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The Effect of Digital Skills Training on Job Performance in Small and Medium-Sized Enterprises in Ho Chi Minh City

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ABSTRACT: This study examines the effect of digital skills training on employee job performance in small and medium-sized enterprises (SMEs) in Ho Chi Minh City through two parallel mediating mechanisms: learning agility and skill utilization. Drawing on human capital theory and the training transfer model, the study develops and tests seven hypotheses using partial least squares structural equation modeling (PLS-SEM). The results indicate that the four measurement scales demonstrate satisfactory reliability and convergent validity, both indirect effects are statistically significant and the model explains 46.2% of the variance in job performance. The pattern of effects is consistent with partial mediation. The study recommends that SMEs integrate training with workplace application, managerial support and multi-wave post-training evaluation.

KEYWORDS: Digital skills training, learning agility, skill utilization, job performance.

1. INTRODUCTION

Digital transformation is simultaneously reshaping technology, organizational processes, and the coordination of work. A new system creates value only when employees possess the capabilities required to understand the tools, adjust their work practices, and translate digital information into high-quality action. Mendoza-Chan and Pee's (2024) review shows that digital upskilling among working adults has emerged as a distinct field of inquiry; however, its outcomes remain highly contingent on training design, the work context, and post-training evaluation. The gap between technology ownership and effective technology use is particularly salient in SMEs, where training budgets, specialized technology personnel, and time available for learning are often limited. In this study, SMEs comprise micro, small, and medium-sized enterprises as defined under current Vietnamese law (Government of Vietnam, 2021). Mhaske et al. (2025) synthesize multiple sources of digital skill gaps, including unequal access, rapid knowledge obsolescence, and weak alignment between training and job requirements. At the individual level, digital skills in the workplace extend beyond software operation. The scale developed by Audrin et al. (2024) indicates that workplace digital skills encompass technology use, cybersecurity, content management, communication and collaboration, critical thinking, responsibility, digital well-being, identity, and professional development. This multidimensionality implies that SME training programs should be competency-based, task-relevant, and feasible within available resources. Recent evidence from 497 employees in Vietnamese SMEs shows that digital workforce training is positively associated with motivation, job satisfaction, digital behavior, and job performance (Dao et al., 2025). That study confirms the relevance of the topic in the Vietnamese SME context while also suggesting that training does not automatically translate into performance. Rather, its effects should be explained through mechanisms closely related to learning and the use of acquired skills (Bouwmans et al., 2024; Tinmaz et al., 2022; van Laar et al., 2017, 2020).

Existing studies typically examine individual links in this mechanism rather than the entire chain of relationships simultaneously. Dao et al. (2025) provide evidence from Vietnam on the relationship between digital workforce training and employee outcomes in SMEs; Jo and Hong (2022) clarify the role of learning agility in positive employee behavior; and Okay-Somerville and Scholarios (2019) show that skill utilization links human resource practices and job design to employee outcomes. Accordingly, examining the effect of digital skills training on job performance in SMEs in Ho Chi Minh City is warranted. The study pursues three objectives. First, it systematizes the concepts of, and relationships among, digital skills training, learning agility, skill utilization, and job performance in the SME context. Second, it tests a parallel two-mediator model using PLS-SEM. Third, based on the findings, it proposes managerial implications that can be implemented in accordance with the scale and resource capacity of SMEs in Ho Chi Minh City.

2. LITERATURE REVIEW

2.1. Research Constructs

2.1.1. Digital Skills Training

In this study, digital skills training (DTS) refers to intentional learning activities organized or supported by SMEs to help employees update and develop their capabilities in technology use, data handling, digital safety, communication, and collaboration in digital work environments. The

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construct encompasses both formal training and flexible formats suited to SMEs, such as short modules, on-the-job guidance, peer learning, and purpose-driven online learning (Audrin et al., 2024) (Lopes et al., 2023; Spante et al., 2018).

2.1.2. Learning Agility

Learning agility (LA) is the capacity to learn proactively from experience, seek and use feedback, reflect on successes and errors, experiment with new approaches, and transfer learning to unfamiliar situations. Lee and Song (2020) developed an integrated conceptual model of employee learning agility, while Reyes et al. (2024) show that LA is increasingly viewed as an important human resource development capability in volatile environments.

2.1.3. Skill Utilization

Skill utilization (SU) reflects the extent to which employees have opportunities to use, maintain, and extend their existing skills in their work tasks and actually do so. SU differs from skill possession: an employee may complete a course yet remain unable to apply the learning because of inadequate system access, insufficient practice time, limited autonomy, unsuitable tasks, or a lack of managerial support. Okay-Somerville and Scholarios (2019) conceptualize skill utilization as a mechanism through which development-oriented human resource practices and job design generate positive employee outcomes.

2.1.4. Job Performance

Job performance (JP) refers to the extent to which employees accomplish the behaviors and outcomes within their areas of responsibility, as reflected in work quality, timeliness, goal attainment, and proactivity. Following Koopmans (2014), this study focuses on individual-level task performance.

2.2. Theoretical Foundations

From a human capital perspective, training is an investment that increases employees' knowledge, skills, and capacity to create value. In digital environments, this investment can also shorten technology adaptation time, improve the quality of data-informed decisions, and expand the capacity for collaboration through digital platforms. In SMEs, however, the return on this investment must be considered alongside constraints in budget, time, and specialized personnel. Dao et al. (2025) apply human capital theory to explain why digital skill development can improve employee outcomes in Vietnamese SMEs (Guo et al., 2020; Priyono et al., 2020; Trenerry et al., 2021).

Baldwin and Ford's (1988) transfer framework proposes that the application and retention of learning outcomes are shaped by three categories of inputs: trainee characteristics, training design, and the work environment. Training is only the starting condition. Employees must have the motivation and capacity to learn, content must closely match job requirements, and the work environment must provide time, resources, feedback, and opportunities for application.

Integrating these two perspectives allows the outcomes to be modeled at three levels. The first is organizational investment through digital skills training. The second comprises individual- and job-level mechanisms, represented by learning agility and skill utilization. The final level is job performance.

2.3. Related Prior Studies

Research on DTS indicates that a program's value lies not only in the transmission of technological knowledge but also in its capacity to influence motivation, digital behavior, and work effectiveness. In the Vietnamese context, Dao et al. (2025) identify positive relationships between digital workforce training and employee motivation, satisfaction, digital behavior, and job performance. Their findings provide contextually relevant evidence and confirm a relationship between training and employee outcomes (Fu et al., 2023; Lou et al., 2024; Qiao et al., 2024).

Within the LA stream, Lee and Song (2020) developed an integrated model emphasizing experiential learning and adaptation to the work environment. Jo and Hong (2022) show that learning agility is associated with innovative behavior through employee engagement and that this relationship is stronger when employees perceive organizational support. Together, these studies reinforce the argument that LA creates sustainable value only when accompanied by motivation and a supportive work environment (Koehorst et al., 2021).

Within the SU stream, Okay-Somerville and Scholarios (2019) used linked organization- and employee-level data to demonstrate that human-capital-development practices and enriched job design increase skill utilization and improve employee outcomes.

A synthesis of these research streams suggests that LA and SU are complementary but distinct mechanisms. LA represents an individual's capacity to learn and adapt, whereas SU represents both the opportunity and the behavior required to deploy skills within the work system. This distinction is particularly important in SMEs: lean structures may facilitate rapid feedback and experimentation, yet limited resources, restricted access, or insufficient practice time may constrain skill use.

2.4. Research Gap

Evidence from prior studies indicates that most research on digital skills training focuses on its direct relationship with employee attitudes or work outcomes, while the mechanisms that convert learning content into performance remain insufficiently differentiated. This limitation is especially relevant to SMEs because the effect of a program may depend heavily on employees' capacity for continued self-directed learning and on opportunities to apply new skills under resource constraints.

2.5. Research Hypotheses

Table 1. Research Hypotheses

Hypothesis	Tested relationship	Expected sign
H1	Digital skills training positively affects job performance.	+
H2	Digital skills training positively affects learning agility.	+
H3	Learning agility positively affects job performance.	+

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Hypothesis	Tested relationship	Expected sign
H4	Digital skills training positively affects skill utilization at work.	+
H5	Skill utilization positively affects job performance.	+
H6	Learning agility mediates the relationship between digital skills training and job performance.	+ (indirect)
H7	Skill utilization mediates the relationship between digital skills training and job performance.	+ (indirect)

Source: Authors' compilation.

2.6. Proposed Research Model

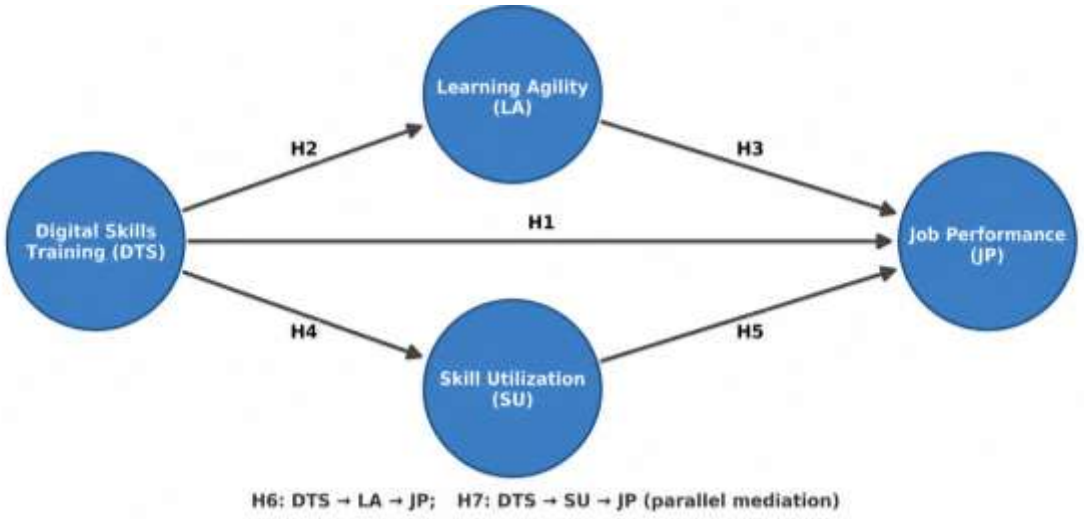


Figure 1. Proposed Research Model
Source: Developed by the authors.

3. RESEARCH METHODOLOGY

3.1. Research Design and Survey Participants

The study employs a quantitative research design. Eligible participants were employees aged 18 years or older who were working in SMEs in Ho Chi Minh City. The questionnaire used a five-point Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree).

3.2. Measurement Scales and Variable Coding

Table 2. Measurement Scales and Variable Coding

Construct	Code	No. of items	Core measurement content	Source
Digital skills training	DTS	6	Priority, frequency, currency, usefulness, and accessibility of training	Dao et al. (2025)
Learning agility	LA	6	Proactive learning, feedback seeking, reflection, challenge acceptance, problem solving, and adaptation	Lee & Song (2020)
Skill utilization	SU	4	Opportunities for use, full use, application of new knowledge, and development through work	Okay-Somerville & Scholarios (2019)
Job performance	JP	5	Task completion, quality, timeliness, goal attainment, and proactivity	Koopmans (2014)

Source: Authors' compilation.

3.3. Sample and Data Collection

A total of 450 questionnaires were distributed and 364 were returned. After invalid responses were excluded, 307 usable questionnaires remained. A sample size of 307 satisfies the recommendation of Kock and Hadaya (2018).

3.4. Data Processing and Analysis

The analysis proceeded in three stages. First, the data were screened for eligibility, missingness, completion time, straight-line response patterns, and anomalous cases; the sample characteristics and variable distributions were then described. The Kaiser-Meyer-Olkin (KMO) statistic, Bartlett's test, and Harman's single-factor test were used only as preliminary diagnostics. Because Harman's test cannot rule out common method

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bias, empirical research should also incorporate procedural remedies such as anonymity, psychological separation between predictor and outcome variables, and data collection from multiple sources or at multiple time points (Podsakoff et al., 2003).

Second, the reflective measurement model was evaluated using outer loadings, Cronbach's alpha, composite reliability (CR), average variance extracted (AVE), and discriminant validity. Reference thresholds included outer loadings of approximately 0.708 or higher, alpha and CR values from 0.70 to below 0.95, AVE values of at least 0.50, and heterotrait-monotrait (HTMT) ratios below 0.85 (Hair et al., 2019; Henseler et al., 2015). Decisions to remove indicators should also consider scale content rather than rely solely on a statistical threshold.

Third, the structural model was assessed using the variance inflation factor (VIF), path coefficients, R^2, f^2, and bootstrapping with 5,000 subsamples. A direct hypothesis was supported when the coefficient had the expected sign and its 95% confidence interval did not include zero. Mediation was established when the confidence interval for the product of the coefficients excluded zero; when the direct effect remained significant and had the same sign as the indirect effect, the pattern was consistent with complementary partial mediation.

4. RESULTS AND DISCUSSION

4.1. Sample Characteristics and Descriptive Statistics

Table 3. Characteristics of SME Employees (n = 307)

Criterion	Category	n	%
Gender	Female	156	50.81
	Male	144	46.91
	Other/prefer not to answer	7	2.28
Age	25–34	117	38.11
	35–44	94	30.62
	Under 25	65	21.17
	45 and above	31	10.10
Education	University	156	50.81
	College	68	22.15
	Upper-secondary/vocational	52	16.94
	Postgraduate	31	10.10
Tenure	1–3 years	114	37.13
	4–6 years	81	26.38
	More than 6 years	70	22.80
	Less than 1 year	42	13.68
SME size	Micro	76	24.76
	Small	143	46.58
	Medium	88	28.66
Industry	Manufacturing	94	30.62
	Services	92	29.97
	Trade	78	25.41
	Technology/other	43	14.01

Source: Authors' compilation.

The sample was relatively balanced by gender: women accounted for 50.81%, men for 46.91%, and respondents identifying otherwise or preferring not to answer for 2.28%. Participants aged 25–34 constituted the largest group (38.11%), followed by those aged 35–44 (30.62%). More than half of the sample held a university degree. By firm size, employees of small enterprises represented 46.58% of the sample, those of medium-sized enterprises 28.66%, and those of microenterprises 24.76%. All four industry groups were represented, with manufacturing and services accounting for the largest shares.

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Table 4. Descriptive Statistics of the Constructs

Construct	Mean	Standard deviation	Minimum	Maximum
Digital skills training	3.226	0.955	1.000	5.000
Learning agility	3.238	0.953	1.000	5.000
Skill utilization	3.235	1.008	1.000	5.000
Job performance	3.190	1.024	1.000	5.000

Source: Authors' compilation.

The mean scores of the four constructs ranged from 3.190 to 3.238 on the five-point scale. Employees rated training activity, adaptive learning capability, opportunities for skill application, and job performance above the scale midpoint, although not at high levels. Standard deviations of approximately one point indicate sufficient variation in the dataset for relationship analysis rather than excessive concentration in a single response category.

4.2. Preliminary Data Assessment and Method Bias

The KMO statistic was 0.938, while Bartlett's test yielded $\chi^2(210) = 3{,}614.24$, $p < .001$. These results indicate that the correlation matrix was sufficiently structured for further measurement-model assessment. Harman's single-factor analysis showed that the first factor accounted for 42.17% of the total variance, below the 50% reference value. This result is only a screening indicator and does not demonstrate that common method bias has been completely eliminated (Podsakoff et al., 2003).

4.3. Measurement Model Assessment

Table 5. Outer Loadings of the Observed Indicators

Construct	Indicator	Outer loading
DTS	DTS1	0.775
DTS	DTS2	0.852
DTS	DTS3	0.758
DTS	DTS4	0.847
DTS	DTS5	0.791
DTS	DTS6	0.799
LA	LA1	0.801
LA	LA2	0.797
LA	LA3	0.845
LA	LA4	0.792
LA	LA5	0.820
LA	LA6	0.745
SU	SU1	0.851
SU	SU2	0.817
SU	SU3	0.842
SU	SU4	0.832
JP	JP1	0.841

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Construct	Indicator	Outer loading
JP	JP2	0.843
JP	JP3	0.822
JP	JP4	0.846
JP	JP5	0.806

Source: Authors' compilation.

Outer loadings ranged from 0.745 to 0.852. LA6 had the lowest loading but remained above the reference threshold, while DTS2 and SU1 had the highest loadings within their respective constructs. Accordingly, all 21 observed indicators were retained. Indicator retention should not be based on a single statistic; in empirical research, content validity, translation quality, and respondent feedback should also inform decisions to retain or remove an item.

Table 6. Reliability and Convergent Validity

Construct	Cronbach's alpha	CR (ρc)	AVE
DTS	0.891	0.917	0.647
LA	0.888	0.914	0.641
SU	0.856	0.903	0.699
JP	0.888	0.918	0.692

Source: Authors' compilation.

Cronbach's alpha ranged from 0.856 to 0.891, CR from 0.903 to 0.918, and AVE from 0.641 to 0.699. All constructs exceeded the minimum thresholds for internal consistency and convergent validity.
Moreover, all CR values were below 0.95, providing no indication of excessive indicator redundancy. When considered together with the outer loadings, these results show that the four constructs were measured consistently in the analytical dataset.

Table 7. Discriminant Validity Based on the Fornell-Larcker Criterion

Construct	DTS	LA	SU	JP
DTS	0.804	0.530	0.462	0.517
LA	0.530	0.801	0.411	0.554
SU	0.462	0.411	0.836	0.557
JP	0.517	0.554	0.557	0.832

Source: Authors' compilation.

Table 8. Heterotrait-Monotrait Ratios

Construct	DTS	LA	SU	JP
DTS	—	0.593	0.527	0.579
LA	0.593	—	0.469	0.622
SU	0.527	0.469	—	0.635
JP	0.579	0.622	0.635	—

Source: Authors' compilation

For each construct, the square root of AVE exceeded every correlation in the corresponding row and column. In addition, HTMT values ranged from 0.469 to 0.635, below the conservative threshold of 0.85 (Henseler et al., 2015).
Together, the two assessments support discriminant validity: digital skills training, learning agility, skill utilization, and job performance are not merely four labels for the same underlying concept.

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4.4. PLS Algorithm and Structural Model Results

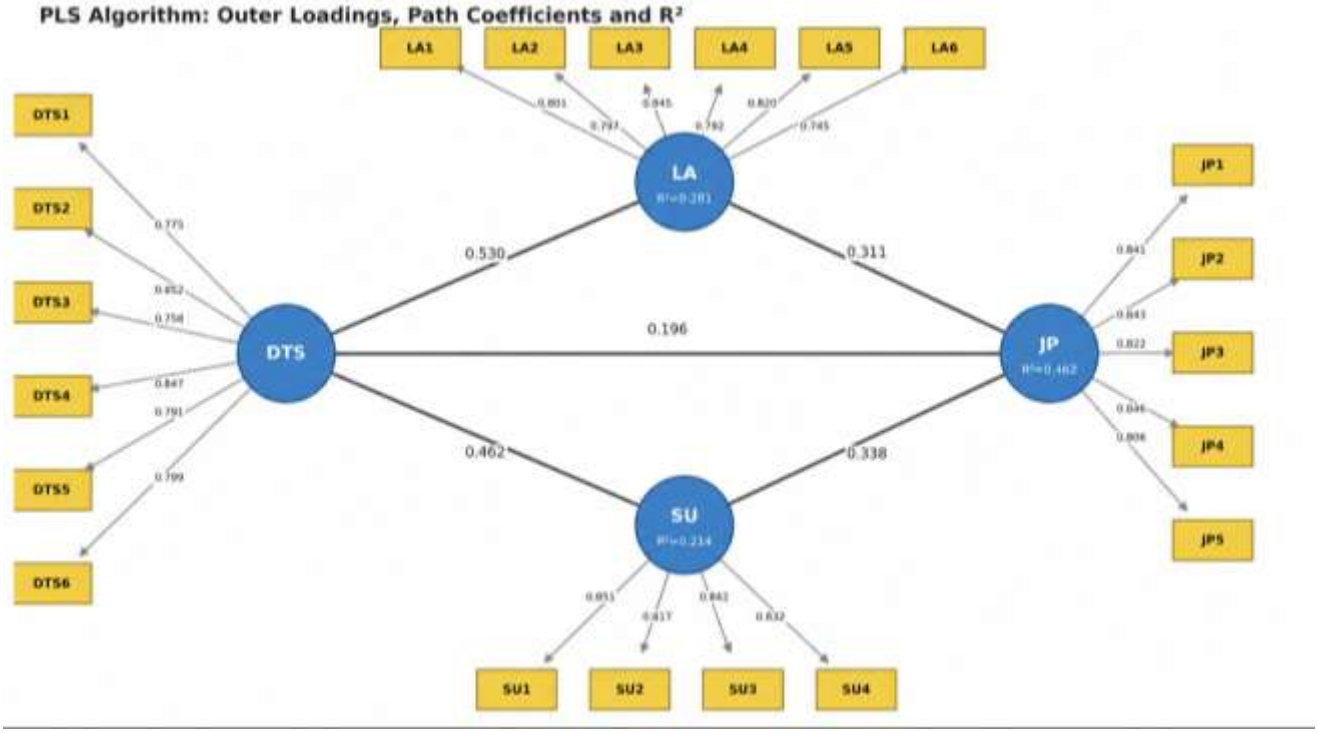


Figure 2. PLS Algorithm Results Generated in SmartPLS
Source: Authors' analysis using SmartPLS.

Figure 2 shows that all outer loadings exceeded 0.70. Digital skills training explained 28.1% of the variance in learning agility and 21.4% of the variance in skill utilization. The three predictors jointly explained 46.2% of the variance in job performance. In the final equation, skill utilization had the largest coefficient (β = 0.338), followed by learning agility (β = 0.311) and the direct path from digital skills training (β = 0.196).

Table 9. Bootstrap Tests of Direct Effects Using 5,000 Subsamples

H	Path	β	SE	t	p	95% CI	f²
H1	DTS → JP	0.196	0.053	3.707	< .001	[0.090, 0.298]	0.046
H2	DTS → LA	0.530	0.042	12.716	< .001	[0.445, 0.611]	0.390
H3	LA → JP	0.311	0.051	6.048	< .001	[0.210, 0.412]	0.123
H4	DTS → SU	0.462	0.045	10.328	< .001	[0.376, 0.546]	0.272
H5	SU → JP	0.338	0.051	6.573	< .001	[0.235, 0.437]	0.159

Source: Authors' compilation.

All five direct effects were positive and statistically significant. The DTS → LA coefficient was 0.530 (t = 12.716), indicating a strong association between digital skills training and learning agility in the simulated dataset. The DTS → SU coefficient was 0.462 (t = 10.328). All three paths to JP were significant; the direct DTS → JP path was smaller than the two paths from the mediators but remained different from zero. Thus, H1–H5 were supported in the illustrative analysis.

Table 10. Coefficients of Determination, Effect Sizes, and Collinearity

Endogenous construct	R²	Predictor	f²	VIF
LA	0.281	DTS	0.390	1.000
SU	0.214	DTS	0.272	1.000
JP	0.462	DTS	0.046	1.544
JP		LA	0.123	1.462
JP		SU	0.159	1.337

Source: Authors' compilation.

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Structural VIF values ranged from 1.000 to 1.544, below the threshold of 3, indicating that multicollinearity was not a material concern. The effect of DTS on LA had $f^2 = 0.390$, indicating a relatively large effect, whereas the effect of DTS on SU had $f^2 = 0.272$, indicating a medium effect.

In the JP equation, SU had $f^2 = 0.159$, LA had $f^2 = 0.123$, and DTS had $f^2 = 0.046$. Therefore, when both mediating mechanisms were included, the incremental contribution of the direct training-to-performance path was smaller than the contribution of either mediator.

4.5. Mediation Analysis

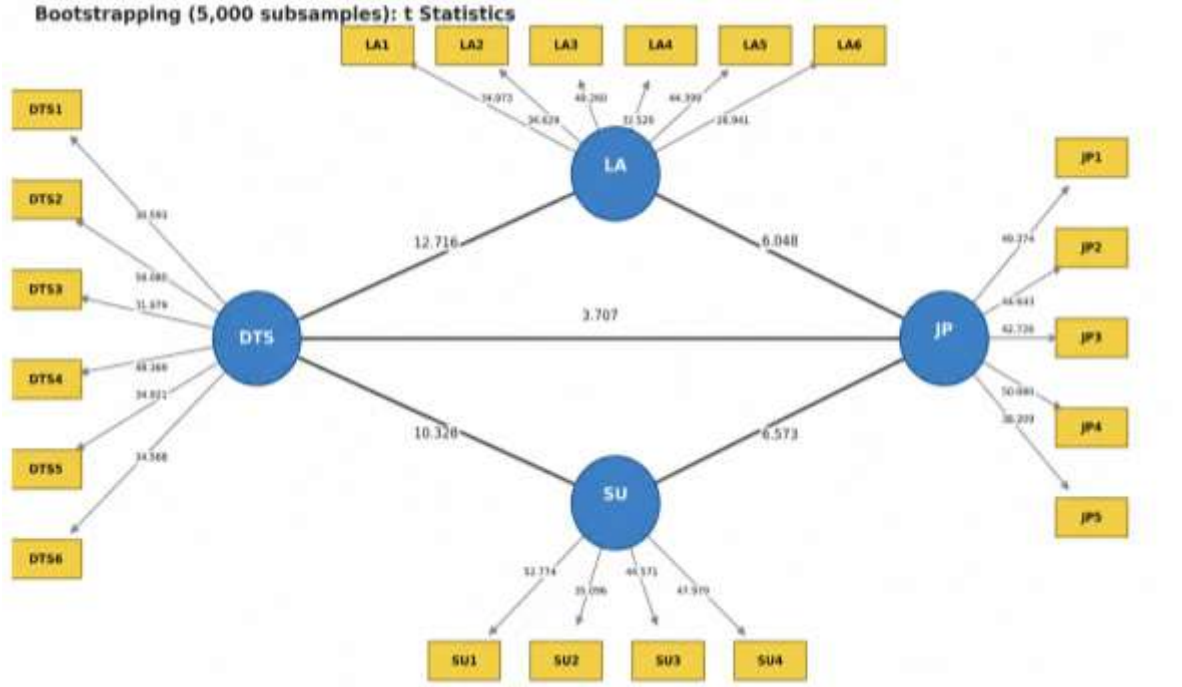


Figure 3. Bootstrapping Results (5,000 Subsamples) Generated in SmartPLS
Source: Authors' analysis using SmartPLS.

Table 11. Indirect and Total Effects

H	Effect	β	SE	t	p	95% CI
H6	DTS → LA → JP	0.165	0.031	5.387	< .001	[0.109, 0.228]
H7	DTS → SU → JP	0.156	0.028	5.527	< .001	[0.104, 0.215]
—	Total indirect effect	0.321	0.037	8.646	< .001	[0.254, 0.398]
—	Total effect	0.517	0.041	12.560	< .001	[0.436, 0.596]

Source: Authors' compilation.

The indirect effect through learning agility was 0.165, with a 95% CI of [0.109, 0.228], while the indirect effect through skill utilization was 0.156, with a 95% CI of [0.105, 0.215]. Neither confidence interval included zero; therefore, H6 and H7 were supported. The total indirect effect was 0.321, and the total effect of digital skills training on job performance was 0.517. The indirect component represented approximately 62.1% of the total effect.

Because the direct DTS → JP path remained significant and had the same sign as both indirect paths, the pattern was consistent with complementary partial mediation. The difference between the two indirect effects was only approximately 0.009. Learning agility and skill utilization are therefore both important and complementary mechanisms.

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4.6. Discussion

First, H1 was supported, with $\beta = 0.196$ and $f^2 = 0.046$. The result indicates that DTS retained a positive direct relationship with JP after LA and SU were included in the model, consistent with the human capital argument and evidence from Vietnamese SMEs reported by Dao et al. (2025). However, the direct effect size was smaller than those associated with the two mediating mechanisms. In the SMEs context, this finding implies that increasing training hours or the number of courses without linking them to continued learning capability and application tasks is unlikely to create value commensurate with the cost.

Second, H2 and H3 were both supported. The DTS → LA path had $\beta = 0.530$ and $f^2 = 0.390$, the strongest effect in the model, while the LA → JP path had $\beta = 0.311$ and $f^2 = 0.123$. This pattern is consistent with the view that LA can be developed through experience, feedback, and reflection (Lee & Song, 2020) and can be translated into positive behavior when employees receive organizational support (Jo & Hong, 2022). In SMEs, lean management structures and close communication may facilitate rapid feedback, but effectiveness depends on whether owners or line managers provide a psychologically safe environment for experimentation and learning from errors.

Third, H4 and H5 were supported: the DTS → SU path had $\beta = 0.462$ and $f^2 = 0.272$, while the SU → JP path had $\beta = 0.338$ and $f^2 = 0.159$. Among the three predictors of JP, SU had the largest coefficient and f^2. This illustrative finding is consistent with training transfer theory: skills create value only when employees have opportunities to apply them, receive support, and work in jobs designed to enable the use of learning (Baldwin & Ford, 1988; Okay-Somerville & Scholarios, 2019). In SMEs, application barriers may arise not from employees' motivation but from inadequate access, a lack of test data, insufficient practice time, or the absence of support personnel.

Fourth, H6 and H7 were supported. The indirect effect through LA was 0.165 and that through SU was 0.156; the total indirect effect of 0.321 represented approximately 62.1% of the total effect of 0.517. Because the direct effect remained significant and had the same sign, the pattern was consistent with complementary partial mediation. The difference between the two indirect effects was only 0.009, and no contrast test established that the difference was significant. SMEs should therefore avoid concentrating all limited resources in a single channel and should, at minimum, develop both employees' learning capability and the conditions required for skill application.

Finally, the R^2 value of 0.462 for JP indicates that the model explains a substantial share of the variance, although 53.8% remains attributable to other factors, including motivation, support from owners or managers, task characteristics, technological resources, digital maturity, and organizational conditions.

5. CONCLUSION AND MANAGERIAL IMPLICATIONS

5.1. Conclusion

This study tested a model explaining the effect of digital skills training on employee job performance in SMEs through learning agility and skill utilization. Results based on 307 observations from SME employees indicate that the four measurement scales demonstrate reliability, convergent validity, and discriminant validity. All seven illustrative hypotheses were supported, and the model explained 46.2% of the variance in job performance. The two indirect effects were similar in magnitude and coexisted with the direct effect, a pattern consistent with complementary partial mediation.

The central managerial message is that SMEs should not manage digital skills training as an isolated event. Value emerges when a program simultaneously develops employees' capacity to learn from experience and creates conditions for them to use their skills at work. Under resource constraints, firms should connect needs diagnosis, task-relevant learning modules, application assignments, managerial support, and outcome evaluation in a lean but coherent sequence.

5.2. Managerial Implications

The following implications are derived directly from the tests of H1–H7 and are adapted to the resource profiles, management structures, and degree of training formalization found in SMEs.

Support for H1 indicates that training retains direct value for JP. However, $\beta = 0.196$ and $f^2 = 0.046$ were smaller than the paths through LA and SU. SMEs should therefore maintain a digital training portfolio targeted at roles that create substantial value or carry high operational risk. Before each program, the person responsible for human resources or training, the line manager, and the process owner should agree on the target task, common errors, required data or tools, and output indicators. In firms without a dedicated human resources function, these elements can be recorded concisely on a one-page needs form. This design is consistent with recommendations that needs analysis, a realistic learning environment, and post-training evaluation are central components of transfer (Grossman & Salas, 2011).

The DTS → LA path had $\beta = 0.530$ and $f^2 = 0.390$, the largest values in the model, while the LA → JP path had $\beta = 0.311$ and $f^2 = 0.123$. SMEs programs should therefore move beyond teaching standard procedures and cultivate the capacity to continue learning as tools change. Each short module should include an unfamiliar situation, permission to experiment in a safe environment, brief feedback, a reflection log, and an after-action review. Peer-learning groups or experienced employees mentoring newcomers can reduce implementation costs. Employees should be asked to explain what they tried, where errors occurred, which lessons can be transferred to other tasks, and what support they require. This approach is aligned with Lee and Song's (2020) integrated model of LA and with evidence on the role of organizational support in translating LA into positive behavior (Jo & Hong, 2022).

Business owners and line managers should act as coaches by asking questions rather than merely providing answers, offering prompt feedback, recognizing controlled experimentation, and creating short-term job-rotation opportunities. SMEs may track the number of feedback cycles, completion rates for new tasks, the number of lessons shared, or changes in LA scores from pre- to post-intervention. A single LA score should not be used to assign permanent labels to employees or exclude them.

5.2.3. Designing Work to Increase Skill Utilization under H4 and H5

The DTS → SU path had $\beta = 0.462$ and $f^2 = 0.272$, while the SU → JP path had $\beta = 0.338$ and $f^2 = 0.159$ and was the largest path into JP. A direct implication is that each SME training course should be accompanied by a concise transfer plan specifying the application task, deadline, access rights, test data, support person, and completion criteria. During the four to eight weeks after training, managers should assign at least one

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real task with an appropriate risk level, observe implementation difficulties, and remove process barriers. Evidence from Okay-Somerville and Scholarios (2019) and Mehner et al. (2025) shows that job design, social support, and knowledge sharing are important conditions for skill use.

Transfer indicators suitable for SMEs may include the proportion of employees who have used the skill in an authentic task, frequency of use, the proportion of tasks completed without assistance, processing time, error rates, use of digital features, or the number of improvements standardized. Firms should distinguish unwillingness to apply a skill from a lack of opportunity to apply it. The latter often reflects barriers related to tools, access rights, time, or job design and should not be attributed entirely to the learner.

H6 and H7 were both supported, with indirect effects of 0.165 through LA and 0.156 through SU. The total indirect effect represented approximately 62.1% of the total effect, while the direct path remained significant, indicating complementary partial mediation. Even under resource constraints, SMEs should therefore maintain two minimum intervention packages: an LA-development package focused on experimentation, feedback, and reflection, and an SU-transfer package focused on access, tasks, support, and workplace measurement. The 0.009 difference between the two channels is insufficient to conclude that one is more important; firms should adjust investment according to actual barriers rather than eliminate either mechanism.

Evaluation in SMEs can be implemented through a lean T0–T3 sequence. T0 records capabilities and KPIs before training; T1 assesses knowledge or skills immediately after training; T2, four to eight weeks later, assesses LA, SU, and evidence of application; and T3, after one work cycle, assesses JP and operational KPIs. Simple electronic forms or existing data may be used instead of specialized systems. Results should be interpreted alongside changes in technology, workload, processes, and staffing to avoid incorrectly attributing outcomes to training. This monitoring approach is consistent with the view that transfer is an extended process influenced by the learner, training design, and the work environment (Baldwin & Ford, 1988; Blume et al., 2010).

Because one person may perform multiple roles in an SME, responsibilities should be assigned by function rather than requiring a full departmental structure. The owner or executive approves priorities and resources; the person responsible for human resources or training diagnoses needs, organizes learning, and consolidates data; the line manager assigns application tasks, provides feedback, and validates evidence; the technology lead provides access, a test environment, and technical support; and the process owner tracks KPIs and standardizes improvements. Employees prepare application plans, document lessons, and report barriers. Each program should designate at least one person with final accountability so that responsibility for transfer is not left unassigned.

Microenterprises may prioritize on-the-job guidance, peer learning, and one short application task; small enterprises may add role-based modules, practice-sharing groups, and T0–T3 monitoring through a common form; and medium-sized enterprises may connect learning data with system-use logs and managerial assessments. Regardless of size, firms must communicate the purpose of data collection, access restrictions, retention periods, and feedback mechanisms. Learning data should not be used for opaque monitoring or punitive purposes; its primary purpose should be to identify barriers and improve transfer.

5.3. Limitations and Directions for Future Research

The cross-sectional design, non-probability sampling, and reliance on self-reports for both predictors and JP create risks of common-source bias, reverse causality, and insufficient representation across industries, firm sizes, or levels of digitalization. Harman's single-factor analysis is only a preliminary diagnostic and cannot establish the absence of common method bias (Podsakoff et al., 2003).

Future research could test measurement invariance and conduct multigroup analyses by micro-, small, and medium-sized enterprise status, industry, tenure, or digital maturity; compare the two indirect effects using a confidence interval for their difference; and incorporate PLSpredict or experimental and quasi-experimental designs to strengthen predictive relevance and causal inference.

ADDITIONAL ETHICAL DISCLOSURE

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