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DIGITAL TRANSFORMATION SUPPORT, JOB PERFORMANCE, AND SELF-REPORTED INCOME CATEGORY AMONG VIETNAMESE SME WORKERS: EVIDENCE FROM SURVEY DATA

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ABSTRACT

This study examines the associations among firm-level digital transformation support, job performance, and self-reported income category among workers in Vietnamese small and medium-sized enterprises (SMEs), while assessing the measurement properties of five digital-skill dimensions based on the DigComp 2.1 framework. Data from 650 valid survey observations were analyzed using partial least squares structural equation modeling (PLS-SEM). The measurement results show satisfactory reliability, convergent validity, and discriminant validity for the five digital-skill dimensions and for the structural-model constructs digital transformation support and job performance. Digital transformation support is positively associated with job performance ($\beta = 0.232$; $t = 6.265$; $p < 0.001$), and job performance is positively associated with income category ($\beta = 0.628$; $t = 25.860$; $p < 0.001$). The indirect association between digital transformation support and income category through job performance is also positive and statistically significant ($\beta = 0.146$; $t = 6.068$; $p < 0.001$). The model explains 5.4% of the variance in job performance and 39.4% of the variance in income category. The findings suggest that firm-level digital support is related to better job performance, while job performance is the stronger correlate of income category. Because the study uses non-probability, self-reported, cross-sectional data and an ordered income measure, the results should be interpreted as associations rather than causal effects.

Keywords: Digital transformation support, job performance, income category, digital skills, SMEs, PLS-SEM.

1. INTRODUCTION

Digital transformation is reshaping how workers acquire information, communicate, produce digital content, protect data, and solve work-related problems. In this setting, digital skills can be understood as a contemporary form of human capital because they help workers perform tasks more efficiently and adapt to technology-intensive work environments. Human capital theory argues that education, skills, and training can raise productivity and earnings [1, 2]. In the digital economy, this logic is increasingly mediated by the quality of workers' digital capabilities and the organizational conditions under which these capabilities are used.

The issue is particularly relevant for small and medium-sized enterprises (SMEs). SMEs often adopt digital tools unevenly because of constraints in infrastructure, budgets, technical support, and training capacity. As a result, the same digital tool may generate different labor outcomes depending on whether workers know how to use it and whether firms provide sufficient support. This concern is also connected to the skill-biased technical change perspective, which suggests that technological change tends to complement skilled workers and may increase income differences between workers with different levels of capability [3, 4].

A second issue concerns the measurement of digital skills. Digital skill is not a single ability. The DigComp framework conceptualizes digital competence through several domains, including information and data literacy, communication and collaboration, content creation, safety, and problem solving [5]. Similarly, the Internet Skills Scale emphasizes the need to measure multiple skill dimensions rather than treating digital ability as simple Internet access or frequency of use [6]. Therefore, this study retains digital skills as a multidimensional measurement construct and evaluates the reliability and validity of its components.

The study addresses two analytically distinct but related objectives. First, it assesses the measurement properties of five digital-skill dimensions—information and data literacy, communication and collaboration, digital content creation, safety, and problem solving—among Vietnamese SME workers. Second, it examines the structural associations among digital transformation support (SUP), job performance (JP), and income category (INC). Digital skills are therefore treated as a multidimensional measurement component that provides contextual evidence on workers' digital capabilities, whereas the structural model is limited to SUP, JP, and INC.

This study makes three contributions. First, it provides sample-specific evidence on the reliability, convergent validity, and discriminant validity of five digital-skill dimensions among Vietnamese SME workers. Second, it estimates the association between job performance and workers' income category. Third, it shows that firm-level digital transformation support is positively associated with job performance and has a positive indirect association with income category through job performance. The study does not decompose income inequality or establish causal effects; its contribution is limited to the measurement evidence and cross-sectional associations reported in the empirical analysis.

2. LITERATURE REVIEW

2.1. Human capital theory and digital skills

Human capital theory views education, skills, knowledge, and experience as productive assets that can improve labor productivity and income [1, 2]. In digitalized workplaces, digital skills are increasingly important because workers must search for information, evaluate data credibility, communicate through digital channels, create digital outputs, protect information, and solve technology-related problems. These abilities may help workers complete tasks more accurately and efficiently, thereby strengthening the link between capability and earnings.

The skill-biased technical change perspective extends this argument by suggesting that technological change often increases the relative value of skilled labor [3, 4]. Workers who are better able to use digital technologies may benefit more from digital transformation, while those with weaker skills may not experience the same returns. This theoretical argument supports the need to examine digital skills in a detailed and multidimensional way.

2.2. Multidimensional digital skills

The DigComp 2.1 framework defines digital competence as a broad set of abilities covering information and data literacy, communication and collaboration, digital content creation, safety, and problem solving [5]. This multidimensional perspective is important for research in SMEs because workers may be strong in some domains, such as communication tools, but weaker in other domains, such as digital safety or task automation.

The Internet Skills Scale also shows that digital skills should be measured through multiple components rather than simple indicators of technology access or frequency of use

[6]. In this study, digital skills are represented by five lower-order components. The measurement analysis evaluates whether these dimensions are reliable and empirically distinct in the sample; it does not rank their substantive importance or estimate their associations with performance or income.

2.3. Digital transformation support and job performance

Digital transformation support refers to the extent to which an enterprise provides tools, software, procedures, training opportunities, and technical assistance that allow employees to perform work through digital means. This construct is theoretically related to facilitating conditions in the unified theory of acceptance and use of technology (UTAUT), which highlights the importance of infrastructure and support in enabling effective technology use [7].

Nevertheless, support does not automatically translate into performance. If support is general, fragmented, or disconnected from actual job tasks, employees may not experience measurable improvements in work outcomes. In-role job performance is commonly understood as the extent to which employees meet formal job requirements and complete assigned tasks [8]. Therefore, any association between digital support and performance is likely to depend on how well support mechanisms are embedded in the work process.

2.4. Job performance and income category

Job performance may be associated with economic outcomes because employees who fulfill core task requirements can create greater value for firms and may receive higher compensation. In SMEs, where pay-setting procedures may be less standardized, individual contribution and role performance may be particularly visible. Nevertheless, compensation also depends on occupation, education, tenure, firm size, location, and institutional factors; therefore, a positive path from job performance to income should be interpreted as an association rather than a complete explanation of earnings.

In this study, income is measured using one self-reported ordered item representing average take-home monthly income over the preceding three months, coded from 1 to 6. A single-item measure can be appropriate for a concrete and narrowly defined construct [9]. However, the use of ordered categories reduces precision relative to exact income values and does not support a formal analysis of income inequality.

2.5. Research hypotheses

Based on the preceding arguments, the study tests the following hypotheses for the structural model. The five digital-skill dimensions are assessed separately as a measurement component and are not specified as antecedents in the reported structural model.

H1: Digital transformation support (SUP) is positively associated with job performance (JP).

H2: Job performance (JP) is positively associated with workers' income category (INC).

H3: Digital transformation support (SUP) has a positive indirect association with income category (INC) through job performance (JP).

3. METHODOLOGY

This study uses a quantitative, cross-sectional survey design. The target population comprises employees working in Vietnamese SMEs. Respondents were recruited through a non-probability sampling approach combining convenience and purposive recruitment. The analytic data set contains 650 valid observations and no missing values in the indicators used for the re-estimated structural model (SUP1-SUP4, JP1-JP4, and INC). Because the available analytic file does not include the original fieldwork log, the exact survey period, sampling frame, number of invitations, and response rate could not be verified; this limitation is considered when interpreting the results.

The measurement scales were adopted and adapted from established sources. Digital skills were operationalized using five domains derived from DigComp 2.1 [5] and the Internet Skills Scale [6]. Digital transformation support was adapted from the facilitating-conditions construct in UTAUT [7], and in-role job performance was adapted from Williams and Anderson [8]. Income was captured through one self-reported ordered item representing average take-home monthly income over the preceding three months, coded from 1 to 6 [9].

Overall digital skills were conceptualized as a higher-order construct formed by five lower-order components: information and data literacy (DS_IDL), digital communication and collaboration (DS_CCO), digital content creation (DS_DCC), digital safety (DS_SAF), and problem solving (DS_PRB). The five lower-order components were specified reflectively, whereas the higher-order digital-skills construct was specified formatively [10, 11].

PLS-SEM was re-estimated using a PLS-PM implementation configured to reproduce the default SmartPLS 4 algorithm settings: path weighting, Mode A for the reflective constructs, a maximum of 3,000 iterations, and a stopping criterion of 10^-7. Statistical inference used 10,000 bootstrap subsamples, 95% percentile confidence intervals, and a fixed random seed. Reflective measurement quality was evaluated using outer loadings, Cronbach's alpha, rho_A, composite reliability (rho_c), average variance extracted (AVE), and the heterotrait-monotrait ratio (HTMT). The higher-order formative specification was evaluated using collinearity diagnostics. The structural model was assessed using path coefficients, bootstrapped standard errors, t-statistics and p-values, indirect and total associations, R^2, adjusted R^2, and f^2 effect sizes [12].

Because all variables were collected through a self-report survey, common method bias was considered. The reported VIF values were examined as a limited supplementary diagnostic following the full-collinearity approach [13]; however, indicator-level and structural VIF values are not equivalent to a complete assessment applied to all latent variables. Procedurally, established scales, clear item wording, and separate construct blocks were used to reduce ambiguity and evaluation apprehension [14]. Common method bias therefore cannot be ruled out and remains a limitation of the study.

The study followed ethical procedures. Respondents were informed that participation was voluntary, that their answers would be used only for academic purposes, and that no personally identifying information would be reported. Informed consent was obtained before respondents completed the questionnaire.

Table 1. Measurement scales of the study variables

Construct	Variable code	No. of indicators	Measurement type	Source
Overall digital skills (HOC)	DS	5 LOC	Formative (Mode B)	[5, 6, 10, 11]
Information & data literacy	DS_IDL	3	Reflective (Mode A)	[5, 6]
Digital communication & collaboration	DS_CCO	3	Reflective (Mode A)	[5]
Digital content creation	DS_DCC	3	Reflective (Mode A)	[5]
Digital safety	DS_SAF	3	Reflective (Mode A)	[5]
Problem solving	DS_PRB	3	Reflective (Mode A)	[5, 6]

Construct	Variable code	No. of indicators	Measurement type	Source
Digital transformation support	SUP	4	Reflective (Mode A)	[7]
Job performance (in-role)	JP	4	Reflective (Mode A)	[8]
Income category	INC	1	Single-item	Self-report; [9]

Source: Compiled by the author

Table 2. List of observed variables used in the survey

Construct	Code	Observed variables/items	Source
DS_IDL	IDL1	I can search for and filter information for work purposes effectively.	[5, 6]
DS_IDL	IDL2	I can evaluate the credibility of information/data before using it for work.	[5, 6]
DS_IDL	IDL3	I can organize, store, and retrieve work files/data in a systematic manner.	[5]
DS_CCO	CCO1	I communicate work matters effectively via email/messaging applications.	[5]
DS_CCO	CCO2	I use online meetings/communication tools effectively.	[5]
DS_CCO	CCO3	I coordinate work via digital platforms.	[5]
DS_DCC	DCC1	I can create and edit digital content for work.	[5]
DS_DCC	DCC2	I can combine/edit content from multiple sources to produce work outputs.	[5]
DS_DCC	DCC3	I understand and comply with copyright/licensing rules when using digital content at work.	[5]
DS_SAF	SAF1	I know how to protect work accounts/devices.	[5]
DS_SAF	SAF2	I can recognize suspicious emails/messages and handle them safely.	[5]
DS_SAF	SAF3	I know how to share documents with appropriate access permissions.	[5]
DS_PRB	PRB1	I can quickly self-learn new tools/software when required by my job.	[5, 6]
DS_PRB	PRB2	I can diagnose and fix common technical issues at a basic level.	[5]
DS_PRB	PRB3	I can choose suitable digital tools to optimize a task.	[5]
SUP	SUP1	The enterprise provides sufficient equipment/systems/software for me to work effectively.	[7]
SUP	SUP2	The enterprise provides clear guidance/procedures for using digital tools at work.	[7]
SUP	SUP3	I receive training or learning opportunities to improve my digital skills for work.	[7]

Construct	Code	Observed variables/items	Source
SUP	SUP4	When technical problems arise, I receive timely support.	[7]
JP	JP1-JP4	Four in-role job performance items assessing task completion and fulfillment of formal job requirements.	[8]
INC	INC	Average take-home monthly income over the last 3 months, reported in one of six ordered categories.	Self-report

Source: Compiled by the author

Table 3. Sample coding and descriptive statistics

Variable	Description/coding	Statistic	Interpretation
N	Valid observations after screening	650	No missing values were reported in the SmartPLS data summary.
GEN	Gender, coded 0/1	Mean = 0.506	50.6% of respondents were coded as category 1; the category label was unavailable in the analytic file.
AGE	Age in years	Mean = 33.049; SD = 6.773; range = 18-53	The sample mainly represents working-age employees.
EDU	Education level, coded category	Mean = 2.438; SD = 0.901; range = 1-4	Descriptive statistics reflect numerical coding; category labels were unavailable in the analytic file.
TEN	Tenure in years	Mean = 5.964; SD = 4.120; range = 0-19.2	Respondents include both newer and more experienced employees.
POS	Position, coded category	Mean = 1.858; SD = 0.764; range = 1-3	Descriptive statistics reflect numerical coding; category labels were unavailable in the analytic file.
URBAN	Work/residence area, coded 0/1	Mean = 0.609	60.9% of respondents were coded as category 1; the category label was unavailable in the analytic file.
INC	Ordered income category (1-6)	Mean = 3.643; SD = 1.446; range = 1-6	A higher code represents a higher income category; exact category cut-points were unavailable.

Source: Compiled by the author

3.1. Higher-order measurement model

For the digital-skills construct, the study applied the disjoint two-stage approach for hierarchical component models [11, 12]. In Stage 1, the five lower-order components were estimated using their respective indicators, and latent-variable scores were obtained. In Stage 2, these scores served as indicators of the formative higher-order digital-skills construct. The reported results evaluate the reliability and validity of the lower-order components and the collinearity of the higher-order specification.

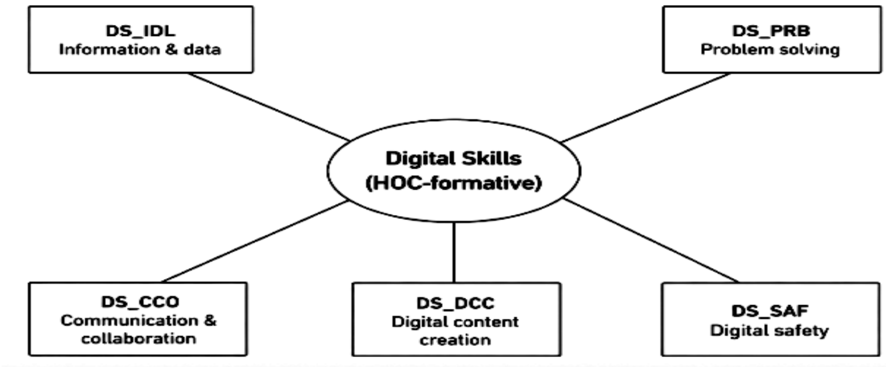

Figure 1. Higher-order measurement model of digital skills
Source: Compiled by the author

The structural model examines the path from digital transformation support to job performance and the subsequent path from job performance to income category. Digital skills are not included as structural antecedents in the reported model; they are retained only as a separately assessed multidimensional capability construct.

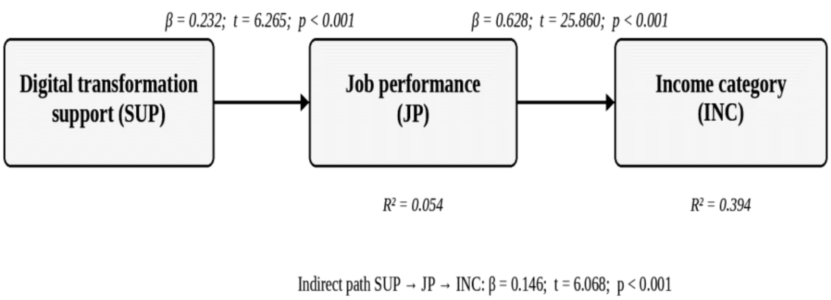

Figure 2. Structural model and estimated path coefficients
Source: Compiled by the author

4. RESULTS

4.1. Assessment of the measurement model for digital skills components

The outer loadings of the indicators for the five first-order digital-skill components range from 0.872 to 0.898. All values exceed the commonly used 0.708 benchmark for reflective indicators, indicating adequate indicator reliability [12].

Table 4. Outer loadings of digital skills components

Indicator	DS_CCO	DS_DCC	DS_IDL	DS_PRB	DS_SAF
CCO1	0.879				
CCO2	0.893				
CCO3	0.874				
DCC1		0.882			
DCC2		0.895			

DCC3		0.875			
IDL1			0.884		
IDL2			0.895		
IDL3			0.887		
PRB1				0.891	
PRB2				0.898	
PRB3				0.893	
SAF1					0.886
SAF2					0.872
SAF3					0.883

Source: Compiled by the author

Reliability and convergent validity are satisfactory for the five first-order digital-skill components and for both structural-model constructs. For the digital-skill components, Cronbach's alpha ranges from 0.855 to 0.875, rho_c ranges from 0.912 to 0.923, and AVE ranges from 0.775 to 0.799. For digital transformation support, Cronbach's alpha = 0.903, rho_A = 0.905, rho_c = 0.932, and AVE = 0.775. For job performance, Cronbach's alpha = 0.893, rho_A = 0.894, rho_c = 0.926, and AVE = 0.757. These values meet the conventional criteria for internal consistency and convergent validity [12].

Table 5. Reliability and convergent validity

Construct	Cronbach's alpha	rho_A	rho_c	AVE
DS_CCO	0.857	0.858	0.913	0.778
DS_DCC	0.860	0.861	0.915	0.782
DS_IDL	0.867	0.867	0.918	0.790
DS_PRB	0.875	0.875	0.923	0.799
DS_SAF	0.855	0.856	0.912	0.775
SUP	0.903	0.905	0.932	0.775
JP	0.893	0.894	0.926	0.757

Source: Compiled by the author

Problem solving (DS_PRB) and information and data literacy (DS_IDL) have the highest rho_c and AVE values among the five components. These statistics indicate comparatively strong internal consistency and convergent validity within this sample; they do not, by themselves, establish that these domains are more important for performance or income than the other digital-skill dimensions.

Table 6. HTMT ratios

Relationship	HTMT
DS_DCC <-> DS_CCO	0.523
DS_IDL <-> DS_CCO	0.511
DS_IDL <-> DS_DCC	0.536
DS_PRB <-> DS_CCO	0.536
DS_PRB <-> DS_DCC	0.545

Relationship	HTMT
DS_PRB <-> DS_IDL	0.468
DS_SAF <-> DS_CCO	0.572
DS_SAF <-> DS_DCC	0.548
DS_SAF <-> DS_IDL	0.604
DS_SAF <-> DS_PRB	0.532
SUP <-> JP	0.257

Source: Compiled by the author

Table 7. HTMT inference

Relationship	O	M	5.00%	95.00%
DS_DCC <-> DS_CCO	0.523	0.522	0.465	0.576
DS_IDL <-> DS_CCO	0.511	0.511	0.447	0.572
DS_IDL <-> DS_DCC	0.536	0.537	0.477	0.592
DS_PRB <-> DS_CCO	0.536	0.535	0.472	0.594
DS_PRB <-> DS_DCC	0.545	0.545	0.486	0.599
DS_PRB <-> DS_IDL	0.468	0.468	0.408	0.526
DS_SAF <-> DS_CCO	0.572	0.571	0.516	0.625
DS_SAF <-> DS_DCC	0.548	0.548	0.491	0.604
DS_SAF <-> DS_IDL	0.604	0.603	0.549	0.656
DS_SAF <-> DS_PRB	0.532	0.531	0.471	0.588

Source: Compiled by the author

All HTMT ratios among the five digital-skill components are below 0.85, and their reported 90% bootstrap confidence intervals do not include 1.00. The HTMT ratio between digital transformation support and job performance is 0.257, with a 95% bootstrap confidence interval from 0.173 to 0.337. These results support satisfactory discriminant validity in the analyzed sample [12].

Additional assessment of the structural-model constructs shows that the SUP indicator loadings are 0.872 (SUP1), 0.880 (SUP2), 0.898 (SUP3), and 0.871 (SUP4), while the JP indicator loadings are 0.879 (JP1), 0.876 (JP2), 0.864 (JP3), and 0.861 (JP4). All loadings exceed 0.708. Indicator VIF values range from 2.354 to 2.963 for SUP and from 2.311 to 2.489 for JP, indicating no problematic indicator collinearity under the conservative 3.3 threshold.

Taken together, the outer loadings, internal-consistency coefficients, AVE values, HTMT result, and indicator VIF statistics support the reliability, convergent validity, and discriminant validity of the intended JP1-JP4 measurement model and the SUP measurement model. INC is a single-item ordered measure; therefore, conventional internal-consistency and within-construct validity statistics are not substantively informative for INC and are fixed at 1.000 by construction.

4.2. Assessment of the structural model

Before estimating the structural paths, collinearity was assessed for the structural and measurement specifications. The structural VIF values are 1.000 because each endogenous construct has one structural predictor in the reported model. The lower-order component VIFs for the digital-skills higher-order construct range from 1.523 to 1.684, the SUP indicator VIFs range from 2.354 to 2.963, and the JP indicator VIFs range from 2.311 to 2.489. These values do not indicate problematic collinearity under conservative thresholds [12]. They should not be interpreted as a definitive test of common method bias.

Table 8. Collinearity diagnostics

Model component	VIF / range	Assessment
JP -> INC	1.000	No structural collinearity problem
SUP -> JP	1.000	No structural collinearity problem
Digital-skill lower-order components -> DS HOC	1.523-1.684	No serious collinearity among HOC components
SUP reflective indicators	2.354-2.963	Acceptable indicator-level collinearity
JP reflective indicators	2.311-2.489	Acceptable indicator-level collinearity

Source: Compiled by the author

Bootstrapping shows that digital transformation support is positively and statistically significantly associated with job performance ($\beta = 0.232$; $t = 6.265$; $p < 0.001$), supporting H1. Job performance is also positively and statistically significantly associated with income category ($\beta = 0.628$; $t = 25.860$; $p < 0.001$), supporting H2.

Table 9. Direct path coefficients

Path	O	M	STDEV	t	p	Decision
SUP -> JP	0.232	0.234	0.037	6.265	< 0.001	Supported
JP -> INC	0.628	0.628	0.024	25.860	< 0.001	Supported

Source: Compiled by the author

The estimated indirect association between digital transformation support and income category through job performance is positive and statistically significant ($\beta = 0.146$; $t = 6.068$; $p < 0.001$; 95% bootstrap CI [0.100, 0.195]). H3 is therefore supported.

Table 10. Indirect path coefficient

Path	O	M	STDEV	t	p	Decision
SUP -> JP -> INC	0.146	0.147	0.024	6.068	< 0.001	Supported

Source: Compiled by the author

Table 11. Total path coefficients

Path	O	M	STDEV	t	p
SUP -> JP	0.232	0.234	0.037	6.265	< 0.001
JP -> INC	0.628	0.628	0.024	25.860	< 0.001
SUP -> INC	0.146	0.147	0.024	6.068	< 0.001

Source: Compiled by the author

The model accounts for 5.4% of the variance in job performance ($R^2 = 0.054$; adjusted $R^2 = 0.053$) and 39.4% of the variance in income category ($R^2 = 0.394$; adjusted $R^2 = 0.393$).

Thus, digital transformation support has limited explanatory power for job performance, whereas job performance explains a substantial share of the variation in the ordered income outcome within the present model.

Table 12. R^2 and adjusted R^2

Endogenous construct	R^2	Adjusted R^2
JP	0.054	0.053
INC	0.394	0.393

Source: Compiled by the author

Table 13. f^2 effect sizes

Path	O	M	STDEV	t	p
SUP -> JP	0.057	0.060	0.020	2.896	0.004
JP -> INC	0.651	0.657	0.084	7.751	< 0.001

Source: Compiled by the author

The f^2 value for SUP -> JP is 0.057, indicating a small contribution to the explained variance in job performance. The f^2 value for JP -> INC is 0.651, indicating a large contribution to the explained variance in income category under conventional PLS-SEM guidelines [12].

5. DISCUSSION

The strongest structural result is the positive association between job performance and income category ($\beta = 0.628$). This pattern is compatible with human capital theory because employees who meet core task requirements may generate greater value and obtain higher compensation. However, the cross-sectional design, self-reported measures, ordered income categories, and absence of controls for occupation, education, tenure, firm characteristics, and location prevent a causal interpretation. The result should therefore be read as a conditional association within the analyzed sample.

Digital transformation support is positively associated with job performance ($\beta = 0.232$), but its effect size is small ($f^2 = 0.057$), and the model explains only 5.4% of the variance in job performance. This finding suggests that access to equipment, procedures, training opportunities, and technical assistance may support employees' task performance, while most performance variation is likely attributable to other factors. Potentially relevant omitted variables include employees' digital skills, job autonomy, task complexity, digital culture, supervisor support, occupational differences, and the quality and intensity of training.

The measurement results indicate satisfactory reliability, convergent validity, and discriminant validity for all five digital-skill components, digital transformation support, and job performance. Problem solving and information/data literacy have the highest rho_c and AVE values among the digital-skill dimensions, but these psychometric statistics should not be interpreted as evidence of greater substantive importance. For managerial purposes, the five domains can be used as a diagnostic framework for identifying training needs, while their relative associations with performance should be tested explicitly in the structural model.

In the reported model, SUP is specified as an antecedent of job performance rather than as a moderator. A moderation hypothesis would require an explicit interaction term between digital skills and digital transformation support and a corresponding test of the interaction effect in SmartPLS.

5.1. Limitations and future research

This study has several limitations. First, income is measured through one self-reported ordered category rather than an exact monetary value; the measure therefore captures income only coarsely and does not permit formal inequality analysis. Second, the available analytic file does not include the original fieldwork log, so the survey period, sampling frame, response rate, and detailed category labels for several demographic variables could not be verified. Third, the cross-sectional, non-probability, self-report design limits generalizability and does not establish temporal or causal ordering. Fourth, common method bias cannot be excluded because no marker variable, time separation, or objective data were available. Fifth, the reported chain model does not include a direct SUP -> INC path, so the analysis establishes a significant indirect association but does not classify the mediation pattern as partial or full mediation.

Future research should estimate the direct SUP -> INC path together with the indirect path, incorporate theoretically relevant control variables, and use time-lagged or multisource data. It should also estimate direct and indirect effects of the higher-order digital-skills construct on job performance and income, compare the relative structural relevance of the five skill domains, and test whether firm-level support strengthens the conversion of digital skills into performance and income outcomes.

6. CONCLUSION

This study assessed five dimensions of digital skills and examined the structural associations among digital transformation support, job performance, and income category among workers in Vietnamese SMEs. The measurement results support the reliability, convergent validity, and discriminant validity of information and data literacy, digital communication and collaboration, digital content creation, digital safety, and problem solving in the analyzed sample.

Digital transformation support is positively associated with job performance, job performance is positively associated with income category, and the indirect association between support and income through job performance is statistically significant. The effect of support on performance is comparatively small, whereas the association between job performance and income category is large. These findings suggest that digital tools, procedures, training opportunities, and technical assistance may contribute to performance when they are connected to concrete job requirements, and that performance is an important correlate of workers' income category. The conclusions remain associational because the study is cross-sectional and relies on non-probability, self-reported data.

Future studies should include the direct path from digital transformation support to income, estimate the structural roles of the higher-order digital-skills construct, compare the five skill domains, and test whether firm-level support strengthens the translation of digital skills into performance and income. More precise income measures, objective performance data, and longitudinal designs are needed before making claims about income inequality or causal effects.

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