.338, 0.540]	< 0.001
QRIC → MQP	0.470	0.459	0.011	[0.362, 0.554]	< 0.001
DLAC → MQP	0.190	0.181	0.009	[0.082, 0.279]	< 0.001
DLAC → QIE → QRIC → MQP	0.114	0.107	0.007	[0.067, 0.154]	< 0.001

Table 11 reports the principal model estimates, the marker adjusted estimates, and the corresponding changes in standardized coefficients. Accounting for the marker construct produced only small changes in the estimated structural relationships. The DLAC to QIE coefficient decreased from 0.540 to 0.531, while the DLAC to QRIC coefficient changed from 0.250 to 0.241. The QIE to QRIC and QRIC to MQP coefficients changed from 0.450 to 0.439 and from 0.470 to 0.459, respectively. The direct association between DLAC and MQP also remained positive and statistically significant, decreasing only from 0.190 to 0.181. Across the five structural paths, the largest absolute change was 0.011, indicating that adjustment for variance captured by the marker construct had little influence on the magnitude of the focal associations. The sequential indirect association from DLAC to MQP through QIE and QRIC remained statistically significant after the marker adjustment. Its standardized estimate changed from 0.114 to 0.107, with a bootstrap 95% confidence interval from 0.067 to 0.154. The confidence interval remained clearly above zero, and the substantive interpretation of H1–H5 was unchanged. The weak correlations between the marker construct and the focal variables, together with the stability of the structural and indirect estimates, indicate that shared method variance captured by the marker variable is unlikely to account for the observed relationships in the proposed quality intelligence framework.

5 Discussion

5.1 Interpretation of Key Findings

The results provide a coherent empirical pattern linking Deep Learning Application Capability (DLAC), Quality Inspection Effectiveness (QIE), Quality Risk Identification Capability (QRIC), and Manufacturing Quality Performance (MQP) in integrated circuit manufacturing. H1 received support because DLAC was positively associated with QIE, with a standardized coefficient of 0.54. This was the strongest path originating from DLAC and indicates that organizational capability to apply deep learning is closely related to the effectiveness of manufacturing inspection. The result is consistent with semiconductor research showing that deep learning can recognize complex wafer patterns, extract relevant features from manufacturing information, and support automated defect analysis[2]. Research on anomaly detection also shows that deep neural architectures can identify unusual wafer structures that may be difficult to represent through fixed inspection rules[4]. The present result extends this technical evidence by locating deep learning within an organizational capability framework. The relevant association is not limited to whether one algorithm performs well on a classification task. It reflects whether the organization can analyze manufacturing data, integrate analytical applications with existing systems, and maintain those applications as production information changes. The positive DLAC to QIE relationship suggests that these organizational conditions are closely connected with more accurate, timely, and consistent quality inspection.

H2 and H3 clarify how quality risk identification is related to both analytical capability and inspection effectiveness. DLAC was positively associated with QRIC at 0.25, while QIE showed a stronger association with QRIC at 0.45. The smaller direct DLAC to QRIC coefficient suggests that deep learning capability is related to risk identification both directly and through its relationship with inspection effectiveness. This pattern fits the distinction between recognizing an abnormal condition and interpreting the manufacturing significance of that condition. Predictive quality research has emphasized that manufacturing analytics can move beyond defect recognition by linking process information with expected quality outcomes and decision support[11]. Quality 4.0 research similarly treats quality management as an information intensive activity in which large and heterogeneous data sets must be converted into actionable quality information[12]. The present findings indicate that effective inspection may serve as an important informational foundation for this interpretive process. When defects and abnormalities are identified more accurately and consistently, organizations have a stronger basis for distinguishing risk levels, identifying issues requiring priority attention, and evaluating possible effects on later manufacturing activities.

H4 was also supported, with QRIC positively associated with MQP at 0.47. This result indicates that organizations reporting stronger risk identification capability also reported better defect control, process quality stability, product consistency, abnormality response, and control of rework and scrap. The finding is consistent with broader manufacturing research showing that analytical capabilities are associated with operational performance when information is integrated with organizational decision processes[21]. The sequential indirect association proposed in H5 was 0.114, with a 95% bootstrap confidence interval from 0.073 to 0.164. This result supports the statistical sequence from DLAC to QIE, from QIE to QRIC, and from QRIC to MQP. The direct association between DLAC and MQP remained positive at 0.190 after the mediators were included, while the combined indirect association was 0.232. This pattern suggests that QIE and QRIC account for a substantial portion of the relationship between DLAC and MQP without exhausting that relationship. The result is compatible with the possibility that deep learning application capability is also related to manufacturing quality through other organizational processes, such as process monitoring, equipment diagnosis, production optimization, or engineering decision support. Because the research design is cross sectional, the sequential result is interpreted as a theoretically ordered statistical association rather than confirmed evidence of temporal or causal mediation.

5.2 Theoretical Contributions

The first theoretical contribution is the development of a deep learning-enabled quality intelligence framework for integrated circuit manufacturing. Existing semiconductor research has predominantly examined deep learning through technical outcomes such as wafer defect classification, anomaly detection, segmentation, and recognition accuracy[7]. Although this literature demonstrates the technical feasibility of advanced analytical methods, it provides less explanation of how deep learning-enabled analytics become embedded in a broader manufacturing quality information process. The present study addresses this gap by conceptualizing quality intelligence as an information processing framework through which analytical capability is translated into reliable quality information, interpretable risk knowledge, and manufacturing quality outcomes. Within this framework, Deep Learning Application Capability (DLAC) serves as the analytical enabling capability rather than the ultimate theoretical focus. It reflects the organizational capacity to analyze complex manufacturing data, extract meaningful patterns, deploy deep learning applications, integrate analytical outputs with existing systems, and continuously improve those applications as new information becomes available. This role is consistent with research conceptualizing artificial intelligence capability as an organizational capacity created through the combination of technological and organizational resources[13], as well as research emphasizing the organizational deployment of analytical resources[14]. The framework therefore extends semiconductor deep learning research beyond isolated algorithmic performance toward an integrated view of AI-enabled quality intelligence in

manufacturing.

The second theoretical contribution is the identification of two distinct information processing stages within the proposed quality intelligence framework. Quality Inspection Effectiveness (QIE) represents the generation of reliable information about current manufacturing defects and abnormalities, whereas Quality Risk Identification Capability (QRIC) represents the interpretation of that information in terms of potential severity, priority, downstream consequences, and decision relevance. This distinction suggests that quality intelligence involves more than accurate defect recognition. Reliable quality signals must also be interpreted and contextualized before they can support manufacturing decisions. The empirical results provide support for this two-stage conceptualization. The proposed four-factor measurement model demonstrated substantially better fit than an alternative model combining QIE and QRIC, while the HTMT value between the two constructs remained below the discriminant validity threshold. These findings indicate that inspection effectiveness and risk identification are closely related but empirically distinct. The study therefore extends predictive quality research by distinguishing the generation of quality information from its subsequent transformation into actionable risk knowledge[11]. This separation provides a more differentiated account of how AI-supported manufacturing information can evolve from defect detection toward quality intelligence.

The third theoretical contribution concerns the sequential information processing architecture through which deep learning-enabled analytics are associated with manufacturing quality performance. Organizational Information Processing Theory suggests that organizations facing complex and uncertain operating environments require sufficient capacity to acquire, process, interpret, and use information. Integrated circuit manufacturing represents such an environment because quality-related decisions depend on large volumes of process, equipment, inspection, and historical manufacturing information. The proposed framework specifies a theoretically ordered sequence in which DLAC provides the analytical foundation for processing complex manufacturing information, QIE represents the generation of reliable quality signals, QRIC represents the transformation of those signals into risk knowledge, and Manufacturing Quality Performance (MQP) represents the quality-related organizational outcome. The significant sequential indirect association is consistent with the coherence of this ordered information processing framework. Importantly, the contribution is not simply the identification of an association between technological capability and performance. Rather, the framework specifies two distinct quality intelligence processes—quality information generation and quality risk interpretation—through which deep learning-enabled analytical capability may become connected with manufacturing quality outcomes. In this way, the study provides an information processing explanation of how AI-enabled analytical resources can contribute to manufacturing intelligence and quality decision support.

5.3 Practical Implications

The findings have several implications for integrated circuit manufacturers seeking to obtain quality related value from deep learning technologies. Investment in analytical algorithms alone may be insufficient when the organization lacks the capability to connect those algorithms with manufacturing data, information systems, inspection routines, and engineering decisions. The strong association between DLAC and QIE suggests that managers should view deep learning implementation as a continuing organizational capability development process. Relevant priorities include improving access to usable manufacturing data, establishing stable interfaces between analytical applications and quality information systems, creating procedures for model maintenance, and ensuring that engineers can interpret analytical outputs within their production context. Quality personnel and data specialists also require effective communication because model outputs become more useful when they can be translated into inspection criteria and operational knowledge. This perspective is consistent with Quality 4.0 research, which emphasizes the integration of analytical information with quality management activities rather than the isolated adoption of digital tools[12].

The distinction between inspection effectiveness and risk identification also has direct managerial relevance. Manufacturing organizations can benefit from treating defect detection as the beginning of a quality information process rather than its endpoint. An inspection system may accurately identify an abnormal wafer pattern, process deviation, or quality defect, while the operational response still depends on understanding the significance of that information. Quality management systems can strengthen this transition by linking inspection outputs with historical defect records, process parameters, equipment conditions, downstream quality information, and risk prioritization rules. Risk information can then be organized according to severity, urgency, possible downstream effects, and required engineering attention. The positive association between QRIC and MQP suggests that this interpretive capability deserves explicit attention in digital quality programs. Performance evaluation can also distinguish inspection indicators from risk management indicators so that organizations do not assume that improved defect recognition automatically implies stronger risk identification. This distinction can help manufacturing managers identify whether limitations arise from detection capability, risk interpretation, or the organizational process connecting the two.

5.4 Limitations and Future Research

Several limitations define the scope within which the findings should be interpreted. The study used a cross sectional survey design, which allows examination of associations among DLAC, QIE, QRIC, and MQP but cannot establish temporal ordering among the constructs. The sequential indirect model was theoretically specified and statistically supported, yet the data do not demonstrate that changes in DLAC occur before changes in QIE or that subsequent changes in QRIC produce changes in MQP.

Longitudinal research could collect organizational information at multiple time points and examine whether development of deep learning capability precedes changes in inspection effectiveness and risk identification. Field studies conducted before and after implementation of specific manufacturing analytical systems could provide stronger evidence concerning temporal relationships. Experimental or quasi experimental designs may also be useful when comparable production lines, facilities, or quality processes allow the effects of changes in analytical capability to be examined under more controlled conditions.

The use of purposive and referral based sampling creates a second limitation. Respondents were selected because they possessed relevant experience in semiconductor manufacturing and sufficient familiarity with organizational AI or deep learning applications. This approach improves the informational relevance of the responses but does not provide a probability sample of the complete integrated circuit manufacturing workforce in China. The sample also combines respondents from wafer fabrication, integrated device manufacturing, packaging, testing, equipment, and related manufacturing services. These settings share important quality management characteristics but differ in process structure, inspection technologies, defect types, and digital maturity. Future research could collect larger samples from individual semiconductor segments and use multigroup structural equation modeling to assess whether the proposed relationships differ across foundries, integrated device manufacturers, packaging organizations, and testing enterprises. Research across regions within China could also examine whether differences in industrial concentration, enterprise scale, or digital infrastructure are associated with variation in the proposed model.

A further limitation concerns the use of perceptual organizational measures reported by individual respondents. MQP was assessed through perceived defect control, quality stability, product consistency, abnormality response, and control of rework and scrap rather than through confidential production indicators. Although the measurement model showed satisfactory reliability and validity and the common method assessments did not indicate a dominant common source factor, self report data may still contain differences in respondent knowledge or organizational perspective. Future studies could combine questionnaire measures with objective indicators such as defect density, first pass yield, rework frequency, scrap rate, process capability indices, equipment alarm information, or inspection cycle time. Multi respondent designs could also obtain separate assessments of DLAC from digital or automation personnel, QIE from inspection and quality personnel, QRIC from quality managers or process engineers, and MQP from production records. Such designs would provide a stronger basis for evaluating the proposed organizational information processing sequence and determining the conditions under which deep learning application capability is most strongly associated with manufacturing quality performance.

6 Conclusion

This study developed and empirically examined a deep learning enabled manufacturing quality intelligence framework for integrated circuit manufacturing. Rather than focusing primarily on whether Deep Learning Application Capability (DLAC) is associated with manufacturing performance, the framework explains how deep learning enabled analytical resources can be transformed into reliable quality information, interpretable risk knowledge, and manufacturing quality outcomes. Within this architecture, DLAC provides the analytical foundation, Quality Inspection Effectiveness (QIE) represents the generation of reliable information about current defects and abnormalities, Quality Risk Identification Capability (QRIC) represents the interpretation of that information in terms of severity, priority, and downstream consequences, and Manufacturing Quality Performance (MQP) represents the resulting quality outcome. Organizational Information Processing Theory explains the transformation of manufacturing data into progressively more decision relevant quality information, while the dynamic capability perspective provides a complementary explanation for the integration, adaptation, and renewal of analytical resources as manufacturing conditions evolve. The empirical results provide support for this quality intelligence architecture. Based on questionnaire data from 384 professionals working in integrated circuit manufacturing and related semiconductor manufacturing activities in mainland China, the measurement model demonstrated satisfactory reliability, convergent validity, and discriminant validity for DLAC, QIE, QRIC, and MQP. The structural results supported all five hypotheses. DLAC was positively associated with QIE and QRIC, QIE was positively associated with QRIC, and QRIC was positively associated with MQP. Bootstrap analysis also supported the sequential indirect association from DLAC to MQP through QIE and QRIC, with a standardized indirect effect of 0.114 and a 95% confidence interval from 0.073 to 0.164. These results are consistent with an ordered information processing architecture in which deep learning enabled analytical capability supports the generation of reliable quality signals, those signals provide a basis for quality risk interpretation, and risk knowledge is associated with stronger manufacturing quality outcomes.

The main contribution lies in shifting the interpretation of deep learning in integrated circuit manufacturing from isolated algorithm performance or a single organizational capability toward a broader manufacturing quality intelligence perspective. Quality intelligence in this framework is not represented by defect detection alone. It develops through the transformation of complex manufacturing data into quality information and the subsequent interpretation of that information into actionable risk knowledge. The distinction between QIE and QRIC is central to this architecture because accurate detection and meaningful risk interpretation represent related but different stages of manufacturing intelligence. This distinction provides a more detailed

explanation of how AI based analytical resources can become connected with manufacturing quality outcomes and extends the role of deep learning from technical recognition tasks toward integrated quality decision support. The framework also provides practical guidance for integrated circuit manufacturers developing intelligent quality management systems. The value of deep learning can be strengthened by integrating analytical models with manufacturing information systems, improving the accuracy and timeliness of quality inspection, and establishing mechanisms that convert inspection outputs into prioritized risk knowledge. Such an architecture can support more informed responses to manufacturing abnormalities, more focused allocation of engineering attention, stronger process stability, improved product consistency, and better control of rework and scrap. The results also suggest that investments in deep learning should be considered together with the organizational processes required to maintain analytical applications, interpret their outputs, and connect them with quality decisions.

The findings should be interpreted within the limitations of the research design. The focal constructs were measured using cross sectional questionnaire data, so the estimated structural and indirect relationships represent statistical associations consistent with the proposed quality intelligence architecture rather than established temporal or causal effects. Longitudinal studies can examine how analytical capability, inspection effectiveness, and risk interpretation develop over time. Multi respondent designs can separate assessments of analytical capability, inspection, risk identification, and performance across relevant organizational functions. Future research can also integrate questionnaire measures with production indicators such as defect density, first pass yield, scrap rate, rework frequency, process capability, equipment signals, and inspection cycle time. Such research can provide a stronger basis for evaluating how deep learning enabled quality intelligence operates across different semiconductor manufacturing environments and how its information processing architecture contributes to manufacturing performance.

Ethics approval and informed consent

According to the applicable research ethics requirements of Beijing University of Posts and Telecommunications, formal ethics review was not required for this study because it involved a voluntary, anonymous online questionnaire of adults, did not collect directly identifying information, and did not include sensitive questions or interventions. Before accessing the questionnaire, all participants received information about the study purpose, voluntary participation, data handling, and their right to discontinue. All participants provided informed consent electronically before completing the survey. The study was conducted in accordance with applicable institutional guidelines and the Declaration of Helsinki.

Conflict of Interest Statement

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

Author Contributions

RongHao Zhang was responsible for the conceptualization, methodology, investigation, data analysis, interpretation of the results, and preparation of the original draft. RongHao Zhang also conducted the review and editing of the manuscript, approved the final version for submission, and accepts responsibility for the accuracy and integrity of the work.

Funding

This research received no external funding.

Data availability

The questionnaire items and analysis specification for this study are available at https://snippets.cacher.io/snippet/29b557b734440d8a132f. Individual-level questionnaire responses are not included in the public snippet because combinations of professional and organizational characteristics may permit re-identification. Requests for access to the de-identified analytic data may be directed to the corresponding author and will be considered in accordance with the information provided to participants and applicable institutional requirements.

References

1. Lee, K. B., Cheon, S. & Kim, C. O. A convolutional neural network for fault classification and diagnosis in semiconductor manufacturing processes. *IEEE Transactions on Semicond. Manuf.* **30**, 135–142, DOI: 10.1109/TSM.2017.2676245 (2017).

2. Nakazawa, T. & Kulkarni, D. V. Wafer map defect pattern classification and image retrieval using convolutional neural network. *IEEE Transactions on Semicond. Manuf.* **31**, 309–314, DOI: 10.1109/TSM.2018.2795466 (2018).

3. Yu, J., Zheng, X. & Liu, J. Stacked convolutional sparse denoising auto-encoder for identification of defect patterns in semiconductor wafer map. *Comput. Ind.* **109**, 121–133, DOI: 10.1016/j.compind.2019.04.015 (2019).

4. Nakazawa, T. & Kulkarni, D. V. Anomaly detection and segmentation for wafer defect patterns using deep convolutional encoder-decoder neural network architectures in semiconductor manufacturing. *IEEE Transactions on Semicond. Manuf.* **32**, 250–256, DOI: 10.1109/TSM.2019.2897690 (2019).

5. Zheng, X., Zheng, S., Kong, Y. & Chen, J. Recent advances in surface defect inspection of industrial products using deep learning techniques. *The Int. J. Adv. Manuf. Technol.* **113**, 35–58, DOI: 10.1007/s00170-021-06592-8 (2021).

6. Ma, J. *et al.* Review of wafer surface defect detection methods. *Electronics* **12**, 1787, DOI: 10.3390/electronics12081787 (2023).

7. Saqlain, M., Abbas, Q. & Lee, J. Y. A deep convolutional neural network for wafer defect identification on an imbalanced dataset in semiconductor manufacturing processes. *IEEE Transactions on Semicond. Manuf.* **33**, 436–444, DOI: 10.1109/TSM.2020.2994357 (2020).

8. Yu, J. *et al.* Deep transfer wasserstein adversarial network for wafer map defect recognition. *Comput. & Ind. Eng.* **161**, 107679, DOI: 10.1016/j.cie.2021.107679 (2021).

9. Li, K. S. M. *et al.* Wafer defect pattern labeling and recognition using semi-supervised learning. *IEEE Transactions on Semicond. Manuf.* **35**, 291–299, DOI: 10.1109/TSM.2022.3159246 (2022).

10. Nag, S., Makwana, D., R., S. C. T., Mittal, S. & Mohan, C. K. WaferSegClassNet: A light-weight network for classification and segmentation of semiconductor wafer defects. *Comput. Ind.* **142**, 103720, DOI: 10.1016/j.compind.2022.103720 (2022).

11. Tercan, H. & Meisen, T. Machine learning and deep learning based predictive quality in manufacturing: A systematic review. *J. Intell. Manuf.* **33**, 1879–1905, DOI: 10.1007/s10845-022-01963-8 (2022).

12. Escobar, C. A., McGovern, M. E. & Morales-Menendez, R. Quality 4.0: A review of big data challenges in manufacturing. *J. Intell. Manuf.* **32**, 2319–2334, DOI: 10.1007/s10845-021-01765-4 (2021).

13. Mikalef, P. & Gupta, M. Artificial intelligence capability: Conceptualization, measurement calibration, and empirical study on its impact on organizational creativity and firm performance. *Inf. & Manag.* **58**, 103434, DOI: 10.1016/j.im.2021.103434 (2021).

14. Akter, S., Wamba, S. F., Gunasekaran, A., Dubey, R. & Childe, S. J. How to improve firm performance using big data analytics capability and business strategy alignment? *Int. J. Prod. Econ.* **182**, 113–131, DOI: 10.1016/j.ijpe.2016.08.018 (2016).

15. Alawieh, M. B., Boning, D. & Pan, D. Z. Wafer map defect patterns classification using deep selective learning. In *Proceedings of the 57th ACM/IEEE Design Automation Conference*, DOI: 10.1109/DAC18072.2020.9218580 (2020).

16. Yu, J. Enhanced stacked denoising autoencoder-based feature learning for recognition of wafer map defects. *IEEE Transactions on Semicond. Manuf.* **32**, 613–624, DOI: 10.1109/TSM.2019.2940334 (2019).

17. Wang, J., Xu, C., Yang, Z., Zhang, J. & Li, X. Deformable convolutional networks for efficient mixed-type wafer defect pattern recognition. *IEEE Transactions on Semicond. Manuf.* **33**, 587–596, DOI: 10.1109/TSM.2020.3020985 (2020).

18. Chien, J.-C., Wu, M.-T. & Lee, J.-D. Inspection and classification of semiconductor wafer surface defects using CNN deep learning networks. *Appl. Sci.* **10**, 5340, DOI: 10.3390/app10155340 (2020).

19. Chen, H.-C. Automated detection and classification of defective and abnormal dies in wafer images. *Appl. Sci.* **10**, 3423, DOI: 10.3390/app10103423 (2020).

20. Dalenogare, L. S., Benitez, G. B., Ayala, N. F. & Frank, A. G. The expected contribution of industry 4.0 technologies for industrial performance. *Int. J. Prod. Econ.* **204**, 383–394, DOI: 10.1016/j.ijpe.2018.08.019 (2018).

21. Dubey, R. *et al.* Big data analytics and artificial intelligence pathway to operational performance under the effects of entrepreneurial orientation and environmental dynamism: A study of manufacturing organisations. *Int. J. Prod. Econ.* **226**, 107599, DOI: 10.1016/j.ijpe.2019.107599 (2020).

22. Wang, X., Gu, Y., Ahmad, M. & Xue, C. The impact of digital capability on manufacturing company performance. *Sustainability* **14**, 6214, DOI: 10.3390/su14106214 (2022).

23. Fosso Wamba, S., Queiroz, M. M. & Trinchera, L. The role of artificial intelligence-enabled dynamic capability on environmental performance: The mediation effect of a data-driven culture in france and the USA. *Int. J. Prod. Econ.* **268**, 109131, DOI: 10.1016/j.ijpe.2023.109131 (2024).

24. Ameen, N., Tarba, S., Cheah, J.-H., Xia, S. & Sharma, G. D. Coupling artificial intelligence capability and strategic agility for enhanced product and service creativity. *Br. J. Manag.* **35**, 1916–1934, DOI: 10.1111/1467-8551.12797 (2024).

25. Pathak, S., Krishnaswamy, V. & Sharma, M. A dynamic capability perspective on the impact of big data analytics and enterprise architecture on innovation: An empirical study. *J. Enterp. Inf. Manag.* **38**, 532–563, DOI: 10.1108/JEIM-01-2024-0059 (2025).

26. Appiah, L. O. Does proactive boundary-spanning search drive green innovation? exploring the significance of green dynamic capabilities and analytics capabilities. *Corp. Soc. Responsib. Environ. Manag.* **31**, 2589–2599, DOI: 10.1002/csr.2703 (2024).

27. Dubey, R., Gunasekaran, A., Childe, S. J., Blome, C. & Papadopoulos, T. Big data and predictive analytics and manufacturing performance: Integrating institutional theory, resource-based view and big data culture. *Br. J. Manag.* **30**, 341–361, DOI: 10.1111/1467-8551.12355 (2019).

28. Zheng, T., Ardolino, M., Bacchetti, A. & Perona, M. The applications of industry 4.0 technologies in manufacturing context: A systematic literature review. *Int. J. Prod. Res.* **59**, 1922–1954, DOI: 10.1080/00207543.2020.1824085 (2021).

29. Hong, S., Zhong, D. & Um, K.-H. The impact of artificial intelligence (AI) adoption on operational performance in manufacturing. *J. Manuf. Technol. Manag.* **37**, 295–317, DOI: 10.1108/JMTM-03-2025-0227 (2026).

30. Fosso-Wamba, S., Guthrie, C., Queiroz, M. M. & Oyedijo, A. Building AI-enabled capabilities for improved environmental and manufacturing performance: Evidence from the US and the UK. *Int. J. Prod. Res.* **64**, 545–564, DOI: 10.1080/00207543.2024.2428427 (2026).

31. Yu, J. & Liu, J. Two-dimensional principal component analysis-based convolutional autoencoder for wafer map defect detection. *IEEE Transactions on Ind. Electron.* **68**, 8789–8797, DOI: 10.1109/TIE.2020.3013492 (2021).

32. Yu, J., Shen, Z. & Wang, S. Wafer map defect recognition based on deep transfer learning-based densely connected convolutional network and deep forest. *Eng. Appl. Artif. Intell.* **105**, 104387, DOI: 10.1016/j.engappai.2021.104387 (2021).

33. Yang, J. *et al.* Using deep learning to detect defects in manufacturing: A comprehensive survey and current challenges. *Materials* **13**, 5755, DOI: 10.3390/ma13245755 (2020).

34. Chiu, M.-C. & Chen, T.-M. Applying data augmentation and mask R-CNN-based instance segmentation method for mixed-type wafer maps defect patterns classification. *IEEE Transactions on Semicond. Manuf.* **34**, 455–463, DOI: 10.1109/TSM.2021.3118922 (2021).

35. Wang, S., Zhong, Z., Zhao, Y. & Zuo, L. A variational autoencoder enhanced deep learning model for wafer defect imbalanced classification. *IEEE Transactions on Components, Packag. Manuf. Technol.* **11**, 2055–2060, DOI: 10.1109/TCPMT.2021.3126083 (2021).

36. Zheng, H., Sherazi, S. W. A., Son, S. H. & Lee, J. Y. A deep convolutional neural network-based multi-class image classification for automatic wafer map failure recognition in semiconductor manufacturing. *Appl. Sci.* **11**, 9769, DOI: 10.3390/app11209769 (2021).

37. Yoon, S. & Kang, S. Semi-automatic wafer map pattern classification with convolutional neural networks. *Comput. & Ind. Eng.* **166**, 107977, DOI: 10.1016/j.cie.2022.107977 (2022).

38. Shinde, P. P., Pai, P. P. & Adiga, S. P. Wafer defect localization and classification using deep learning techniques. *IEEE Access* **10**, 39969–39974, DOI: 10.1109/ACCESS.2022.3166512 (2022).

39. Chen, S. *et al.* Wafer map defect pattern detection method based on improved attention mechanism. *Expert. Syst. with Appl.* **230**, 120544, DOI: 10.1016/j.eswa.2023.120544 (2023).

40. Yu, N., Chen, H., Xu, Q., Hasan, M. M. & Sie, O. Wafer map defect patterns classification based on a lightweight network and data augmentation. *CAAI Transactions on Intell. Technol.* 1029–1042, DOI: 10.1049/cit2.12126 (2023).

41. Shin, E. & Yoo, C. D. Efficient convolutional neural networks for semiconductor wafer bin map classification. *Sensors* **23**, 1926, DOI: 10.3390/s23041926 (2023).

42. Jeong, I. *et al.* Wafer map failure pattern classification using geometric transformation-invariant convolutional neural network. *Sci. Reports* **13**, 8127, DOI: 10.1038/s41598-023-34147-2 (2023).

43. Saberironaghi, A., Ren, J. & El-Gindy, M. Defect detection methods for industrial products using deep learning techniques: A review. *Algorithms* **16**, 95, DOI: 10.3390/a16020095 (2023).

44. Guo, L. & Xu, L. The effects of digital transformation on firm performance: Evidence from china's manufacturing sector. *Sustainability* **13**, 12844, DOI: 10.3390/su132212844 (2021).

45. Tortorella, G. L., Giglio, R. & van Dun, D. H. Industry 4.0 adoption as a moderator of the impact of lean production practices on operational performance improvement. *Int. J. Oper. & Prod. Manag.* **39**, 860–886, DOI: 10.1108/IJOPM-01-2019-0005 (2019).

46. Wang, H., Cao, W. & Wang, F. Digital transformation and manufacturing firm performance: Evidence from china. *Sustainability* **14**, 10212, DOI: 10.3390/su141610212 (2022).