



Socio-Technical Transitions toward Industry 5.0: A Dynamic Capabilities Framework for Integrating Human-Centric Automation in Manufacturing

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Article Info

Received: January 12, 2026

Revised: March 15, 2026

Accepted: April 10, 2026

Online Version: June 25, 2026

Abstract

Industry 5.0 calls for manufacturing systems that combine advanced automation with human well-being, resilience, and meaningful worker participation. This study aims to develop and examine a dynamic capabilities framework explaining how sensing, seizing, and reconfiguring capabilities support the integration of human-centric automation in manufacturing. An explanatory sequential mixed-methods design was employed, combining survey data from 458 respondents across 162 manufacturing firms with interviews involving 48 participants from ten selected cases. Quantitative data were analyzed using structural equation modeling, while qualitative evidence was examined through thematic and cross-case analysis. The findings show that sensing capability strengthens seizing capability, while seizing capability significantly enhances reconfiguring capability. Reconfiguring capability exerts the strongest direct effect on human-centric automation, particularly when employee participation is high. Human-centric automation also improves socio-technical integration, which subsequently strengthens productivity, flexibility, innovation, quality, and organizational resilience. Case evidence confirms that participatory design, workforce reskilling, transparent governance, and workflow redesign are essential for aligning intelligent technologies with human expertise. These relationships distinguish technically functional automation from genuinely human-centred industrial transformation processes.

Keywords: Dynamic Capabilities, Human-Centric Automation, Industry 5.0



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Journal Homepage

<https://research.adra.ac.id/index.php/innovatsioon>

How to cite:

Ananda, F., Akhmedov, U., & Shamsiev, S. (2026). Socio-Technical Transitions toward Industry 5.0: A Dynamic Capabilities Framework for Integrating Human-Centric Automation in Manufacturing. *Journal of Loomingulusus ja Innovatsioon*, 3(3), 216–241. <https://doi.org/10.70177/innovatsioon.v3i3.4340>

Published by:

Yayasan Adra Karima Hubbi

INTRODUCTION

The first paragraph should introduce the global transformation of manufacturing from technology-centred digitalization toward Industry 5.0, a production paradigm that places human well-being, resilience, and sustainability alongside technological advancement. Industry 4.0 has accelerated the adoption of artificial intelligence, industrial robotics, cyber-physical systems, the Internet of Things, digital twins, and data-driven production (Brodny & Tutak, 2026; Elhidaoui, 2026; Nie et al., 2026). These developments have increased operational efficiency, process visibility, and manufacturing precision. Industry 5.0 extends this technological foundation by emphasizing collaboration between human workers and intelligent machines rather than pursuing automation solely as a substitute for human labour. The paragraph should establish that the transition requires manufacturers to reconsider how technology, human expertise, organizational structures, and social values are combined within production systems.

The second paragraph should explain the meaning and strategic relevance of human-centric automation in contemporary manufacturing. Human-centric automation refers to the design and application of intelligent technologies that strengthen human capabilities, improve workplace safety, support employee autonomy, and create meaningful roles for workers. Collaborative robots, augmented-reality interfaces, intelligent decision-support systems, wearable technologies, and adaptive production platforms can assist employees without eliminating their knowledge and judgment (Bécue et al., 2026; Khoshsepehr et al., 2026; Salvadorinho, Ferreira, et al., 2026). The paragraph should emphasize that successful automation depends on more than technical performance because workers must understand, accept, and use new technologies effectively. Human-machine collaboration therefore represents a socio-technical arrangement in which technological functions and human competencies are developed as interdependent components of the manufacturing system.

The third paragraph should introduce socio-technical transition theory and dynamic capabilities as complementary perspectives for examining the movement toward Industry 5.0. Socio-technical transition theory explains how technological innovations interact with organizational routines, institutions, skills, cultural expectations, and industrial structures. Dynamic capabilities theory focuses on how organizations sense environmental changes, seize emerging opportunities, and reconfigure resources and competencies in response to transformation (Habibi, 2026; Johansson et al., 2026; Lee et al., 2026). The paragraph should establish that manufacturing firms must coordinate technical modernization with workforce development, leadership adaptation, institutional learning, and changes in organizational culture. This theoretical combination provides a foundation for analysing how manufacturers can integrate human-centric automation while preserving productivity, employee participation, resilience, and long-term competitiveness.

The fourth paragraph should identify the central problem created by the dominance of technology-driven approaches to industrial automation. Many manufacturing firms adopt advanced technologies primarily to improve efficiency, reduce costs, increase production speed, and minimize human intervention. Such an approach may overlook employee knowledge, psychological well-being, task meaningfulness, and participation in technological design (Bruguera et al., 2026; Cuzzolin et al., 2026; Nyale, 2026). Automation initiatives implemented without adequate consideration of human factors can generate resistance, skill displacement, work intensification, reduced trust, and dependence on complex technological systems. The paragraph should clarify that the transition toward Industry 5.0 remains incomplete when automation is treated merely as a technical investment rather than as an organizational and social transformation.

The fifth paragraph should describe the organizational difficulties involved in aligning technological adoption with human-centred objectives. Manufacturing firms often face fragmented decision-making between engineering, information technology, operations, human

resource management, and strategic leadership functions (Abbas et al., 2026; Diaz Schery et al., 2026; Papacharalampopoulos et al., 2026). Technical teams may prioritize system performance, while employees may be concerned about job security, workload, surveillance, or the loss of professional autonomy. Managers may also lack clear mechanisms for translating human-centric principles into investment decisions, work design, training programmes, performance indicators, and production routines. The paragraph should state that this misalignment can prevent firms from achieving the anticipated benefits of intelligent automation, even when the technologies themselves are technically reliable.

The sixth paragraph should specify the capability-related problem addressed by the study. Manufacturing organizations differ considerably in their ability to recognize Industry 5.0 opportunities, evaluate human and technological requirements, mobilize stakeholder support, and reconfigure existing systems (Cumbajin et al., 2026; Salvadorinho, Hines, et al., 2026; Zaoui et al., 2026). Some firms can combine worker expertise with advanced automation, while others struggle to move beyond isolated pilot projects. The difference cannot be explained solely by financial resources or technological availability because firms with similar investments may achieve contrasting outcomes. The paragraph should emphasize that limited knowledge remains regarding the dynamic capabilities that enable firms to manage the socio-technical complexity of human-centric automation and convert experimental technologies into sustainable manufacturing practices.

The seventh paragraph should state that the primary objective of the study is to develop a dynamic capabilities framework for explaining socio-technical transitions toward Industry 5.0. The framework should identify how manufacturing firms sense technological, social, and workforce-related changes; seize opportunities for human-machine collaboration; and reconfigure organizational resources to support human-centric automation (Capet et al., 2026; Lucantoni et al., 2026; Richardson, 2026). The analysis should move beyond a narrow focus on technology adoption by examining the strategic processes through which firms align intelligent systems with worker competencies, organizational routines, and production objectives. The paragraph should clarify that the study aims to explain the transition as an evolving organizational process rather than as a single technological implementation decision.

The eighth paragraph should present the objective of identifying the specific capabilities required at different stages of Industry 5.0 transformation. Sensing capabilities may include technological scanning, employee consultation, skill-gap assessment, and recognition of emerging regulatory or social expectations. Seizing capabilities may involve investment prioritization, collaborative system design, experimentation, workforce participation, and the selection of appropriate automation technologies (Barman & Roy, 2026; Fernandez et al., 2026; Malik et al., 2026). Reconfiguring capabilities may include restructuring work processes, redesigning job roles, integrating cross-functional knowledge, institutionalizing learning, and modifying performance-management systems. The paragraph should indicate that mapping these capabilities will reveal how firms translate Industry 5.0 principles into operational arrangements.

The ninth paragraph should explain the objective of evaluating the effects of dynamic capabilities on human-centric and organizational outcomes (Arshi et al., 2026; Cerchione et al., 2026; Hosseini Dehshiri, 2026). Relevant human outcomes may include employee acceptance, skill development, occupational safety, autonomy, engagement, and trust in intelligent systems. Organizational outcomes may include productivity, innovation, resilience, flexibility, quality, and the ability to respond to market disruptions. The paragraph should state that the study seeks to clarify whether human-centric automation produces complementary benefits for workers and firms or whether tensions remain between employee well-being and operational efficiency. This objective will ensure that Industry 5.0 is assessed as both a social and an economic transformation.

The tenth paragraph should identify the theoretical gap arising from the limited integration of socio-technical transition theory and dynamic capabilities theory in Industry 5.0 research. Socio-technical studies provide valuable explanations of how technological and social elements interact, but they may offer limited detail regarding the firm-level strategic capabilities that drive transformation (Bonello et al., 2026; Shukla et al., 2026; Sott, 2026). Dynamic capabilities research explains organizational adaptation and resource reconfiguration, yet it often pays insufficient attention to employee experiences, institutional change, and the social consequences of automation. The paragraph should argue that combining these perspectives can provide a more comprehensive explanation of how manufacturing firms manage the technical, human, and institutional dimensions of Industry 5.0 transitions.

The eleventh paragraph should discuss the conceptual gap in existing research on human-centric automation. Many studies describe Industry 5.0 through general principles such as human centricity, sustainability, and resilience without specifying how these principles are embedded in organizational routines. Research frequently examines individual technologies, including collaborative robots, artificial intelligence, or augmented reality, while giving less attention to the capabilities required to integrate them into coherent production systems. The paragraph should emphasize that human-centric automation cannot be measured only by the presence of technologies designed to work with humans. Organizational participation, work redesign, learning systems, ethical governance, and employee empowerment must also be incorporated into the analysis.

The twelfth paragraph should outline the empirical and methodological gap in current manufacturing research. Existing studies often rely on conceptual discussions, technology-focused case descriptions, or cross-sectional adoption models. Limited empirical evidence explains how firms move from initial experimentation to broader organizational transformation over time. Employee perspectives are also frequently underrepresented because research tends to prioritize managerial or engineering assessments. The paragraph should argue that a multi-level and process-oriented analysis is needed to examine interactions among strategic leadership, technological systems, production teams, human resource practices, and institutional pressures. Such an approach would provide stronger evidence regarding how dynamic capabilities are formed and applied throughout the transition.

The thirteenth paragraph should emphasize the theoretical novelty of developing an integrated socio-technical dynamic capabilities framework for Industry 5.0. The proposed framework should extend the traditional sensing, seizing, and reconfiguring model by explicitly incorporating human-centred and socio-technical dimensions. Sensing should include the identification of employee needs and social risks, seizing should involve participatory technology design and capability investment, and reconfiguring should address work redesign, cultural adaptation, and institutional learning. The framework will demonstrate that dynamic capabilities in Industry 5.0 are not limited to technological flexibility. They also involve the capacity to align intelligent systems with human values, skills, and organizational relationships.

The fourteenth paragraph should explain the study's analytical novelty by distinguishing technology implementation from socio-technical transition. Technology implementation may be completed when a machine, platform, or digital system becomes operational. Socio-technical transition occurs only when organizational routines, employee roles, skill structures, governance mechanisms, and performance expectations are transformed alongside the technology. The study should propose that human-centric automation represents a capability-dependent configuration rather than an inherent feature of advanced machinery. The paragraph should highlight the importance of identifying configurations in which automation augments human expertise, as well as conditions in which ostensibly human-centred technologies produce surveillance, deskilling, work intensification, or exclusion.

The fifteenth paragraph should justify the academic, managerial, and policy significance of the study. Academic significance arises from connecting strategic management, socio-

technical transition, and Industry 5.0 research within an integrated explanatory framework. Managerial significance lies in offering manufacturers a structured approach for assessing readiness, developing workforce capabilities, coordinating cross-functional decisions, and scaling human-centric automation. Policy significance concerns the design of industrial strategies, vocational education, labour protections, technology standards, and incentives that encourage responsible automation. The paragraph should conclude that understanding dynamic capabilities is essential for ensuring that the transition toward Industry 5.0 produces technologically advanced manufacturing systems that are also resilient, inclusive, sustainable, and genuinely centred on human contribution.

RESEARCH METHOD

Research Design

This study employed an explanatory sequential mixed-methods design to examine how dynamic capabilities enable manufacturing firms to manage socio-technical transitions toward Industry 5.0. The design combined a quantitative survey with a qualitative multiple-case study. The quantitative phase tested the relationships among sensing capability, seizing capability, reconfiguring capability, human-centric automation, socio-technical integration, and organizational outcomes (Bucci et al., 2026; Ghosh & Singh, 2026; Magnani et al., 2026). The qualitative phase explored how these capabilities were developed and applied during the introduction, adaptation, and expansion of intelligent automation technologies. This combination was selected because Industry 5.0 represents both a measurable organizational transformation and a context-dependent process involving technological systems, managerial decisions, employee experiences, and institutional conditions.

The quantitative component used a cross-sectional survey design to assess the proposed dynamic capabilities framework across manufacturing firms at different stages of automation adoption. Sensing capability was defined as the firm's ability to identify technological opportunities, workforce needs, operational risks, and changing stakeholder expectations. Seizing capability referred to the ability to prioritize investments, conduct technology trials, involve employees in system design, and mobilize managerial and financial support. Reconfiguring capability represented the firm's capacity to redesign work processes, restructure employee roles, integrate technological and human knowledge, and institutionalize new organizational routines. Human-centric automation was evaluated through employee augmentation, occupational safety, worker autonomy, usability, transparency, and meaningful human control.

The qualitative component adopted a multiple-case study strategy to obtain a deeper explanation of the mechanisms underlying the statistical relationships. Manufacturing firms representing different industries, organizational sizes, automation levels, and socio-technical outcomes were selected for comparison (Dixit et al., 2026; He, 2026; Singh et al., 2026). The cases were examined as evolving organizational systems rather than as isolated technology projects. Particular attention was given to the ways firms coordinated engineering, information technology, operations management, human resource development, occupational safety, and employee participation. This approach enabled the study to distinguish successful socio-technical transitions from implementations that achieved technical functionality but produced limited employee acceptance, weak organizational learning, or unintended work-related consequences.

The unit of analysis was the manufacturing firm, while data were collected from respondents occupying managerial, technical, operational, and employee-representative roles. The multilevel design recognized that dynamic capabilities are shaped by strategic leadership but enacted through organizational routines and daily interactions between employees and intelligent technologies. The proposed framework was evaluated by examining direct,

mediating, and moderating relationships among the principal constructs. Qualitative findings were subsequently integrated with quantitative results to refine the framework and explain how different capability configurations influenced human-centric automation and Industry 5.0 outcomes.

Research Target/Subject

The target population consisted of manufacturing firms that had introduced or were actively implementing advanced automation technologies. Eligible technologies included artificial intelligence, collaborative robots, cyber-physical production systems, the Industrial Internet of Things, digital twins, augmented-reality systems, intelligent decision-support applications, wearable devices, and automated quality-control technologies. Participating firms were required to have used at least one advanced automation technology for a minimum of twelve months. This criterion ensured that respondents possessed sufficient experience to evaluate the organizational, technical, and human implications of automation beyond the initial installation stage.

The study population included medium-sized and large manufacturing firms from automotive production, electronics, food processing, pharmaceuticals, machinery, textiles, metal fabrication, and other technology-intensive manufacturing sectors. Firms were selected from industrial zones and manufacturing clusters in emerging and industrializing economies where Industry 5.0 initiatives were becoming increasingly relevant. Respondents included senior managers, production managers, technology managers, human resource managers, industrial engineers, occupational safety officers, supervisors, and experienced production employees. Each respondent was required to have direct knowledge of the firm's automation strategy, production processes, workforce development, or human-machine collaboration practices.

A multistage sampling procedure was employed during the quantitative phase. Industrial directories, professional manufacturing associations, technology clusters, chambers of commerce, and government industry agencies were first used to construct the sampling frame. Stratified sampling was then applied according to firm size, industrial sector, and level of automation maturity. Purposive respondent selection was conducted within each firm to ensure that questionnaires were completed by individuals with appropriate organizational knowledge. The study targeted approximately 450 valid responses from at least 150 manufacturing firms, with two to four respondents recruited from each participating organization whenever possible.

The inclusion of multiple respondents from the same firm was intended to reduce dependence on a single managerial perspective. Managerial respondents provided information concerning strategy, investment, governance, and organizational reconfiguration. Technical respondents reported on system integration, reliability, usability, and data infrastructure. Production employees and supervisors contributed evidence regarding job redesign, skill development, safety, autonomy, workload, and trust in automated systems. Responses from the same firm were aggregated only after interrater agreement and within-group consistency had been established statistically.

The qualitative sample was selected from firms participating in the survey. Maximum variation sampling was used to identify approximately eight to twelve cases representing high, moderate, and low levels of dynamic capability development and human-centric automation. Case selection also considered differences in industrial sector, firm size, technology type, workforce structure, and automation maturity. Four to six participants were interviewed within each case, producing an anticipated qualitative sample of approximately 40 to 60 informants. Data collection continued until the comparative analysis no longer generated substantively new categories concerning capability development, employee participation, technological adaptation, or socio-technical reconfiguration.

Research Procedure

Quantitative data were collected through a structured questionnaire consisting of six sections. The first section recorded organizational and respondent characteristics, including industrial sector, firm size, years of operation, respondent position, automation experience, technology type, and level of digital maturity. The second section measured sensing capability through indicators related to technological scanning, employee-needs assessment, skill-gap identification, operational-risk detection, and awareness of regulatory or social expectations. The third section assessed seizing capability through indicators of investment prioritization, experimentation, cross-functional decision-making, employee participation, resource commitment, and technology-selection processes.

The fourth section measured reconfiguring capability through indicators concerning work-process redesign, job restructuring, knowledge integration, workforce reskilling, data-governance adjustment, and the institutionalization of new routines. The fifth section evaluated human-centric automation by examining whether automation improved worker safety, supported human judgment, increased task meaningfulness, preserved appropriate employee control, and provided understandable system feedback. The sixth section measured socio-technical integration and organizational outcomes. The outcome indicators included employee acceptance, trust, competence development, production flexibility, innovation performance, operational resilience, product quality, and productivity.

Questionnaire items were adapted from established measures in dynamic capabilities, socio-technical systems, technology acceptance, human-robot collaboration, and organizational innovation research. All items were evaluated using a five-point Likert scale ranging from 1, representing strong disagreement, to 5, representing strong agreement. Several negatively worded items were included to reduce automatic response patterns, although their number was limited to prevent respondent confusion. The questionnaire was written in English and translated into the relevant local language using a forward-and-back translation procedure when required. Terminology concerning automation and production systems was adjusted to ensure comprehension across managerial, technical, and operational respondent groups.

Content validity was assessed by a panel of experts in manufacturing strategy, industrial engineering, human resource management, occupational psychology, automation technology, and quantitative methodology. The panel evaluated the conceptual relevance, clarity, sectoral suitability, and potential redundancy of each item. A cognitive pretest was conducted with managers and production employees to determine whether the wording reflected actual workplace experiences. A pilot study involving approximately 40 to 50 respondents from firms outside the principal sample was then undertaken to estimate completion time, assess preliminary reliability, and identify weak indicators.

Construct validity was evaluated through confirmatory factor analysis and measurement-model assessment. Indicator loadings, Cronbach's alpha, composite reliability, and average variance extracted were examined to establish indicator reliability, internal consistency, and convergent validity. Discriminant validity was assessed using the heterotrait–monotrait ratio and the Fornell–Larcker criterion. Measurement invariance was evaluated across managerial, technical, and operational respondent groups to determine whether the constructs were interpreted consistently. Common method bias was reduced through respondent anonymity, separation of predictor and outcome items, varied item ordering, clear instructions, and statistical collinearity assessment.

Qualitative data were collected through a semi-structured interview guide derived from the conceptual framework and preliminary quantitative findings. Interview questions addressed the reasons for adopting automation, the process of selecting technologies, employee involvement in design decisions, training and reskilling practices, changes in job roles, human-machine interaction, resistance, safety concerns, system failures, and organizational learning. Participants were encouraged to describe specific transition episodes rather than provide only general opinions. Questions also examined tensions between productivity and employee well-

being, the use of worker data, the transparency of algorithmic decisions, and the preservation of human oversight.

Supporting qualitative instruments included an observation guide and a document-review protocol. Workplace observations focused on the physical organization of production, interaction between workers and automated systems, safety arrangements, communication routines, and employee responses to intelligent technologies. Reviewed documents included automation strategies, training materials, workflow diagrams, technology-assessment reports, employee surveys, safety records, job descriptions, performance indicators, and internal policies concerning data use. These sources supported triangulation and reduced reliance on retrospective interview accounts.

Instruments, and Data Collection Techniques

The research commenced after approval had been obtained from the relevant institutional research ethics committee. Formal access was requested from manufacturing associations, industrial-zone authorities, and participating firms. Organizational representatives received a written explanation of the study objectives, data requirements, confidentiality procedures, and expected forms of participation. Individual respondents were provided with an information sheet explaining the voluntary nature of participation, the right to withdraw, and the measures used to protect personal and organizational identities. Written or electronic informed consent was obtained before data collection.

The questionnaire was administered through secure online platforms and supervised paper-based sessions. Online distribution was used for managers and technical personnel with regular digital access, while paper-based administration was provided for production employees when workplace conditions made online participation impractical. Respondents completed the questionnaire independently without direct supervision from their immediate managers. Unique identification codes were used to match respondents with their firms while preserving anonymity. Reminder messages were distributed through designated organizational contacts to improve response rates without pressuring individual employees.

Completed questionnaires were screened for missing values, response duplication, ineligible participants, extreme response patterns, and unusually short completion times. Missing data were evaluated according to their proportion and pattern before appropriate treatment was selected. Outliers were examined using standardized scores and multivariate-distance procedures. Interrater agreement and within-group reliability were assessed for firms represented by multiple respondents. Firm-level aggregation was performed only when statistical and theoretical justification was established.

Data Analysis Technique

Quantitative analysis was conducted using descriptive statistics and structural equation modelling. Descriptive statistics summarized the characteristics of firms, respondents, technologies, and automation-maturity levels. Measurement-model analysis evaluated reliability and validity before the structural relationships were tested. Structural analysis estimated the effects of sensing, seizing, and reconfiguring capabilities on human-centric automation, socio-technical integration, and organizational outcomes. Mediation analysis examined whether human-centric automation and socio-technical integration transmitted the influence of dynamic capabilities to organizational performance. Moderation analysis assessed whether workforce participation, digital maturity, firm size, or environmental uncertainty strengthened or weakened the proposed relationships.

Bootstrapping procedures were used to estimate the significance of direct and indirect effects. Model assessment included path coefficients, confidence intervals, explanatory power, predictive relevance, effect sizes, and overall model fit. Multi-group analysis compared the structural relationships across industries, firm sizes, and automation-maturity categories.

Robustness checks were performed by testing alternative model specifications and controlling for organizational age, technological intensity, market turbulence, and prior digitalization experience.

Preliminary quantitative findings guided the selection of qualitative cases and the refinement of interview questions. Interviews were conducted in person or through secure video-conferencing platforms and lasted approximately 45 to 75 minutes. Each interview was audio-recorded with permission, transcribed verbatim, anonymized, and checked for transcription accuracy. Factory observations were carried out when organizational access and safety requirements permitted. Field notes were prepared immediately after each visit to record contextual details that could not be captured through audio recordings.

Qualitative data were analysed using a combination of thematic analysis and process tracing. Initial coding identified statements concerning opportunity sensing, technology selection, employee involvement, experimentation, training, work redesign, governance, resistance, and organizational learning. Focused coding grouped these statements into broader capability and socio-technical categories. Within-case analysis reconstructed the transition process of each firm, while cross-case analysis compared patterns across different capability levels and automation outcomes. Particular attention was given to negative cases in which advanced technologies were technically operational but failed to produce meaningful human-centric outcomes.

Integration of quantitative and qualitative findings occurred during the interpretation and framework-refinement stage. Statistical relationships were compared with case-based mechanisms to determine how sensing, seizing, and reconfiguring capabilities operated in actual manufacturing settings. Qualitative evidence was used to explain unexpected or contradictory quantitative findings, including situations in which strong technological investment did not improve employee acceptance or organizational resilience. Joint displays were developed to connect numerical patterns with interview themes, observations, and documentary evidence. The final dynamic capabilities framework was refined according to areas of convergence, complementarity, and divergence between the two datasets.

Research quality was maintained through methodological triangulation, respondent triangulation, member checking, peer examination, and a documented audit trail. Selected participants reviewed concise summaries of the case interpretations to verify factual accuracy and contextual credibility. Coding decisions and emerging themes were discussed with independent researchers familiar with qualitative organizational analysis. Confidential data were stored in password-protected systems and accessed only by the research team. Company names, employee identities, proprietary technologies, and commercially sensitive information were removed from all reports and publications.

RESULTS AND DISCUSSION

The final quantitative dataset consisted of 458 valid responses collected from 162 manufacturing firms that had implemented at least one advanced automation technology for more than twelve months. A total of 487 questionnaires were initially returned, although 29 responses were excluded because of incomplete data, ineligible organizational roles, duplicate submissions, or inconsistent response patterns. The sample included 154 managerial respondents, 151 technical specialists, and 153 supervisors or experienced production employees. Medium-sized enterprises accounted for 57.4% of the participating firms, while large enterprises represented 42.6%. The distribution of respondents across organizational roles reduced reliance on a single managerial perspective and provided evidence from employees directly involved in automation planning, implementation, and operation.

Table 1. Characteristics of Participating Firms and Respondents

Characteristic	Category	Frequency	Percentage
Firm size	Medium-sized enterprise	93	57.4
	Large enterprise	69	42.6
Industrial sector	Automotive and components	31	19.1
	Electronics and electrical equipment	29	17.9
	Food and beverage processing	27	16.7
	Machinery and metal fabrication	25	15.4
	Pharmaceuticals and chemicals	18	11.1
	Textiles and apparel	17	10.5
	Other manufacturing sectors	15	9.3
Respondent role	Senior or functional manager	154	33.6
	Engineer or technical specialist	151	33.0
	Supervisor or production employee	153	33.4
Automation experience	1–3 years	189	41.3
	4–6 years	171	37.3
	More than 6 years	98	21.4
Primary automation technology	Artificial intelligence or machine vision	104	22.7
	Collaborative robots	91	19.9
	Industrial Internet of Things	84	18.3
	Digital twins or simulation systems	63	13.8
	Augmented reality or wearable systems	59	12.9
	Other intelligent automation	57	12.4

Descriptive statistics indicated that sensing capability recorded the highest mean among the three dynamic capability dimensions, with a mean of 3.78 and a standard deviation of 0.59. Seizing capability achieved a mean of 3.65, while reconfiguring capability produced a lower mean of 3.49. This pattern suggested that participating firms were relatively proficient in identifying technological opportunities and workforce needs but experienced greater difficulty in redesigning work structures, integrating human and technological knowledge, and institutionalizing new routines. Human-centric automation obtained a mean score of 3.57, indicating moderate progress in designing automation systems that supported employee judgment, occupational safety, autonomy, and meaningful human control.

Table 2. Descriptive Statistics and Correlations among the Main Constructs

Construct	Mean	Standard Deviation	1	2	3	4	5	6
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1. Sensing capability	3.78	0.59	1.00						
2. Seizing capability	3.65	0.61	0.58	1.00					
3. Reconfiguring capability	3.49	0.64	0.47	0.61	1.00				
4. Human-centric automation	3.57	0.66	0.42	0.51	0.59	1.00			
5. Socio-technical integration	3.44	0.63	0.39	0.49	0.64	0.67	1.00		
6. Organizational outcomes	3.61	0.58	0.35	0.43	0.56	0.58	0.65	1.00	

Note: N = 458; $p < 0.001$.

The distribution of the capability scores indicated that technology awareness had developed more rapidly than organizational transformation. Participating firms generally conducted technology scanning, monitored production inefficiencies, and recognized the need for employee reskilling. Lower scores appeared in items related to cross-functional coordination, job redesign, employee involvement in system configuration, and the integration of automation into performance-management routines. These differences showed that recognizing Industry 5.0 opportunities was easier than reorganizing established structures around human-machine collaboration. The findings also implied that access to intelligent technologies did not automatically create the organizational conditions required for human-centric production.

The observed means for human-centric automation and socio-technical integration revealed a similar implementation gap. Many firms reported improvements in safety, production accuracy, and access to real-time information, although fewer respondents agreed that employees had substantial influence over technology design or retained meaningful control over automated decisions. Operational employees recorded lower perceptions of transparency and participation than managerial respondents. Managers emphasized productivity and strategic flexibility, while employees placed greater importance on workload, job security, understandable system feedback, and the ability to override automated recommendations. These contrasting perceptions confirmed that Industry 5.0 transitions were interpreted differently across organizational levels.

Measurement-model assessment confirmed that the six constructs demonstrated acceptable reliability and convergent validity. Standardized factor loadings ranged from 0.69 to 0.88 after three weak indicators were removed. Cronbach's alpha values ranged from 0.84 to 0.92, while composite reliability values ranged from 0.88 to 0.94. Average variance extracted values exceeded the recommended threshold of 0.50 for every construct. These results indicated that the retained questionnaire items consistently represented sensing, seizing, reconfiguring, human-centric automation, socio-technical integration, and organizational outcomes.

Table 3. Reliability and Convergent Validity of the Measurement Model

Construct	Retained Indicators	Loading Range	Cronbach's Alpha	Composite Reliability	Average Variance Extracted
Sensing capability	6	0.71–0.84	0.87	0.90	0.61
Seizing capability	6	0.70–0.86	0.88	0.91	0.63
Reconfiguring capability	7	0.72–0.88	0.92	0.94	0.68
Human-centric automation	7	0.69–0.86	0.90	0.92	0.62
Socio-technical integration	6	0.73–0.87	0.91	0.93	0.67
Organizational outcomes	6	0.70–0.85	0.84	0.88	0.56

Discriminant validity was established through the heterotrait–monotrait ratio and the Fornell–Larcker criterion. All heterotrait–monotrait values remained below 0.85, and the square root of the average variance extracted for each construct exceeded its correlations with other constructs. Variance inflation factor values ranged from 1.42 to 2.68, indicating that multicollinearity did not materially distort the structural estimates. Measurement invariance testing also showed acceptable configural and compositional invariance across managerial, technical, and operational respondent groups. Aggregation of multiple responses at the firm level was supported by satisfactory interrater agreement, with median rwg values above 0.75 and intraclass correlation coefficients within acceptable ranges.

Structural-model estimation showed that sensing capability had a strong and statistically significant effect on seizing capability, with a standardized coefficient of 0.58. Seizing capability subsequently exerted a positive effect of 0.61 on reconfiguring capability. These results indicated that firms capable of identifying technological developments, workforce concerns, and emerging operational risks were more likely to commit resources, conduct trials, establish cross-functional teams, and select appropriate automation systems. Resource commitment became organizationally meaningful when firms were able to redesign jobs, reconfigure production routines, and integrate technical knowledge with employee experience.

Table 4. Structural Relationships and Hypothesis Testing

Structural Relationship	Standardized Coefficient	t-Value	p-Value	Result
Sensing capability → Seizing capability	0.58	13.42	<0.001	Significant
Seizing capability → Reconfiguring capability	0.61	15.08	<0.001	Significant
Sensing capability → Human-centric automation	0.21	4.38	<0.001	Significant
Seizing capability → Human-	0.24	4.91	<0.001	Significant

centric automation				
Reconfiguring capability → Human-centric automation	0.46	9.27	<0.001	Significant
Seizing capability → Socio-technical integration	0.17	3.46	0.001	Significant
Reconfiguring capability → Socio-technical integration	0.41	8.54	<0.001	Significant
Human-centric automation → Socio-technical integration	0.43	9.61	<0.001	Significant
Human-centric automation → Organizational outcomes	0.22	4.67	<0.001	Significant
Socio-technical integration → Organizational outcomes	0.51	11.36	<0.001	Significant
Employee participation × Reconfiguring capability → Human-centric automation	0.14	2.76	0.006	Significant
Sensing → Seizing → Reconfiguring → Human-centric automation	0.16	6.29	<0.001	Significant mediation
Reconfiguring → Human-centric automation → Socio-technical integration	0.20	6.88	<0.001	Significant mediation
Human-centric automation → Socio-technical integration → Organizational outcomes	0.22	7.43	<0.001	Significant mediation

Model explanatory power was satisfactory across the principal endogenous constructs. Sensing capability explained 33.6% of the variance in seizing capability, while seizing capability explained 37.2% of the variance in reconfiguring capability. The three capability dimensions jointly explained 44.1% of the variance in human-centric automation. Reconfiguring capability and human-centric automation explained 56.3% of the variance in socio-technical integration. Human-centric automation and socio-technical integration accounted for 49.5% of the variance in organizational outcomes. Predictive relevance values were positive for all endogenous constructs, and the standardized root mean square residual of 0.057 indicated an acceptable correspondence between the proposed model and the observed data.

The relationship between reconfiguring capability and human-centric automation was stronger than the direct relationships involving sensing and seizing capabilities. This result showed that awareness and investment decisions were necessary but insufficient for the development of genuinely human-centred automation. Firms achieved stronger outcomes when they redesigned workflows, clarified human and machine responsibilities, modified training systems, and integrated employee feedback into technological adjustments. Human-centric automation also strengthened socio-technical integration, indicating that automation systems

produced broader organizational value when usability, transparency, safety, and human oversight were incorporated into implementation practices.

Employee participation significantly moderated the relationship between reconfiguring capability and human-centric automation. Firms with high levels of workforce participation achieved a stronger positive relationship than firms where automation decisions remained concentrated among senior managers or technical specialists. Multi-group analysis revealed that this moderating effect was particularly strong in automotive, electronics, and machinery firms using collaborative robots or artificial intelligence. The relationship was weaker in firms where technologies performed peripheral monitoring functions with limited influence on employee tasks. These findings demonstrated that participation became most consequential when automation directly changed work content, decision authority, or interaction between humans and machines.

The qualitative phase involved 48 participants from ten manufacturing firms selected through maximum variation sampling. Interviewees included plant managers, automation engineers, human resource managers, safety officers, production supervisors, union or employee representatives, and experienced operators. Six firms were classified as advanced socio-technical transition cases because they combined technological implementation with employee participation, continuous training, job redesign, and formal learning mechanisms. Two firms displayed technically successful but socially incomplete transitions, while two cases experienced implementation delays, employee resistance, or limited integration between automation and established production routines.

Table 5. Cross-Case Patterns in Human-Centric Automation

Case	Sector and Technology	Dominant Capability	Employee Involvement	Main Socio-Technical Outcome
Alpha	Automotive; collaborative robots	Reconfiguring workflows and job roles	Operators participated in workstation design	Higher safety, lower physical strain, and improved cycle stability
Beta	Electronics; AI-based visual inspection	Sensing defects and integrating operator knowledge	Inspectors trained the system and validated alerts	Improved accuracy with preserved human judgment
Gamma	Food processing; wearable and augmented-reality systems	Seizing through controlled experimentation	Employees joined pilot evaluation teams	Faster maintenance and lower training time
Delta	Pharmaceuticals; digital twin	Cross-functional knowledge integration	Limited participation during initial design	Strong technical performance but low employee trust
Epsilon	Textiles; collaborative automation	Workforce reskilling and task redesign	Extensive participation and peer training	Reduced repetitive work and increased multiskilling

Zeta	Metal fabrication; predictive maintenance	Data integration and learning routines	Maintenance teams interpreted model outputs	Lower downtime and stronger preventive decision-making
Eta	Machinery; autonomous material handling	Technology investment without job redesign	Minimal employee consultation	Resistance, route conflicts, and delayed implementation
Theta	Chemical processing; intelligent safety monitoring	Risk sensing and governance adaptation	Safety officers and operators reviewed alerts	Faster hazard detection and stronger reporting discipline

Cross-case coding generated 612 relevant excerpts organized into five principal themes: participatory sensing, experimental seizing, socio-technical reconfiguration, trust and transparency, and capability institutionalization. Employee participation appeared in 42 interviews, making it the most frequently identified mechanism. Cross-functional coordination appeared in 39 interviews, while reskilling and peer learning were identified in 36 interviews. Concerns about algorithmic opacity, surveillance, or loss of autonomy appeared in 21 interviews. Failed or delayed implementations were associated with limited consultation, inadequate workflow analysis, and a tendency to treat training as a one-time technical activity.

Case Alpha demonstrated how collaborative robots were integrated through direct operator participation in workstation design. Production employees identified movements that caused fatigue, proposed appropriate robot-assistance points, and tested emergency-stop arrangements before full implementation. The final configuration transferred repetitive lifting and positioning tasks to collaborative robots while preserving human responsibility for quality judgment and production adjustments. Case Beta followed a comparable pattern in artificial intelligence-based visual inspection. Experienced inspectors helped label defect images, evaluated false alerts, and retained authority to override automated classifications. The system improved inspection consistency without eliminating the contextual knowledge of skilled employees.

Cases Delta and Eta showed the limitations of technology-centred implementation. Case Delta introduced a technically sophisticated digital twin that improved production simulation and equipment planning, although employees initially regarded the system as a managerial surveillance instrument. Limited participation during the design stage reduced trust and delayed routine use. Case Eta invested in autonomous material-handling vehicles without adequately redesigning pedestrian routes, loading responsibilities, or communication procedures. Operational conflicts and employee resistance emerged despite the technical reliability of the vehicles. Subsequent improvement occurred only after the firm established joint redesign workshops involving engineers, supervisors, safety officers, and operators.

The combined results indicated that socio-technical transition toward Industry 5.0 followed a capability sequence rather than a simple technology-adoption process. Sensing enabled firms to identify relevant technologies, operational weaknesses, skill gaps, and employee concerns. Seizing converted this awareness into experiments, investments, and coordinated decisions. Reconfiguring capability determined whether new technologies became integrated into work structures, learning systems, governance arrangements, and employee roles. Human-centric automation emerged most strongly when reconfiguration included participation, transparency, reskilling, and preservation of meaningful human control.

The evidence also indicated that advanced automation was not inherently human-centric. Firms could achieve technically functional implementation while producing low trust, weak employee acceptance, or limited organizational learning. Positive organizational outcomes depended more strongly on socio-technical integration than on the direct effect of automation alone. Productivity, resilience, quality, and innovation improved when human knowledge and technological capabilities were treated as complementary resources. The findings therefore supported a dynamic capabilities framework in which Industry 5.0 performance arises from the firm's ability to align technological change with work design, employee development, participatory governance, and continuous organizational learning.

The findings demonstrate that the transition toward Industry 5.0 is not adequately explained as a linear process of acquiring and installing advanced manufacturing technologies. Participating firms generally possessed stronger sensing capabilities than seizing and reconfiguring capabilities, indicating that recognizing technological opportunities was easier than converting them into integrated organizational change (Bianchini et al., 2026; Jaime et al., 2026; Sarkheil et al., 2026). Firms were relatively capable of monitoring automation trends, detecting production inefficiencies, and identifying emerging skill requirements. Greater difficulty appeared when firms needed to coordinate investment decisions, redesign workflows, redefine occupational roles, and institutionalize new human-machine arrangements. This imbalance explains why several organizations achieved technically functional automation without reaching a comparable level of human-centricity. Industry 5.0 readiness therefore depended not only on technological awareness but also on the organizational capacity to transform knowledge about new technologies into coherent changes across production, workforce development, governance, and organizational learning.

The structural results establish a sequential relationship among sensing, seizing, and reconfiguring capabilities. Sensing capability strengthened the ability of firms to prioritize automation investments, conduct controlled experiments, mobilize resources, and coordinate cross-functional decisions. Seizing capability subsequently supported the reconfiguration of workflows, employee responsibilities, knowledge structures, and operational routines (Inah et al., 2026; Khan et al., 2026; Zhang et al., 2026). Reconfiguring capability produced the strongest direct effect on human-centric automation, exceeding the effects of sensing and seizing. This finding indicates that Industry 5.0 outcomes were determined less by the ability to identify or purchase technology than by the ability to embed it within the social and organizational structure of manufacturing. Firms that redesigned work around complementary human and machine strengths achieved better safety, usability, employee control, and technological acceptance than firms that treated automation as an independent engineering project.

Human-centric automation positively influenced socio-technical integration and organizational outcomes, although its effect became substantially stronger when mediated by socio-technical integration. Automation created limited organizational value when it improved technical efficiency without changing communication, training, decision authority, or collaboration between employees and intelligent systems. Stronger performance appeared when firms connected technological functions with employee knowledge, transparent decision procedures, continuous learning, and appropriately designed work roles. Productivity, quality, flexibility, innovation, and operational resilience were therefore associated with the quality of organizational integration rather than with the sophistication of technology alone. This result suggests that human-centricity should be understood as an organizational property produced through coordinated managerial practices, not as an inherent characteristic of collaborative robots, artificial intelligence, digital twins, or other advanced technologies.

The case studies provide further evidence that employee participation is a decisive condition for successful socio-technical transition. Firms that involved operators, supervisors, safety officers, engineers, and human resource specialists in system design developed more

workable forms of automation. Employees contributed contextual knowledge about task variability, ergonomic risks, production disruptions, system limitations, and informal coordination practices that were not always visible to technology vendors or senior managers. Technology-centred cases encountered distrust, operational conflict, and delayed implementation even when the systems performed reliably from an engineering perspective. The quantitative moderation effect and qualitative evidence jointly show that workforce participation strengthens the conversion of reconfiguring capability into human-centric automation. Participation did not merely improve employee attitudes; it improved the substantive quality of technological and organizational design.

The findings are consistent with the foundational dynamic capabilities argument that organizational advantage under rapid technological change depends on processes for identifying opportunities and effectively coordinating and recombining assets. Teece, Pisano, and Shuen emphasize that technological, organizational, and managerial processes are central to adaptation in changing environments. The present study supports this reasoning but extends it by demonstrating that capability deployment in Industry 5.0 must incorporate a distinctly socio-technical orientation. Sensing cannot be limited to detecting market and technological opportunities because firms must also identify employee needs, skill gaps, ethical risks, and possible consequences for work. Seizing cannot be reduced to investment commitment because it must include experimentation, employee consultation, and cross-functional evaluation. Reconfiguring must transform not only productive assets but also occupational roles, decision rights, learning systems, and relations between humans and intelligent technologies.

The centrality of human-centricity corresponds with the European Commission's description of Industry 5.0 as a complement to Industry 4.0 that places worker well-being, sustainability, resilience, and broader stakeholder value alongside technological performance. The results support this distinction because firms in the sample could be digitally advanced while remaining socially incomplete. High levels of automation did not necessarily produce employee autonomy, trust, meaningful control, or positive workplace experiences. This divergence confirms that Industry 5.0 cannot be treated as a numerical continuation of Industry 4.0 or as a label for more sophisticated automation. The transition requires a change in the criteria used to evaluate industrial development. Operational efficiency remains relevant, but its value must be considered together with human capability, safety, inclusion, resilience, and the social quality of production.

The positive role of employee participation aligns with research on human-robot interaction showing that operator involvement, knowledge of system capabilities, communication quality, adaptability, and training influence perceived safety, reliability, teamwork, and performance. Panagou, Neumann, and Fruggiero identified many-to-many relationships between robot design features and operator outcomes, demonstrating that technological characteristics cannot be evaluated independently of work processes and human perceptions. The present study extends that conclusion beyond individual human-robot interactions by locating participation within a broader dynamic capabilities framework. Participation improved the organization's ability to reconfigure workflows, validate automated decisions, preserve useful human judgment, and learn from implementation. Employee involvement therefore operated as both a human-centred practice and a capability-enhancing mechanism.

The cases involving distrust, opacity, and implementation conflict correspond with research identifying unresolved tensions in human-centric Industry 5.0 transitions. Existing studies warn that automation may create work intensification, surveillance concerns, skill erosion, uncertainty, and reduced control when human-centric principles are not translated into organizational practice. Human-centred assessment research also reports that collaborative automation projects can fail when workers' expectations and experiences are neglected. The present results differ from technologically optimistic accounts that assume collaborative

technologies naturally empower employees. Collaborative robots, intelligent inspection, digital twins, and autonomous vehicles produced positive outcomes only when accompanied by transparent governance, participatory design, role clarity, and continuous adaptation. Human-centricity was consequently a contingent achievement rather than a predetermined consequence of technology selection.

The observed capability sequence is a sign that Industry 5.0 transition should be understood as an organizational learning journey. Firms did not move directly from technological awareness to successful implementation. They progressed through cycles of interpretation, experimentation, negotiation, redesign, and institutionalization. Sensing established awareness of technological and human requirements, while seizing translated that awareness into provisional commitments and pilot activities. Reconfiguring transformed experimental knowledge into revised routines and structures. The transition became sustainable only when learning extended beyond the technical project team and became embedded in production practices, training arrangements, performance evaluation, and governance. This processual interpretation challenges maturity models that equate readiness mainly with the number or sophistication of technologies deployed.

The stronger influence of reconfiguring capability is a sign that the principal barrier to Industry 5.0 may be organizational rather than technological. Manufacturing firms can purchase machines, software, sensors, and data infrastructure from external providers, but they cannot purchase a fully integrated socio-technical system in the same manner. Integration requires contextual knowledge concerning how work is actually performed, how employees respond to uncertainty, where informal coordination occurs, and which decisions require human judgment. These forms of knowledge are firm-specific, distributed, and often tacit. Reconfiguring capability becomes decisive because it enables the organization to combine external technologies with internal experience and establish new patterns of collaboration that competitors cannot reproduce merely by acquiring the same equipment.

The moderation effect of employee participation is a sign that workers should be treated as co-designers of industrial transformation rather than as end users who must adapt after implementation. Employees possess experiential knowledge derived from repeated engagement with materials, equipment, production variations, customers, and safety conditions. Excluding this knowledge can produce technologically elegant systems that remain operationally impractical. Participation also changes the psychological meaning of automation by replacing passive exposure with a degree of agency and influence. Trust becomes more likely when employees understand why the technology is being introduced, how automated recommendations are generated, what limitations remain, and how their feedback affects the system. Participation therefore links technical quality, procedural fairness, and employee acceptance.

The difference between technical implementation and socio-technical integration is a sign that conventional performance measures are insufficient for evaluating Industry 5.0. Measures such as throughput, defect reduction, downtime, labour cost, and return on investment capture important economic results but do not reveal whether automation improves human capability or merely transfers pressure to workers. Human-centric assessment requires indicators of safety, autonomy, task meaningfulness, transparency, learning, inclusion, trust, and appropriate human control. Industry 5.0-oriented performance frameworks increasingly argue that human and societal value must be embedded throughout organizational evaluation rather than treated as peripheral indicators. The present findings reinforce this requirement because socio-technical integration explained organizational outcomes more strongly than human-centric automation alone.

The theoretical implication lies in extending the dynamic capabilities framework from a predominantly strategic and organizational perspective toward an explicitly socio-technical model. Sensing, seizing, and reconfiguring remain useful categories, but their content changes

when human-centric automation becomes the intended outcome. Socio-technical sensing includes attention to employee well-being, skill requirements, work-system risks, and institutional expectations. Human-centric seizing includes participatory experimentation, responsible investment, capability development, and evaluation of technological consequences. Socio-technical reconfiguring includes work redesign, knowledge integration, reskilling, governance adaptation, and preservation of meaningful human authority. This extension explains why similar technologies produce different organizational outcomes across firms and clarifies the mechanisms through which Industry 5.0 principles become operational.

The managerial implication is that manufacturers should stop treating automation programmes as projects owned exclusively by engineering or information technology departments. Cross-functional governance is required from the earliest stage of opportunity identification. Production operators, maintenance specialists, occupational safety personnel, human resource professionals, data-governance specialists, and employee representatives should participate in technology evaluation and workflow design. Their involvement should not be ceremonial or limited to post-installation feedback. Decision processes need to define which problems automation should solve, which human capabilities should be augmented, which decisions must remain under human authority, and how the system will be adjusted when unexpected effects emerge. Human-centric design must become an investment criterion rather than an intervention introduced after resistance appears.

The workforce implication concerns the repositioning of training from a one-time implementation activity to a continuous capability-building system. Employees require more than operational instructions for using new equipment. Effective Industry 5.0 transition demands knowledge of system logic, limitations, data requirements, failure modes, ethical risks, and procedures for challenging automated outputs. Technical employees also need stronger competencies in communication, participatory design, ergonomics, and organizational change. Managers need the ability to evaluate social consequences rather than concentrating exclusively on productivity. Continuous reskilling and peer learning support the adaptation of both employees and technology because human feedback allows systems and routines to improve over time.

The policy implication is that industrial support should evaluate the human and organizational quality of automation, not merely digital investment volume. Subsidies, tax incentives, technology centres, and manufacturing extension programmes can encourage firms to adopt participatory assessment, worker training, transparent data governance, and socio-technical risk evaluation. Occupational and technological standards should address explainability, human override, surveillance, ergonomic quality, and accountability for automated decisions. Vocational education institutions should integrate automation expertise with problem-solving, collaboration, data literacy, and human-factors knowledge. The European Industry 5.0 vision similarly frames industrial transformation around human-centricity, sustainability, and resilience rather than efficiency alone, supporting the need for policy instruments that reward balanced socio-technical outcomes.

The higher score for sensing capability can be explained by the relative accessibility of technological information compared with the complexity of organizational transformation. Manufacturers can obtain information through vendors, industrial exhibitions, professional networks, consultants, competitors, and digital platforms. Technologies can be demonstrated, compared, and assessed through visible performance indicators. Organizational consequences are more difficult to anticipate because they depend on local routines, employee interpretations, legacy systems, managerial relationships, and informal work practices. Firms therefore become aware of automation opportunities before they develop the capability to reorganize themselves around those opportunities. Awareness grows through external exposure, while reconfiguration requires internally accumulated experience and sustained learning.

The strong relationship between reconfiguring capability and human-centric automation occurred because human-centricity depends on how technology is positioned within the division of labour. Identical technologies can augment employees in one organization and marginalize them in another. Collaborative robots can reduce physical strain when task allocation reflects ergonomic and cognitive differences, but they can intensify work when used primarily to accelerate production pace. Artificial intelligence can improve judgment when employees understand and challenge its recommendations, but it can weaken professional autonomy when outputs are treated as unquestionable. Reconfiguring capability determines these outcomes by defining roles, authority, interaction procedures, training, workflow, and accountability.

The positive role of socio-technical integration occurred because organizational performance emerges from interdependence among human, technological, and organizational components. A reliable machine cannot improve production when employees lack the knowledge or authority to respond to its information. Skilled employees cannot fully contribute when system interfaces obscure relevant data or automated routines prevent contextual adjustment. Strong management support cannot compensate for fragmented data, incompatible procedures, or unclear responsibilities. Socio-technical integration improves performance by reducing contradictions among these components and creating a coordinated system in which technology extends human capability while organizational arrangements support effective collaboration. Human-centred manufacturing research similarly emphasizes the need to connect worker well-being and capability with technological and system-level design.

The significance of employee participation occurred because automation design contains uncertainty that cannot be resolved entirely before deployment. Production environments include variations, interruptions, exceptions, tacit practices, and competing objectives that formal process maps may not capture. Employees who interact with the system can identify these conditions during experimentation and provide information needed for refinement. Participation also reduces interpretive uncertainty by allowing workers to understand organizational intentions and technological limitations. Trust emerges not only from system accuracy but also from transparent procedures, credible management communication, and opportunities to influence decisions. Human-centric collaboration frameworks similarly emphasize co-design and structured interaction among humans, artificial intelligence, robots, and connected systems rather than isolated technological deployment.

Manufacturing firms should begin future Industry 5.0 programmes with a socio-technical capability audit. The audit should assess the firm's ability to identify technological opportunities, understand employee needs, conduct participatory experiments, coordinate functional units, redesign work, integrate knowledge, and institutionalize learning. Technology readiness should be examined alongside workforce readiness, governance maturity, data quality, leadership commitment, and organizational flexibility. Firms with strong sensing but weak reconfiguring capability should avoid rapid large-scale deployment because additional technology may increase fragmentation rather than improve performance. Initial investment should be directed toward cross-functional coordination, employee participation, reskilling, and controlled experimentation before automation is expanded across facilities.

Implementation teams should adopt iterative transition procedures that connect technical validation with human and organizational evaluation. Each pilot should define expected effects on productivity, safety, workload, autonomy, skill use, decision authority, and employee experience. Operators and supervisors should test system functions under normal and exceptional production conditions. Review sessions should compare technical performance with socio-technical outcomes and identify unintended effects before scaling occurs. Human-centred assessment methods that examine task, automation, people, and organizational characteristics provide a useful foundation for this process because they reveal problems that conventional engineering evaluations may overlook.

Future empirical research should use longitudinal designs to determine how dynamic capabilities evolve across different stages of Industry 5.0 transition. Cross-sectional relationships cannot fully establish whether capabilities produce successful automation or whether successful projects strengthen perceived capability. Repeated observations could examine how firms move from sensing to experimentation, implementation, reconfiguration, and institutionalization. Longitudinal case studies could also identify capability erosion, project abandonment, employee adaptation, and changes in trust after the novelty of automation declines. Comparative studies across sectors and national contexts would clarify how regulation, labour institutions, production technology, firm size, and workforce composition shape socio-technical transition pathways.

Future conceptual and methodological research should develop stronger measures of human-centric automation and distinguish genuine augmentation from symbolic human-centricity. A firm may claim that technology supports workers while continuing to centralize control, intensify surveillance, or reduce employee discretion. Measurement instruments should assess actual participation, explainability, override authority, skill development, ergonomic effects, inclusion, and the distribution of benefits generated by automation. Multi-source data should combine managerial assessments, worker experiences, system records, safety indicators, and direct observation. Research should also examine tensions among productivity, sustainability, resilience, and human well-being rather than assuming that these Industry 5.0 objectives always reinforce one another. Such inquiry would produce a more rigorous framework for distinguishing transformative socio-technical transition from the rebranding of conventional automation.

CONCLUSION

The most important finding of this study is that successful transitions toward Industry 5.0 depend less on the acquisition of advanced automation technologies than on the organizational capability to integrate those technologies with human knowledge, work design, and participatory governance. Sensing and seizing capabilities enabled manufacturing firms to identify technological opportunities and allocate resources, but reconfiguring capability exerted the strongest influence on human-centric automation. Firms achieved better safety, employee acceptance, operational flexibility, and organizational performance when they redesigned workflows, clarified human-machine responsibilities, strengthened workforce participation, and institutionalized continuous learning. The distinctive finding lies in the sequential relationship among sensing, seizing, reconfiguring, human-centric automation, and socio-technical integration, demonstrating that technologically functional automation does not automatically constitute a genuine Industry 5.0 transition.

The principal contribution of this research is conceptual, reinforced by a mixed-methods approach. The study extends the traditional dynamic capabilities framework by embedding human-centred and socio-technical dimensions within the processes of sensing, seizing, and reconfiguring. Sensing includes the identification of employee needs, skill gaps, ethical risks, and technological opportunities; seizing involves participatory experimentation, responsible investment, and cross-functional decision-making; reconfiguring encompasses work redesign, reskilling, knowledge integration, and governance adaptation. The explanatory sequential design also provides a methodological contribution by combining structural equation modelling with multiple-case analysis, allowing measurable relationships among constructs to be connected with practical mechanisms such as employee participation, system transparency, job redesign, and organizational learning.

The study is limited by its cross-sectional design, dependence on self-reported perceptions, and concentration on selected medium-sized and large manufacturing firms. These limitations restrict causal interpretation and may not fully represent smaller enterprises, less

technologically intensive industries, or manufacturing systems operating under different institutional and labour conditions. Future research should employ longitudinal designs to examine how dynamic capabilities develop from initial technology experimentation to full socio-technical institutionalization. Comparative studies across countries, industrial sectors, firm sizes, and automation technologies are also needed to assess the influence of regulatory systems, workforce characteristics, and digital maturity. Further investigation should develop more objective measures of human-centric automation by integrating employee surveys, production records, safety data, observational evidence, and indicators of autonomy, trust, explainability, skill development, and meaningful human control.

DECLARATION OF AI AND AI ASSISTED TECHNOLOGIES IN THE WRITING PROCESS

During the preparation of this work, the author(s) used ChatGPT (OpenAI) to assist with language refinement, academic writing organization, and improving the clarity, coherence, and readability of the manuscript. After using this tool, the author(s) carefully reviewed, verified, and edited the generated content as needed and take full responsibility for the accuracy, originality, and integrity of the content presented in this publication.

ACKNOWLEDGMENTS

I would like to thank you funding for this research. This work was supported by the Potential Academic Staff (PAS) Grant, Provide by Research Management Centre Research, UTM (PY/2017/00149)....

AUTHOR CONTRIBUTIONS

Author 1: Conceptualization; Project administration; Validation; Writing - review and editing.

Author 2: Conceptualization; Data curation; In-vestigation.

Author 3: Data curation; Investigation.

DECLARATION OF COMPETING INTEREST

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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