IEEE Access
Multidisciplinary ⋮ Rapid Review ⋮ Open Access Journal

Received 30 October 2024, accepted 23 November 2024, date of publication 2 December 2024, date of current version 26 December 2024.

Digital Object Identifier 10.1109/ACCESS.2024.3509623

RESEARCH ARTICLE

Robotic Digitalization and Business Success: The Central Role of Trust and Leadership in Operational Efficiency–A Hybrid Approach Using PLS-SEM and fsQCA

MIGUEL GONZÁLEZ-MOHÍNO [1], MARIO J. DONATE [2], GUZMÁN A. MUÑOZ-FERNÁNDEZ [1], AND L. JAVIER CABEZA-RAMÍREZ [1]

[1]Department of Business Organization, University of Córdoba, 14002 Córdoba, Spain
[2]Department of Business Administration, University of Castilla-La Mancha, 13003 Ciudad Real, Spain

Corresponding author: Guzmán A. Muñoz-Fernández (guzman.munoz@uco.es)

This work was supported in part by Junta de Comunidades de Castilla-La Mancha, and in part by European Regional Development Fund (ERDF) of European Union (EU) under Grant SBPLY/21/180501/000260.

This work involved human subjects or animals in its research. The authors confirm that all human/animal subject research procedures and protocols are exempt from review board approval.

ABSTRACT While digitalization and robotics are a reality for companies and contribute to value creation, few studies have examined their impact on operational performance. This study examines how digitalization (with robots and artificial intelligence-AI) in companies contributes to improving operational performance, emphasizing the importance of trust and effective knowledge-oriented leadership to create a positive context for its implementation. The research included ten companies, where an engineer in a managerial position was surveyed to obtain a strategic perspective, complemented by responses from 108 employees to reflect the operational perspective. Through qualitative comparative analysis with fuzzy sets (fsQCA) and Partial Least Squares Structural Equation Modeling (PLS-SEM), combinations of factors leading to business success from the perspective of digitalization are identified. Findings reveal that trust in robots and AI and effective leadership are crucial for improving operational efficiency in an increasingly digitized business environment. This study provides valuable insights into how the integration of advanced digital technologies through organizational factors such as knowledge-oriented leadership can contribute to improved operational performance, offering practical perspectives to managers on how to handle digitalization in organizations.

INDEX TERMS Digital trust, digitalization, knowledge-oriented leadership, operational performance, robots, time management.

I. INTRODUCTION

The current digital age is centered around leveraging new technologies that add value to businesses [1]. At the forefront of this transformation is Industry 4.0, also known as the Fourth Industrial Revolution, which represents a significant shift in manufacturing and production processes. This new phase is based on the digitalization and intelligent connection of systems, machines, and processes to optimize production, improve efficiency, and facilitate real-time decision-making.

Industry 4.0 not only focuses on enhancing efficiency and productivity but also promotes mass customization, allowing businesses to tailor products to meet the specific needs of customers. This transformation impacts multiple sectors, including manufacturing, logistics, automotive, and energy,

The associate editor coordinating the review of this manuscript and approving it for publication was Okyay Kaynak.

driving innovation and creating new opportunities across the value chain.

Recent scientific research has underscored the advantages of utilizing cutting-edge technologies such as blockchain [2], the Internet of Things [3], or *Big Data* [4]. These technologies can be seen as a cohesive system that significantly enhances companies' knowledge management capabilities and operational performance, highlighting their role in enabling more strategic decision-making and operational efficiency. Operational performance (OP) is a part of the company's overall performance. While operational performance measures how internal operations function (e.g., production times, operating costs, or the level of automation), overall performance evaluates the organization's total performance, also integrating external and strategic factors (e.g., total revenue, sales growth, social impact, etc.).

However, the implementation of Industry 4.0 does come with challenges, such as the need to develop new skills within the workforce, the necessity for substantial investment in technology, and the requirement to manage cultural changes within organizations. Despite these hurdles, the potential benefits, including increased competitiveness, greater flexibility in production, and reduced operational costs, make Industry 4.0 a transformative force shaping the future of various industries.

This work reflects key aspects of the digital transformation of companies. Firstly, digitalization is a broad concept that encompasses the use of numerous digital tools. Although these interconnected technology systems should be studied and promoted to enhance productivity, they are not yet fully implemented in companies. Organizations vary significantly in their stages of digital development [1]. Janger et al., [5] argue that companies have higher levels of profitability and productivity when they implement adequately digital tools, but they need to effectively manage this implementation and have a clear strategy about the factors (digital and not digital) that lead a firm to superior performance. However, they must manage this implementation effectively and develop a clear strategy regarding the digital and non-digital factors that drive superior performance. The specific factors or combinations of factors leading to superior performance remain unidentified.

In this study, we examine how the use of these new technologies (robots and artificial intelligence-AI) can influence operational performance. In particular, the current study is based on the theory of Resource-Based View (RBV) [6]. The RBV suggests that companies can achieve and sustain competitive advantages through the effective management and utilization of their valuable, rare, inimitable, and non-substitutable resources (VRIN) [7]. The application of RBV is particularly relevant in the context of digital transformation, where technologies such as robots and chatbots can be leveraged as critical resources that enhance operational efficiency and innovation [8], [9]. We focus on robots and chatbots because they represent emerging technological resources that can significantly transform business operations. These tools not only automate routine processes but also improve efficiency and accuracy, freeing up time and human resources for more strategic and creative tasks. Trust in these tools is a critical factor for their adoption and effective use, as distrust can limit their integration and potential benefits.

Additionally, we consider factors such as knowledge-oriented leadership and time management because both are essential to maximizing the benefits of digital technologies. Effective leadership that values and promotes the use of knowledge can facilitate the adoption of new technologies and foster a continuous learning environment. Time management is equally crucial as it allows for better planning and utilization of resources, thereby optimizing the impact of digital technologies on operational performance. Digital transformation requires organizations to assess their business models, operations, and technological strategy, involving a cultural change that must be led by top management as it is no longer a future strategy but offers an indispensable competitive advantage for survival [10].

The aim of this study is to identify the combination of conditions and factors that lead firms to improve their operational performance through the implementation of digitalization, utilizing both qualitative comparative analysis with fuzzy sets (fsQCA) and Partial Least Squares Structural Equation Modeling (PLS-SEM). To achieve this goal, the structure of this document includes, firstly, the development of the literature review and hypothesis development; next, the methodology used, and the sample will be presented, followed by the results of the analysis, a discussion, and the conclusions of this study.

II. LITERATURE REVIEW

A. THEORETICAL FRAMEWORK

Digitalization can be defined as the use of digital technologies to create value for a company [1]. Digital transformation offers a wide range of benefits to firms, including automation and process optimization to improve productivity, cost savings, streamline production, human errors reduction, and fostering a culture of innovation [11], [12]. In this era of digital transformation, various technologies and systems are shaping the business landscape, with a notable impact on operational performance, which can be understood as actions developed that meet prescribed job functions and formal job descriptions, also contributing to the provision of products or services to customers [13]. This improvement in operational performance translates into greater efficiency, as companies can optimize their processes, reduce costs, and improve service quality, resulting in a sustainable competitive advantage.

The Resource-Based View (RBV) theory suggests that resources (both tacit and tangible) are necessary to create valuable and inimitable capabilities that enhance firm performance [14], [15]. Resource-Based View (RBV) refers to when a company gains a superior competitive advantage based on resources and capabilities that are rare, unique, and difficult to imitate. The RBV theory illustrates that when a company accumulates both tangible and intangible assets, it can potentially yield a wealth of competitive advantages [16]. The businesses to flexibly adjust and expand their resources according to shifting environmental dynamics [17]. Furthermore, the RBV framework enhances understanding of the crucial interplay between resources and capabilities [18].

In the era of digitalization, companies are discovering new ways to create value for their customers by enhancing innovation and organizational culture, driven by the effective use of digital technology [19]. Embracing digital technologies cultivates a culture of experimentation, learning, and innovation, which enhances sustainable company performance and promotes the development of new value-creating products and services, thereby boosting competitiveness. This digital culture also streamlines internal processes and improves decision-making efficiency, positively impacting the company's long-term sustainability [19].

Overall, the RBV could be an appropriate theoretical framework to explain digital capabilities [20]. Enhancing digital capabilities and resources can lead to improvements in processes, culture, stability, and performance, granting companies a sustainable competitive edge [21]. Consequently, the Resource-Based View (RBV) theory serves as a valuable framework for elucidating the connection between digitalization and company performance, and for supporting the relationship between intangible resources such as knowledge and time management and their impact on operational performance.

In this context, technological advancements, such as robotics and broader technological changes, are seen as catalysts for increased productivity. Specifically, these advancements are expected to increase enhanced operational performance often translates into streamlined processes, reduced waste, and better use of time and technology, all of which contribute to higher efficiency [22]. Therefore, it is crucial to analyze which factors, and their combinations, lead to superior performance for companies when the company is involved in digital transformation. This study considers four conditions that may have an important influence in digitalization which drives a company to improve its operational performance (OP): (1) knowledge-oriented leadership (K-OL), (2) effective time management, (3) digitalization with robots and Artificial Intelligence (DI-RAI), and (4) trust in robots and Artificial Intelligence (TR-RAI). We will explain each factor next.

B. KNOWLEDGE-ORIENTED LEADERSHIP

Existing studies in Management indicate that leadership constitutes a determining factor that influences organizational performance, either directly or indirectly [23]. The impact of leadership styles on organizational performance is well-documented in academic literature, with transformational and transactional leadership approaches frequently highlighted for their effectiveness. Transformational leadership inspires and motivates employees to exceed their expectations, while transactional leadership focuses on structured tasks, clear objectives, and reward-based performance. Combining these two approaches leads to what is known as knowledge-oriented leadership (K-OL), a leadership style specifically designed to enhance organizational knowledge management [24].

K-OL integrates the best aspects of both transformational and transactional leadership, focusing on creating a culture that values knowledge as a core asset. This approach involves a range of behaviors aimed at building and promoting knowledge within the organization. For example, leaders practicing K-OL actively facilitate learning experiences by encouraging employees to engage in continuous development, seek out new information, and incorporate external knowledge into their daily routines. They create opportunities for staff to attend workshops, industry conferences, and knowledge-sharing sessions to expand their expertise and bring fresh ideas into the organization [25].

A key component of K-OL is rewarding behaviors that align with ethical standards and knowledge-sharing principles. For instance, leaders might implement recognition programs that acknowledge team members who contribute innovative solutions or openly share their insights with colleagues, thus reinforcing a culture of collaboration and trust. K-OL also focuses on fostering a cohesive environment conducive to teamwork, where open communication and mutual respect are prioritized, enabling employees to learn from one another and tackle challenges collectively.

Moreover, K-OL emphasizes guiding employees through the processes of acquiring, sharing, and applying knowledge while maintaining a tolerance for errors. This means that leaders support their teams not only in the exploration of new ideas but also in learning from mistakes as part of the growth process. Such an environment encourages experimentation and the safe exchange of knowledge without fear of failure [26]. By creating a workplace culture where knowledge is valued, shared, and utilized effectively, K-OL ultimately drives innovation, adaptability, and sustained organizational success [27]. It contributes to creating a conducive environment for teamwork and trust among employees. Additionally, K-OL supports acquiring external knowledge, leading to improved innovation, research collaborations, and technological solutions [28]. It also fosters a learning culture, enhancing organizational performance [29]. Based on these arguments, we establish the first hypothesis of this work.

Hypothesis 1: Knowledge-oriented leadership positively influences company operational performance.

C. TIME MANAGEMENT

Efficient time management is identified as a critical factor for the operational performance of organizations. Time management is the strategic organization and planning of tasks and activities to ensure the most efficient use of time. It encompasses a set of behaviors and techniques aimed at maximizing productivity and minimizing wasted effort, particularly when working toward clearly defined goals.

By effectively managing time, individuals can prioritize their responsibilities, reduce distractions, and ensure that their efforts align with their objectives [30].

Effective time management requires carefully organizing work hours to enhance productivity and efficiency. It is suggested that employees who excel in managing their time are better at minimizing distractions and avoiding engagement in non-work-related activities during the workday [31]. For example, a professional who organizes their day by setting specific time blocks for priority tasks is more capable of meeting goals efficiently and reducing the stress of tight deadlines. Additionally, when individuals effectively plan, schedule, and prioritize their daily activities and have a clear confidence in their goals, they not only enhance their operational performance but also improve their work-life quality [32]. This planning allows for greater focus on important tasks and quick adaptation to unexpected changes, contributing to higher job satisfaction and a better work-life balance.

In Spain, according to Steelcase [33], a company specializing in workspace solutions, each person working in an open office loses an average of 86 minutes of their work time due to distractions in the workplace environment. According to a study conducted by Workmeter [34], a leading company in creating performance and productivity measurement software solutions in Spain, time lost in the workplace reaches 30% of the workday. Specifically, employees spend an average of 9 hours and 19 minutes in their workplace, but the total productive hours are only 6 hours and 34 minutes, spending 62 minutes in micro-breaks of less than 10 minutes, which, rounded up, equates to losing 30% of work time each day. Actions such as excessively checking messaging applications, taking constant micro-breaks, and impulsively checking email are too frequent in Spanish companies. This fact leads to an increase in presenteeism, which is nothing more than fulfilling the workday without being truly productive.

The implementation of robust time management strategies, such as effective resource allocation and process optimization, can result in a significant improvement in operational performance. Sahito and Vaisanen [35] argue that effective time management requires the adoption of a diverse set of practices that address the specific needs of the organization. However, researchers in the field of projects and management have reported various applicable practices that include considerations of economic policy, management, and motivation [36], as the most relevant for efficiently project conclusion. From these arguments, we establish the second hypothesis of our study.

Hypothesis 2: Effective time management positively influences company operational performance.

D. DIGITALIZATION WITH ROBOTS AND AI

The global service robotics market is expected to experience substantial growth, with projections indicating an increase from $37 billion in 2020 to $102.5 billion by 2025. This growth reflects a compound annual growth rate of 22.6% during the forecast period [37]. As for industrial robots, the World Robotics Report estimates an average global robot density in manufacturing industries of 126 robots per 10,000 employees, a number that continues to rise (see Figure 1) [38]. Driven by artificial intelligence (AI) and equipped with sensors, service robots are capable of carrying out valuable tasks for people or machines, excluding applications related to industrial automation [38], [39]. Service robots, described as autonomous physical systems that can operate and provide services without constant human supervision [40], play a crucial role in service-related activities. Automation through robots and AI can increase efficiency and accuracy in various tasks. The digitalization of production systems can also improve operational performance by providing greater data availability and adapting manufacturing and sales to changing market demands [41]. The effective implementation of these digital technologies, especially robotics and artificial intelligence, can substantially contribute to business performance by minimizing errors, speeding up processes, and freeing employees from repetitive and routinized tasks [42].

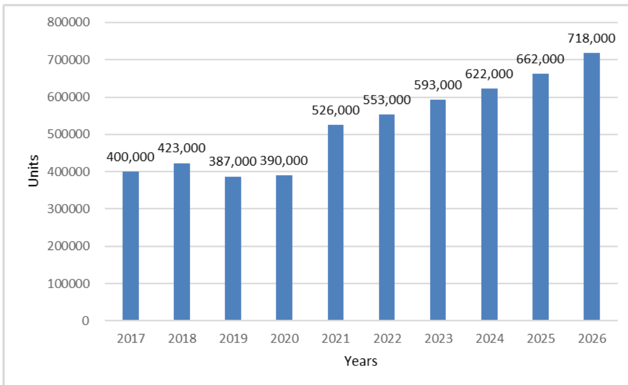

FIGURE 1. Annual installations of industrial robots in 2017-2022 and 2023-2026. Source: Own elaboration based on data extracted from robotics [38].

In this context, automation through robots and artificial intelligence can increase efficiency. The use of robotics and artificial intelligence is considered an advanced form of digitalization, as it enables the automation of complex processes and improves the operational efficiency of companies, as noted in previous studies. The proper implementation of these technologies can significantly contribute to operational performance by reducing errors, speeding up processes, and freeing employees from repetitive tasks, positioning the company favorably in the minds of customers and against competitors [43]. Therefore, a third hypothesis is presented.

Hypothesis 3: The use of robots and AI (digitalization) influences company operational performance.

E. TRUST IN ROBOTS AND AI

Limited trust in advanced technology can result in significant costs, including wasted time and reduced labor efficiency, as well as the risk of improper use. Conversely, excessive trust in underperforming technology can create overconfidence and misuse, potentially leading to security risks and other negative consequences [44]. For example, if a highly sophisticated AI-powered robot is not trusted by workers to handle critical tasks, they might spend unnecessary time double-checking its work or performing tasks manually, leading to inefficiencies. On the other hand, if too much trust is placed in an unreliable chatbot for handling sensitive customer data, it could result in security breaches or data mismanagement, with serious repercussions for the organization. This dynamic is especially relevant in human-robot and human-artificial intelligence interaction, due to the perceived risk, complexity, and unpredictability of their behaviors, as well as their growing role in work environments. Davis [45] points out that AI is perceived as a technology capable of replacing different types of human jobs and transforming organizational structure. However, it remains unclear whether employees with lower skill levels face a higher risk of being replaced by AI [46], [47] compared to knowledge workers and senior managers. These higher-level roles rely on analytical and rational decision-making processes, and their high cost may make AI-driven replacement less financially appealing [4], [48]. Currently, some human tasks are already being performed by AI [49].

Madhavan and Wiegmann [50] highlight that, unlike trust in humans, which generally increases overtime and frequent interactions, trust in technology tends to decrease with experience of errors and failures. However, the opposite could also hold true in the context of AI. Some researchers argue that the widespread skepticism linked to the current immaturity of AI technologies [51] and the challenges in adopting new technologies [52], may lead to initial low trust. For instance, employees may be hesitant to rely on an AI-driven customer service tool first. However, after using it and seeing its ability to handle routine inquiries efficiently, their trust in the system may increase. This demonstrates how firsthand experience can shift perceptions, improving trust over time through direct interaction with the technology [53].

Therefore, trust in these technologies is crucial. If employees trust in the capability and reliability of robots and AI, they are more likely to use these tools effectively. Lack of trust could generate resistance and negatively affect operational performance. Thus, we propose the fourth hypothesis of this study.

Hypothesis 4: Trust in robots and AI positively influences company operational performance.

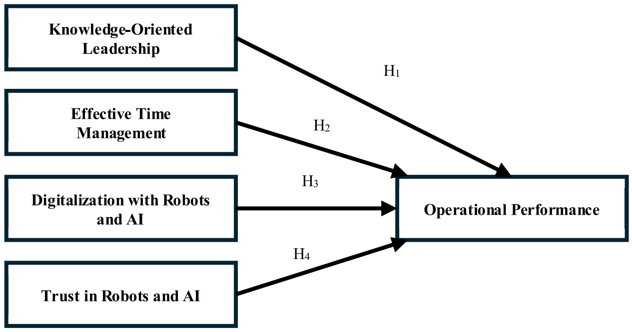

FIGURE 2. Research model proposed.

III. METHODOLOGY

A. RESEARCH DESIGN

In this section, we present the methods used in this study to examine and evaluate the proposed hypotheses. The study was conducted with workers from 10 companies that use robots, employing the PLS-SEM model to analyze the data. The structural model of PLS-SEM was used to test our model and hypotheses. Additionally, a fuzzy-set qualitative comparative analysis (fsQCA) was utilized with the executives of these companies to check if similar results were obtained. This configurational approach based on fsQCA allowed us to investigate how the combined conditions of independent factors lead to better outcomes for the sampled companies, offering a holistic view of the interrelationships that jointly impact the adoption of digitalization [54].

B. MEASURES AND DATA COLLECTION

We designed a questionnaire, which was first distributed to engineers with managerial positions and later to employees, to collect information about their experiences with changes in working methods due to digitalization (use of robots and artificial intelligence) (see appendix). Specifically, we selected engineers with managerial roles and responsibilities within the company who had modified their working methods in the past 24 months in response to a strategic decision to implement robot-based or AI-based technologies in their organizations. Similarly, we surveyed employees to understand how these changes have affected their operational performance and daily tasks.

The research objective is exploratory, focusing on a selected set of cases to investigate relationships from specific instances to broader generalizations. This approach ensures a comprehensive understanding of the impact of digitalization at different organizational levels. By administering the questionnaire separately, we can obtain nuanced perspectives from both management and staff, which is crucial for identifying potential discrepancies or alignments in their viewpoints.

To ensure the validity of responses, the questionnaire began by asking whether the companies where the respondents work had changed their working methods in the past 24 months and whether they had implemented robots and/or artificial intelligence during that period. Only respondents who answered affirmatively were included in the sample. Data was collected between October-November 2023, from a total of 10 companies, with responses obtained from 10 engineers with managerial responsibilities (one engineer per company) and a total of 108 employees from these companies (see Table 1).

TABLE 1. Descriptive data of the respondents.

		Managers		Staff	
		N º	%	N º	%
Gender	Male	8	80%	65	60.2%
	Female	2	20%	43	39.8%
Education Level	Master`s	4	40%	40	37.0 %
	Doctorate	1	10%	2	1.85%
	Bachelor's, Degree, Graduate	5	50%	66	61.11%
Engineering Background	Civil Engineering	3	30%	12	11.1%
	Telecommunications	1	10%	15	13.9%
	Computer Science	1	10%	20	18.5%
	Chemical Engineering	1	10%	10	9.3%
	Mechanical Engineering	1	10%	18	16.7%
	Electrical Engineering	2	20%	18	16.7%
	Electronics and Robotics	1	10%	15	13.9%
Professional Sector	-Information Technology, Information and Communications	3	30%	30	27.8%
	-Energy and Environment	3	30%	20	18.5%
	-Professional, Scientific and Technical Activities	2	20%	30	27.8%
	-Construction	1	10%	15	13.9%
	-Agriculture, Livestock, Forestry and Fishing	1	10%	13	12.0%
Professional Department	Technology	3	30%	45	41.7%
	Project Management	5	50%	35	32.4%
	Logistics and Operations	2	20%	28	25.9%

Given the exploratory nature of this research, a convenience sampling method was used to select the participating companies. This approach is suitable for making initial approximations to understudied phenomena, allowing the identification of preliminary patterns and generating hypotheses that can be validated in future studies with more representative samples. According to Schreuder et al., non-probability sampling is recommended under these circumstances, when the main objective is to delve into specific cases and understand emerging phenomena. Accordingly, the sample comprises companies from key sectors where digitalization has a significant impact (see the previous table). Regarding the selection of employees within these companies, the same technique was applied. Workers were chosen based on their direct involvement with work processes impacted by digitalization using robots and AI, ensuring the relevance of their perspectives to the research objectives.

C. PREVIOUS DATA ANALYSIS

To test the structure of the variables model, the dataset was analyzed using IBM SPSS to conduct exploratory factor analysis (EFA). The grouping of items resulted in five factors (four latent variables and one outcome variable) proposed in the conceptual part of the paper (see appendix). Validated questionnaire items were used on: K-OL [24], Digitalization with robots and AI (DI-RAI) [55], [56], Effective Time Management [57], [58] Trust in robots and AI (TR-RAI) [59] and Operational performance (OP) [60].

Following the recommendations of Podsakoff et al. (2003), our study adopted procedural and statistical measures to mitigate common method bias (CMB). Measures such as content validation through pilot testing and the use of specific and easy-to-understand statements were employed. Furthermore, the anonymity and confidentiality of respondents was guaranteed by stating this on the first page of the questionnaire.

The results showed that most of the factor loadings were insignificant, while the substantive variance exceeded the method variance, suggesting that CMB was not a cause for concern. In addition, we employed Harman's single factor test and an unmeasured latent factor approach to further assess CMB risks. Factor analysis indicated that no single factor explained most of the variance, and the critical ratios of differences in regression weights were below the threshold, confirming that CMB did not compromise the validity of the study.

D. DATA ANALYSIS APPROACH

The data were analyzed using PLS-SEM to assess both the measurement and structural models [61], and fsQCA to reveal the combinations of antecedent conditions influencing the outcomes [62].

1) PLS-SEM APPROACH

PLS-SEM provides greater flexibility in modeling complex structures, such as formative constructs, and is more accommodating of smaller sample sizes and non-normally distributed data compared to other methods [61]. Based on these strengths, our study aims to pinpoint the key ''driver'' constructs within a complex structural model. As a result, we selected PLS-SEM as the most appropriate method and employed SmartPLS 4.0 software [63]. This method is particularly effective for analyzing complex relationships where traditional methods may fall short, especially when working with smaller datasets. The flexibility of PLS-SEM allows for robust analysis even when data deviates from normality, making it an ideal choice for this research, which seeks to uncover significant patterns among multiple variables.

2) QUALITATIVE COMPARATIVE ANALYSIS OF FUZZY SETS

Through a qualitative configurational method (fsQCA), we argue that adopting a broad range of causal assumptions can better explain overall performance. Using Fuzzy-Set/Qualitative Comparative Analysis 4.0 software [64], we assessed causal complexity and multiple solutions with different condition combinations. FsQCA, developed by Ragin [65], has gained attention in business and strategic management studies for its ability to identify necessary and sufficient conditions related to outcomes, overcoming limitations of traditional quantitative methods like regression analysis.

FsQCA offers three key advantages: it assumes multiple pathways (equifinality) to the same outcome, evaluates the effect of condition combinations (configurations), and requires numerical calibration to reflect how well cases fit the conditions. Recent literature highlights growing interest in fsQCA for analyzing combined effects and causal connections in business and strategic management [62], [66], [67], [68].

PLS-SEM and fsQCA operate on different underlying principles, making fsQCA a valuable complementary method to PLS-SEM, especially when unobserved heterogeneity is present. FsQCA helps explain how various factors combine to generate specific outcomes [69]. As a result, many studies have applied both methods—using PLS-SEM's asymmetrical approach and fsQCA's symmetrical approach—to empirically test models and examine causal relationships and outcomes in complex contexts like technology adoption [70].

IV. RESULTS

A. PLS RESULTS

1) MEASUREMENT MODEL

The evaluation of the reflective measurement model assessed key factors such as indicator reliability, internal consistency, and validity. Outer loadings were above the recommended threshold of 0.7, ensuring strong indicator reliability [61]. Some indicators were excluded to enhance the model's overall reliability and validity (K-OL6, DI-RAI2, TR-RAI3, TR-RAI4, OP4, and OP5 were excluded). Internal consistency was confirmed through measures like Cronbach's alpha and Composite Reliability, all exceeding the 0.7 benchmark, indicating solid consistency across the model (see table 2).

TABLE 2. Analysis of the measurement instrument: Reliability and convergent validity.

	Indicators	Loads λ	α Cronbach	rho_A	Composite reliability	AVE
Knowledge-Oriented Leadership	K-OL_1.	0.727	0.714	0.732	0.806	0.655
	K-OL_2.	0.722				
	K-OL_3.	0.783				
	K-OL_4.	0.707				
	K-OL_5.	0.716				
Digitalization with Robots and AI	DI-RAI_1.	0.702	0.743	0.782	0.781	0.533
	DI-RAI_3.	0.752				
	DI-RAI_4.	0.875				
	DI-RAI_5.	0.877				
Effective Time Management	ETM_1	0.738	0.715	0.800	0.784	0.570
	ETM_2.	0.824				
	ETM_3.	0.796				
	ETM_4.	0.720				
	ETM_5.	0.740				
Trust in Robots and AI	TR RAI_1.	0.761	0.766	0.817	0.786	0.727
	TR RAI_2.	0.713				
	TR RAI_5.	0.883				
	TR RAI_6.	0.937				
Operational Performance	OP_1.	0.784	0.773	0.769	0.753	0.659
	OP_2.	0.840				
	OP_3.	0.832				

K-OL: Knowledge-Oriented Leadership; DI-RAI: Digitalization with Robots and AI; ETM: Effective Time Management; TR-RAI: Trust in Robots and AI; OP: Operational Performance

The discriminant validity of the constructs was confirmed using the Fornell-Larcker criterion and Heterotrait-Monotrait (HTMT) ratios. The Fornell-Larcker criterion showed that the square root of the AVE for each construct was greater than its correlations with other constructs, indicating strong internal relationships [71]. HTMT values were below the 0.9 threshold, further confirming discriminant validity [72]. These results, detailed in table 3, ensure that the constructs are distinct, supporting the reliability of the measurement model and allowing for confident evaluation of the structural model.

TABLE 3. Discriminant validity.

	K-OL	DI-RAI	ETM	TR-RAI	OP
Knowledge-Oriented Leadership	**0.809**	0.509	0.438	0.507	0.470
Digitalization with Robots and AI	0.509	**0.730**	0.670	0.690	0.610
Effective Time Management	0.438	0.670	**0.755**	0.730	0.590
Trust in Robots an AI	0.507	0.690	0.730	**0.853**	0.680
Operational Performance	0.470	0.610	0.590	0.680	**0.812**

Diagonal: Discriminant validity according to Fornell's criterion. Below the diagonal: correlations between factors (significant with p<0.01 and with p<0.05). Above the diagonal HTMT criterion is shown.

2) STRUCTURAL MODEL

The evaluation of the structural model includes analyzing the coefficient of determination (R^2) and the significance of the path coefficients [61]. To ensure robust findings, the study used PLS bootstrapping with 5000 resampling iterations, following guidelines from Hair et al., [73] and Sarstedt et al., [74]. The results, shown in figure 3 and table 4, highlight the explained variance (R^2) and standardized path coefficients (β), offering insights into the strength and relevance of the relationships within the model. This approach provides a clear understanding of how well the model predicts the dependent variables.

TABLE 4. Results of PLS.

Hypothesis	Relation	(β)	SD	T-Value	P-values	Support/ not support
H_1	K-OL -> OP	0.448	0.119	3.765	0.000	Support
H_2	ETM -> OP	0.150	0.108	1.389	0.040	Support
H_3	DI-RAI -> OP	0.228	0.149	1.530	0.027	Support
H_4	TR-RAI -> OP	0.384	0.118	3.254	0.000	Support

Notes: *p<0.05 ** p<0.01 *** p<0.001 (β): Path coefficient
SD: Standard Deviation
K-OL: Knowledge-Oriented Leadership; DI-RAI: Digitalization with Robots and AI; ETM: Effective Time Management; TR-RAI: Trust in Robots and AI; OP: Operational Performance

All the proposed hypotheses are supported by the data. The relationships between the constructs K-OL, ETM, DI-RAI, TR-RAI, and OP are positive and statistically significant. This suggests that knowledge-oriented leadership, effective time management, digitization with robots and AI, and trust in robots and AI have a positive impact on operational performance.

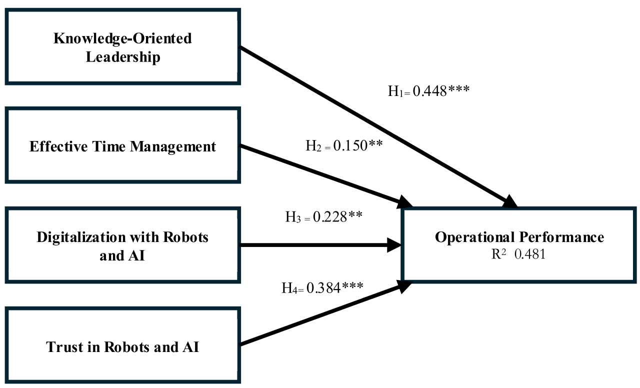

FIGURE 3. Research model. Notes: *p<0.05 ** p<0.01 *** p<0.001.

The coefficient of determination R^2 of 0.481 in the context of this study indicates that 48.1% of the studied variables are effective in explaining the variations in operational performance, highlighting the importance of KOL, ETM, DI-RAI, and TR-RAI (see figure 3). This result demonstrates that the model used in the study is robust and that the analyzed factors are relevant for understanding operational performance.

The F^2 values provide insights into the effect sizes of exogenous constructs on endogenous constructs, highlighting their relevance within the model (see table 5). The F^2 values indicate that K-OL dominates the OP construct, being the priority factor, while ETM, DI-RAI, and TR-RAI contribute moderately, reflecting a balanced model where all factors play a role in understanding the construct.

TABLE 5. Results of predictive model.

	Q^2	F^2 in OP
Knowledge-Oriented Leadership **(K-OL)**		0.56
Effective Time Management **(ETM)**		0.14
Digitalization with robots and AI **(DI-RAI)**		0.11
Trust in robots and AI **(TR-RAI)**		0.16
Operational Performance **(OP)**	0.418	

To further evaluate the predictive relevance of the model, we computed the Stone–Geisser Q^2 statistic. As noted by Chin (2010), a construct demonstrates predictive relevance when the Q^2 value is greater than 0, a condition that is met by dependent variable in our model. Finally, the goodness of fit analysis revealed that the model's Standardized Root Mean Square Residual (SRMR) index had a value of 0.091. This indicates that the theoretical model aligns appropriately with the observed data.

B. QUALITATIVE COMPARATIVE ANALYSIS

The constructs and datasets applied in the PLS-SEM analysis were also evaluated using fsQCA to compare its outcomes with those derived from PLS-SEM. The fsQCA process includes several key stages: developing the model, selecting the sample, calibrating the data, analyzing necessary conditions, evaluating sufficient conditions, and interpreting the results [69]. By conducting both analyses, a more thorough comparison is possible, leading to a richer understanding of the relationships among the variables.

1) CALIBRATION

In preparation for fsQCA analysis, we calibrated the conditions (e.g., resources for knowledge-oriented leadership, use of robots and AI, effective time management, and trust) and the outcome condition (operational performance) into fuzzy sets. Membership values ranged from 0 (no membership) to 1 (full membership). According to Ragin [54], membership degrees are defined by three anchors: complete membership (0.95), incomplete membership (0.05), and the crossover point (0.50). Consistent calibration rules set the crossover point at the median, with incomplete and complete memberships at the 10th and 90th percentiles, respectively [75].

We calculated a factor score for each latent construct by averaging the related items, with scores ranging from 1 to 7. Following Ordanini et al., [76], we set complete membership at values above 4, the crossover point at 4, and incomplete membership at values below 4.

2) ANALYSIS OF NECESSARY CONDITIONS

In the second step, a necessity analysis was performed to identify whether any conditions were essential for the outcome. This involved checking if any of the four conditions were consistently present or absent when the outcome occurred [77], [78]. A condition is considered necessary if its consistency exceeds 0.9. The analysis revealed that two conditions—knowledge-oriented leadership and trust—had consistency values above 0.90 (see table 6), indicating they are necessary for the outcome [79]. However, high consistency does not guarantee high operational performance, and the other conditions were not deemed necessary.

TABLE 6. Analysis of necessary conditions.

	Consistency	Coverage
Knowledge-Oriented Leadership	0.947674 (0.110465)	0.900553 (1.00)
Digitalization with Robots and AI	0.633721 (0.424419)	0.923729 (0.890244)
Effective Time Management	0.686047 (0.372093)	0.929134 (0.876712)
Trust in Robots and AI	0.947674 (0.162791)	1.000000 (0.756757)

Note: Values for the negation of the condition are shown in parentheses.

3) ANALYSIS OF SUFFICIENT CONDITIONS

The third step in the process involves constructing a truth table [62], [77], [80]. This table includes columns for the explanatory variables and rows representing all possible combinations of conditions, with an additional column indicating the outcome. For four conditions, the truth table generates 16 possible combinations. The next task is to simplify the table by including only significant configurations, which are determined by the frequency of empirical instances. In this study, a minimum of three cases per configuration was required, with configurations having two or fewer observations classified as "remaining." A consistency threshold of 0.75 was applied to determine whether a configuration was sufficient to produce the outcome, similar to how correlation functions in statistical analysis [81]. In the final step, the Quine-McCluskey algorithm was used to reduce the truth table rows into simplified solutions based on Boolean algebra, allowing for a clearer interpretation of the results.

4) EVALUATION OF SOLUTIONS

The Quine-McCluskey minimization procedure offers three solution types: complex, parsimonious, and intermediate. The intermediate solution strikes a balance between detail and simplicity, making it easier to interpret by incorporating assumptions from the parsimonious solution while retaining useful detail [62]. Core conditions appear in both parsimonious and intermediate solutions, while peripheral conditions only appear in intermediate ones. This study chose intermediate solutions for better interpretation (see table 7).

To evaluate fsQCA solutions, consistency and coverage are used. Consistency values above 0.75 indicate sufficient alignment with the outcome, while coverage measures the empirical relevance of a configuration [62]. Gross coverage shows the total proportion of the outcome explained by each configuration, and unique coverage reflects how much each configuration uniquely explains [78]. In this study, all configurations had unique coverage, contributing to the explanation of the outcome [77].

TABLE 7. Intermediate solutions for operational performance.

	S1	S2	S3	S4	S5	S6
Knowledge - Oriented Leadership	○			●		
Digitalization with Robots and AI	○	●	●		○	
Effective Time Management	○	●				●
Trust in Robots and AI	●	●	●	●	●	●
Raw Coverage	0.31976	0.63372	0.63372	0.89534	0.37209	0.68604
Unique Coverage	0.20930	0.52325	0.52325	0.89534	0.20930	0.52325
Consistency	1			1		
Total Coverage of the Solution	0.843023			0.895349		
Total Consistency of the Solution	1			1		

Note: * Black circles indicate the presence of a condition, white circles indicate their absence, and blank spaces indicate "does not matter".

Based on the causal configuration of four conditions, six solutions (S1 to S6) aimed at analyzing operational performance are revealed [82]. These conditions include knowledge-oriented leadership, utilization of robots and AI, effective time management, and trust in robots and AI. In the representation, black circles (•) indicate the presence of a condition, white circles (○) indicate its absence, and blank spaces denote "does not matter," indicating that the causal condition can be present or absent without affecting the outcome [68].

Solution 1 is solely based on trust in robots and artificial intelligence, while the other conditions (knowledge-oriented leadership, DI-RAI, and effective time management) are absent. Solution 2 implies the presence of robot digitization, effective time management, and trust in robots and artificial intelligence, regardless of the presence or absence of knowledge-oriented leadership for the outcome. Solution 3 implies robot digitization and trust in robots and artificial intelligence, while knowledge-oriented leadership and effective time management do not influence operational performance. S4 implies having knowledge-oriented leadership and trust in robots and artificial intelligence, while the other conditions do not alter the outcome. S5 implies trust in robots and artificial intelligence, allowing knowledge-oriented leadership and effective time management to be present or absent, while robot digitization does not affect the outcome (it is absent). S6 implies the presence of both effective time management and trust in robots and artificial intelligence, regardless of the presence or absence of knowledge-oriented leadership and robot digitization for the outcome.

The coverage of each solution indicates the percentage of cases explained, with S4 having a high coverage of 89.53%, showing significant effectiveness in explaining operational performance. Unique coverage specifies the proportion of cases explained exclusively by each configuration, with S4 also exclusively explaining 89.53% of cases.

All solutions exhibit perfect consistency (1), indicating that each configuration is sufficient to achieve the desired operational performance. The overall coverage reflects the total percentage of cases explained by all solutions combined, while the overall consistency shows that all configurations collectively are sufficient to produce the desired outcome. These results underscore that the six identified solutions have high levels of coverage and consistency, effectively explaining operational performance in the analyzed context.

V. DISCUSSION OF RESULTS

The significant positive relationship between Knowledge-Oriented Leadership (K-OL) and Operational Performance (OP) ($\beta = 0.448$, $p < 0.001$) highlights the crucial role of leadership that emphasizes knowledge management. Leaders who promote continuous learning, knowledge sharing, and intellectual growth can drive significant improvements in efficiency and effectiveness. This underscores the need for organizations to invest in leadership development programs that prioritize knowledge management strategies. The results of this study indicate similarities with previous findings, such as those of Malik et al., [83], who observed that supervisors' knowledge-oriented leadership positively influenced the performance of knowledge workers both directly and through participation in knowledge management [34]. These findings are consistent with the research by Bashir and Pradhan [84], which highlighted the beneficial impact of knowledge-oriented leadership on open innovation and market intelligence. Our study emphasizes the importance for companies to recruit and recognize leaders who can effectively create, transform, store, and apply knowledge resources. Organizations that prioritize this type of leadership are more likely to encourage the development and sharing of new ideas, which facilitates the exploration of innovative strategies, improves operational performance, and helps in securing a competitive edge.

Although the impact of Effective Time Management on OP ($\beta = 0.150$, $p < 0.05$) is smaller, it remains statistically significant. This indicates that while ETM contributes to operational performance, its influence is not as strong as K-OL or Trust in Robots and AI (TR-RAI). Nevertheless, ETM is an essential component of operational efficiency, suggesting that organizations should continue to emphasize time management training and tools for employees to optimize productivity.

The positive influence of Digitalization with Robots an AI (DI-RAI) on OP ($\beta = 0.228$, $p < 0.05$) highlights the role of automation and robotic technologies in improving operational outcomes. Integrating robots into workflows can lead to moderate but significant gains in operational performance, likely through increased precision, speed, and consistency in tasks. Organizations should focus on adopting robotic technologies and ensuring that employees are adequately trained to work alongside these systems.

The strong positive relationship between TR-RAI and OP ($\beta = 0.384$, $p < 0.001$) signifies the importance of trust in robotic systems for realizing their potential benefits. High levels of trust among employees in the reliability and effectiveness of robots correlate with better operational performance. This suggests that fostering trust in technology is as important as the technology itself. Companies should invest in building this trust through transparency, effective communication about the capabilities and limitations of robots, and involving employees in the digital transformation process.

The intermediate solutions (S1 to S6) identified incorporate conditions such as K-OL, utilization of robots and AI, ETM, and trust in robots and AI. These conditions are essential elements in explaining operational performance. Metrics like gross coverage and unique coverage are crucial for assessing each solution's effectiveness. Solution 4, with a coverage of 89.53%, stands out as particularly effective in explaining operational performance. Perfect consistency across all solutions suggests that each configuration is sufficient to achieve the desired outcome.

The consistent presence of "Trust in robots and AI" in all solutions underscores its importance for operational performance. This trust affects the adoption and acceptance of technology, collaboration, decision-making, employee well-being, and skill development. High trust in robots and AI contributes to a positive work environment where employees feel supported by technology. These results are in line with the findings of Bhargava et al., [85], where they argue that participants were confident in the digital skills they possessed, which would result in greater job satisfaction and job security. This might indicate that investing in AI and robot technologies, as well as in training and communication programs to foster trust in these technologies, could provide significant benefits to the company in terms of operational efficiency and competitiveness [86], [87]. Therefore, in the pursuit of improvements in operational performance, attention to building and maintaining trust in technology emerges as a fundamental strategic component.

The presence of knowledge-oriented leadership (S4) suggests that a leadership approach focused on acquiring, sharing, and applying knowledge is beneficial for operational performance. This study's results are like those of Malik et al., [83], who found that supervisors' K-OL positively influenced knowledge workers' performance. Bashir and Pradhan [84] also found a positive influence of K-OL on open innovation and market intelligence. Companies should employ and value leaders capable of managing knowledge resources, fostering new knowledge creation, and exploring innovative approaches to enhance organizational effectiveness and generate competitive advantages.

The strong presence of robot and AI usage in various solutions (S2 and S3) highlights its critical role. Solution S3 suggests that implementation alone can have a positive impact, while S2 indicates that combining it with effective time management can further enhance operational performance. The inclusion of ETM in some solutions (S2 and S6) suggests that temporal efficiency is relevant for operational performance. These results align with those found by Korzynski and Protsiuk [88], indicating that time management skills increase job satisfaction and enhance performance, highlighting the need to provide practical training in time management and efficient use of technology to employees. Practical training in time management and efficient technology use is essential for employees.

Evaluating the solutions shows that S4, focused on trust in robots and AI, leads in both gross and unique coverage. It covers a wide range of cases and includes a significant proportion of exclusive cases. Solution S6 also shows a strong presence, covering many cases with unique cases to a lesser extent. Solutions S2 and S3 share third place with similar gross coverage but fewer unique cases. Solution S5 has intermediate coverage but does not significantly stand out, while S1 ranks last, showing the lowest coverage and minimal unique cases.

This study corroborates that the opinions of employees are consistent across two distinct methodologies, reinforcing the validity of the findings and providing a robust understanding of the factors influencing operational performance.

A. THEORETICAL AND PRACTICAL IMPLICATIONS

The theoretical implications of this study broaden our understanding of a variety of knowledge-related factors that influence operational performance. Furthermore, the use of methodologies such as fsQCA to address the complexity of this phenomenon. The identification of intermediate solutions provides a more nuanced view of the causal relationships in this context.

This study highlights trust in robots and AI as a critical and valuable resource for companies, aligning with the RBV principles that emphasize the importance of valuable, rare, inimitable, and non-substitutable (VRIN) resources for achieving and maintaining competitive advantage. Trust in technology facilitates the adoption of technological innovations and improves operational performance. The identification of knowledge-oriented leadership as a key factor suggests that this type of leadership can be seen as a strategic resource within the RBV framework. Leaders who promote the creation, transformation, and utilization of knowledge help develop unique organizational capabilities that are difficult to imitate, providing a sustained competitive advantage.

The inclusion of effective time management as a critical resource indicates that these skills can enhance operational efficiency and are thus considered valuable within the RBV context. This resource complements and amplifies the positive impact of other technological and leadership resources. The study reinforces the idea that digitalization-based capabilities are essential for the competitiveness of modern companies. The RBV suggests that companies must develop and protect their unique resources and capabilities. The ability of a company to integrate and trust digital technologies becomes a crucial strategic resource that must be properly managed and developed to maintain a competitive advantage.

B. LIMITATIONS AND FUTURE RESEARCH

This study is not free of limitations, the cross-sectional data excludes the possibility of analyzing changes in market conditions and technological advancements that could affect the long-term relevance of the conclusions. Although effective strategies were identified, focusing on solutions may have overlooked other possible strategies that could contribute to improving operational performance. Exploring a broader range of solutions and their interconnections is suggested for future research. The study's limitations may include some subjectivity in the process of selecting intermediate solutions following the application of the Quine-McCluskey algorithm. Another potential limitation of this study lies in the use of a convenience sample, which may restrict the generalizability of the findings. It has not proven to be a significant issue as there was no bias; however, a different sampling method could be considered for future studies.

Future research can include exploring the adaptability of the identified strategies in various industries and organizational contexts, considering the diversity of company structures. Longitudinal studies are also proposed to evaluate the sustainability and evolution of these strategies, providing a deeper understanding of their impact at different stages. Investigating the influence of external variables, such as technological changes or global events, would allow the researchers to have a more comprehensive perspective on the applicability of these strategies in dynamic environments. Another limitation of this study lies in the use of convenience sampling, which limits the generalization of the findings. The selection of companies and workers focused on specific sectors and particular cases, restricting the applicability of the results to similar contexts. To overcome this limitation, future research should consider employing probabilistic sampling techniques, which would enable the collection of more representative samples and, consequently, more generalized results. Additionally, exploring multidisciplinary approaches that integrate psychological, sociological, and ethical aspects would better help to understand the dynamics of trust in technology and its impact on operational performance. Finally, the development of practical tools and guidelines for the effective implementation of these strategies would facilitate their adoption by leaders and professionals.

VI. CONCLUSION

This study confirms that the opinions of employees and managers are consistent across two distinct methodologies, reinforcing the validity of the findings and providing a robust understanding of the factors influencing operational performance. The PLS-SEM methodology was applied to employees, while fsQCA was used for managers. PLS-SEM reveals that the factors studied have significant impacts on operational performance. While both methodologies indicate that these factors are crucial for operational performance, fsQCA provides a deeper understanding of how these conditions interact together to achieve successful outcomes. The combination of both methodologies reinforces the validity of the findings and offers a more comprehensive view of the factors influencing operational performance.

This study suggests that adopting leadership strategies that foster trust in technology and promote effective management practices can be crucial for driving operational performance in organizational settings. The acceptance of technology by employees and leaders is essential to fully leverage the advantages it offers to firms. For management, these findings provide strategic insights into where to focus their efforts. Enhancing knowledge-oriented leadership should be a priority, given its substantial impact on operational performance. Concurrently, management should continue to support effective time management practices and the integration of robotic technologies. Most importantly, building and maintaining trust in these technologies is essential. This comprehensive strategy will help create an environment where employees are equipped and motivated to achieve higher operational performance.

This research supports the need for a holistic approach when addressing improvements in operational performance. Considering not only individual factors but also their interrelationships is vital for developing effective strategies. Indeed, digitalization-based capabilities have become a lifesaver for most companies. From the perspective of resource-based theory, this study yields significant results by highlighting corporate trust in technology and robotics as a key factor in improving operational performance. Trust in these technological resources is seen as a crucial asset that enhances the company's ability to leverage innovation and gain a competitive advantage. With the development of more advanced AI systems, such as machine learning and computer vision, robots will be able to perform more complex tasks, such as real-time inventory management based on demand or even automatically adapting to changes in operational priorities. For example, in a manufacturing plant, AI could automatically adjust production lines according to market fluctuations, enabling more agile and customized production. This would not only enhance operational efficiency but also allow companies to respond quickly to customer needs, gaining a competitive advantage.

APPENDIX

Construct and Source	Items (7-point Likert scale, strongly disagree – strongly agree)
Knowledge-Oriented Leadership **Donate and Sánchez de Pablo [24]**	K-OL_1. The management style implemented in the company has created an environment conducive to responsible behavior, teamwork, and knowledge sharing. K-OL_2. Managers in the company take on the role of knowledge leaders, primarily characterized by promoting open ideas, error tolerance, and mediation to achieve company goals. K-OL_3. The management style implemented in the company is characterized by fostering learning from experience and tolerance for mistakes (to a certain extent). K-OL_4. Managers act as knowledge advisors, and controls are only an assessment of goal and objective achievement. K-OL_5. The management style implemented in the company promotes the acquisition of external knowledge and communication among employees. K-OL_6. Company managers reward employees who share and apply their knowledge.
Digitalization (utilization of robots and AI) **Pelau et al., [55]** y **Chung et al., [56]**	DI-RAI_1. I use robots, chatbots, or artificial intelligence in interactions with companies or services. DI-RAI_2. I use robots, chatbots, or artificial intelligence to provide quick and accurate responses to my questions or inquiries. DI-RAI_3. Automation with robots or chatbots has improved my experience by reducing waiting time and providing more convenient service. DI-RAI_4. The use of artificial intelligence in business decision making improves the quality and accuracy of results. DI-RAI_5. Robots, chatbots, or artificial intelligence are improving the customization of my services and products.

Construct and Source	Items (7-point Likert scale, strongly disagree – strongly agree)
Effective Time Management White et al., [57] and Olmstead [58]	ETM_1. I complete my tasks on time. ETM_2. I can estimate the necessary duration to perform routine tasks. ETM_3. I recognize my most productive moments and use them to perform important tasks. ETM_4. I have well-established routines and habits, including times for recovery and sleep. ETM_5. I can plan, order, and follow a sequence while monitoring outcomes.
Trust (in robots and AI) Nordheim et al., [59]	TR-RAI_1. I consider the accuracy and relevance of the information provided by the robot or chatbot important. TR-RAI_2. The correct interpretation and understanding of the user's request by the robot or chatbot, as well as clear expressions of what it does not understand, are important for building trust. TR-RAI_3. I consider it important for the robot or chatbot to provide specific, clear, and easily understandable answers. TR-RAI_4. It is important for robot or chatbot to provide professionally formulated responses. TR-RAI_5. I consider it important to receive quick responses from the chatbot. TR-RAI_6. Human-like characteristics of the chatbot, such as friendly expressions and courtesy, enhance trust in its interaction.
Operational Performance De Simone et al., [60]	OP_1. I believe that the integration of technologies has influenced efficiency and speed of performance. OP_2. I consider that the presence of technologies has contributed to greater accuracy and consistency in tasks. OP_3. Technological implementation has led to a decrease in physical workload and a possible increase in mental workload. OP_4. I believe that the integration of technologies has improved the flexibility and adaptability of operations in response to changes in demand. OP_5. Process automation has contributed to the reduction of operational errors.

REFERENCES

[1] M. Sommarberg and S. J. Mäkinen, "A method for anticipating the disruptive nature of digitalization in the machine-building industry," *Technol. Forecasting Social Change*, vol. 146, pp. 808–819, Sep. 2019, doi: 10.1016/j.techfore.2018.07.044.

[2] C. H. Liu, Q. Lin, and S. Wen, "Blockchain-enabled data collection and sharing for industrial IoT with deep reinforcement learning," *IEEE Trans. Ind. Inf.*, vol. 15, no. 6, pp. 3516–3526, Jun. 2019, doi: 10.1109/TII.2018.2890203.

[3] S. Bresciani, A. Ferraris, and M. D. Giudice, "The management of organizational ambidexterity through alliances in a new context of analysis: Internet of Things (IoT) smart city projects," *Technol. Forecasting Social Change*, vol. 136, pp. 331–338, Nov. 2018, doi: 10.1016/j.techfore.2017.03.002.

[4] C. Loebbecke and A. Picot, "Reflections on societal and business model transformation arising from digitization and big data analytics: A research agenda," *J. Strategic Inf. Syst.*, vol. 24, no. 3, pp. 149–157, Sep. 2015, doi: 10.1016/j.jsis.2015.08.002.

[5] J. Janger, T. Schubert, P. Andries, C. Rammer, and M. Hoskens, "The EU 2020 innovation indicator: A step forward in measuring innovation outputs and outcomes?" *Res. Policy*, vol. 46, no. 1, pp. 30–42, Feb. 2017, doi: 10.1016/j.respol.2016.10.001.

[6] J. B. Barney and A. M. Arikan, "The resource-based view," in *The Blackwell Handbook of Strategic Management*. Oxford, U.K.: Blackwell, 2005, pp. 123–182.

[7] J. Barney, "Firm resources and sustained competitive advantage," *J. Manage.*, vol. 17, no. 1, pp. 99–120, Mar. 1991, doi: 10.1177/014920639101700108.

[8] R. M. Grant, "The resource-based theory of competitive advantage: Implications for strategy formulation," *California Manage. Rev.*, vol. 33, no. 3, pp. 114–135, Apr. 1991, doi: 10.2307/41166664.

[9] R. M. Grant, "Toward a knowledge-based theory of the firm," *Strategic Manag. J.*, vol. 17, no. 2, pp. 109–122, 1996, doi: 10.1002/smj.4250171110.

[10] C. Favoretto, G. H. D. S. Mendes, M. G. Filho, M. G. de Oliveira, and G. M. D. Ganga, "Digital transformation of business model in manufacturing companies: Challenges and research agenda," *J. Bus. Ind. Marketing*, vol. 37, no. 4, pp. 748–767, Feb. 2022, doi: 10.1108/jbim-10-2020-0477.

[11] V. Parida, D. Sjödin, and W. Reim, "Reviewing literature on digitalization, business model innovation, and sustainable industry: Past achievements and future promises," *Sustainability*, vol. 11, no. 2, p. 391, Jan. 2019, doi: 10.3390/su11020391.

[12] S. Scott, P. Hughes, I. Hodgkinson, and S. Kraus, "Technology adoption factors in the digitization of popular culture: Analyzing the online gambling market," *Technol. Forecasting Social Change*, vol. 148, Nov. 2019, Art. no. 119717, doi: 10.1016/j.techfore.2019.119717.

[13] M. Rotundo and P. R. Sackett, "The relative importance of task, citizenship, and counterproductive performance to global ratings of job performance: A policy-capturing approach.," *J. Appl. Psychol.*, vol. 87, no. 1, pp. 66–80, 2002, doi: 10.1037/0021-9010.87.1.66.

[14] J. B. Barney, "The emergence of resource-based theory: A personal journey," *J. Manage.*, vol. 47, no. 7, pp. 1663–1676, Sep. 2021, doi: 10.1177/01492063211015272.

[15] M. Singh, "Integrating organizational theory, resource-based view, and big data culture to improve manufacturing performance," in *Proc. 3rd Int. Conf. Advancement Electron. Commun. Eng. (AECE)*, Nov. 2023, pp. 800–804, doi: 10.1109/aece59614.2023.10428620.

[16] C. Chadwick and C. Flinchbaugh, "Searching for competitive advantage in the HRM-firm performance relationship," *Acad. Manage. Perspect.*, vol. 35, no. 2, pp. 181–207, May 2021, doi: 10.5465/amp.2018.0065.

[17] H. Mao and J. Lu, "Big data management capabilities and green innovation: A dynamic capabilities view," *Sustainability*, vol. 15, no. 19, p. 14637, Oct. 2023. [Online]. Available: https://www.mdpi.com/2071-1050/15/19/14637

[18] B. Nayak, S. S. Bhattacharyya, and B. Krishnamoorthy, "Integrating the dialectic perspectives of resource-based view and industrial organization theory for competitive advantage—A review and research agenda," *J. Bus. Ind. Marketing*, vol. 38, no. 3, pp. 656–679, Jan. 2023, doi: 10.1108/jbim-06-2021-0306.

[19] D. D. Bhatta, M. Sarfraz, L. Ivascu, and M. Pislaru, "The Nexus of corporate affinity for technology and firm sustainable performance in the era of digitalization: A mediated model," *Sustainability*, vol. 15, no. 12, p. 9765, Jun. 2023. [Online]. Available: https://www.mdpi.com/2071-1050/15/12/9765

[20] B. Cho, S. Y. Ryoo, and K. K. Kim, "Interorganizational dependence, information transparency in interorganizational information systems, and supply chain performance," *Eur. J. Inf. Syst.*, vol. 26, no. 2, pp. 185–205, Mar. 2017, doi: 10.1057/s41303-017-0038-1.

[21] R. W. Cuthbertson and P. I. Furseth, "Digital services and competitive advantage: Strengthening the links between RBV, KBV, and innovation," *J. Bus. Res.*, vol. 152, pp. 168–176, Nov. 2022, doi: 10.1016/j.jbusres.2022.07.030.

[22] A. Jungmittag and A. Pesole, "The impact of robots on labour productivity: A panel data approach covering 9 industries and 12 countries," in *Proc. JRC Work. Papers Ser. Labour, Educ. Technol.*, 2019, pp. 1–27.

[23] U. U. Rehman and A. Iqbal, "Nexus of knowledge-oriented leadership, knowledge management, innovation and organizational performance in higher education," *Bus. Process Manage. J.*, vol. 26, no. 6, pp. 1731–1758, Mar. 2020, doi: 10.1108/bpmj-07-2019-0274.

[24] M. J. Donate and J. D. Sánchez de Pablo, "The role of knowledge-oriented leadership in knowledge management practices and innovation," *J. Bus. Res.*, vol. 68, no. 2, pp. 360–370, Feb. 2015, doi: 10.1016/j.jbusres.2014.06.022.

[25] M. M. Naqshbandi and S. M. Jasimuddin, "Knowledge-oriented leadership and open innovation: Role of knowledge management capability in france-based multinationals," *Int. Bus. Rev.*, vol. 27, no. 3, pp. 701–713, Jun. 2018, doi: 10.1016/j.ibusrev.2017.12.001.

[26] C. C. Farrell and C. E. Coburn, "Absorptive capacity: A conceptual framework for understanding district central office learning," *J. Educ. Change*, vol. 18, no. 2, pp. 135–159, May 2017, doi: 10.1007/s10833-016-9291-7.

[27] M. J. Donate, M. González-Mohíno, F. P. Appio, and F. Bernhard, "Dealing with knowledge hiding to improve innovation capabilities in the hotel industry: The unconventional role of knowledge-oriented leadership," *J. Bus. Res.*, vol. 144, pp. 572–586, May 2022, doi: 10.1016/j.jbusres.2022.02.001.

[28] C. N.-L. Tan, "Enhancing knowledge sharing and research collaboration among academics: The role of knowledge management," *Higher Edu.*, vol. 71, no. 4, pp. 525–556, Apr. 2016, doi: 10.1007/s10734-015-9922-6.

[29] A. I. Choudhary, S. A. Akhtar, and A. Zaheer, "Impact of transformational and servant leadership on organizational performance: A comparative analysis," *J. Bus. Ethics*, vol. 116, no. 2, pp. 433–440, Aug. 2013, doi: 10.1007/s10551-012-1470-8.

[30] B. J. C. Claessens, W. van Eerde, C. G. Rutte, and R. A. Roe, "A review of the time management literature," *Personnel Rev.*, vol. 36, no. 2, pp. 255–276, Feb. 2007, doi: 10.1108/00483480710726136.

[31] F. Bozbayındır, "The relationship between the time management skills and cyberloafing behavior of school administrators: A quantitative analysis," *Educ. Policy Anal. Strategic Res.*, vol. 14, no. 3, pp. 178–199, Sep. 2019.

[32] A. B. Ötken, A. Bayram, S. G. Beşer, and Ç. Kaya, ''Are time management and cyberloafing related? Investigating Employees' attitudes,'' *Global Bus. Rev.*, vol. 24, no. 5, pp. 874–886, Oct. 2023, doi: 10.1177/0972150920931060.
[33] Steelcase. (2014). *Cada Empleado Pierde Al Día 86 Minutos De Su Tiempo De Trabajo Debido a Las Distracciones Producidas En Sus Oficinas, in Steelcase Comunicados De Prensa*. [Online]. Available: https://www.steelcase.com/eu-es/comunicados-de-prensa/cada-empleado-pierde-al-dia-86-minutos-de-su-tiempo-de-trabajo-debido-las-distracciones-producidas-en-sus-oficinas/
[34] Workmeter. (2021). *Cuánto Tiempo Perdemos Al Día En Nuestro Puesto De Trabajo*. [Online]. Available: https://www.workmeter.com/blog/cuanto-tiempo-perdemos-puesto-de-trabajo/#:: text=Al%20d%C3%ADa%20perdemos%20un%2030,100%20empresas%20y%203.770%20trabajadores
[35] Z. Sahito and P. Väisänen, ''Factors affecting job satisfaction of teacher educators: Empirical evidence from the universities of sindh province of Pakistan.,'' *J. Teacher Edu. Educators*, vol. 6, no. 1, pp. 5–30, Jun. 2017.
[36] O. Ugwu and I. Attah, ''An appraisal of construction management practice in Nigeria,'' *Nigerian J. Technol.*, vol. 35, no. 4, pp. 754–760, 2016. [Online]. Available: http://dx.doi.org/10.4314/njt.v35i4.1
[37] MarketsandMarkets. (2025). *Service Robotics Market Worth $102.5 Billion By 2025*. [Online]. Available: https://www.marketsandmarkets.com/PressReleases/service-robotics.asp
[38] IIF Robot. (2023). *World Robot Report*. [Online]. Available: https://ifr.org/
[39] S. H.-W. Chuah, E. C.-X. Aw, and D. Yee, ''Unveiling the complexity of consumers' intention to use service robots: An fsQCA approach,'' *Comput. Hum. Behav.*, vol. 123, Oct. 2021, Art. no. 106870, doi: 10.1016/j.chb.2021.106870.
[40] Y. Lee, S. Lee, and D.-Y. Kim, ''Exploring hotel guests' perceptions of using robot assistants,'' *Tourism Manage. Perspect.*, vol. 37, Jan. 2021, Art. no. 100781, doi: 10.1016/j.tmp.2020.100781.
[41] J. Stoldt, T. U. Trapp, S. Toussaint, M. Süße, A. Schlegel, and M. Putz, ''Planning for digitalisation in SMEs using tools of the digital factory,'' *Proc. CIRP*, vol. 72, pp. 179–184, Aug. 2018, doi: 10.1016/j.procir.2018.03.100.
[42] K. Horváth and L. Szerb, ''Managerial practices and the productivity of knowledge-intensive service businesses: An analysis of digital/IT and cash management practices,'' *Strategic Change*, vol. 27, no. 2, pp. 161–172, Mar. 2018, doi: 10.1002/jsc.2191.
[43] P. Kotler, G. Armstrong, S. H. Ang, S. M. Leong, C. T. Tan, and O. Yau, *Principles of Marketing: An Global Perspective*. Singapore: Prentice-Hall, 2008.
[44] K. A. Hoff and M. Bashir, ''Trust in automation: Integrating empirical evidence on factors that influence trust,'' *Hum. Factors, J. Hum. Factors Ergonom. Soc.*, vol. 57, no. 3, pp. 407–434, May 2015, doi: 10.1177/0018720814547570.
[45] S. E. Davis, ''Individual differences in operators' trust in autonomous systems: A review of the literature,'' Defence Sci. Technol. Group (DST), Fairbairn, CBR, Australia, Tech. Rep. TR-3587, 2019.
[46] M.-H. Huang and R. T. Rust, ''Artificial intelligence in service,'' *J. Service Res.*, vol. 21, no. 2, pp. 155–172, May 2018, doi: 10.1177/1094670517752459.
[47] S. Paluch and J. Wirtz, ''Artificial intelligence and robots in the service encounter,'' *J. Service Manage. Res.*, vol. 4, no. 1, pp. 3–8, 2020, doi: 10.15358/2511-8676-2020-1-3.
[48] X. Ferràs-Hernández, ''The future of management in a world of electronic brains,'' *J. Manage. Inquiry*, vol. 27, no. 2, pp. 260–263, Apr. 2018, doi: 10.1177/1056492617724973.
[49] E. Brynjolfsson and T. Mitchell, ''What can machine learning do? Workforce implications,'' *Science*, vol. 358, no. 6370, pp. 1530–1534, Dec. 2017, doi: 10.1126/science.aap8062.
[50] P. Madhavan and D. A. Wiegmann, ''Similarities and differences between human–human and human–automation trust: An integrative review,'' *Theor. Issues Ergonom. Sci.*, vol. 8, no. 4, pp. 277–301, Jul. 2007, doi: 10.1080/14639220500337708.
[51] M. Hengstler, E. Enkel, and S. Duelli, ''Applied artificial intelligence and trust—The case of autonomous vehicles and medical assistance devices,'' *Technol. Forecasting Social Change*, vol. 105, pp. 105–120, Apr. 2016, doi: 10.1016/j.techfore.2015.12.014.
[52] P. M. Leonardi, ''Crossing the implementation line: The mutual constitution of technology and organizing across development and use activities,'' *Commun. Theory*, vol. 19, no. 3, pp. 278–310, Aug. 2009, doi: 10.1111/j.1468-2885.2009.01344.x.
[53] D. Ullman and B. F. Malle, ''Human-robot trust: Just a button press away,'' in *Proc. Companion ACM/IEEE Int. Conf. Hum.-Robot Interact.*, Mar. 2017, pp. 309–310.
[54] C. Ragin, ''User's guide to fuzzy-set/qualitative comparative analysis 3.0,'' Dept. Sociology Univ. California, Irvine, CA, USA, Tech. Rep., 2018. [Online]. Available: https://sites.socsci.uci.edu/ cragin/fsQCA/download/fsQCAManual.pdf
[55] C. Pelau, D.-C. Dabija, and I. Ene, ''What makes an AI device human-like? The role of interaction quality, empathy and perceived psychological anthropomorphic characteristics in the acceptance of artificial intelligence in the service industry,'' *Comput. Hum. Behav.*, vol. 122, Sep. 2021, Art. no. 106855, doi: 10.1016/j.chb.2021.106855.
[56] M. Chung, E. Ko, H. Joung, and S. J. Kim, ''Chatbot e-service and customer satisfaction regarding luxury brands,'' *J. Bus. Res.*, vol. 117, pp. 587–595, Sep. 2020, doi: 10.1016/j.jbusres.2018.10.004.
[57] S. M. White, A. Riley, and P. Flom, ''Assessment of time management skills (ATMS): A practice-based outcome questionnaire,'' *Occupational Therapy Mental Health*, vol. 29, no. 3, pp. 215–231, Jan. 2013, doi: 10.1080/0164212x.2013.819481.
[58] J. W. Olmstead, ''Effective time management skills & practices: Self-assessment questionnaire,'' Olmstead & Associates, Lake Oswego, OR, USA, Tech. Rep., 2010. [Online]. Available: https://www.olmsteadassoc.com/wp-content/uploads/2017/01/Effective-Time-Management-Skills-Self-Assessment-Questionnaire.pdf
[59] C. B. Nordheim, A. Følstad, and C. A. Bjørkli, ''An initial model of trust in chatbots for customer service—Findings from a questionnaire study,'' *Interacting Comput.*, vol. 31, no. 3, pp. 317–335, May 2019, doi: 10.1093/iwc/iwz022.
[60] V. D. Simone, V. D. Pasquale, V. Giubileo, and S. Miranda, ''Human-robot collaboration: An analysis of worker's performance,'' *Proc. Comput. Sci.*, vol. 200, pp. 1540–1549, May 2022, doi: 10.1016/j.procs.2022.01.355.
[61] J. F. Hair, J. J. Risher, M. Sarstedt, and C. M. Ringle, ''When to use and how to report the results of PLS-SEM,'' *Eur. Bus. Rev.*, vol. 31, no. 1, pp. 2–24, Jan. 2019, doi: 10.1108/ebr-11-2018-0203.
[62] C. Ragin, ''Measurement versus calibration: A set-theoretic approach,'' in *The Oxford Handbook of Political Methodology*, J. M. Box-Steffensmeier, H. E. Brady, and D. Collier, Eds. OXford, U.K.: Academic, Sep. 2009, doi: 10.1093/oxfordhb/9780199286546.003.0008.
[63] C. Ringle, S. Wende, and J. Becker, ''SmartPLS 4, Bönningstedt: SmartPLS,'' 2022. [Online]. Available: https://www.smartpls.com
[64] C. Ragin and D. Sean, ''Fuzzy-set/qualitative comparative analysis 4.0,'' Dept. Sociology, Univ. California, Irvine, CA, USA, Tech. Rep., 2022. [Online]. Available: https://www.fsqca.com
[65] C. C. Ragin, ''The logic of qualitative comparative analysis,'' *Int. Rev. Social Hist.*, vol. 43, no. S6, pp. 105–124, Dec. 1998, doi: 10.1017/s0020859000115111.
[66] M. Beynon, P. Jones, and D. Pickernell, ''Innovation and the knowledge-base for entrepreneurship: Investigating SME innovation across European regions using fsQCA,'' *Entrepreneurship Regional Develop.*, vol. 33, nos. 3–4, pp. 227–248, Mar. 2021, doi: 10.1080/08985626.2021.1872936.
[67] C. Ragin, *The Comparative Method: Moving Beyond Qualitative and Quantitative Strategies*. Berkeley, CA, USA: Univ. of California Press, 2014.
[68] C. C. Ragin and P. C. Fiss, ''Net effects analysis versus configurational analysis: An empirical demonstration,'' *Redesigning Social Inquiry, Fuzzy Sets Beyond*, vol. 240, pp. 190–212, Jan. 2008.
[69] I. O. Pappas and A. G. Woodside, ''Fuzzy-set qualitative comparative analysis (fsQCA): Guidelines for research practice in information systems and marketing,'' *Int. J. Inf. Manage.*, vol. 58, Jun. 2021, Art. no. 102310, doi: 10.1016/j.ijinfomgt.2021.102310.
[70] F. McLeay, H. Olya, H. Liu, C. Jayawardhena, and C. Dennis, ''A multi-analytical approach to studying customers motivations to use innovative totally autonomous vehicles,'' *Technol. Forecasting Social Change*, vol. 174, Jan. 2022, Art. no. 121252, doi: 10.1016/j.techfore.2021.121252.
[71] C. Fornell and D. F. Larcker, ''Evaluating structural equation models with unobservable variables and measurement error,'' *J. Marketing Res.*, vol. 18, no. 1, pp. 39–50, Feb. 1981, doi: 10.1177/002224378101800104.
[72] J. F. Hair Jr., M. Sarstedt, L. Hopkins, and V. G. Kuppelwieser, ''Partial least squares structural equation modeling (PLS-SEM): An emerging tool in business research,'' *Eur. Bus. Rev.*, vol. 26, no. 2, pp. 106–121, Mar. 2014, doi: 10.1108/ebr-10-2013-0128.
[73] J. F. Hair, G. T. M. Hult, C. M. Ringle, M. Sarstedt, and K. O. Thiele, ''Mirror, mirror on the wall: A comparative evaluation of composite-based structural equation modeling methods,'' *J. Acad. Marketing Sci.*, vol. 45, no. 5, pp. 616–632, Sep. 2017, doi: 10.1007/s11747-017-0517-x.

[74] M. Sarstedt, C. M. Ringle, D. Smith, R. Reams, and J. F. Hair, "Partial least squares structural equation modeling (PLS-SEM): A useful tool for family business researchers," *J. Family Bus. Strategy*, vol. 5, no. 1, pp. 105–115, Mar. 2014, doi: 10.1016/j.jfbs.2014.01.002.

[75] G. Linton and J. Kask, "Configurations of entrepreneurial orientation and competitive strategy for high performance," *J. Bus. Res.*, vol. 70, pp. 168–176, Jan. 2017, doi: 10.1016/j.jbusres.2016.08.022.

[76] A. Ordanini, A. Parasuraman, and G. Rubera, "When the recipe is more important than the ingredients: A qualitative comparative analysis (QCA) of service innovation configurations," *J. Service Res.*, vol. 17, no. 2, pp. 134–149, May 2014, doi: 10.1177/1094670513513337.

[77] C. C. Ragin, "Set relations in social research: Evaluating their consistency and coverage," *Political Anal.*, vol. 14, no. 3, pp. 291–310, 2006, doi: 10.1093/pan/mpj019.

[78] P. C. Fiss, "A set-theoretic approach to organizational configurations," *Acad. Manage. Rev.*, vol. 32, no. 4, pp. 1180–1198, Oct. 2007, doi: 10.5465/amr.2007.26586092.

[79] C. Q. Schneider and C. Wagemann, "Standards of good practice in qualitative comparative analysis (QCA) and fuzzy-sets," *Comparative Sociol.*, vol. 9, no. 3, pp. 397–418, 2010, doi: 10.1163/156913210x12493538729793.

[80] P. C. Fiss, "Building better causal theories: A fuzzy set approach to typologies in organization research," *Acad. Manage. J.*, vol. 54, no. 2, pp. 393–420, Apr. 2011, doi: 10.5465/amj.2011.60263120.

[81] P.-L. Wu, S.-S. Yeh, T.-C. T. Huan, and A. G. Woodside, *Complexity Theory, Configural Analysis, and Deepening the Service Dominant Logic, in Bad To Good*. Bingley, U.K.: Emerald Group Publishing Limited, pp. 181–243.

[82] C. C. Ragin, *Redesigning Social Inquiry: Fuzzy Sets Beyond*. Chicago, IL, USA: University of Chicago Press, 2009.

[83] M. Malik, M. Abbas, and H. Imam, "Knowledge-oriented leadership and workers' performance: Do individual knowledge management engagement and empowerment matter?" *Int. J. Manpower*, vol. 44, no. 7, pp. 1382–1398, Nov. 2023, doi: 10.1108/ijm-07-2022-0302.

[84] M. Bashir and S. Pradhan, "The influence of knowledge-oriented leadership on business model innovation and open innovation: Mediating role of absorptive capacity," *Manage. Decis.*, vol. 2023, pp. 1–27, Aug. 2023, doi: 10.1108/md-10-2022-1481.

[85] A. Bhargava, M. Bester, and L. Bolton, "Employees' perceptions of the implementation of robotics, artificial intelligence, and automation (RAIA) on job satisfaction, job security, and employability," *J. Technol. Behav. Sci.*, vol. 6, no. 1, pp. 106–113, Mar. 2021, doi: 10.1007/s41347-020-00153-8.

[86] S. Ivanov and C. Webster, "Conceptual framework of the use of robots, artificial intelligence and service automation in travel, tourism, and hospitality companies," in *Robots, Artificial Intelligence, and Service Automation in Travel, Tourism and Hospitality*, S. Ivanov and C. Webster, Eds., Bingley, U.K.: Emerald Publishing Limited, 2019, pp. 7–37.

[87] S.-L. Wamba-Taguimdje, S. F. Wamba, J. R. K. Kamdjoug, and C. E. T. Wanko, "Influence of artificial intelligence (AI) on firm performance: The business value of AI-based transformation projects," *Bus. Process Manage. J.*, vol. 26, no. 7, pp. 1893–1924, May 2020, doi: 10.1108/bpmj-10-2019-0411.

[88] P. Korzynski and O. Protsiuk, "What leads to cyberloafing: The empirical study of workload, self-efficacy, time management skills, and mediating effect of job satisfaction.," *Behav. Inf. Technol.*, vol. 43, no. 1, pp. 200–211, Jan. 2024, doi: 10.1080/0144929x.2022.2159525.

MIGUEL GONZÁLEZ-MOHÍNO received the Ph.D. degree in economics and business from the University of Castilla-La Mancha. He obtained a Margarita Salas postdoctoral contract from UCLM, in 2021. He was with the University of Seville. He is currently an Assistant Professor with the University of Córdoba, Spain. He is a Teacher and a Researcher with the Faculty of Law and Economic and Business Sciences, Córdoba. His research interests include knowledge management and strategies in communication, collaboration, and innovation in human resources. He received the first prize from the Center for Financial Studies (CEF) in the Human Resources Category, in 2024.

MARIO J. DONATE is currently an Associate Professor with the Department of Business Organization, University of Castilla-La Mancha (UCLM). He teaches and conducts research with the Faculty of Law and Social Sciences, Ciudad Real Campus. He teaches undergraduate and master's courses, including strategic management, innovation strategies and knowledge management, and strategic aspects in new business management. His research interests include corporate knowledge strategies in the digital era, organizational factors that facilitate knowledge management, and innovation strategies in specific sectors.

GUZMÁN A. MUÑOZ-FERNÁNDEZ is currently a Professor of business organization and teaches in the Master's Program for Secondary and Pre-University Teacher Training with the University of Córdoba, Spain. He has taught with the secondary and pre-university levels for over 15 years. His research interests include the analysis of teacher candidates and cultural tourism.

L. JAVIER CABEZA-RAMÍREZ is currently an Assistant Professor with the University of Córdoba, specializing in consumer behavior, entrepreneurship, innovation, and video games. He has published over 30 articles in indexed journals, with an H-index of 13 on Google Scholar. His research has been recognized for its impact on areas, such as sustainable tourism and the adoption of streaming platforms. Additionally, he has participated in projects funded by the FEDER Program and has been awarded the Extraordinary Doctoral Award in Social and Legal Sciences.