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Smart Manufacturing Outcomes

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ABSTRACT

This study investigates the influence of continuous learning and upskilling, ergonomics and safety, and the optimisation of human-cyber-physical interfaces on workforce adaptability and the performance of smart factories. Furthermore, it explores the mediating role of workforce adaptability within this context. Data were collected from a sample of 316 participants employed in the manufacturing sector of Saudi Arabia and analysed using the statistical software JASP version 0.95.4.0. The findings reveal that optimisation of human-cyber-physical interfaces exerts a significant effect on both workforce adaptability and smart factory performance. Regarding continuous learning and upskilling, results indicate a significant relationship with workforce adaptability, yet no direct association with smart factory performance was observed. Similarly, ergonomics and safety practices significantly affect workforce adaptability, but do not directly influence smart factory performance. Workforce adaptability itself was found not to have a direct impact on smart factory performance. Nonetheless, the analysis confirmed that workforce adaptability serves as a mediating factor between continuous learning and upskilling, ergonomics and safety integration, human-cyber-physical interface optimisation, and smart manufacturing performance. The empirical model proposed in this study represents a novel and valuable addition to existing literature. Additionally, the study offers practical recommendations for enhancing smart manufacturing performance within the Saudi Arabian context.

1. Introduction

The global manufacturing industry is experiencing a substantial transformation driven by the integration of digital technologies, automation, data analytics, and evolving operational paradigms collectively referred to as Industry 4.0. Within this framework, smart manufacturing systems have emerged as strategic mechanisms to meet increasing demands for flexibility, precision, and operational efficiency [47]. These systems employ cyber-physical technologies, sensor networks, and artificial intelligence to facilitate real-time decision-making and predictive control throughout production processes [46]. Despite rapid advancements in technological infrastructure, the human aspect of this transition remains insufficiently examined. In numerous industrial contexts,

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particularly within metal forming and other high-precision sectors, technological developments frequently surpass workforce adaptability, creating a gap between human capability and system complexity [60].

Research increasingly recognises that successful digital transformation in manufacturing relies not only on implementing advanced machinery and software but also on human-centred strategies that cultivate employee competencies, resilience, and adaptability [31]. Employees now operate within hybrid human-machine environments, where decision-making acumen, learning agility, and ergonomic well-being are critical determinants of overall system effectiveness [36]. As automation permeates production processes, strategic human resource management assumes an expanded role, shifting from administrative functions to actively enabling technological adoption and fostering organisational learning [30]. Consequently, understanding the impact of HR-related practices on smart manufacturing performance holds both theoretical and practical significance [52].

The literature identifies several human-centric domains that are vital for Industry 4.0 implementation [17]. Firstly, continuous learning and upskilling equip employees with the technical and digital skills necessary to operate sophisticated manufacturing systems [62]. Evidence from workforce development studies indicates that structured, relevant training programmes enhance employee confidence, reduce operational errors, and support ongoing innovation [24]. Secondly, the integration of ergonomics and safety remains essential to sustain productivity, particularly in high-force or repetitive manufacturing tasks [35]. Inadequate workstation design and insufficient safety measures can lead to fatigue, musculoskeletal strain, and diminished efficiency, threatening long-term sustainability. Thirdly, the quality of human-cyber-physical interfaces, including dashboard design, decision-support systems, and human-machine interactions, directly influences workers' ability to interpret system feedback and respond to dynamic production conditions [3]. Together, these human-centred elements determine whether digital technologies achieve tangible performance improvements or remain underutilized.

Despite growing recognition of these factors, empirical research connecting specific HR practices and human-system integration with smart manufacturing performance is limited [29]. Many studies address human factors and technological systems separately, resulting in fragmented insights [2]. A more integrative approach is needed to examine how human-centred practices function through internal mechanisms, such as workforce adaptability—the capacity of employees to adjust behaviours, skills, and mindsets in response to technological change [16]. Adaptability constitutes a dynamic competency that mediates the relationship between organisational practices and performance outcomes, serving as the link between HR interventions and technological effectiveness [15]. Employees who are confident in utilising new tools and receptive to procedural modifications are more likely to exploit digital systems efficiently, enhancing throughput, product quality, and machine utilisation [58].

Addressing these conceptual gaps, the present study proposes and empirically tests a human-integrated model of smart manufacturing performance. Specifically, it investigates the impact of learning and upskilling, ergonomics and safety integration, and optimization of human-cyber-physical interfaces on workforce adaptability and subsequent smart manufacturing outcomes. The mediating function of workforce adaptability is also examined. The study offers both theoretical and practical contributions. Theoretically, it integrates perspectives from strategic human resource management, human factors engineering, and operations management to present a comprehensive model of human-driven performance in an Industry 4.0 context. Empirically, it provides evidence from a manufacturing setting where digital integration and human interaction coexist, addressing calls for data-driven validation of conceptually developed Industry 4.0 frameworks. Practically, the findings offer guidance for manufacturing leaders and HR strategists in developing training

programmes, ergonomics protocols, and interface policies that strengthen workforce adaptability and enhance operational performance.

2. Review of Literature

With the progression of technology, machines have assumed an increasingly critical role in the manufacturing sector [32]. Their effectiveness, however, depends on proper installation and the presence of user-friendly interfaces that facilitate human interaction. The primary objective of incorporating these machines is to transform production processes into smarter modes of operation, prioritizing the optimization of human-machine physical interfaces [13]. Machine design should be aligned with human requirements, enabling operators to perform a variety of customized tasks efficiently. When effectively implemented, these systems can enhance productivity by improving the interaction between humans and machines, leading to better operational outcomes [54]. Consequently, machines should be tailored to execute specific, customized jobs, where active human involvement can further boost production efficiency [48]. Conversely, inadequate integration of human-cyber-physical interfaces limit the potential benefits of technological advancement within manufacturing. In addition, workforce training is essential to ensure that employees can utilize these interfaces optimally, maximizing the advantages offered by smart manufacturing environments [20]. Based on these considerations, the following hypotheses are formulated.

H1: There is a relationship between human-cyber-physical interface optimization and workforce adaptability.

H2: There is a relationship between human-cyber-physical interface optimization and smart manufacturing performance.

Continuous learning constitutes a critical determinant for enhancing workforce skills and enabling employees to perform a diverse range of tasks within the manufacturing sector [5]. It is essential to prioritize the workforce and ensure that all activities related to their development are effectively managed. Regular training programmes, conducted on a weekly or monthly basis, are necessary to equip employees with the capability to leverage the advanced functionalities of smart machinery effectively [66]. Establishing a continuous upskilling mechanism is crucial to improve workforce adaptability, allowing employees to address challenges efficiently and generate multiple solutions. Adaptability within the manufacturing context is particularly important for promoting product diversity and innovation [67]. Therefore, employees must receive targeted training and upskilling opportunities designed by top management, enabling them to perform various tasks through a well-structured continuous learning framework [65]. Such measures are essential for increasing productivity, as they facilitate the creative and efficient utilization of modern technologies and intelligent tools. Conversely, neglecting continuous learning and creativity can diminish workforce performance, negatively affecting human-machine interaction and overall operational outcomes [10]. Based on these considerations, the following hypotheses have been formulated.

H3: There is a relationship between continuous learning & upskilling and workforce adaptability.

H4: There is a relationship between continuous learning & upskilling and smart manufacturing performance.

Ensuring the safe operation of machinery is a fundamental requirement in any manufacturing environment where human labor is involved. It is imperative to prevent harm to employees arising from the utilisation of advanced machinery [1]. Consequently, workers must be trained in safety-related competencies that not only enhance productivity but also protect their well-being [49]. Within the context of improving smart manufacturing performance, integrating ergonomics and

safety is essential, as it directly affects both human life and workplace security. Employees require targeted training to maintain safety standards that minimize risk during emergency situations in manufacturing operations [69]. The workforce should be equipped to operate smart machinery efficiently while maximizing the benefits of technological tools. Simultaneously, safety integration must be prioritized, with daily training routines providing continuous updates and guidance on machine usage and operational best practices [51]. While smart technologies are vital for enhancing manufacturing performance, their effective deployment depends on embedding safety measures that enable employees to utilise machines optimally in daily tasks [6]. Therefore, the integration of ergonomics and safety is regarded as a critical determinant of both workforce adaptability and overall manufacturing performance [11]. Based on these considerations, the following hypotheses have been formulated.

H5: There is a relationship between ergonomics & safety integration and workforce adaptability.

H6: There is a relationship between ergonomics & safety integration and smart manufacturing performance.

Workforce adaptability plays a pivotal role in enabling employees to utilise machinery effectively for contemporary manufacturing tasks, thereby maximising benefits through the acquisition of new skills and enhanced operational proficiency [27]. Employees must maintain an open mindset and possess creative capabilities that allow them to undertake new tasks and explore alternative product manufacturing approaches using advanced robots and machinery [70]. This adaptability facilitates a deeper understanding of machine functionalities, enabling workers to leverage these systems for optimal outcomes [57]. Conversely, a restricted approach or lack of adaptability among the workforce can lead to reduced productivity, undermining performance reliability and limiting operational advantages [38]. Therefore, targeted training is essential to ensure that employees know how and when to apply creativity and extract maximum productivity from smart manufacturing systems. Based on these considerations, the following hypothesis has been developed.

H7: There is a relationship between workforce adaptability and smart manufacturing performance.

Workforce adaptability is a critical factor in the manufacturing sector, particularly when creativity is enhanced through continuous learning and the application of modern technologies [12]. It is the responsibility of the human resource department to strengthen employee capabilities, enabling effective utilization of human–cyber–physical interface optimization within smart manufacturing environments. Employees must also be trained to operate and interact with new machine interfaces that are central to manufacturing operations [64]. Additionally, workforce adaptability underpins continuous learning and upskilling, ensuring that smart operational mechanisms are employed effectively while maintaining a focus on manufacturing performance. Human resource initiatives should provide advanced, work-integrated training programmes that elevate workforce competencies to match technological advancements [68]. Equally important is training employees to uphold safety standards in environments where modern machinery is deployed. Incorporating ergonomics and safety protocols into daily training manuals ensures that the workforce engages with these practices consistently at the start of each workday [63]. Such measures enhance workforce adaptability, enabling employees to utilize technological tools and models efficiently, thereby maximizing operational benefits. Furthermore, upskilling initiatives reinforce these mechanisms, supporting the integration of modern technologies and robotic systems into daily manufacturing processes [53]. Based on these considerations, the following mediating hypotheses have been formulated.

H8: There is a mediating role of workforce adaptability between human-cyber-physical interface optimization and smart manufacturing performance.

H9: There is a mediating role of workforce adaptability between continuous learning & upskilling and smart manufacturing performance.

H10: There is a mediating role of workforce adaptability between ergonomics & safety integration and smart manufacturing performance.

The conceptual framework of this study is illustrated in Figure 1.

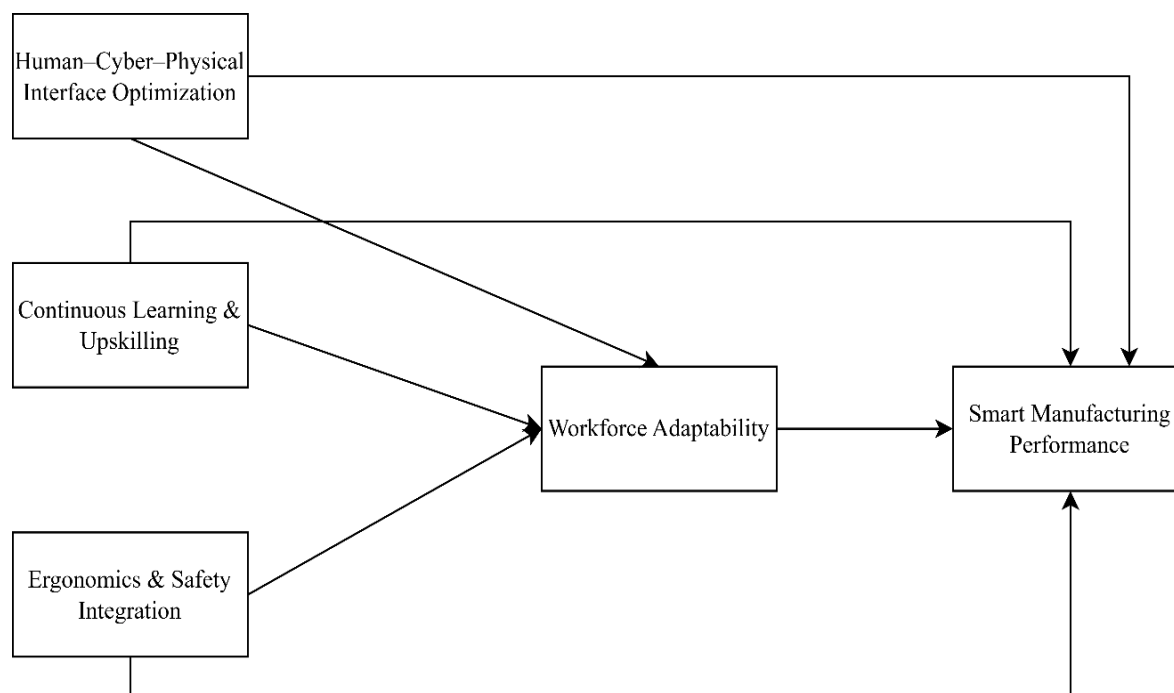


Fig.1: Model of the Study

3. Methodology

This study employed primary data to examine the relationships among the variables and to test the proposed model. Data were collected using a Likert-scale instrument adapted from previous research. These instruments were customized to align with the specific requirements of the study and the operationalization of the variables. Prior to data collection, the adapted instruments were reviewed by a panel of five experts, and items were revised based on their feedback and evaluation reports. A pilot study was subsequently conducted with 54 respondents drawn from the same target population to assess the reliability of the instruments, specifically by calculating Cronbach's alpha for each variable. Data from the pilot study were entered into IBM SPSS version 26, and all instruments achieved Cronbach's alpha values exceeding 0.70, confirming their reliability [56]. The pilot responses were not included in the final dataset.

The target population for this research consisted of employees within the manufacturing sector in Saudi Arabia, particularly those working in industries that have integrated Industry 4.0 technologies into smart manufacturing operations. Probability sampling was employed, specifically using simple random sampling, with prior consideration of the employee payroll distribution within the sector. Since the study collected behavioral data rather than biological samples, informed consent was obtained from all participants before data collection. To achieve the desired sample size, 400 questionnaires were distributed, anticipating a 50% response rate [37]. A total of 371 responses were received, exceeding the minimum expected threshold. After data cleaning using IBM SPSS 26, responses with outliers were removed, resulting in a final sample of 316 valid responses for analysis. The final analysis of the proposed model was conducted using the statistical software JASP [41].

4. Data Analysis and Findings

The study initially examined the demographic characteristics of the respondents. As presented in Table 1, the largest age groups were 31–40 years (28%) and 20–30 years (27%), reflecting a relatively young workforce within the manufacturing sector. Gender distribution was almost equal, with 52% male and 48% female participants. Regarding educational attainment, most respondents held either a bachelor's degree (16%) or a diploma (16%), while smaller proportions possessed a doctorate (19%) or technical/other qualifications (17–19%), indicating a varied academic profile. Work experience among participants was diverse, with the largest segment reporting 11–20 years in the industry (38%). A substantial majority (78%) indicated high exposure to smart manufacturing technologies, suggesting that most participants operate in digitally advanced environments. In terms of perceptions of digital transformation, responses were distributed fairly evenly across low (33%), moderate (34%), and high (34%) importance levels, demonstrating a balanced perspective on the strategic relevance of digital innovation in manufacturing operations.

Table 1
Demographics

Variable	Level	Counts	Proportion
Age Group	20–30 Years	84	27%
	31–40 Years	87	28%
	41–50 Years	79	25%
	Above 50 Years	66	21%
Gender	Male	165	52%
	Female	151	48%
Education Level	Diploma	51	16%
	Bachelor's Degree	50	16%
	Master's Degree	41	13%
	Doctorate	61	19%
	Technical Certificate	54	17%
	Others	59	19%
Work Experience in Manufacturing	Less than 5 Years	47	15%
	5–10 Years	49	16%
	11–15 Years	59	19%
	16–20 Years	59	19%
	Above 20 Years	47	15%
	Not Specified	55	17%
Smart Manufacturing Exposure	Low Exposure	71	23%
	High Exposure	245	78%
Perception of Digital Transformation Importance	Low Importance	103	33%
	Moderate Importance	106	34%
	High Importance	107	34%

Following the demographic analysis, descriptive statistics were examined to assess the quality and distribution of the data. All responses were found to be valid, with no missing values identified. Data were collected using a 5-point Likert scale, and the mean values clustered around 3, which is considered acceptable [56]. Standard deviation values were approximately 1, indicating an appropriate level of dispersion. The study also evaluated the skewness and kurtosis of the data. As shown in Table 2, both skewness and kurtosis values fell within the range of -2 to +2, indicating that the data were normally distributed [56]. Furthermore, the minimum and maximum responses for all variables were 1 and 5, respectively. Overall, the descriptive statistics confirm that the dataset met the assumptions of normality and was suitable for further analysis.

Table 2
Descriptive Statistics

	HCP	CLU	ESI	WA	SMP
Valid	316	316	316	316	316
Missing	0	0	0	0	0
Mean	3.551	3.709	3.661	3.563	3.592
Std. Deviation	0.888	0.827	0.86	0.869	0.877
Skewness	-0.305	-0.363	-0.374	-0.108	-0.183
Std. Error of Skewness	0.137	0.137	0.137	0.137	0.137
Kurtosis	0.466	0.517	0.267	0.173	0.146
Std. Error of Kurtosis	0.273	0.273	0.273	0.273	0.273
Minimum	1	1	1	1	1
Maximum	5	5	5	5	5

Note: WA = Workforce Adaptability, HCP = Human Cyber Physical Interface, SMP = Smart Manufacturing Performance, CLU = Continuous Learning & Upskilling and ESI = Ergonomics & Safety Integration

The study further examined the relationships among the research variables to determine the strength and direction of their associations. Pearson correlation analysis was employed for this purpose, allowing the investigation of both the nature and magnitude of the relationships. As presented in Table 3, the results indicate that all variables were significantly and positively correlated with one another. These correlations were deemed positive, as the p-values for all relationships were below 0.001, confirming statistical significance [9].

Table 3
Correlations

Correlations		Pearson's r	p
HCP	- CLU	0.808	< .001
HCP	- ESI	0.798	< .001
HCP	- WA	0.762	< .001
HCP	- SMP	0.371	< .001
CLU	- ESI	0.835	< .001
CLU	- WA	0.742	< .001
CLU	- SMP	0.308	< .001
ESI	- WA	0.762	< .001
ESI	- SMP	0.334	< .001
WA	- SMP	0.344	< .001

The study also examined the relationships among the research variables using regression analysis. Initially, the direct effects were assessed, with a t-value greater than 1.96 considered indicative of statistical significance [21]. The results for H1 revealed a significant positive relationship between human–cyber–physical interface optimization and workforce adaptability. For H2, the analysis indicated a significant association between human–cyber–physical interface optimization and smart manufacturing performance. The findings for H3 demonstrated that continuous learning and upskilling significantly influence workforce adaptability. In contrast, H4 indicated no significant relationship between continuous learning and upskilling and smart manufacturing performance. Regarding ergonomics and safety integration, H5 showed a significant positive relationship with workforce adaptability, whereas H6 revealed no significant effect on smart manufacturing performance.

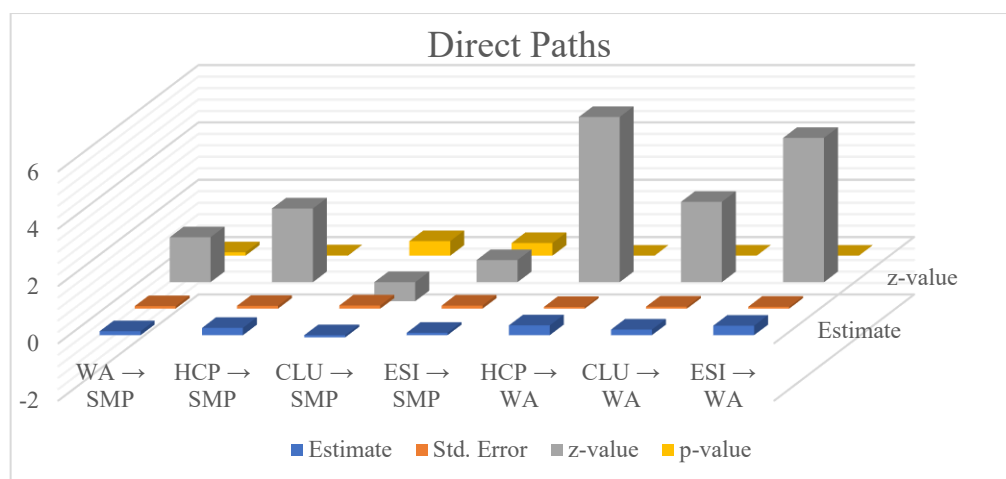


Fig.2: Direct Paths

Finally, H7 confirmed that workforce adaptability did not have a direct relationship with smart manufacturing performance. The outcomes of these direct relationship analyses are summarized in Figure 2 and Table 4.

Table 4

Direct Paths

Path	Estimate	Std. Error	z-Value	p-Value
WA → SMP	0.139	0.089	1.566	0.117
HCP → SMP	0.254	0.099	2.570	0.010
CLU → SMP	-0.074	0.112	-0.665	0.506
ESI → SMP	0.083	0.108	0.771	0.441
HCP → WA	0.342	0.059	5.760	< .001
CLU → WA	0.196	0.070	2.801	0.005
ESI → WA	0.331	0.066	5.033	< .001

The study further assessed the mediating effects proposed in the research model. The results for H8 confirmed that workforce adaptability plays a significant mediating role between human–cyber–physical interface optimisation and smart manufacturing performance. Similarly, H9 demonstrated that workforce adaptability significantly mediates the relationship between continuous learning and upskilling and smart manufacturing performance. Finally, H10 indicated that workforce adaptability serves as a significant mediator between ergonomics and safety integration and smart manufacturing performance.

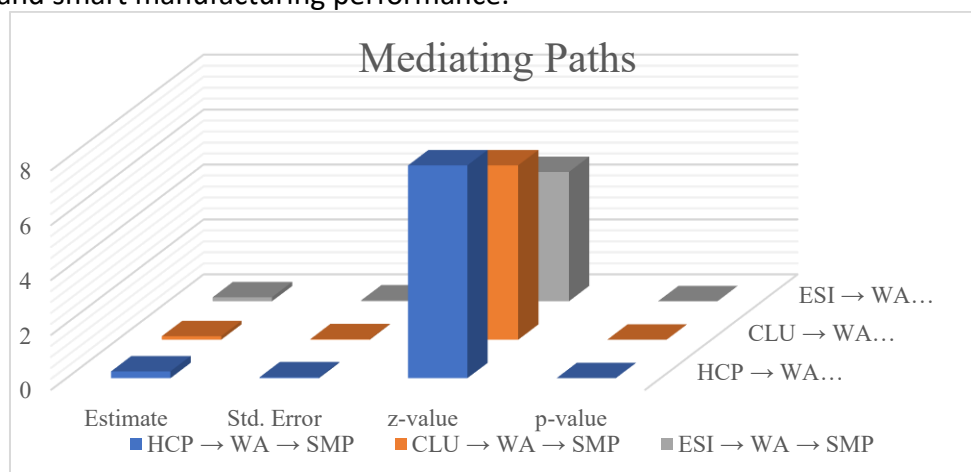


Fig.3: Mediating Paths

The results of these mediating analyses are presented in Figure 3 and Table 5.

Table 5
Mediating Paths

Path	Estimate	Std. Error	z-Value	p-Value
HCP → WA → SMP	0.248	0.032	7.750	< .001
CLU → WA → SMP	0.127	0.020	6.350	< .001
ESI → WA → SMP	0.146	0.031	4.709	< .001

5. Discussion and Conclusion

The study successfully achieved its objectives by examining the relationships among the research variables. The results for H1 indicated a significant positive relationship between human–cyber–physical interface optimization and workforce adaptability. This finding aligns with previous research, which emphasizes that optimizing human–cyber–physical interfaces enhances workforce capabilities in organizational contexts [25]. Similarly, Hammad et al. [22] noted that workforce adaptability and operational capacity improve when employees are provided with structured mechanisms to engage with modern robotic technologies within Industry 4.0. Furthermore, Nachiappan et al. [42] highlighted that the optimization of human–cyber–physical interfaces is a critical factor in integrating technology into modern manufacturing, where workforce effectiveness is essential. These studies collectively support the current finding that human–cyber–physical interface optimization is crucial for workforce adaptability in the manufacturing sector.

H2 revealed a significant relationship between human–cyber–physical interface optimization and smart manufacturing performance. Previous studies corroborate this result, with Gouda and Tiwari [19] emphasizing the importance of interface optimisation for enhancing manufacturing productivity. Baptista et al. [8] further argued that employees capable of utilising advanced technologies and robotics require well-designed interfaces and operational mechanisms to maximise output. In addition, Goraya et al. [18] asserted that optimising physical interfaces is essential for productive technological integration in manufacturing environments. These studies provide strong empirical support for the observed relationship in H2. The results for H3 demonstrated a positive association between continuous learning and upskilling and workforce adaptability. Samal [55] highlighted that ongoing learning and skill development enhances workforce productivity, which is essential for effective performance in manufacturing contexts. Similarly, Nioata et al. [45] emphasised that structured training provided by human resource departments aligns employee skills with contemporary work requirements, thereby improving overall performance. Neo et al. [44] also noted that continuous learning is necessary for advancing employee behaviour and developing competencies in line with manufacturing demands.

Conversely, H4 indicated no significant relationship between continuous learning and upskilling and smart manufacturing performance. While prior studies, such as Nancy et al. [43] and Bagherian et al. [7], suggest that learning and skills enhancement are critical for smart manufacturing, the present finding suggests that the current continuous learning initiatives in Saudi Arabian manufacturing may be insufficiently aligned with practical sector requirements. This underscores the need for human resource departments to refine training programmes to enhance employee productivity. H5 showed a significant positive relationship between ergonomics and safety integration and workforce adaptability. Supporting evidence from Ajgaonkar et al. [4] indicates that integrating ergonomics and safety measures is vital for improving workforce productivity. Hashemi-Petroodi et al. [23] further emphasised that well-trained employees develop the necessary skills to implement safety protocols effectively. Ambrogio et al. [5] also highlighted that workforce capability and productivity are enhanced when ergonomics and safety considerations are incorporated.

In contrast, H6 revealed no significant relationship between ergonomics and safety integration and smart manufacturing performance. Although Tenakwah and Watson [61] and Muduli and Choudhury [40] argue that safety and ergonomic integration can enhance smart manufacturing outcomes, this study found no such effect in the Saudi Arabian context [50]. This suggests that targeted training may be required to ensure that ergonomics and safety measures contribute effectively to smart manufacturing performance. H7 confirmed that workforce adaptability did not have a direct relationship with smart manufacturing performance. While previous research emphasizes the importance of workforce adaptability for enhancing performance [23; 34; 39], the current findings indicate that direct impacts may be limited in the observed context, highlighting the potential need for mediating mechanisms.

Regarding mediating effects, H8 was supported, indicating that workforce adaptability significantly mediates the relationship between human–cyber–physical interface optimization and smart manufacturing performance. Ajgaonkar et al. [4] and Muduli and Choudhury [40] similarly reported that workforce adaptability enhances the effective use of modern technologies, thereby improving manufacturing outcomes. H9 also confirmed a significant mediating role of workforce adaptability between continuous learning and upskilling and smart manufacturing performance. Sony and Mekoth [59] noted that workforce adaptability, supported by structured training, can enhance operational efficiency, while [26] highlighted that trained employees equipped with modern technological skills contribute to improved manufacturing performance.

Finally, H10 indicated that workforce adaptability mediates the relationship between ergonomics and safety integration and smart manufacturing performance. Daher and Ziade [14] emphasized that workforce training in safety protocols enhances productivity, while [33] highlighted that employees with appropriate skills and training can improve sector performance. Kumi et al. [28] also noted that workforce development strengthens safety integration, which, in turn, supports smart manufacturing outcomes. These findings collectively validate the mediating role of workforce adaptability in connecting human-centric practices with performance improvements in smart manufacturing.

6. Theoretical and Practical Implications

This study offers significant theoretical and practical contributions. From a theoretical perspective, it extends the existing body of knowledge by empirically testing a comprehensive model within the manufacturing sector in Saudi Arabia. Specifically, the study demonstrates that workforce adaptability functions as a significant mediator between ergonomics and safety integration and smart manufacturing performance. Moreover, workforce adaptability was found to mediate the relationship between continuous learning and upskilling and smart manufacturing performance. Similarly, it was established as a mediator between human–cyber–physical interface optimization and smart manufacturing outcomes. These findings contribute to scholarly discourse by emphasizing the critical and positive role of workforce adaptability in translating human-centric interventions into measurable performance improvements within Industry 4.0 environments.

Practically, the study provides actionable insights for enhancing manufacturing sector performance in Saudi Arabia. It underscores the necessity of prioritizing workforce adaptability when designing employee training and upskilling programmes. Human resource departments and organizational stakeholders are encouraged to implement strategies that strengthen both technical competencies and safety practices, enabling employees to work efficiently with multiple operational alternatives while contributing effectively to smart manufacturing processes. Additionally, the optimization of human–cyber–physical interfaces emerge as a key consideration for management when integrating modern technologies, ensuring that workforce productivity and

overall manufacturing performance are maximized. Consequently, the study's findings offer guidance for stakeholders, practitioners, and managers to develop workforce capabilities, thereby enhancing both operational efficiency and performance outcomes in Saudi Arabia's manufacturing sector.

7. Future Directions

Despite the significant contributions of this study to the existing body of knowledge, several methodological limitations should be acknowledged. First, the study relied exclusively on primary data, collecting responses directly from participants to examine the proposed model. This approach limits the understanding of smart manufacturing processes from the perspective of secondary sources, such as industry reports and statistical records, which could provide a more comprehensive assessment of actual performance. Future research is encouraged to incorporate secondary data to offer a broader evaluation of smart manufacturing performance in the Saudi Arabian context. Second, the data were collected at a single point in time and from a single country, which restricts the generalizability of the findings to other contexts, including neighboring Gulf countries. Subsequent studies should consider multi-country sampling within the region to enhance the external validity of the results. Third, this research employed only quantitative methods, which limits the depth of insight regarding participants' perspectives and real-time experiences. Future investigations should adopt a mixed-methods approach, integrating interviews and qualitative observations alongside surveys. Such an approach would provide richer insights, validate empirical findings, and further extend theoretical understanding of the relationships under study.

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