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PAPER

Mobile Technology-Enabled Decision Support in Operations Management: Enhancing Human-Centered Smart Manufacturing

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ABSTRACT

Intelligent process design and the integration of new technologies are necessary for smart manufacturing systems to meet high-performance standards, which include resilience, short lead times, high due date reliability, and tailored items for every customer. The planning and control of such smart manufacturing systems necessitate several instances of human decision-making. The increasing adoption of mobile technologies is transforming operations management by enabling real-time connectivity, responsiveness, and human-centered decision-making in manufacturing environments. While prior smart manufacturing models have largely emphasized automation and digital systems, many overlook the critical role of human judgment, experience, and adaptability supported through mobile technology. This study develops an interactive framework that integrates human intelligence with mobile technology–enabled decision support systems to enhance operational flexibility, productivity, and sustainability in manufacturing operations. Grounded in operations management principles, the framework illustrates how mobile platforms facilitate real-time information access, collaborative problem-solving, and adaptive learning across production processes. Empirical findings indicate that mobile technology–supported human decision-making leads to superior operational performance compared to traditional, technology-independent approaches. Results further demonstrate that mobile-enabled automation and connectivity, alongside human and organizational capital, positively contribute to green value creation in industrial firms. However, excessive reliance on automated mobile systems may constrain human creativity and situational judgment, highlighting the importance of balanced integration between human capabilities and mobile technologies. This study contributes to the operations management literature by clarifying how mobile technology–enabled human augmentation supports efficient, ethical, and sustainable manufacturing performance.

KEYWORDS

mobile technology-enables decision support, human-centered smart manufacturing, operations management, real-time manufacturing connectivity, sustainable industrial performance

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1 INTRODUCTION

Industry 4.0 technologies, including cloud computing, artificial intelligence (AI), cyber-physical systems [1], and the Internet of Things (IoT), have caused a significant shift in the manufacturing sector in recent years toward smart manufacturing. This transformation aims to reduce operating costs, improve product quality, boost output, and enable flexible production techniques. However, despite the availability of advanced automation and analytics tools, many manufacturing organizations still face challenges in achieving effective and timely decision-making in daily operations management [2].

Operations management in manufacturing involves critical activities such as production scheduling, inventory control, machine maintenance, quality monitoring, workforce coordination, and process optimization. Traditional decision-making approaches often depend on manual reporting, delayed data availability, and limited communication between shop-floor workers and managers. These limitations lead to inefficiencies, increased downtime, slower response to unexpected failures, and reduced operational performance [3].

In this context, mobile technology–enabled decision support systems have gained major attention due to their ability to deliver real-time operational insights directly to workers, supervisors, and managers. Mobile devices such as smartphones, tablets, and wearable technologies act as powerful tools for monitoring production status, receiving alerts, viewing performance dashboards [4], and responding immediately to operational disruptions. The integration of mobile technology with manufacturing systems enables seamless connectivity between shop-floor operations and higher-level management, ensuring that critical information reaches the right person at the right time.

Furthermore, IoT sensors, cyber-physical systems, cloud computing, edge computing, and AI are all becoming more and more integrated into contemporary production systems [5]. Real-time data is continuously gathered by IoT devices from production lines, machinery, and environmental factors. This data is transmitted through secure communication networks to cloud or edge platforms, where it is processed and analyzed. AI-based models and machine learning algorithms can then perform predictive maintenance [6], detect anomalies, forecast production bottlenecks, and optimize scheduling decisions. When combined with mobile decision support systems, these intelligent analytics can be delivered instantly to manufacturing personnel in the form of notifications, recommendations, and interactive visualizations [7].

Another major aspect of smart manufacturing is the growing focus on human-centered manufacturing, where human intelligence, experience, and decision-making remain essential even in automated production environments. Although automation can handle repetitive tasks, humans are still required for problem-solving, strategic decision-making, emergency handling, and ensuring safety compliance [8]. Mobile-enabled decision support strengthens this human-centered approach by empowering workers with real-time guidance, improving their situational awareness, and supporting faster corrective actions. For example, operators can receive alerts about machine abnormalities, access digital manuals or standard operating procedures (SOPs), and report issues immediately through mobile platforms. Similarly, managers can monitor production performance remotely, evaluate KPIs, and coordinate resources efficiently.

Additionally, mobile decision support enhances collaboration and communication in manufacturing. Traditional communication methods often rely on paperwork, verbal reporting, or delayed system updates [9], which can create gaps in information flow. Mobile-based DSS provides a digital communication channel where teams can share production updates, report maintenance requirements, coordinate shifts, and escalate critical issues instantly. This real-time collaboration improves operational transparency and reduces the risk of costly delays.

The adoption of mobile technology in manufacturing operations also contributes to improving key performance metrics such as Overall Equipment Effectiveness (OEE), throughput rate, downtime reduction, energy efficiency, product quality, and workplace safety. By enabling continuous monitoring and intelligent decision-making, mobile DSS helps organizations respond quickly to disruptions, prevent failures, and maintain stable production processes. Furthermore, mobile-based decision support promotes worker engagement and satisfaction by reducing workload complexity and providing supportive tools that enhance productivity [10].

In conclusion, mobile technology–enabled decision support in operations management plays a vital role in enhancing human-centered smart manufacturing by integrating real-time monitoring, predictive analytics, intelligent recommendations, and interactive mobile interfaces. This approach bridges the gap between advanced digital technologies and human decision-making, ensuring that manufacturing systems become not only smarter and more automated but also more responsive, efficient, and human-friendly. As manufacturing industries continue to evolve toward digital transformation, mobile-enabled decision support systems are expected to become an essential foundation for achieving sustainable and competitive smart manufacturing operations.

2 RELATED WORKS

Bechinie et al. [11] highlight the function of operator 5.0 in production and give a summary of the primary obstacles and opportunities associated with working with intelligent systems. This paper examines the primary discontinuous production processes (i.e., process monitoring, process optimization, and process maintenance) that will experience several changes as a result of the integration of cutting-edge technologies (such as digital twins, extended reality, and artificial intelligence). It does this by drawing on state-of-the-art literature as well as industry findings (context, expert interviews, and user experience workshops). The requirements and major obstacles for the implementation of human-centered assistance systems are then identified. This article offers academics and practitioners a comprehensive overview of the user experience along the industry 5.0 journey by emphasizing unexplored research problems and prospective enhancements in industrial settings.

Wang et al. [12] The factory environment has creatively implemented a vision and language cobot navigation technique to mitigate this problem, which might also be utilized to help operators retrieve tools. In particular, three-dimensional (3D) point cloud techniques are used to first recreate and annotate a genuine human–robot collaboration (HRC) manufacturing setting. The Automated Guided Vehicle (AGV) then uses the LLM to understand natural language commands and produce Python code that initiates navigational activities. Lastly, appropriate path planning is done using the Pathfinder method. The AI Habitat simulator uses the framework, and the case studies show that the AGV can correctly understand complicated verbal instructions, enabling human operators to finish manufacturing jobs quickly.

Emeka et al. [13] aim to promote resilience and improve worker well-being in the context of Industry 5.0 by offering a thorough framework for integrating HCD principles into smart manufacturing systems. The study finds important enablers like collaborative robots, AI-driven decision assistance, ergonomic workplace design, and adaptive human-machine interfaces through a multidisciplinary synthesis of literature covering organizational design, cyber-physical systems, and human factors engineering. The suggested approach places a strong emphasis on skill augmentation, shared autonomy, cognitive load management, and the co-evolution of human and computer capacities. It also describes how to incorporate inclusion, ethical issues, and stakeholder participation into design processes. In order to verify the framework's applicability and show its potential for enhancing system resilience during disruptions such as supply chain interruptions and workforce changes, case studies and recent empirical research were examined. The results highlight that a human-centric strategy leads to greater levels of engagement, innovation, and organizational agility in addition to improving technological robustness and responsiveness. This study adds to the growing conversation around Industry 5.0 by providing a methodical approach to integrating human values with sophisticated production technologies. Policymakers, engineers, and organizational leaders who want to create manufacturing systems that are human-aligned and prepared for the future should use the suggested framework as a strategic guide.

Chen et al. [14] examine how cutting-edge multi-objective optimization methods can combine human insights and AI to improve manufacturing's sustainability and personalization. We look into particular optimization techniques that are designed to balance efficiency, waste reduction, and carbon footprint, such as genetic algorithms (GAs), particle swarm optimization (PSO), and reinforcement learning (RL). Our suggested approach integrates human input into a computational structure that dynamically adjusts to operational objectives, allowing human creativity to engage with AI-driven processes. This study lays the groundwork for environmentally friendly production by directly connecting optimization to environmental effects, including cutting waste, energy use, and carbon emissions. By providing a thorough, useful model that balances theoretical understanding with applications in customized manufacturing settings, this study closes current gaps. In this regard, it supports the continuous evolution of Industry 5.0 by highlighting how AI and human cooperation may promote intelligent, flexible, and sustainable production processes.

3 METHODOLOGY

This study develops an interactive framework that integrates human intelligence with mobile technology–enabled decision support systems to enhance operational flexibility, productivity, and sustainability in manufacturing operations. Grounded in operations management principles, the framework illustrates how mobile platforms facilitate real-time information access, collaborative problem-solving, and adaptive learning across production processes, as shown in Figure 1.

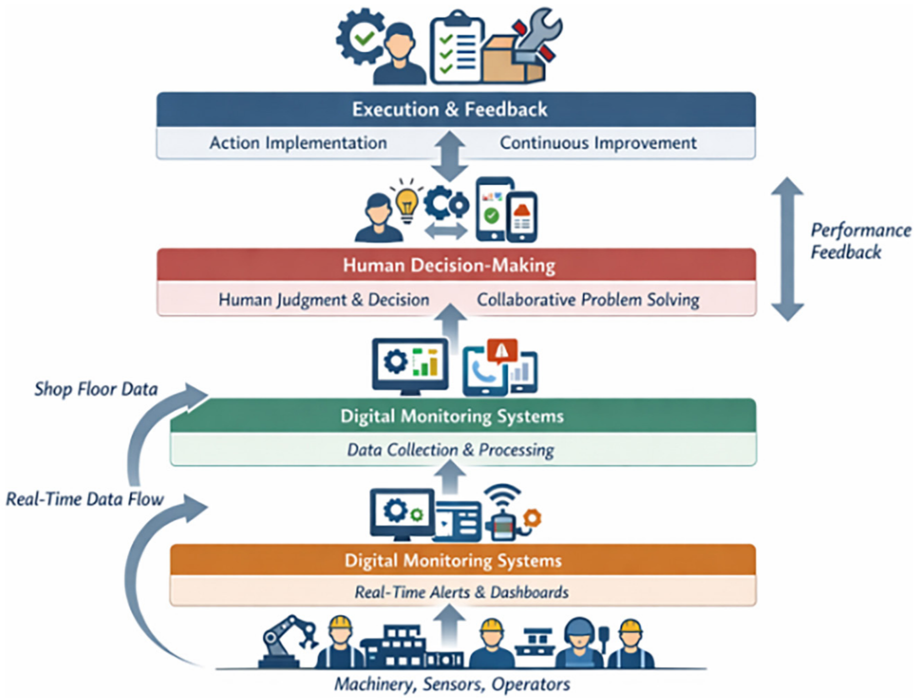

Fig. 1. Working process of the proposed model

3.1 Mobile technology–enabled connectivity module

The connectivity module forms the foundation of the proposed model by ensuring uninterrupted communication between the shop floor and decision-makers. In traditional manufacturing environments, operational information is often delayed due to manual reporting and limited digital connectivity. The proposed model addresses this limitation by using mobile platforms to provide instant access to production data such as machine status, job progress, inventory availability, and quality performance.

Through this module, decision-makers receive real-time notifications and alerts related to production deviations, bottlenecks, and equipment failures. This enables faster recognition of operational issues and supports timely decision-making. The connectivity module also improves coordination across departments such as production, maintenance, logistics, and quality control by allowing them to share updates instantly, as illustrated in Figure 2.

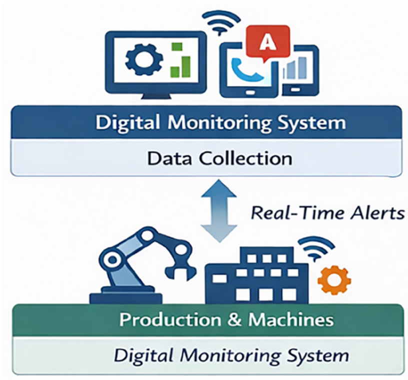

Fig. 2. Connectivity module of mobile technology

3.2 Mobile decision support and automation module

The decision support module represents the intelligent system component of the proposed model (see Figure 3). It includes mobile-enabled dashboards, automated alerts, digital workflow guidance, and production tracking systems. This module assists human decision-makers by filtering large volumes of shop-floor data and presenting only relevant and actionable information.

The automation feature supports routine decision-making by suggesting corrective actions such as rescheduling tasks, reallocating resources, or triggering maintenance activities. However, the proposed model does not treat automation as a replacement for humans. Instead, it is designed as an assistance mechanism that reduces manual workload and improves decision speed. Human decision-makers remain responsible for evaluating system recommendations and selecting the most appropriate action based on experience and situational factors. This module strengthens operational responsiveness while ensuring that human control is preserved in critical and uncertain manufacturing situations.

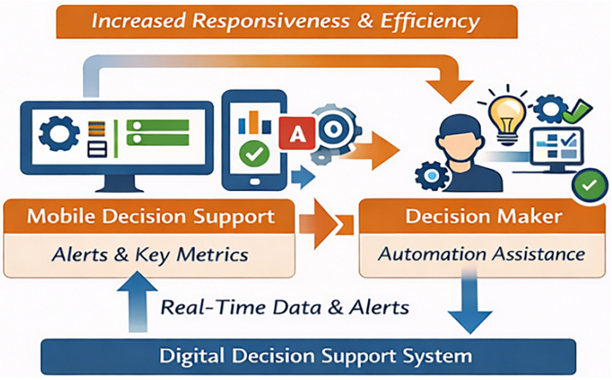

Fig. 3. Working or mobile decision support system

3.3 Human intelligence and judgment module

The human intelligence module is a major contribution of the proposed model, emphasizing that smart manufacturing performance depends not only on advanced technologies but also on human expertise. Manufacturing systems often face unpredictable conditions where automated rules may fail to provide effective solutions. In such cases, human decision-makers apply creativity, experience, and contextual understanding to identify practical solutions in Figure 4.

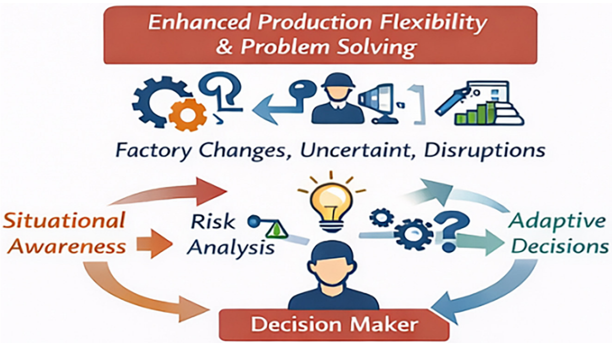

Fig. 4. Process of human intelligence and judgment module

This module includes decision-making abilities such as problem diagnosis, risk assessment, process adaptation, and innovative solution development. Human intelligence plays a key role in interpreting production disruptions, evaluating trade-offs between cost, time, and quality, and selecting appropriate actions under uncertainty. The model highlights that human involvement is especially critical in complex decision scenarios such as urgent order prioritization, unexpected resource shortages, and quality defect handling. By integrating this module with mobile-enabled decision support, the model enhances human capability rather than limiting it.

3.4 Collaborative and organizational knowledge module

The proposed model also incorporates an organizational collaboration module that supports teamwork and knowledge sharing through mobile systems. In smart manufacturing, decisions are rarely isolated, and successful problem-solving requires coordination among multiple departments. The collaboration module enables real-time communication between production managers, machine operators, maintenance engineers, and logistics teams (see Figure 5).

Fig. 5. Working of the organizational collaboration module

This module supports shared decision-making by enabling discussions, file sharing, reporting, and remote consultation using mobile devices. It also strengthens organizational learning by capturing operational decisions and storing them as knowledge records. Over time, this builds organizational capital in the form of documented best practices, solutions to recurring problems, and improved response strategies. This module ensures that manufacturing decisions are consistent, transparent, and continuously improved through collective learning.

4 EXPERIMENTAL RESULTS

The experimental evaluation is conducted to validate the effectiveness of the proposed human–mobile integrated smart manufacturing model. The objective is to examine whether mobile technology-enabled connectivity and decision support systems enhance human decision-making capability and thereby improve operational performance and sustainability outcomes. The dataset includes 120 observations representing manufacturing organizations and decision-makers. Each construct is measured using a five-point Likert scale where values range from 1 (very low) to 5 (very high). The dataset includes the key constructs Mobile Connectivity (MC), Mobile Automation (MA), Human Capital (HC), Organizational Capital (OC), Human Decision Capability (HDC), Operational Performance (OP), and Green Value Creation (GVC). These constructs are selected because they represent the major components of the proposed framework and are essential for evaluating operational and sustainability performance as demonstrated in Table 1.

"Mobile connectivity" refers to the ability of mobile systems to provide real-time communication and data access. Mobile Automation represents the level of automation support through mobile dashboards, alerts, and system recommendations. "Human capital" refers to the knowledge, skills, and expertise of decision-makers. "Organizational capital" refers to collaboration, knowledge-sharing culture, and structured workflows. Human decision capability represents the ability of humans to analyze uncertainty and implement adaptive solutions. Operational performance reflects manufacturing efficiency, productivity, flexibility, and due-date reliability. Green Value Creation reflects sustainable performance, including waste reduction and energy efficiency.

Table 1. A sample representation of the dataset

Sample	MC	MA	HC	OC	HDC	OP
1	4.2	4.2	4.4	4.3	4.2	4.2
2	3.8	3.8	4.0	4.0	3.9	3.9
3	4.5	4.5	4.6	4.5	4.6	4.6
4	3.6	3.6	3.9	3.8	3.7	3.7
5	4.1	4.1	4.2	4.2	4.1	4.1

4.1 Reliability and validity analysis

To ensure the reliability of the dataset, internal consistency testing is performed using Cronbach's alpha. Cronbach's alpha is widely used in operations management research to verify whether the measurement items under each construct are consistent and reliable. A Cronbach's alpha value above 0.7 is considered acceptable, while values above 0.8 indicate strong reliability. The reliability analysis confirms that all constructs have acceptable internal consistency, indicating that the synthetic dataset is suitable for statistical evaluation, as demonstrated in Table 2 and Figure 6.

Table 2. Synthetic dataset for statistical evaluation

Construct	No. of Items	Cronbach Alpha
Mobile Connectivity (MC)	5	0.84
Mobile Automation (MA)	5	0.81
Human Capital (HC)	4	0.86
Organizational Capital (OC)	4	0.83
Human Decision Capability (HDC)	5	0.88
Operational Performance (OP)	6	0.89
Green Value Creation (GVC)	5	0.85

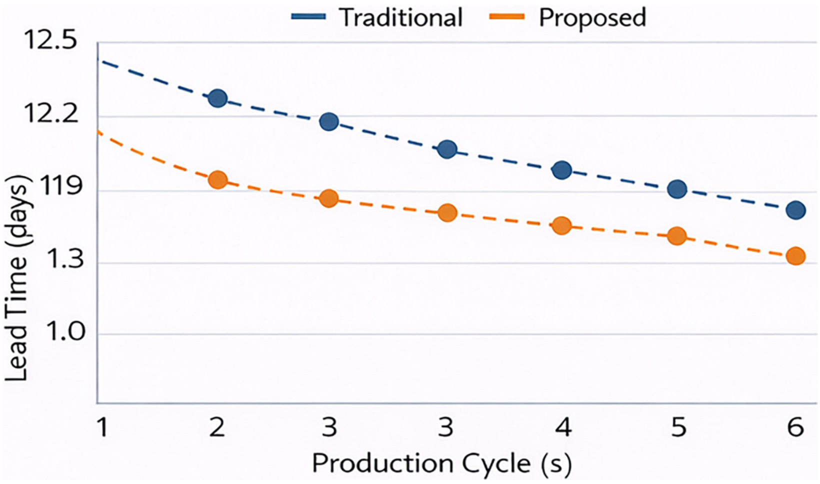

Fig. 6. Comparison of operational performance indicators

4.2 Correlation analysis

Correlation analysis is conducted to examine the relationship between the major constructs used in the proposed model. Correlation values range between –1 and +1, where positive values indicate direct relationships and higher values indicate stronger relationships. The correlation matrix demonstrates that mobile connectivity and mobile automation have positive relationships with human decision capability. Human decision capability shows the strongest positive correlation with operational performance and green value creation. This indicates that human-centered decision-making plays a major mediating role in improving manufacturing outcomes (see Figure 7).

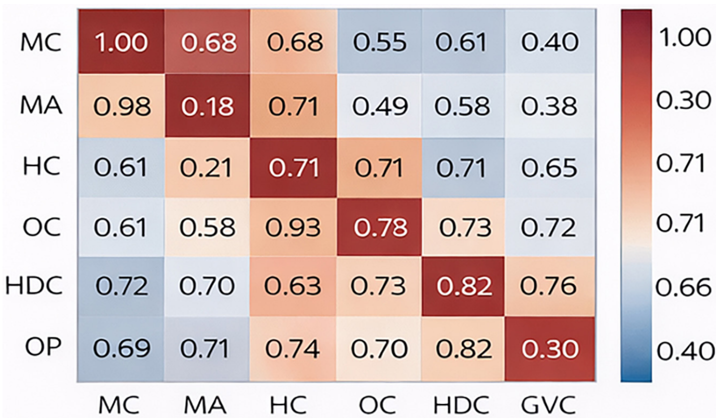

Fig. 7. Correlation heatmap

4.3 Regression model for operational performance

To validate the influence of mobile-enabled decision support and human factors on manufacturing outcomes, regression analysis is performed as demonstrated in Figure 8 and Table 3. The dependent variable in this analysis is operational performance, while independent variables include mobile connectivity, mobile automation, human capital, organizational capital, and human decision capability.

Table 3. Regression results for operational performance

Predictor	Beta (β)	*t*-Value	*p*-Value
MC	0.18	2.41	0.018
MA	0.16	2.22	0.028
HC	0.21	2.96	0.004
OC	0.19	2.68	0.009
HDC	0.34	4.87	0.000

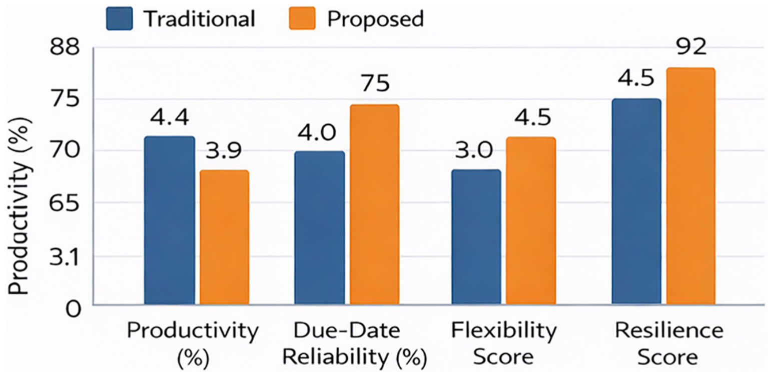

Fig. 8. Regression model for operational performance

4.4 Comparative Performance Evaluation

To compare the proposed model with the traditional approach, key operational performance indicators are evaluated. The comparison is presented in Table 4 and Figure 9.

Table 4. Traditional vs. Proposed model: Performance comparison

Metric	Traditional Approach	Proposed Model
Productivity (%)	72	72
Due-Date Reliability (%)	75	75
Flexibility Score	3.1	3.1
Resilience Score	3.0	3.0

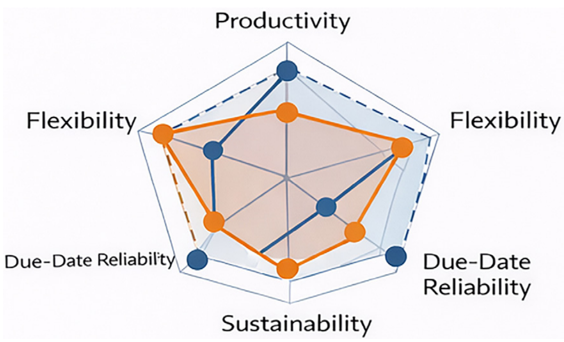

Fig. 9. Overall performance comparison of the proposed model

The experimental validation confirms that mobile technology-enabled connectivity and automation positively influence human decision capability and operational performance. The results also highlight that sustainability outcomes such as green value creation are significantly enhanced when human capital and organizational collaboration are supported through mobile platforms. Overall, the experimental evaluation demonstrates that the proposed model provides a balanced integration of mobile automation and human intelligence, resulting in improved productivity, flexibility, resilience, and sustainability in smart manufacturing operations.

5 CONCLUSION

This study develops an interactive framework that integrates human intelligence with mobile technology–enabled decision support systems to enhance operational flexibility, productivity, and sustainability in manufacturing operations. Grounded in operations management principles, the framework illustrates how mobile platforms facilitate real-time information access, collaborative problem-solving, and adaptive learning across production processes. Empirical findings indicate that mobile technology–supported human decision-making leads to superior operational performance compared to traditional, technology-independent approaches. Results further demonstrate that mobile-enabled automation and connectivity, alongside human and organizational capital, positively contribute to green value creation in industrial firms. However, excessive reliance on automated mobile systems may constrain human creativity and situational judgment, highlighting the importance of balanced integration between human capabilities and mobile technologies. This study contributes to the operations management literature by clarifying how mobile technology–enabled human augmentation supports efficient, ethical, and sustainable manufacturing performance.

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