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Digital technology acceptance and self-reported mastery–use differences during teaching practicum among preservice vocational teachers

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ABSTRACT

Drawing on an adapted Unified Theory of Acceptance and Use of Technology 2 framework, this study examined factors associated with behavioral intention and reported digital-technology use and compared self-reported mastery with frequent teaching use during school-based practicum. A non-probability sample of 119 preservice vocational teachers from eight programs was analyzed using partial least squares structural equation modeling, a Wilcoxon signed-rank test, and exact McNemar tests with Holm adjustment. Internal consistency and convergent validity were acceptable overall, although one facilitating-conditions indicator loaded weakly. Habit was associated with intention and use; social influence was associated with intention; and facilitating conditions and intention were associated with use. Post-hoc power was high for the two habit paths and the intention-to-use path, but lower for several smaller paths. Self-reported mastery breadth exceeded frequent-use breadth, with adjusted category-level differences for social media, YouTube, and e-learning. The findings provide complementary, noncausal indicators of digital readiness during practicum.

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Introduction

School-based teaching practicum in vocational secondary schools requires preservice vocational teachers to plan, deliver, assess, and reflect on lessons that connect classroom activity with occupational competence. In this context, the pedagogical value of digital technology lies not in the presence of a tool itself but in whether it is selected for an instructional function: representing procedures that are difficult to observe directly, supporting guided practice and feedback, organizing assessment and documentation, or enabling communication and collaboration around workplace-oriented tasks. Vocational teachers differ in the technologies they use and in their teaching profiles (Cattaneo et al., 2025), and Indonesian vocational-school teachers also report distinct patterns across platforms (Widarto et al., 2024). School-based teaching practicum is therefore an important setting for examining technology use as a pedagogical decision rather than as simple exposure to digital tools.

Teacher education accordingly faces a transfer problem: familiarity with digital technologies as a user does not necessarily become pedagogically appropriate enactment in a lesson. Training can connect technical knowledge with pedagogical planning (Çebi et al., 2022), while authentic experience, modeling, and reflection

are emphasized in recent syntheses of preparation for teaching with technology (Tondeur et al., 2025). Field experiences are also associated with preservice teachers' technology beliefs and practices (Nelson & Voithofer, 2022). Wang & Ko (2024) similarly show that the status of preservice teachers as digital users does not itself establish pedagogical competence. In the present study, self-reported mastery therefore means that respondents regarded themselves as able to use a named technology, whereas frequent teaching use means that they reported using it frequently during practicum. These measures describe perceived repertoire and reported enactment; neither is an observation-based measure of competence, pedagogical quality, or lesson effectiveness.

The Extended Unified Theory of Acceptance and Use of Technology (UTAUT2) was originally developed to explain consumer technology acceptance and use (Venkatesh et al., 2003, 2012) , but its distinction between behavioral intention and use behavior provides a useful starting point for examining technology enactment during practicum. The present study adapts that framework rather than treating the consumer model as a complete theory of teaching. Performance expectancy represents perceived teaching benefits, effort expectancy perceived ease of use, social influence perceived expectations from important others, and facilitating conditions perceived access to organizational and technical support. Habit represents automaticity developed through repeated experience. The instrument uses the label motivation for enjoyment or intrinsic appeal associated with using digital technologies; because the adapted item set does not reproduce the original consumer hedonic motivation construct verbatim, the present study retains the label motivation and does not assume full construct equivalence. Performance expectancy, effort expectancy, social influence, facilitating conditions, motivation, and habit were modeled in relation to behavioral intention, while facilitating conditions, habit, and behavioral intention were modeled in relation to use behavior. These paths are treated as prespecified statistical relations, not as proof of causal ordering in cross-sectional data.

An intellectual gap remains between two strands of research. Technology-acceptance studies typically summarize intention and use at the construct level, whereas teacher-education research shows that perceived competence, field experience, and enacted technology use need not align. This creates a specific empirical puzzle for vocational teacher preparation: a preservice teacher may report favorable acceptance and general use while bringing only a narrow subset of technologies into lessons, or may perceive mastery of several tools that are not routinely enacted. UTAUT2 alone does not identify the breadth or composition of that repertoire, and competence-focused studies do not necessarily model the acceptance conditions associated with reported use. This distinction matters in vocational education because technologies are not interchangeable across procedural demonstration, guided practice, assessment, feedback, and collaboration. Category-level research shows variation in perceived competence and use across technologies (Cattaneo et al., 2025; Martin et al., 2024), while self-assessed knowledge does not necessarily predict the quality of technology-enhanced lesson plans (von Kotzebue, 2022). Evidence that combines an acceptance model with paired, within-person mastery–use comparisons across specific technologies during vocational teaching practicum remains limited.

This study therefore combines two complementary but non-equivalent perspectives on digital technology integration during school-based vocational teaching practicum. It addressed two questions: (1) Which factors are statistically associated with behavioral intention and reported use behavior of digital learning technologies during vocational teaching practicum? and (2) To what extent does self-reported mastery correspond to frequent teaching use, both in overall repertoire breadth and for individual technologies? The adapted acceptance model examines conditional associations with behavioral intention and use behavior, whereas paired reports across 13 technology categories examine the breadth and composition of the perceived and enacted technology repertoire. Juxtaposing these analyses provides an instructionally specific account of digital readiness without treating self-reported mastery as objectively demonstrated competence or treating cross-sectional paths as causal mechanisms.

Method

A cross-sectional quantitative study was conducted among students in teacher education programs at the Faculty of Engineering, Universitas Negeri Jakarta, who were undertaking teaching practice in vocational schools in the Greater Jakarta area. Recruitment was non-probability and criterion-based (purposive): eligible participants were students currently undertaking the teaching practice and therefore had direct experience planning and delivering lessons relevant to the research questions. The accessible sample came from eight study programs, and the questionnaire was distributed online through Google Forms. The final analytic sample comprised 119 eligible respondents. The sample is therefore treated as information-rich for the specified questions rather than statistically representative of all preservice vocational teachers.

The research instrument and structural framework adapted the UTAUT2 framework (Venkatesh et al., 2012). The initial instrument contained 44 agreement items: six items each for performance expectancy, effort

expectancy, social influence, and facilitating conditions, and five items each for motivation, habit, behavioral intention, and use behavior. Responses were recorded on a four-point Likert scale. Performance Expectancy (PE) represented perceived teaching benefits (Venkatesh et al., 2012; Xue et al., 2024), Effort Expectancy (EE) represented perceived ease of use (Venkatesh et al., 2012; Xue et al., 2024), Social Influence (SI) represented expectations from significant others (Hakimi et al., 2024; Venkatesh et al., 2012), and Facilitating Conditions (FC) represented perceived access to resources and support (Hakimi et al., 2024; Venkatesh et al., 2012). Motivation (M) represented enjoyment or intrinsic appeal associated with using digital technologies and was not assumed to be psychometrically identical to the original UTAUT2 hedonic-motivation construct (Venkatesh et al., 2012), Habit (H) represented automaticity developed through repeated use (Limayem et al., 2007; Venkatesh et al., 2012), Behavioral Intention (BI) represented willingness to continue using the technologies (Kotler & Kelle, 2022; Venkatesh et al., 2012), and Use Behavior (UB) represented intensity of use (Venkatesh et al., 2003, 2012). During measurement-model assessment, two items with very low loadings, H3 and M4, were removed. The final model therefore contained 42 items. A separate checklist asked whether respondents considered themselves to have mastered each of 13 named technology types and whether they frequently used each type in teaching. These paired binary reports yielded two breadth scores ranging from zero to 13. Self-reported mastery was a perceived ability judgment; frequent use was a reported teaching behavior. Neither measure was an observation, performance test, or direct assessment of lesson quality.

Partial least squares structural equation modeling (PLS-SEM) was conducted in SmartPLS 4 (Ringle et al., 2024). Reflective measurement assessment considered indicator loadings, Cronbach's alpha, rho A, composite reliability, average variance extracted, and heterotrait–monotrait ratios. Following PLS-SEM guidance, loadings around 0.708 or higher were preferred, while indicators between 0.40 and 0.70 were evaluated together with construct reliability, convergent validity, and content coverage rather than removed mechanically (Hair et al., 2019). Values of approximately 0.70 or higher for internal-consistency reliability, .50 or higher for average variance extracted, and below 0.90 for heterotrait–monotrait ratios were used as interpretive benchmarks (Hair et al., 2019; Henseler et al., 2015). Structural assessment included inner variance inflation factors, standardized path coefficients, 10,000-sample bootstrap confidence intervals and p values, effect sizes, and explained variance. Because the analysis was variance-based PLS-SEM rather than covariance-based SEM, covariance-fit indices such as CFI, TLI, and RMSEA were not treated as primary model-fit criteria; standardized root mean square residual was reported as an approximate-fit diagnostic. Predictive assessment used Q-squared-predict values and cross-validated predictive ability tests with ten folds and ten repetitions against indicator-average and linear-model benchmarks (Liengaard et al., 2021). SmartPLS post-hoc power estimates are reported descriptively to indicate sensitivity to effects of the observed magnitude; they are not used as a substitute for prospective sample-size planning. The two within-respondent breadth scores were compared with the Wilcoxon signed-rank test for paired observations (Wilcoxon, 1945). Each paired binary mastery/use category was compared with an exact McNemar test (Fagerland et al., 2013; McNemar, 1947), followed by Holm adjustment across the 13 tests to control the family-wise Type I error rate (Holm, 1979).

Results and Discussions

The respondents in this study included 119 preservice vocational teachers, comprising 62 women (52.1%) and 57 men (47.9%). Participants represented Building Engineering Education (n = 41; 34.5%), Culinary Arts Education (n = 24; 20.2%), Electrical Engineering Education (n = 21; 17.6%), Electronics Engineering Education (n = 15; 12.6%), Mechanical Engineering Education (n = 10; 8.4%), Makeup Artistry Education (n = 5; 4.2%), Fashion Design Education (n = 2; 1.7%), and Informatics and Computer Engineering Education (n = 1; 0.8%). Reported digital experience was less than one year for 45 participants (37.8%), one to two years for 44 (37.0%), three to five years for 19 (16.0%), and more than five years for 11 (9.2%).

The eight constructs met the prespecified construct-level benchmarks for internal consistency and convergent validity (Table 1). Cronbach's alpha ranged from 0.734 to 0.869, composite reliability from 0.833 to 0.905, and average variance extracted from 0.507 to 0.658. Table 1 now reports every retained indicator loading. Several loadings were below the preferred value of about 0.708. The lowest was facilitating conditions item FC1 at 0.516; it was retained because the facilitating-conditions construct still showed acceptable composite reliability (0.862) and average variance extracted (0.515), and the indicator was evaluated together with the construct's intended content coverage rather than deleted solely to optimize a loading threshold (Hair et al., 2019). This decision does not make the weak loading inconsequential, FC1 and the other sub-0.708 indicators reduce measurement precision and are treated as a limitation when the structural results are interpreted.

Table 1. Measurement model assessment

Construct	Items	Outer loading range	α	ρA	ρC	AVE	Mean	SD
BI	5	0.767–0.856	0.869	0.873	0.905	0.656	3.474	0.446
EE	6	0.697–0.827	0.855	0.873	0.892	0.579	3.412	0.418
FC	6	0.516–0.821	0.806	0.826	0.862	0.515	3.396	0.442
H	4	0.694–0.817	0.756	0.772	0.844	0.576	3.275	0.479
M	4	0.690–0.813	0.734	0.743	0.833	0.555	3.422	0.440
PE	6	0.637–0.803	0.809	0.828	0.860	0.507	3.683	0.345
SI	6	0.648–0.785	0.821	0.825	0.870	0.530	3.472	0.401
UB	5	0.715–0.878	0.869	0.879	0.905	0.658	3.239	0.532

All heterotrait-monotrait ratios were below 0.90 (Table 2). The facilitating conditions – motivation ratio was .886 and approached the threshold, indicating greater empirical proximity between perceived support and motivation than among most other construct pairs.

Table 2. Heterotrait-Monotrait Ratio (HTMT)

Construct	BI	EE	FC	H	M	PE	SI	UB
BI								
EE	0.604							
FC	0.611	0.684						
H	0.770	0.618	0.598					
M	0.701	0.682	0.886	0.777				
PE	0.428	0.622	0.501	0.492	0.635			
SI	0.702	0.769	0.730	0.689	0.741	0.684		
UB	0.758	0.563	0.627	0.852	0.656	0.341	0.695	

The model accounted for 53.8% of the variance in behavioral intention and 60.2% of the variance in use behavior (Figure 1). Inner variance inflation factors ranged from 1.424 to 2.401, so collinearity was not severe enough to prevent interpretation of the specified paths (Table 3). The standardized root mean square residual was 0.082 for the saturated model and 0.083 for the estimated model. These values are slightly above the commonly used 0.08 heuristic and are therefore treated as a cautionary approximate-fit diagnostic rather than evidence of exact global fit. Consistent with the variance-based PLS-SEM approach, CFI, TLI, and RMSEA were not used as covariance-model fit criteria. The results describe explained variation and conditional associations within the sample, they do not establish temporal or causal ordering.

Post-hoc power at an alpha level of 0.05 was 0.994 for habit to behavioral intention, 0.999 for habit to use behavior, 0.945 for behavioral intention to use behavior, 0.798 for social influence to behavioral intention, and 0.657 for facilitating conditions to use behavior. For the smaller, statistically nonsignificant paths to behavioral intention, achieved power ranged from 0.164 to 0.456. These estimates indicate strong sensitivity to the largest observed associations but substantially weaker sensitivity to small effects. Consequently, nonsignificant paths should not be interpreted as evidence of absence. The post-hoc calculations are diagnostic and do not replace an a priori sample-size justification.

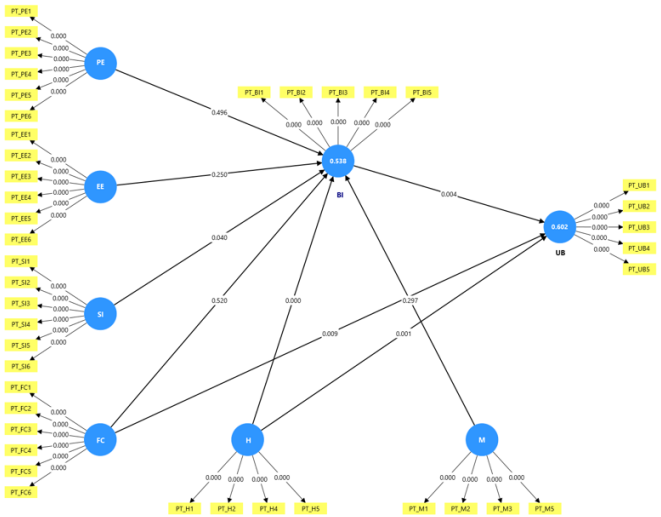


Figure 1. Structural model output

Within the prespecified cross-sectional model, habit showed the largest conditional association with behavioral intention (β = 0.3799, p < 0.001, f^2 = 0.1865) and with use behavior (β = 0.4261, p = 0.0007, f^2 = 0.2544) after the other predictors were included. Respondents with higher habit scores also tended to report higher intention and use scores, but temporal direction cannot be established: repeated use may strengthen habit just as established habit may accompany repeated use. Social influence was conditionally associated with behavioral intention (β = 0.2272, p = 0.0397), whereas facilitating conditions (β = 0.1878, p = 0.0086) and behavioral intention (β = 0.2976, p = 0.0038) were conditionally associated with use behavior. Performance expectancy, effort expectancy, facilitating conditions, and motivation did not show statistically detectable independent associations with behavioral intention in the full model. The bootstrapped specific indirect association linking habit with use behavior through behavioral intention was supported (β = 0.1130, p = 0.0272). For social influence through behavioral intention, the two-sided bootstrap p value was 0.1302 while the percentile 95% confidence interval was [0.001, 0.172]. Inferential decisions therefore follow the prespecified two-sided p-value criterion, and this indirect estimate is not interpreted as statistically supported.

Table 3. Collinearity and structural path

Path	β	t	p	95% CI	f^2	VIF Inner Model
Direct path						
PE → BI	-0.0612	0.6803	0.4963	[-0.234, 0.119]	0.0049	1.669
EE → BI	0.1159	1.1507	0.2499	[-0.078, 0.318]	0.0139	2.092
SI → BI	0.2272	2.0571	0.0397	[0.012, 0.445]	0.0476	2.348
FC → BI	0.0706	0.6430	0.5202	[-0.130, 0.298]	0.0049	2.193
H → BI	0.3799	4.4959	0.0000	[0.225, 0.554]	0.1865	1.674
M → BI	0.1407	1.0421	0.2974	[-0.133, 0.399]	0.0178	2.401
FC → UB	0.1878	2.6261	0.0086	[0.060, 0.343]	0.0622	1.424
H → UB	0.4261	3.4055	0.0007	[0.162, 0.645]	0.2544	1.792
BI → UB	0.2976	2.8937	0.0038	[0.100, 0.503]	0.1154	1.928
Indirect path						
PE → BI → UB	-0.0182	0.6075	0.5435	[-0.087; 0.033]	—	—
EE → BI → UB	0.0345	1.0277	0.3041	[-0.023; 0.110]	—	—
SI → BI → UB	0.0676	1.5134	0.1302	[0.001; 0.172]	—	—
FC → BI → UB	0.0210	0.5814	0.5610	[-0.036; 0.107]	—	—
H → BI → UB	0.1130	2.2088	0.0272	[0.032; 0.233]	—	—
M → BI → UB	0.0419	1.0110	0.3120	[-0.047; 0.124]	—	—

Cross-validated predictive assessment also supported out-of-sample prediction within the resampling procedure. Q-squared-predict was 0.458 for behavioral intention and 0.539 for use behavior, indicating lower prediction error than a naive benchmark for both endogenous constructs. In the cross-validated predictive ability test, PLS-SEM loss was lower than both the indicator-average and linear-model benchmarks for behavioral intention, use behavior, and the overall comparison (Table 4). Thus, the model showed predictive ability under the specified ten-fold, ten-repetition procedure, although this does not imply transportability to other universities or practicum settings.

Table 4. Cross-validated predictive power

Target	PLS loss	IA loss	Difference	p
PLS vs Indicator Average				
BI	0.216	0.306	−0.090	<0.001
UB	0.303	0.446	−0.143	<0.001
Overall	0.259	0.376	−0.117	<0.001
PLS vs Linear Model				
BI	0.216	0.305	−0.089	<0.001
UB	0.303	0.446	−0.143	<0.001
Overall	0.259	0.376	−0.116	<0.001

Preservice vocational teachers reported a mean self-reported mastery breadth of 4.45 technology types and a mean frequent-teaching-use breadth of 3.53 types (Figure 2). The paired difference was statistically detectable (W = 405.5, p < 0.001; rank-biserial correlation = 0.708 among 74 nonzero pairs). The result indicates that the perceived repertoire was broader than the repertoire reported as routinely enacted during teaching. It should not be interpreted as an automatic deficit or as evidence that every mastered technology ought to be used more frequently: vocational lessons may appropriately rely on a smaller set selected for learning purposes. The

comparison concerns two self-reported breadth measures, not objectively demonstrated competence or observed lesson quality.

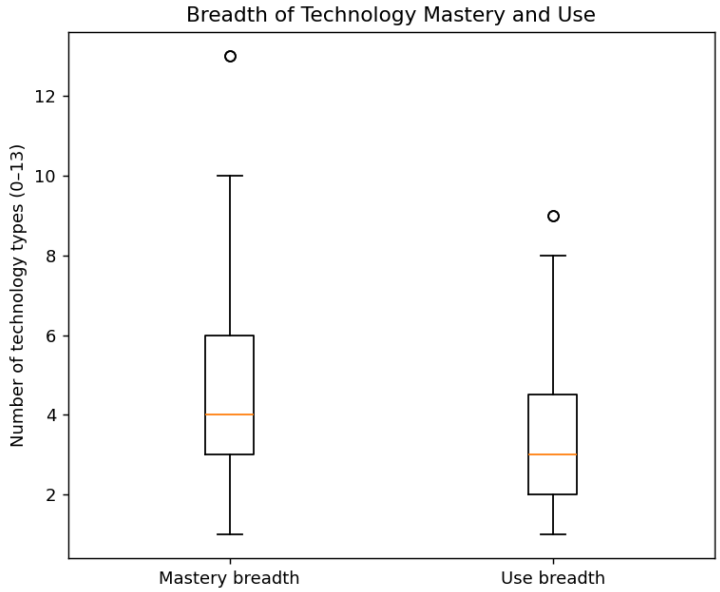


Figure 2. Breadth of technology mastery and use

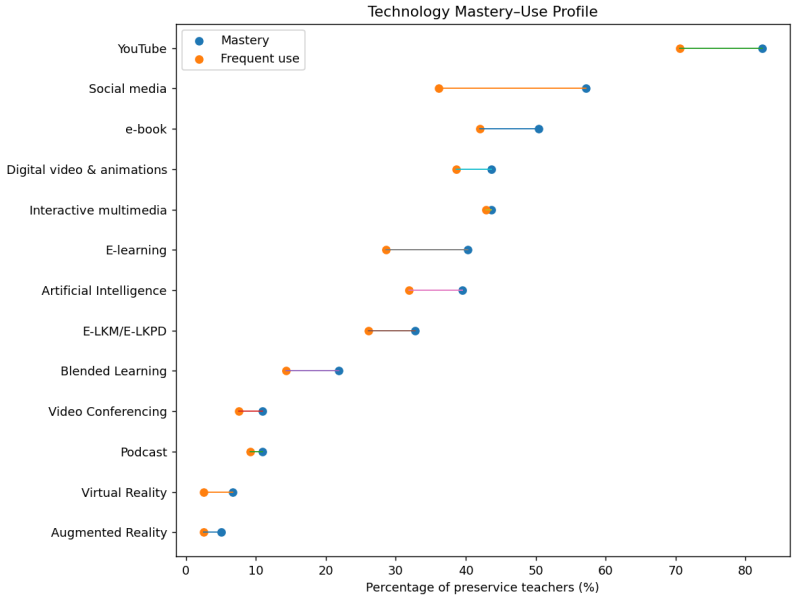


Figure 3. Technology master-use profile

The aggregate breadth difference was not uniform across technology categories (Figure 3; Table 5). YouTube had the highest proportion of frequent use (70.6%), so its statistically significant within-person mastery–use difference coexisted with widespread classroom use. Social media showed the largest gap, at 21.0 percentage points, indicating that self-reported mastery of this category was considerably more common than frequent instructional use. E-learning also retained a paired difference after Holm adjustment. By contrast, virtual reality and augmented reality showed low proportions for both self-reported mastery and frequent use, representing a different pattern from technologies that were relatively familiar but not routinely enacted.

Table 5. Technology-specific mastery and use

Technology	Mastery (%)	Use (%)	Gap (pp)	Holm-adjusted p
YouTube	82.3529	70.5882	11.7647	0.0157
Interactive multimedia	43.6975	42.8571	0.8403	1.0000
e-book	50.4202	42.0168	8.4034	0.5000

Technology	Mastery (%)	Use (%)	Gap (pp)	Holm-adjusted p
Digital video & animations	43.6975	38.6555	5.0420	1.0000
Social media	57.1429	36.1345	21.0084	0.0003
Artificial Intelligence	39.4958	31.9328	7.5630	0.5000
E-learning	40.3361	28.5714	11.7647	0.0283
E-LKM/E-LKPD	32.7731	26.0504	6.7227	0.3472
Blended Learning	21.8487	14.2857	7.5630	0.1172
Podcast	10.9244	9.2437	1.6807	1.0000
Video Conferencing	10.9244	7.5630	3.3613	1.0000
Virtual Reality	6.7227	2.5210	4.2017	0.5000
Augmented Reality	5.0420	2.5210	2.5210	1.0000

Note. Gap pp = mastery percentage minus frequent-use percentage in percentage points. P values are exact McNemar tests adjusted by the Holm method.

Habit showed the largest conditional associations with both endogenous constructs and an indirect association with use behavior through behavioral intention. The pattern is consistent with Avcı (2022) and Xie et al. (2024), but it is not universal. Du & Liang (2024) found that habit did not predict teachers' continued intention to use virtual reality. In the present practicum context, a higher habit score may accompany repeated opportunities to use a relatively small set of technologies for recurring instructional activities such as demonstrations, material distribution, assessment, and communication. The reverse temporal interpretation is equally plausible in cross-sectional data, because repeated enactment can strengthen automaticity. The theoretical implication is therefore not that habit causes use, but that routinization is closely coupled with both willingness and reported enactment in this sample.

Perceived social expectations were conditionally associated with behavioral intention. This is broadly consistent with research on Indonesian preservice science teachers during teaching practice (Habibi et al., 2022) and South African preservice teachers considering virtual-reality classrooms (Ogegbo et al., 2024). Another Indonesian practicum survey found a strong relationship between behavioral intention and reported technology-integration behavior under an extended theory of planned behavior (Habibi et al., 2023). These convergent findings suggest that the social environment surrounding practicum deserves attention, while also cautioning against treating subjective norm, social influence, and reported use as identical constructs. The next step is to distinguish whose expectations, such as mentor teachers, peers, teacher educators, or school staff, are most salient for preservice vocational teachers.

Facilitating conditions were conditionally associated with use behavior without showing an independent association with behavioral intention. This pattern is consistent with the idea that practical access and support may be more closely coupled with enactment than with stated willingness. Xie et al. (2024) likewise found facilitating conditions related to use of a virtual-reality training system, whereas Bervell et al. (2021) did not locate their main role in a direct path to behavioral intention for Google Classroom. Indonesian studies also show that support-related constructs can operate differently across specific technologies and model specifications (Aminah et al., 2024; Riady et al., 2022; Wijaya et al., 2022). The present result should therefore be interpreted as context-specific evidence about reported use during practicum, not as a rule that support matters only after intention has formed.

Performance expectancy, effort expectancy, and motivation did not show statistically detectable independent associations with behavioral intention after the other predictors were considered. A nonsignificant partial path is not evidence that participants lacked those perceptions, especially given the lower post-hoc power for several small paths. The performance-expectancy result differs from Avcı (2022) and from UTAUT-family studies that report stronger expectancy paths in other educational technologies (Shandilya & Kumar, 2025; Talan et al., 2024), while Ogegbo et al. (2024) likewise found several expectancy-related paths nonsignificant for virtual-reality classrooms. Özbek et al. (2024) also found no direct path from ease of use to behavioral intention for a mind-mapping tool. In the present instrument, motivation reflects enjoyment or intrinsic appeal and should not be treated as interchangeable with the original UTAUT2 hedonic-motivation construct. Together, these contrasts suggest that the relative contribution of acceptance constructs can vary with technology, instructional purpose, measurement, and stage of use, and beliefs about particular media can vary within the same preservice teacher (Funke et al., 2025).

Broader UTAUT family evidence reinforces this contextual interpretation. Across Indonesian teacher and education settings, the prominence of performance expectancy, social influence, facilitating conditions, and behavioral intention differs across the *Merdeka Mengajar* platform, social-media use, biology teaching, virtual laboratories, and digital mathematics textbooks (Aminah et al., 2024; Riady et al., 2022; Sofwan, 2023;

Sukmawati et al., 2024; Wijaya et al., 2022). UTAUT-based studies of artificial-intelligence-supported lesson planning, mobile learning, and digital exam pads likewise report different combinations of expectancy, social, support, motivational, and habit constructs as salient (Ratumanan & Krismiyati, 2025; Shandilya & Kumar, 2025; Talan et al., 2024). Read together with Avcı (2022), Bervell et al. (2021), Du & Liang (2024), Ogegbo et al. (2024), Sawiji (2024), and Xie et al. (2024), this variation argues against treating any single acceptance path as invariant across educational technologies and populations. The contribution of the present model is consequently contextual rather than universal. It identifies the conditional pattern observed during vocational school practicum and connects that pattern to a separate, technology-specific mastery–use analysis.

The paired comparison addresses a theoretically different transition: from perceived technology repertoire to recurrent classroom enactment. Preservice vocational teachers reported a broader range of technologies as mastered than as frequently used, but the pedagogical meaning of this gap is not that every mastered tool should appear in every lesson. Instead, it marks the boundary between what candidates believe they can use and what becomes part of their recurring instructional repertoire under practicum conditions. Studies comparing self-reported and enacted or performance-assessed technological pedagogical knowledge likewise caution that perceived competence and demonstrated performance are not interchangeable (Max et al., 2022; Mourlam et al., 2021; Roll & Ifenthaler, 2021; von Kotzebue, 2022). The present measure therefore identifies a self-reported repertoire-to-enactment difference, not a competence deficit. For vocational teacher readiness, this distinction matters because appropriate digital integration requires selective alignment between a tool, an occupational learning objective, and the constraints of the teaching setting.

Category-level analysis also prevents the aggregate mastery-use difference from being treated as a single, uniform preparation problem. Distinct technology-use profiles have been documented among vocational teachers (Cattaneo et al., 2025) and across platforms in Indonesian vocational schools (Widarto et al., 2024), while audits of preservice teachers show that overall scores can obscure substantial differences at the level of specific technologies (Martin et al., 2024; Tomczyk et al., 2023). In the present study, YouTube was frequently used despite a significant paired difference. Social media showed a much larger gap between mastery and use, whereas e-learning showed a smaller difference. Very low self-reported mastery and use of virtual and augmented reality represent yet another pattern. These profiles imply different questions for teacher preparation, why a familiar tool is not selected, versus why an emerging tool is neither familiar nor used, rather than a single mandate to increase the frequency of all technology use.

These distinctions are important because technology categories are not interchangeable as teaching activities. Indonesian preservice teachers interviewed during online teaching practice reported different reasons for using WhatsApp and YouTube and for avoiding other social platforms (Kusuma, 2022). Educational use of social networks among teacher-education students in Spain likewise varied between consuming and producing content (Calderón-Garrido & Gil-Fernández, 2023). Learning objectives, school regulations, access, and mentor-teacher expectations are plausible influences on technology selection, as suggested by other practicum studies (Diaz et al., 2025; Lu et al., 2025). Technology use in teaching, particularly in vocational education, should therefore be aligned with specific tools and the learning objectives they are intended to support rather than with an expectation that every technology should be used more frequently.

For vocational teacher education, the practical contribution is to shift from generic exposure toward justified pedagogical enactment. Vocational lessons often combine conceptual explanation, procedural demonstration, guided practice, assessment, feedback, and workplace-oriented tasks. Preservice teachers therefore need opportunities to explain why a particular technology is appropriate for a particular learning objective and to evaluate whether it improves the task at hand. Authentic practice and reflection are emphasized in teacher-preparation research (Tondeur et al., 2025), modeling by teacher educators is associated with digital-competence development (Momdjian et al., 2025). Field experience is also related to preservice teachers' beliefs and practices (Nelson & Voithofer, 2022). These findings support structured opportunities to plan, enact, and reflect on technology-supported vocational lessons, but the present cross-sectional data does not demonstrate that repetition itself causes better integration. Scenario-based self-assessment can elicit more instruction-specific judgments (Vejvoda et al., 2023), while stronger evidence would require lesson artifacts, classroom observations, and explicit information about the occupational learning purpose supported by each technology.

Several limitations constrain the implications of these findings. The single-university, non-probability sample and uneven representation across the eight programs create potential selection bias and limit external generalization; a verified invitation denominator was unavailable, so nonresponse cannot be quantified. The acceptance constructs and the mastery/use checklist were self-reported, and no independent observational or performance-based validation was available. Measurement quality was acceptable at the construct level, but the FC1 loading of .516 and the near-threshold facilitating conditions–motivation heterotrait–monotrait estimate warrant caution. The post-hoc power results were strong for the largest observed paths but lower for several

small paths, so nonsignificant estimates cannot be interpreted as proof of no relationship. Cross-sectional data also prevent temporal ordering and causal inference. Finally, frequent use was not anchored to observed lesson counts, and broad technology categories can encompass different platforms and pedagogical purposes. Future studies should use larger multisite samples, prospectively justify sample size, follow candidates across practicum periods, combine self-reports with lesson plans and classroom observations, and directly measure infrastructure, mentor practices, and the learning purposes for which specific technologies are selected.

Conclusions

Digital readiness for vocational teaching is not captured by technology familiarity or intention alone. In this cross-sectional sample, higher habit scores co-occurred with higher behavioral-intention and use-behavior scores; social influence co-varied with behavioral intention; and facilitating conditions and behavioral intention co-varied with use behavior after the other specified predictors were considered. The two habit paths had the largest direct effect sizes ($f^2 = 0.187$ for behavioral intention and 0.254 for use behavior) and high post-hoc power, whereas several smaller paths were estimated with less sensitivity. Preservice vocational teachers also reported a broader mastery repertoire than the repertoire they frequently enacted, with Holm-adjusted category-level differences for social media, YouTube, and e-learning. Placing the acceptance model beside the paired category-level reports provides two complementary descriptive lenses: conditions associated with reported routine use and the breadth and composition of the self-perceived repertoire brought into practicum. The mastery–use difference is pedagogically meaningful as a repertoire-to-enactment distinction, not as proof of deficient competence or a requirement to use every available tool. Because the study is single-site, non-probability, self-reported, and cross-sectional, neither the structural paths nor the mastery–use differences support causal claims. Longitudinal, multisite research combining surveys with performance evidence and classroom observation is needed to establish when and why perceived mastery becomes purposeful vocational teaching practice.

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