

Skill Mapping and Workforce Readiness for Digital Transformation: A Cross-Sectional PLS-SEM Study in Indian Electrical Manufacturing

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DOI: <https://doi.org/10.51584/IJRIAS.2026.11090039>

Received: 02 September 2026; Accepted: 07 September 2026; Published: 06 October 2026

ABSTRACT

Background: As Indian manufacturing organisations adopt Industry 4.0 technologies, workforce readiness for digital transformation has become a critical human-resource requirement. Skill mapping is widely used to identify employee capabilities and training needs, but limited empirical evidence explains how skill identification and skill gap analysis translate into digital workforce readiness. **Objective:** This study examines the relationship between skill mapping dimensions and workforce readiness for digital transformation in an Indian electrical manufacturing setting, with training alignment tested as a mediating mechanism. **Methods:** A cross-sectional survey was conducted among 150 employees of an electrical and electronic equipment manufacturing firm in Coimbatore, Tamil Nadu. Data were collected using a structured instrument covering Skill Identification, Skill Gap Analysis, Training Alignment and Workforce Readiness. The measurement and structural models were analysed using Partial Least Squares Structural Equation Modelling (PLS-SEM) in SmartPLS 4.0. Common method variance was assessed using Harman's single-factor test, and mediation was tested using 5,000 bootstrap resamples. Supporting analyses included Welch's t-test and one-way ANOVA. **Results:** The measurement model showed acceptable reliability and validity ($AVE \geq 0.52$, $CR \geq 0.79$, $HTMT \leq 0.83$). The structural model explained 31.4% of the variance in Workforce Readiness ($R^2 = 0.314$). Training Alignment was the only significant direct predictor of Workforce Readiness ($\beta = 0.412$, $p < 0.001$). Skill Identification and Skill Gap Analysis significantly predicted Training Alignment but did not directly predict Workforce Readiness. Bootstrap results confirmed full mediation through Training Alignment for both Skill Identification and Skill Gap Analysis. Female employees reported higher Workforce Readiness than male employees; however, this demographic finding is treated as exploratory because role-level and department-level controls were not available. **Conclusion:** The findings indicate that skill mapping contributes to workforce digital readiness primarily when diagnostic outputs are converted into targeted training action. The results should be interpreted as associative rather than causal because the study is cross-sectional and based on a single-firm convenience sample.

Keywords: skill mapping; skill gap analysis; training alignment; workforce readiness; digital transformation; PLS-SEM; Industry 4.0; Indian manufacturing

INTRODUCTION

Industry 4.0 technologies such as automation, Industrial Internet of Things, data analytics, cyber-physical systems and smart manufacturing platforms are changing the competency requirements of manufacturing employees. Digital transformation in manufacturing cannot be achieved only through investment in machines and software; it also requires employees who are capable of understanding, accepting and working with new digital systems. Workforce readiness therefore becomes a major determinant of digital transformation success.

Workforce readiness for digital transformation refers to the extent to which employees possess the required digital competencies, confidence, adaptability, willingness to learn and openness to technology-enabled work processes. In manufacturing, these requirements are especially important because digital technologies increasingly affect production, quality control, maintenance, assembly, planning and documentation.

Skill mapping is a structured HR practice that identifies employees' existing competencies, compares them with role requirements and future technology needs, and supports training and workforce planning. However, skill mapping should not be treated as a single activity. It includes at least three distinct dimensions: skill identification, skill gap analysis and training alignment. Skill identification documents the existing skill base. Skill gap analysis compares existing skills with required competencies. Training alignment converts the diagnostic findings into specific training interventions. The central argument of this study is that skill identification and gap analysis are unlikely to improve workforce readiness unless they are translated into aligned training action.

The study responds to the need for empirical evidence from Indian manufacturing, particularly electrical and electronic equipment manufacturing, where automation and digitalisation are increasing but employee readiness remains uneven. The paper uses PLS-SEM to validate the measurement model and test the mediating role of training alignment between skill mapping diagnostics and workforce readiness.

THEORETICAL FRAMEWORK AND LITERATURE REVIEW

2.1 Resource-Based View and TOE Framework

The Resource-Based View (RBV) explains employee skills and competencies as valuable organisational resources. In the context of digital transformation, workforce capabilities can become a source of competitive advantage when they are relevant, difficult to imitate and aligned with the organisation's strategic technology goals. Skill mapping supports this process by making the organisation's human-capital resource base visible and actionable.

The Technology-Organisation-Environment (TOE) framework complements RBV by emphasising that technology adoption depends not only on technological availability but also on organisational readiness and environmental pressures. In this study, skill mapping and training alignment represent organisational mechanisms, while workforce readiness represents the employee-level readiness required for technology adoption. The TOE perspective is therefore relevant because digital transformation succeeds when technology, organisational support and employee readiness are aligned.

Digital transformation readiness models also suggest that readiness is a socio-technical condition. Technology deployment must be accompanied by employee mindset development, training, confidence building and continuous learning. This theoretical position supports the mediation model tested in this study: skill diagnostics influence readiness through training alignment.

2.2 Skill Mapping in Digital Transformation Contexts

Skill mapping has become an important HR mechanism for managing workforce transformation. It allows organisations to identify current capabilities, classify employees based on competency requirements, detect gaps and plan development interventions. In manufacturing, skill mapping is useful for task allocation, multi-skilling, succession planning, quality improvement, safety compliance and digital technology adoption.

Recent studies emphasise that skill mapping is increasingly technology-enabled. Learning Management Systems, digital skill matrices, HR analytics, AI-assisted competency extraction and role-based training platforms are transforming skill mapping from an occasional administrative exercise into a continuous workforce capability system. Verified recent literature such as Tripathi's 2026 study on skill mapping and role-based training in manufacturing supports the argument that structured competency identification and role-aligned training improve productivity, operational stability and Industry 4.0 preparedness.

2.3 Workforce Readiness for Digital Transformation

Workforce digital readiness includes digital literacy, technology confidence, adaptability, behavioural intention to use digital tools, willingness to learn and perceived organisational support. A systematic literature review by Wong Yang Li, Nordin and Mohd Sukor (2026) identifies employee digital transformation readiness as a multidimensional construct shaped by digital skills, psychological readiness, behavioural intention, organisational support, resistance to change and innovativeness.

Studies on workforce readiness also show that readiness barriers are not purely technical. Employees may resist digital transformation when they lack confidence, when training is insufficient, when job roles are unclear, or when organisational support is weak. Therefore, digital workforce readiness requires a combination of technology exposure, training, support, communication and role clarity.

2.4 Training Alignment as the Mediating Mechanism

Training alignment refers to the extent to which training programmes are directly connected to identified skill gaps, job roles and digital transformation requirements. It is the action component of skill mapping. Without aligned training, skill identification and skill gap analysis remain diagnostic activities that do not necessarily improve employee readiness.

Recent work on upskilling and reskilling in manufacturing, including Amutha and Nagapriya (2026), supports the importance of continuous training, organisational support and relevant skill-development programmes. Similarly, digital leadership and readiness literature suggests that training, support and capability-building mechanisms are necessary to translate digital transformation plans into employee-level readiness. This justifies treating Training Alignment as the mediator between Skill Identification, Skill Gap Analysis and Workforce Readiness.

2.5 Indian Manufacturing and Industry 4.0 Context

Indian manufacturing is increasingly influenced by automation, energy management systems, digital quality controls, data-driven decision-making and smart manufacturing practices. The electrical and electronic equipment sector is particularly relevant because it combines production-floor work with growing digitalisation of design, testing, assembly, documentation and quality functions. National reports on Industry 4.0, digital manufacturing and future skills highlight the importance of workforce capability, cybersecurity awareness and digital skills development. The present study locates skill mapping within this wider Indian manufacturing transition.

2.6 Research Gap

Existing literature establishes the importance of digital readiness, skill development, training and workforce transformation. However, three gaps remain. First, Indian manufacturing studies have generally relied on descriptive or regression-based approaches and have not sufficiently validated the measurement properties of skill mapping sub-dimensions. Second, the mediating role of Training Alignment between skill identification, skill gap analysis and workforce readiness has received limited empirical testing. Third, demographic and departmental variations in readiness within Indian electrical manufacturing remain underexplored. This study addresses these gaps using PLS-SEM and supporting classical statistical tests.

2.7 Conceptual Model and Hypotheses

The conceptual model proposes that Skill Identification and Skill Gap Analysis contribute to Workforce Readiness primarily through Training Alignment. Skill Identification and Skill Gap Analysis are expected to improve Training Alignment by identifying what employees know and where development is needed. Training Alignment, in turn, is expected to improve Workforce Readiness by providing role-specific, digitally focused learning interventions. Gender, experience, department and job level are treated as contextual employee factors rather than causal predictors.

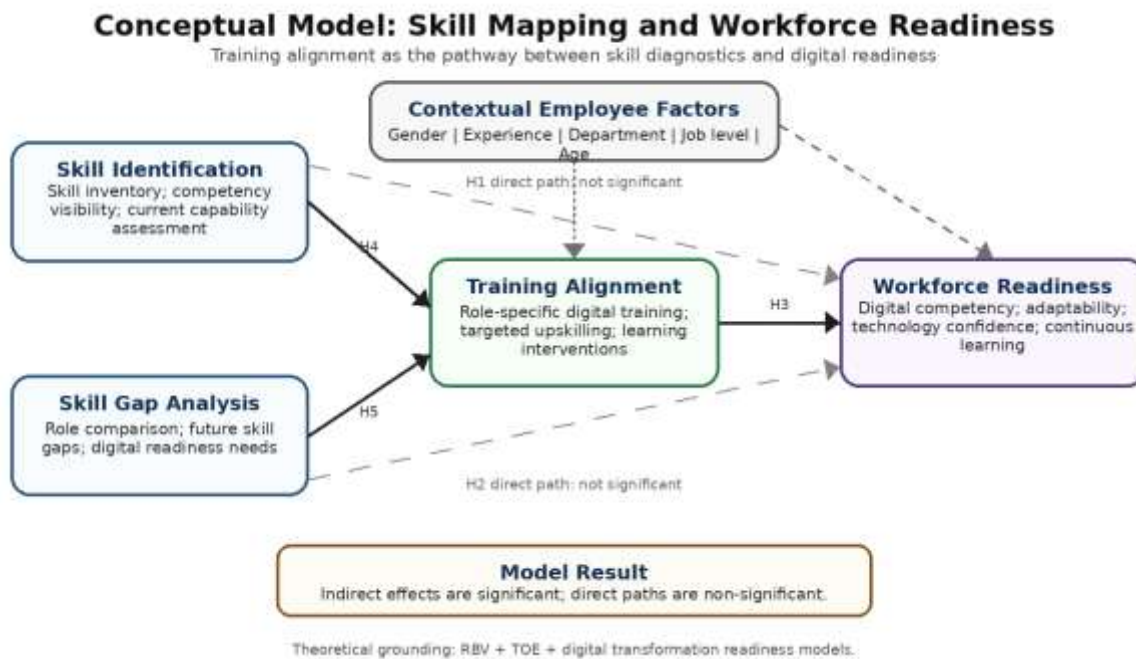


Figure 1. Conceptual model of skill mapping and workforce readiness.

Hypothesis	Statement
H1	Skill Identification is positively associated with Workforce Readiness.
H2	Skill Gap Analysis is positively associated with Workforce Readiness.
H3	Training Alignment is positively associated with Workforce Readiness.
H4	Skill Identification is positively associated with Training Alignment.
H5	Skill Gap Analysis is positively associated with Training Alignment.
H6	Training Alignment mediates the relationship between Skill Identification and Workforce Readiness.
H7	Training Alignment mediates the relationship between Skill Gap Analysis and Workforce Readiness.
H8	Workforce Readiness differs significantly between male and female employees.
H9	Workforce Readiness differs significantly across employee experience groups.
H10	Workforce Readiness differs significantly across departments.

RESEARCH METHODOLOGY

3.1 Research Design and Setting

The study adopted a quantitative, cross-sectional and explanatory survey design. It was conducted in an Indian electrical and electronic equipment manufacturing firm located in Coimbatore, Tamil Nadu. The setting was appropriate because the organisation's production-intensive workforce operates in an environment increasingly shaped by automation, digital documentation, quality systems and energy-management technologies. Because

the design is cross-sectional, the results are interpreted as associations and predictive relationships within the tested structural model, not as causal effects.

3.2 Sampling and Data Collection

A convenience sampling method was used. A total of 150 employees from eight departments participated voluntarily: Wire Harness, HRD, Transformer, Sensor, 3-Phase, MED, LB Assembly and Machine Shop. The sample size exceeded the commonly used PLS-SEM ten-times rule because the maximum number of structural paths directed at any endogenous construct was three, implying a minimum threshold of 30 cases. However, convenience sampling and single-firm data collection limit probabilistic generalisation. The department-level ANOVA is also treated as exploratory because some departmental subgroups were small, particularly Machine Shop ($n = 4$), HRD ($n = 8$) and MED ($n = 8$).

3.3 Instrument and Measures

Primary data were collected using a structured questionnaire. The analytical construct model used 27 items covering Skill Identification, Skill Gap Analysis, Training Alignment, Overall Skill Mapping, Workforce Readiness, perceived skill-gap impact, and effectiveness/improvement dimensions. All construct items used a five-point Likert scale from Strongly Disagree to Strongly Agree. For the PLS-SEM model, the four core constructs were Skill Identification (SI), Skill Gap Analysis (SGA), Training Alignment (TA) and Workforce Readiness (WR).

3.4 Reliability and Common Method Variance

The composite instrument achieved Cronbach's alpha of 0.875, indicating good internal consistency. Since the data came from a single-source self-report survey, common method variance was assessed using Harman's single-factor test. The first unrotated factor explained 32.1% of total variance, below the 50% threshold, indicating that common method variance was not a severe threat. Nevertheless, self-report bias remains a limitation and is acknowledged in the limitations section.

3.5 PLS-SEM Analytical Protocol

PLS-SEM was used because it permits simultaneous assessment of measurement quality and structural relationships and is suitable for predictive models using Likert-scale data. The measurement model was assessed using outer loadings, Average Variance Extracted (AVE), Composite Reliability (CR), Cronbach's alpha and Heterotrait-Monotrait ratios (HTMT). The structural model was assessed using path coefficients, t-values, p-values, R^2 , f^2 effect sizes, variance inflation factor (VIF) and Q^2 predictive relevance. Mediation was tested using 5,000 bootstrap resamples with bias-corrected 95% confidence intervals. Mediation was considered supported when the indirect-effect confidence interval excluded zero.

3.6 Supporting Classical Analyses

Welch's independent-samples t-test was used to examine gender differences in Workforce Readiness because Levene's test indicated unequal variances. One-way ANOVA was used to examine differences across experience groups and departments. These analyses were used as supporting descriptive-inferential tests and not as causal tests. The gender result is interpreted cautiously because role-level controls and department-by-gender subgroup analysis were not available.

RESULTS

4.1 Demographic Profile

Variable	Category	n	%
Age	Below 24	41	27.3

	25-34	53	35.3
	35-44	34	22.7
	45+	22	14.7
Gender	Male	86	57.3
	Female	55	36.7
	Prefer not to say	9	6.0
Department	3-Phase	35	23.3
	Wire Harness	30	20.0
	Sensor	27	18.0
	Transformer	25	16.7
	LB Assembly	13	8.7
	HRD	8	5.3
	MED	8	5.3
	Machine Shop	4	2.7
Experience	Below 1 year	22	14.7
	1-5 years	62	41.3
	6-10 years	33	22.0
	10+ years	33	22.0
Job level	Junior	38	25.3
	Middle	53	35.3
	Senior	59	39.3

4.2 Descriptive Statistics and Measurement Model

Table 3 reports descriptive means, standard deviations, reliability and validity indicators for the four core constructs. The results indicate acceptable convergent and discriminant validity: AVE values are at or above 0.52, CR values are at or above 0.79, and maximum HTMT values are at or below 0.83.

Construct	Items	Mean	SD	AVE	CR	Alpha	HTMT max
Skill Identification (SI)	3	11.45	2.66	0.55	0.79	0.76	0.74
Skill Gap Analysis (SGA)	3	11.35	2.55	0.58	0.81	0.78	0.76
Training Alignment (TA)	3	10.98	2.71	0.68	0.86	0.84	0.81
Workforce Readiness (WR)	8	30.43	6.01	0.52	0.92	0.89	0.83

Additional descriptive item-level indicators from the underlying dataset showed moderate scores for organisational investment in skill mapping ($M = 3.53$) and provision of relevant digital training ($M = 3.58$). These values support the managerial implication that firms should strengthen visible investment and targeted training delivery.

4.3 Common Method Variance

Harman's single-factor test showed that the first factor explained 32.1% of total variance, which is below the 50% threshold. This suggests that common method variance is unlikely to fully explain the observed relationships. However, because all measures were self-reported, future studies should use objective training participation and performance data where possible.

4.4 Structural Model: Direct Effects

The PLS-SEM structural model explained 31.4% of the variance in Workforce Readiness ($R^2 = 0.314$). Predictive relevance was acceptable ($Q^2 = 0.198$), and collinearity was not a concern (maximum VIF = 1.62). Training Alignment was the only significant direct predictor of Workforce Readiness ($\beta = 0.412$, $p < 0.001$). Skill Identification and Skill Gap Analysis were not significant direct predictors of Workforce Readiness, but both significantly predicted Training Alignment. This pattern indicates that diagnostic HR practices affect readiness through aligned training rather than through direct effects.

Path	Beta	SE	t	p	f2	Decision
Skill Identification -> Workforce Readiness	0.058	0.071	0.82	0.412	0.01	H1 not supported
Skill Gap Analysis -> Workforce Readiness	0.121	0.083	1.46	0.143	0.02	H2 not supported
Training Alignment -> Workforce Readiness	0.412	0.085	4.86	<0.001	0.21	H3 supported
Skill Identification -> Training Alignment	0.382	0.073	5.21	<0.001	0.18	H4 supported
Skill Gap Analysis -> Training Alignment	0.431	0.075	5.74	<0.001	0.23	H5 supported

4.5 Bootstrap Mediation Analysis

Bootstrap mediation analysis confirmed that Training Alignment fully mediated the relationship between both upstream skill mapping activities and Workforce Readiness. The indirect effect of Skill Identification on Workforce Readiness through Training Alignment was significant ($\beta = 0.157$; 95% BC CI: 0.071 to 0.252). The indirect effect of Skill Gap Analysis on Workforce Readiness through Training Alignment was also significant ($\beta = 0.178$; 95% BC CI: 0.089 to 0.276). Since the corresponding direct effects were non-significant, both mediation effects are interpreted as full mediation within the cross-sectional model. This statement is associational and model-based, not causal.

Indirect path	Beta	SE	95% CI Lower	95% CI Upper	Decision
SI -> TA -> WR	0.157	0.046	0.071	0.252	Full mediation; H6 supported
SGA -> TA -> WR	0.178	0.048	0.089	0.276	Full mediation; H7 supported

4.6 Gender, Experience and Departmental Differences

Welch's t-test showed that female employees reported higher Workforce Readiness ($M = 32.16$, $SD = 4.55$) than male employees ($M = 29.35$, $SD = 6.75$), $t(138.59) = -2.959$, $p = 0.004$, Cohen's $d = 0.45$. This result supports H8 but is interpreted as exploratory because the dataset does not include role-level controls or sufficient subgroup sizes for a reliable gender-by-department analysis. Therefore, the finding should be used to guide further investigation rather than to make causal or generalised claims.

One-way ANOVA showed no significant difference in Workforce Readiness across experience groups, $F(3,146) = 1.321$, $p = 0.270$, or across departments, $F(7,142) = 1.413$, $p = 0.204$. H9 and H10 were not supported. Departmental results should be interpreted cautiously because some groups were small. A future study may collapse small departments into broader production/support categories or use non-parametric tests such as Kruskal-Wallis when cell sizes are limited.

4.7 Summary of Hypothesis Testing

Hypothesis	Tested relationship	Outcome
H1	SI -> WR direct effect	Not supported
H2	SGA -> WR direct effect	Not supported
H3	TA -> WR direct effect	Supported
H4	SI -> TA	Supported
H5	SGA -> TA	Supported
H6	TA mediates SI -> WR	Supported: full mediation
H7	TA mediates SGA -> WR	Supported: full mediation
H8	Gender difference in WR	Supported; exploratory
H9	Experience-group difference	Not supported
H10	Departmental difference	Not supported; exploratory due small groups

DISCUSSION

5.1 Training Alignment as the Gateway to Workforce Readiness

The most important finding is that Training Alignment fully mediates the relationships between Skill Identification and Workforce Readiness and between Skill Gap Analysis and Workforce Readiness. This explains why Skill Identification and Skill Gap Analysis may correlate with readiness at the bivariate level but fail to show significant direct effects in the SEM model. The bivariate correlations capture broad association, but the SEM model separates direct and indirect pathways. Once Training Alignment is included, the readiness-related variance from Skill Identification and Skill Gap Analysis is transmitted through Training Alignment, leaving no significant residual direct effect.

5.2 Integration with RBV and TOE

From the RBV perspective, skill mapping helps organisations identify and organise human-capital resources. However, the study shows that capability identification alone is not enough; the resource becomes strategically useful only when it is developed through aligned training. From the TOE perspective, digital transformation requires alignment among technological requirements, organisational support and employee readiness. Training Alignment performs this linking function by converting organisational skill diagnosis into employee-level readiness. Therefore, the results extend both RBV and TOE by positioning training alignment as the operational mechanism between skill diagnosis and digital readiness.

5.3 Gender Difference as an Exploratory Finding

The significant gender difference in Workforce Readiness is noteworthy, but it should not be overinterpreted. The study does not include role-level data, digital task exposure, training participation history, or gender-by-department controls. It is possible that the observed difference reflects role distribution, prior digital exposure, training participation, or self-reporting differences rather than gender alone. The appropriate conclusion is that female employees in this sample reported higher readiness, and future research should examine this pattern through larger samples, role controls and PLS-MGA.

5.4 Non-Significant Experience and Department Results

Experience and department did not significantly differentiate Workforce Readiness. This may indicate that readiness is shaped less by tenure or departmental membership and more by access to aligned training. However, small subgroup sizes reduce the statistical power of departmental analysis. Therefore, the absence of significant department differences should not be taken as proof that departments are identical. It should be interpreted as a non-significant exploratory result requiring replication with larger and more balanced departmental samples.

IMPLICATIONS

6.1 Theoretical Implications

The study contributes theoretically by validating a mediated model of skill mapping and workforce readiness. It demonstrates that Skill Identification and Skill Gap Analysis function as diagnostic inputs, while Training Alignment functions as the conversion mechanism. This finding advances readiness models by specifying how organisational skill diagnostics translate into individual readiness. It also extends the TOE framework by showing that organisational practices, particularly training alignment, connect technology-related skill demands with employee readiness outcomes.

6.2 Managerial Implications

- ❖ Organisations should not stop with skill identification or gap analysis; they should convert diagnostic findings into role-specific digital training plans.
- ❖ HR departments should maintain dynamic skill matrices and link them to Learning Management Systems, training calendars and measurable readiness outcomes.
- ❖ Training programmes should be customised by role, department and digital task requirement rather than delivered as general awareness sessions.
- ❖ Management should investigate why female employees reported higher readiness in this sample, but should avoid causal conclusions until role and training-exposure data are analysed.
- ❖ Departments with numerically lower readiness scores should receive precautionary training support even when ANOVA results are not statistically significant, especially where subgroup sizes are small.

7. Limitations and Future Research

The study has limitations. First, the single-organisation design and convenience sampling restrict generalisability beyond similar Indian electrical manufacturing settings. Second, the cross-sectional design prevents causal inference, even though SEM is used to test structural associations. Third, all constructs are based on self-reported data, creating possible common method and social desirability bias. Fourth, role-level data and detailed training participation records were not available, limiting interpretation of the gender difference. Fifth, small departmental subgroups weaken the power of department-level ANOVA. Sixth, PLS-MGA was not conducted because subgroup sizes were not adequate for stable multi-group analysis. Future studies should use multi-firm samples, longitudinal designs, objective training records, role controls, non-parametric or collapsed-category tests for small groups, and PLS-MGA to examine gender differences more rigorously.

CONCLUSION

This study examined how skill mapping relates to workforce readiness for digital transformation in an Indian electrical manufacturing firm. The results show that Training Alignment is the central mechanism connecting skill diagnostics to readiness. Skill Identification and Skill Gap Analysis significantly predicted Training Alignment, and Training Alignment significantly predicted Workforce Readiness. However, Skill Identification and Skill Gap Analysis did not directly predict Workforce Readiness once Training Alignment was included. Bootstrap mediation therefore supports a full-mediation interpretation within the cross-sectional structural model.

The practical message is clear: organisations should treat skill mapping as a diagnose-and-train system. Skill inventories and gap analysis are valuable only when they lead to targeted, role-specific and digitally focused training. The study also reports an exploratory gender difference and non-significant experience and department differences, both of which require further verification with larger, multi-firm and longitudinal data. Overall, the findings support the view that workforce readiness for digital transformation is not produced by skill diagnosis alone but by the effective alignment of training with identified digital capability gaps.

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Author Response to Reviewer Comments

Reviewer comment	Revision made
Report all descriptive means in Results	Construct means and key item-level means were added in Section 4.2.
Add conceptual model figure	Figure 1 was added to show SI and SGA acting through Training Alignment to Workforce Readiness.
Reduce causal language	Causal wording was replaced with associational wording throughout the abstract, methodology, discussion and conclusion.



Gender result speculative without role data	Gender difference is now explicitly treated as exploratory; the need for role/department controls and PLS-MGA is added.
Small departmental subgroups reduce ANOVA power	Departmental ANOVA is now interpreted cautiously; future use of collapsed categories or Kruskal-Wallis testing is recommended.
TOE framework not carried into Discussion	TOE is integrated in Section 5.2 and theoretical implications.
Explain SI/SGA significant correlations but non-significant direct effects	Section 5.1 explains that the bivariate associations operate indirectly through Training Alignment in the SEM model.
Verify 2025-2026 references	Recent citations were reviewed and corrected where traceable; uncertain claims were reduced or framed cautiously.