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Perceived Digital Access Readiness, Digital Entrepreneurial Competence, and Digital Entrepreneurial Intention in Office Administration Education

Muhammad Choerul Umam[1*], Anton Subarno[1], Sandrotua Bali[2], and Ahmad Ziddan Wildan Al-Islami[2]

[1]Office Administration Education Study Programme, Faculty of Teacher Training and Education, Universitas Sebelas Maret, Surakarta, 57126, Indonesia
[2]Center for Teacher Education, National Tsing Hua University, Hsinchu, Taiwan
[3]Istanbul University, Istanbul, Türkiye

ABSTRACT

Purpose – This study examines whether digital entrepreneurial competence accounts for the entire association between perceived digital access readiness and digital entrepreneurial intention, as a recent full-mediation finding implies, among students of one Indonesian office administration education programme.
Design/methodology/approach – A near-census survey of 344 of 400 students (86.0%) at a public university in Surakarta was analysed with confirmatory factor analysis (including robust and ordinal checks), multiple regression, LMG relative-importance analysis, bias-corrected bootstrap decomposition of associations, multiple imputation, measurement-invariance tests across venture-status groups, and equivalent alternative orderings.
Finding/Results – Access readiness and competence jointly accounted for 41.3% of intention variance, and competence made the larger relative predictive contribution (69.2% versus 30.8%). Access readiness had an indirect association through competence (ab = .203, 95% CI [.152, .261]) and a direct association (c′ = .214, 95% CI [.129, .307]). Both held across robustness checks and in students with and without an existing online business, for whom scalar invariance was supported. However, the four access items were empirically inseparable from basic digital-literacy items, and alternative variable orderings fitted the data equally well.
Originality/Value – The study provides a TPB-informed, non-causal decomposition for a population not previously examined, shows that self-reported access measures can capture broader digital readiness, and specifies the objective-access and time-lagged designs needed to test whether competence transmits access effects.

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*Corresponding Author at:
Faculty of Teacher Training and Education, Universitas Sebelas Maret, Jalan Ir. Sutami 36A, Surakarta 57126, Indonesia.
E-mail address: mc_umam07@staff.uns.ac.id (Muhammad Choerul Umam)
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1. Introduction

Indonesia's platform economy has expanded the entry-level opportunities available to administrative graduates. Marketplace and social-commerce platforms have reduced the fixed costs of starting a venture and have changed how new businesses are created and run (Nambisan, 2017; Kraus et al., 2019). For students in office administration programmes (*Pendidikan Administrasi Perkantoran*), which have traditionally prepared graduates for salaried clerical work, digital self-employment has therefore become a realistic alternative. Whether these students intend to pursue that option, and which personal and material conditions are associated with that intention, matters for curriculum design.

Entrepreneurial intention is the most immediate psychological antecedent of venture behaviour. The theory of planned behaviour (TPB) explains intention through attitude, subjective norms, and perceived behavioural control (Ajzen, 1991, 2020), and meta-analytic and cross-cultural evidence supports its use in entrepreneurship research (Krueger et al., 2000; Liñán & Chen, 2009; Schlaegel & Koenig, 2014). Intention does not translate automatically into action, however (Gieure et al., 2020). In digital venturing, capability is consistently associated with intention, as shown for digital competencies (Bachmann et al., 2024; Lam et al., 2025), international digital capabilities (von Arnim & Mrozewski, 2020), internet entrepreneurial self-efficacy (Balgiu et al., 2024), fintech literacy (Nguyen et al., 2024), and broader individual digital characteristics (Elnadi & Gheith, 2023; Vu et al., 2024). Research on the digital divide shows, in parallel, that inequalities have shifted from whether people are connected to the quality and adequacy of their devices and connections, and that these material differences are linked to skills, uses, and outcomes (Scheerder et al., 2017; van Deursen & van Dijk, 2019; Aydin, 2021; Hampton et al., 2021; Ventrella & Cotnam-Kappel, 2024), including entrepreneurial orientation (Barra et al., 2024).

Most studies examine access and capability separately or combine them in a broader construct. Alshebami et al. (2025) are an important exception. Using covariance-based structural equation modelling with 217 female university students in Saudi Arabia, they found that digital literacy mediated the relationship between access to technology and digital entrepreneurial intention, and interpreted the result as showing that access is beneficial only when individuals can use it. Under that interpretation the association between access and intention runs entirely through capability.

Two considerations make this conclusion worth re-examining. Conceptually, access to devices and connectivity is an external enabling condition. In decomposed versions of the TPB, such facilitating conditions are antecedents of perceived behavioural control alongside self-efficacy rather than components of self-efficacy (Taylor & Todd, 1995; Ajzen, 2002; Venkatesh et al., 2003), so there is no theoretical requirement that the access–intention association disappear once capability is controlled. Methodologically, the labels "full" and "partial" mediation depend heavily on sample size and on whether a direct path reaches significance, so they are a weak basis for theoretical conclusions (Zhao et al., 2010; Rucker et al., 2011). A more informative question is how large the indirect and direct associations are and how precisely each is estimated.

This study addresses that question in one Indonesian office administration education programme in which platform use was widespread. Two features of the evidence define its scope. First, the access measure is a self-report that, in these data, could not be separated from basic digital-literacy items; the construct is therefore labelled *perceived digital access readiness* rather than infrastructure access. Second, all variables were measured on one occasion, so the

analysis decomposes associations and cannot establish whether competence transmits an effect of access. Contextual access conditions were not measured, and no low-access comparison group was included.

Within these limits, the study makes three contributions. First, it estimates both the indirect and the direct association between perceived digital access readiness and digital entrepreneurial intention, in unstandardised and standardised units, for a mixed-gender Indonesian programme population that has not been examined in this literature, and it reports the results separately for students with and without an existing online business. Second, it shows that self-reported access items can be empirically indistinguishable from basic digital-literacy items while remaining distinct from entrepreneurial competence, a finding with direct implications for how access should be measured. Third, it compares the relative predictive contributions of access readiness and competence with an LMG decomposition and a bootstrap test of their difference. The study does not test the TPB, and it does not claim that access conditions determine whether mediation is full or partial.

2. Literature Review & Hypothesis Development

2.1. A TPB-informed framework

Digital entrepreneurial intention is the extent to which an individual has formed a conscious plan to establish a digitally mediated business. In the TPB, intention is predicted by attitude, subjective norms, and perceived behavioural control (Ajzen, 1991; Fishbein & Ajzen, 2010). Perceived behavioural control is a psychological construct comprising two facets: self-efficacy, or confidence in one's ability to perform the behaviour, and perceived controllability, or the belief that performance is up to the actor (Ajzen, 2002). These facets are empirically separable and can relate differently to intention (Vamvaka et al., 2020).

The present model is TPB-informed rather than a test or extension of the TPB. Its position relative to the TPB architecture is as follows. Perceived digital access readiness is treated as an external facilitating condition of the kind that decomposed TPB models place *before* perceived behavioural control (Taylor & Todd, 1995; Venkatesh et al., 2003). Digital entrepreneurial competence approximates task-specific capability beliefs and is therefore related to the self-efficacy facet of perceived behavioural control, but it is not the complete construct. Intention is the outcome. Attitude, subjective norms, perceived controllability, and TPB self-efficacy as formally defined were not measured. The psychological mechanisms specified by the TPB are therefore not tested here, and the absence of attitude and subjective norms is one reason why a large share of intention variance is expected to remain unexplained.

2.2. Perceived digital access readiness

Perceived digital access readiness is defined as a student's perception that usable devices, digital platforms, and a stable internet connection are available whenever needed for digital activity. The definition has three features. First, the construct is perceived rather than objective; it is measured through self-reports, not device audits or connection tests. Second, it is an enabling condition, not perceived behavioural control. Third, the label "readiness" acknowledges that self-assessed ease of access is likely to reflect, in part, the user's ability to make that access work. This possibility was confirmed empirically in the present data (Section 4.2), and the more conservative label is used for that reason.

Research on the digital divide supports treating access as a variable even where nominal connectivity is high. The first-level divide has shifted from physical access towards material access, including the quality of devices, the stability of connections, and the costs of

maintaining them (van Deursen & van Dijk, 2019). Variation in access and skills is associated with differences in educational outcomes and aspirations (Hampton et al., 2021), access conditions shape information and communication technology literacy (Aydin, 2021), and institutions can reproduce digital inequality (Ventrella & Cotnam-Kappel, 2024). Among students, digital divide conditions have been linked to entrepreneurial orientation and technology adoption (Barra et al., 2024). Better perceived access may lower the practical cost of trying a digital venture and make that option appear more feasible.

H1. Perceived digital access readiness is positively associated with digital entrepreneurial intention.

2.3. Digital entrepreneurial competence

Digital entrepreneurial competence is the perceived capability to perform the tasks required for digital venturing. It combines a digital facet, such as operating platforms, producing content, and managing transactions, with an entrepreneurial facet, such as recognising opportunities, assessing demand, managing risk, and sustaining customer relationships. The construct is close to self-efficacy in Bandura's (1997) sense of a belief in one's ability to organise and execute the actions required by a task. Its association with digital entrepreneurial intention is supported across contexts and measures, including digital competencies (Bachmann et al., 2024), social cognitive models of digital competence (Lam et al., 2025), internet entrepreneurial self-efficacy (Balgiu et al., 2024), digital capital (Mir et al., 2023), facilitating conditions and digital self-efficacy (Kivuyo et al., 2025), fintech literacy (Nguyen et al., 2024), and readiness for digital business among Indonesian students (Wardoyo et al., 2025).

H2. Digital entrepreneurial competence is positively associated with digital entrepreneurial intention.

Because capability beliefs concern the behaviour itself, whereas enabling conditions concern the circumstances in which it would be performed, competence is expected to be the more proximal predictor. The two predictors are correlated, so their relative contribution cannot be read from regression weights alone (Johnson & LeBreton, 2004) and is stated in terms of an LMG decomposition. The joint explanatory power of the two predictors is reported as a property of the model rather than as a separate hypothesis.

H3. Digital entrepreneurial competence accounts for a larger LMG share of the explained variance in digital entrepreneurial intention than perceived digital access readiness.

2.4. Indirect and direct associations

The statistical model orders the variables from access readiness to competence to intention. One rationale for this ordering is that better access gives students more opportunities to practise digital and commercial tasks and thereby to build capability beliefs. The reverse orderings are equally plausible, however. Students who already intend to start a venture may acquire better devices and connections, and students with stronger competence may judge the same resources as more adequate. Reciprocal relationships are also possible. Because all three constructs were measured on one occasion, the ordering is a modelling choice, not an identified sequence, and Section 4.8 reports alternative orderings for that reason (MacCallum et al., 1993; Thoemmes, 2015).

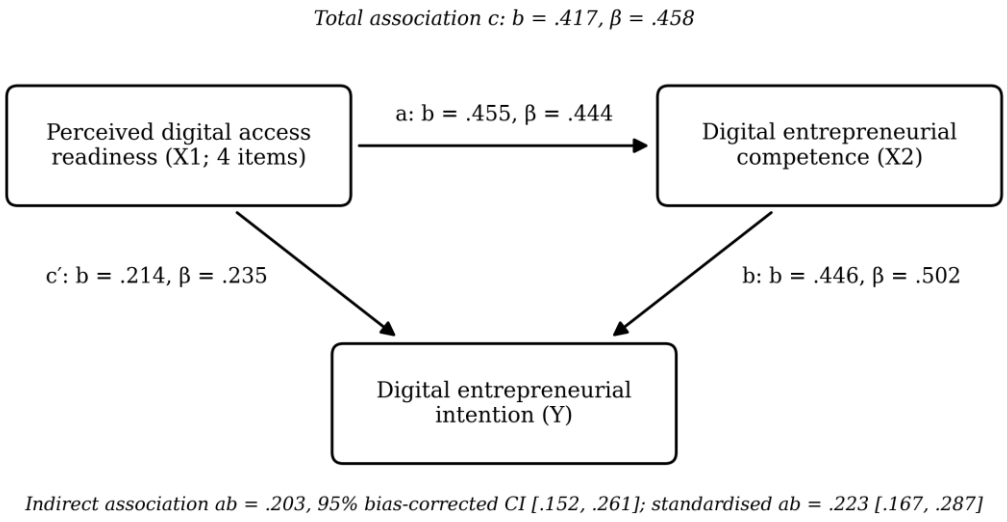
Given this ordering, the disputed question is whether the component of the access–intention association that is shared with competence accounts for the whole association, as the interpretation of Alshebami et al. (2025) implies. Two arguments suggest that a direct component may remain. First, enabling conditions and capability beliefs are distinct

antecedents of perceived behavioural control rather than stages of a single chain (Taylor & Todd, 1995; Ajzen, 2002). Second, where most students have crossed a basic access threshold, remaining differences may indicate how freely they can experiment rather than whether they can participate at all. Because the full/partial distinction should not be decided by the significance of the direct path alone (Zhao et al., 2010; Rucker et al., 2011), the two components are stated as separate, estimable hypotheses.

H4. Perceived digital access readiness has a positive indirect association with digital entrepreneurial intention through digital entrepreneurial competence (ab > 0).

H5. Perceived digital access readiness retains a positive direct association with digital entrepreneurial intention after digital entrepreneurial competence is included (c′ > 0).

Figure 1. Research model with estimated coefficients (n = 344)



Notes: Unstandardised (b) and standardised (β) coefficients. Arrows show the order specified in the statistical model; with cross-sectional data they do not establish causal direction, and alternative orderings fit equally well (Table 7).
Source: Data processed (2026).

3. Methodology

3.1. Design, population, and sampling

The study used a quantitative cross-sectional survey. This design supports inference about association and relative predictive contribution, not causation. The population comprised all 400 undergraduates enrolled in the Office Administration Education Study Programme at Universitas Sebelas Maret, Surakarta, Indonesia, in the 2022 to 2025 intake cohorts. Every student was invited, so the sampling frame coincided with the programme population. Of the 400 students, 350 returned the questionnaire (87.5%). Six respondents selected the same option for all 39 items (four chose 5 and two chose 4 throughout) and were excluded from the primary analysis; a sensitivity analysis including them is reported. The analytic sample comprised 344 students (86.0% of the population).

Because the design is a near-census rather than a probability sample, the main threat to validity is selective participation rather than sampling error. The survey was anonymous, so nonrespondents could not be compared with respondents, and the possibility that they differed in access, competence, or intention cannot be excluded (Groves, 2006). The findings

therefore describe this programme, and generalisation to other programmes or institutions is a question for replication. An a priori power analysis for multiple regression with two predictors (α = .05, power = .80, f^2 = 0.15) indicated a minimum of 68 participants (Faul et al., 2009).

The sample included 82 students from the 2022 cohort (23.8%), 89 from 2023 (25.9%), 95 from 2024 (27.6%), and 78 from 2025 (22.7%). Women comprised 66.3% (n = 228), and the mean grade point average was 3.41 (SD = 0.30). A total of 123 respondents (35.8%) already operated an online business, and 95 (27.6%) had attended digital training. The most frequently reported primary platform was TikTok (27.3%), followed by Instagram (23.0%), Shopee or Tokopedia (19.2%), and WhatsApp (18.6%); 11.9% used no platform. The platform-use rate (88.1%) documents widespread use but is not a measure of device quality, affordability, bandwidth, or freedom from access constraints.

3.2. Data collection and ethics

Data were collected from February to March 2026 through a Google Forms questionnaire distributed by class coordinators and WhatsApp groups. Participation was voluntary and anonymous, all respondents gave informed consent, and no identifying information was collected. The research ethics committee of Universitas Sebelas Maret approved the study (approval number 463/UN27.22/PT.01.03/2026). Following Podsakoff et al. (2003, 2012), anonymity was emphasised, predictor and criterion items were placed in separate sections, and respondents were told that there were no right or wrong answers.

3.3. Measures

All items used five-point scales from 1 (strongly disagree) to 5 (strongly agree). Supplementary Material S1 reproduces the Indonesian wording of all 39 items together with an English translation checked for semantic equivalence. A three-member panel of entrepreneurship lecturers, office administration education lecturers, and digital entrepreneurship practitioners assessed content validity; Aiken's V ranged from 0.78 to 0.94.

Perceived digital access readiness (X1)

The questionnaire contained 12 items in a section headed as digital literacy, covering accessibility (AKS1–AKS3), network and connectivity (JAR1–JAR3), digital communication (KOM1–KOM3), and information processing (INF1–INF3). The four-item focal specification is a *post-data-collection refinement*. It was introduced during the second round of peer review, after results for the original 12-item composite had been reported in earlier versions of this manuscript, in response to a reviewer's concern that several items described capability rather than access. The hypotheses and the structure of the analysis were not changed. Each item was then re-examined against the definition in Section 2.2. Four items describe access conditions: ease of access to a device (AKS1), access to platforms whenever needed (AKS2), adequacy of one's devices (AKS3), and a stable internet connection (JAR1). A sample item is "Saya memiliki akses jaringan internet yang stabil untuk menjalankan aktivitas digital" [I have a stable internet connection for my digital activities]. The other eight items describe resolving connection problems (JAR2), using networks to extend relationships (JAR3), communicating online (KOM1–KOM3), and finding, verifying, and organising information (INF1–INF3). Because the refinement was made after the data were seen, the original 12-item composite is reported in parallel throughout.

Digital entrepreneurial competence (X2)

Was measured with 15 items on digital initiative (seven items) and e-commerce self-efficacy (eight items), for example "Saya percaya diri dapat mengelola transaksi penjualan melalui

platform e-commerce/marketplace" [I am confident that I can manage sales transactions through e-commerce or marketplace platforms]. **Digital entrepreneurial intention (Y)** was measured with 12 items, for example "Saya memiliki keinginan yang kuat untuk menjalankan usaha berbasis digital" [I have a strong desire to operate a digitally based business].

Composite scores are unit-weighted item means. Loadings within each scale were similar, unit weights do not capitalise on sample-specific estimates, and the means correlated .995 (access readiness), .999 (competence), and .999 (intention) with maximum-likelihood factor scores. A latent-variable model is also reported.

3.4. Data analysis

Missing data. After screening, 153 of 13,416 item responses (1.14%) were missing. In the primary analysis, a missing item was replaced with the respondent's mean on the remaining items of the same scale. Because this can understate variability when data are not missing completely at random (Enders, 2022), Little's (1988) test was applied to each scale, respondents with and without missing responses were compared, and multiple imputation by chained equations was run at the item level (20 imputations; values bounded to 1–5 and rounded) with estimates pooled by Rubin's rules (Rubin, 1987; van Buuren & Groothuis-Oudshoorn, 2011).

Measurement. Analyses included corrected item-total correlations, Cronbach's alpha, exploratory factor analysis with parallel analysis (Horn, 1965), and confirmatory factor analysis (CFA) by maximum likelihood (ML), judged against conventional criteria (Hu & Bentler, 1999). Composite reliability (CR), average variance extracted (AVE), the Fornell–Larcker criterion (Fornell & Larcker, 1981), and HTMT ratios (Henseler et al., 2015) were computed, and the focal three-factor model was compared with one-factor and merged-factor alternatives and re-estimated in two random halves. Because the items are five-point ordinal responses, two checks were added: a Satorra–Bentler scaled test statistic for non-normality (Satorra & Bentler, 1994), and a CFA of the polychoric correlation matrix. Five-category items are usually adequately treated as continuous under robust ML (Rhemtulla et al., 2012; Li, 2016); a full WLSMV estimation with a mean-and-variance-adjusted test could not be implemented in the analysis pipeline, so fit indices from the polychoric model are treated as approximate. Measurement invariance across students with and without an existing online business was tested with multi-group CFA at the configural, metric, and scalar levels, using ΔCFI ≤ .010 and ΔRMSEA ≤ .015 as criteria (Cheung & Rensvold, 2002; Chen, 2007).

Structural analyses. The associations were estimated with three ordinary least squares equations:

$$M = i_1 + aX + e_1 \quad (1)$$

$$Y = i_2 + c'X + bM + e_2 \quad (2)$$

$$Y = i_3 + cX + e_3, \text{ with } c = c' + ab \quad (3)$$

X denotes perceived digital access readiness, M digital entrepreneurial competence, and Y digital entrepreneurial intention. The indirect association ab was tested with bias-corrected confidence intervals from 10,000 bootstrap resamples (Hayes, 2022) and is reported in unstandardised and completely standardised form (Preacher & Kelley, 2011). The share ab/c is reported descriptively, as a decomposition of the observed total association, not as the proportion of an effect of access transmitted through competence. HC3 standard errors were used as a check on Equation 2. Relative importance was estimated with the LMG procedure (Lindeman et al., 1980; Grömping, 2006), with bootstrap intervals for the difference between predictors in absolute R^2 units and in shares of explained variance. Because Equations 1 and 2

form a just-identified model, every alternative ordering of the three variables reproduces the observed covariances equally well; five orderings were therefore estimated to show what the data can and cannot distinguish (MacCallum et al., 1993; Thoemmes, 2015). Robustness analyses used multiple imputation, complete cases, inclusion of the six invariant responders, the 12-item composite, a latent-variable structural model, adjustment for venture experience, digital training, cohort, gender, and grade point average, and separate estimation by venture status. Analyses were run in Python 3.12 (statsmodels, scikit-learn, factor_analyzer, and semopy; Igolkina & Meshcheryakov, 2020) with fixed random seeds; the multi-group and robust CFA routines were written for this study and checked against semopy for the single-group model.

4. Result and Discussion

4.1. Data screening and missing data

Item-level missingness ranged from 0.3% to 2.3%; by scale, 1.53% of access-readiness, 1.10% of competence, and 1.02% of intention responses were missing. Of the 344 respondents, 220 had no missing responses, 99 had one, 21 had two, and 4 had three. Little's test did not reject the hypothesis of missingness completely at random for the X1 items, $\chi^2(162) = 181.27$, $p = .143$, the competence items, $\chi^2(248) = 221.25$, $p = .888$, or the intention items, $\chi^2(182) = 181.21$, $p = .503$. Respondents with and without missing responses did not differ in cohort, gender, venture experience, digital training, platform, grade point average, access readiness, or competence (all $p > .08$), but those with missing responses reported slightly higher intention (3.43 versus 3.29, $t = -2.22$, $p = .027$). Multiple imputation was therefore treated as the principal check on the primary estimates.

4.2. Measurement model

All items exceeded the corrected item-total threshold of .30, and parallel analysis retained one factor for each scale. The three-factor model fitted well (Table 1, M1), with standardised loadings between .571 and .758 (Appendix Table A1). It clearly outperformed models in which all items formed one factor, access readiness and competence were merged, or competence and intention were merged (all $p < .001$), and it was stable across random halves. The Satorra–Bentler scaling factor was 1.002, so the robust statistic was virtually identical to the ML statistic, $\chi^2(431) = 441.79$, $p = .349$.

Table 1. Confirmatory factor analysis: competing models (n = 344)

Model	χ^2	df	CFI	TLI	RMSEA	SRMR	$\Delta\chi^2$ (Δdf) vs M1
M1. Access readiness (4 items), competence, intention	442.87	431	.997	.997	.009	.036	—
M1, Satorra–Bentler scaled	441.79	431	—	—	.009	—	—
M1, polychoric correlations (approximate)	745.60	431	.946	.942	.046	.041	—
M2. One factor	1231.89	434	.825	.813	.073	.078	789.02 (3)***
M3. Access readiness and competence merged	677.69	433	.946	.942	.041	.053	234.82 (2)***

Model	χ^2	df	CFI	TLI	RMSEA	SRMR	$\Delta\chi^2$ (Δdf) vs M1
M4. Competence and intention merged	1028.12	433	.870	.860	.063	.072	585.25 (2)***
M5. As M1 with 12-item X1	709.29	699	.998	.998	.007	.037	—
M6. As M5, four access and eight literacy items separated	706.28	696	.998	.998	.007	.036	vs M5: 3.01 (3)
M1, random half A (n = 172)	424.44	431	1.000	1.000	.000	.048	—
M1, random half B (n = 172)	456.02	431	.990	.989	.018	.049	—

*Notes: ML estimation unless stated. The polychoric model applies the ML discrepancy to polychoric correlations, so its χ^2 and fit indices are approximate. In M6 the latent correlation between the four access items and the eight literacy-oriented items was 1.01 ($\Delta\chi^2$ p = .390). *** p < .001.*
Source: Data processed (2026).

Table 2. Construct-level reliability and validity

Construct	Loadings (ML)	α	CR	AVE	√AVE	Loadings (polychoric)	AVE (polychoric)
Access readiness	.618–.725	.769	.771	.458	.677	.664–.778	.523
Competence	.639–.758	.936	.937	.497	.705	.669–.797	.551
Intention	.571–.672	.890	.891	.406	.637	.603–.712	.452

Notes: Latent correlations (ML): access readiness–competence .528, access readiness–intention .539, competence–intention .667 (polychoric: .530, .541, .669). HTMT: .523, .553, and .665. CR (polychoric): .814, .948, and .908.
Source: Data processed (2026).

Construct-level validity is adequate but not fully resolved (Table 2). CR exceeded .77 for every construct and all HTMT ratios were below .70, but AVE was below .50 for all three constructs under ML. The Fornell–Larcker criterion was met for access readiness and competence but not for intention, whose √AVE (.637) was slightly lower than its latent correlation with competence (.667). In the polychoric solution, which accounts for the ordinal response format, loadings and AVE were higher (AVE .523, .551, and .452), and the criterion for intention was met only marginally (√AVE = .673 against r = .669). Intention therefore remains below the conventional AVE threshold under both estimators. One likely reason is that the 15-item competence scale and the 12-item intention scale contain conceptually similar items, so that length raises reliability without raising the average item–construct overlap; loadings of .57–.67 for several intention items are consistent with this. Given the competing-model results, competence and intention are treated as distinct, but their overlap is acknowledged, and item refinement is left to future studies with independent samples rather than optimised on the present data.

The X1 analyses confirm the construct-content concern. The four access items and the eight literacy-oriented X1 items could not be separated (M6 versus M5, $\Delta\chi^2(3) = 3.01$, p = .390; latent r = 1.01). In this sample, reports of device and connection access were indistinguishable from reports of basic digital communication and information skills, which is why the construct is labelled access readiness. All X1 items were nevertheless distinct from entrepreneurial competence: in an exploratory analysis of the X1 and X2 items together, every X1 item loaded on a separate factor, with cross-loadings of .13 or less.

Measurement invariance across venture-status groups was supported (Table 3). For the full three-factor model and for the intention scale alone, constraining loadings (metric) and then intercepts (scalar) to equality produced changes well within the ΔCFI and ΔRMSEA criteria and non-significant $\Delta\chi^2$ values. Under scalar invariance, the latent mean of intention did not differ between groups (standardised difference = .02).

Table 3. Measurement invariance across students without (n = 221) and with (n = 123) an existing online business

Model	χ^2	df	CFI	RMSEA	SRMR	$\Delta\chi^2$ (Δdf), p	ΔCFI	ΔRMSEA
Three-factor: configural	901.09	862	.991	.016	.051	—	—	—
Three-factor: metric	931.43	890	.991	.016	.063	30.34 (28), .347	−.001	.000
Three-factor: scalar	951.10	918	.993	.015	.063	19.67 (28), .876	+.002	−.002
Intention only: configural	125.35	108	.988	.031	.042	—	—	—
Intention only: metric	140.23	119	.985	.032	.063	14.88 (11), .188	−.003	+.002
Intention only: scalar	149.19	130	.986	.029	.063	8.96 (11), .626	+.002	−.003

Notes: Multi-group ML CFA with mean structure. Each Δ is relative to the preceding, less constrained model.
Source: Data processed (2026).

4.3. Descriptive statistics and assumptions

Table 4. Descriptive statistics and correlations (n = 344)

Variable	M	SD	Skew	Kurtosis	1	2	3
1. Access readiness (4 items)	3.85	0.65	−0.14	−0.66	(.769)		
2. Digital entrepreneurial competence	3.56	0.66	−0.34	−0.22	.444	(.936)	
3. Digital entrepreneurial intention	3.34	0.59	−0.16	−0.21	.458	.607	(.890)
X1, original 12 items (sensitivity)	3.73	0.61	−0.09	−0.61	.921	.508	.508

Notes: Cronbach's alpha on the diagonal. Kurtosis is excess kurtosis. All correlations p < .001.
Source: Data processed (2026).

All composites were approximately symmetric. The outcome equation met the regression assumptions (Shapiro–Wilk W = .996, p = .468; Breusch–Pagan LM = 1.53, p = .465; RESET F = 0.01, p = .937; VIF = 1.25). Residuals of the competence equation deviated slightly from normality (W = .986, p = .002; skewness = −0.44), which is of little consequence at n = 344, and the indirect association was tested with bootstrap intervals. HC3 standard errors gave the same conclusions as ordinary standard errors. Harman's first unrotated component accounted for 37.4% of the variance in the 31 focal items, and the one-factor CFA fitted far worse than the three-factor model; neither diagnostic rules out common-method variance (Podsakoff et al., 2012; Kock et al., 2021).

4.4. Regression and relative predictive contribution

The regression model was significant, $F(2, 341) = 119.84$, $p < .001$, $R^2 = .413$, adjusted $R^2 = .409$, $f^2 = 0.70$. Access readiness ($\beta = .235$) and competence ($\beta = .502$) were both positively associated with intention (both $p < .001$), supporting H1 and H2 (Table 5).

Table 5. Regression of digital entrepreneurial intention and LMG decomposition (n = 344)

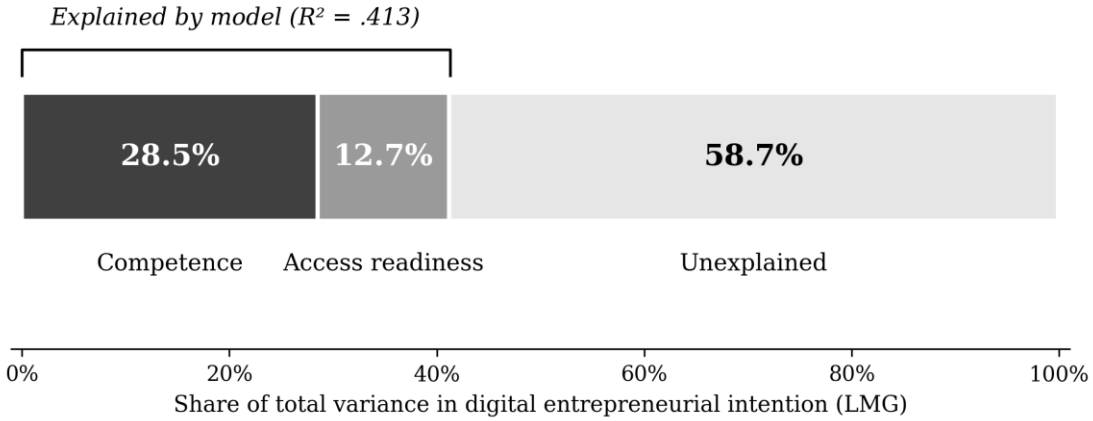
Predictor	b	SE	95% CI	HC3 SE	β	t	LMG R^2	Share
Constant	0.929	0.165	[0.604, 1.254]	0.167	—	5.63	—	—
Access readiness	0.214	0.042	[0.131, 0.297]	0.045	.235	5.07	.127	30.8%
Competence	0.446	0.041	[0.365, 0.527]	0.038	.502	10.85	.285	69.2%
Competence minus access readiness							.158 [.058, .253]	38.4 [14.5, 59.2]

Notes: $R^2 = .413$; adjusted $R^2 = .409$; $F(2, 341) = 119.84$, $p < .001$. Both slopes $p < .001$. LMG intervals are bias-corrected from 10,000 bootstrap resamples; the first refers to absolute R^2 units and the second to percentage points of the explained variance.

Source: Data processed (2026).

Competence contributed 28.5 and access readiness 12.7 percentage points of intention variance, or 69.2% and 30.8% of the explained variance (Figure 2). Both the absolute difference (.158, 95% CI [.058, .253]) and the difference in shares (38.4 points, 95% CI [14.5, 59.2]) excluded zero, supporting H3. These values describe relative predictive contribution within this model and sample, not which variable would change intention more if it were changed.

Figure 2. LMG decomposition of the variance in digital entrepreneurial intention



Source: Data processed (2026).

4.5. Indirect and direct associations

Table 6. Decomposition of the access readiness–intention association (n = 344)

Path	b	SE	Bias-corrected 95% CI	β	p
a: access readiness → competence	.455	.050	[.356, .552]	.444	< .001

Path	b	SE	Bias-corrected 95% CI	β	p
b: competence → intention, controlling X	.446	.041	[.370, .518]	.502	< .001
c: access readiness → intention (total)	.417	.044	[.331, .509]	.458	< .001
c′: access readiness → intention, controlling M	.214	.042	[.129, .307]	.235	< .001
ab: indirect association	.203	.027	[.152, .261]	.223 [.167, .287]	CI excl. 0

Notes: OLS standard errors; the SE of ab is the bootstrap standard deviation (10,000 resamples). Arrows denote the specified model order, not causal direction. The indirect share of the observed total association (ab/c) was 48.7%, 95% CI [36.2%, 64.3%].
Source: Data processed (2026).

The indirect association through competence was positive, ab = .203, 95% CI [.152, .261] (standardised ab = .223), supporting H4, and the direct association remained positive, c′ = .214, 95% CI [.129, .307], supporting H5 (Table 6; Figure 1). About half (48.7%) of the observed total association was shared with competence. This figure is a decomposition of a covariance, not the proportion of an effect of access readiness transmitted through competence.

4.6. Robustness and venture-status groups

Table 7. Robustness, venture-status groups, and alternative orderings

Specification	n	ab [95% CI]	c′ [95% CI]	R^2
A. Robustness (unstandardised)				
Primary (person-mean replacement)	344	.203 [.152, .261]	.214 [.129, .307]	.413
Multiple imputation (m = 20)	344	.203 [.149, .257]	.211 [.123, .299]	.414
Complete cases	220	.208 [.151, .277]	.226 [.121, .340]	.425
Including six invariant responders	350	.223 [.168, .282]	.223 [.136, .312]	.439
Original 12-item X1	344	.231 [.176, .291]	.261 [.169, .364]	.422
Covariate-adjusted	344	.163 [.116, .217]	.217 [.133, .309]	.431
Latent-variable SEM (standardised)	344	.279 [.213, .360]	.258 [.120, .385]	—
B. Venture-status groups (unstandardised)				
No existing online business	221	.181 [.122, .253]	.260 [.150, .382]	.406
Existing online business	123	.240 [.148, .352]	.159 [.016, .292]	.452
C. Alternative orderings (standardised; all $\chi^2 = 0$, df = 0)		Indirect [95% CI]	Direct [95% CI]	
Access readiness → competence → intention (focal)	344	.223 [.167, .287]	.235 [.142, .338]	
Competence → access readiness → intention	344	.104 [.061, .163]	.502 [.417, .584]	
Access readiness → intention → competence	344	.234 [.175, .304]	.210 [.111, .306]	
Intention → competence → access readiness	344	.160 [.084, .238]	.299 [.183, .413]	

Specification	n	ab [95% CI]	c′ [95% CI]	R^2
Competence → intention → access readiness	344	.181 [.109, .261]	.263 [.139, .379]	

Notes: Bias-corrected bootstrap intervals (10,000 resamples; 1,000 for the latent model). Multiple-imputation intervals use Rubin's rules (fraction of missing information ≤ .013). Covariates: venture experience, digital training, cohort, gender, and grade point average. In Panel C the first-named variable is the predictor, the second the intervening variable, and the third the outcome.
Source: Data processed (2026).

The indirect and direct associations were positive, with intervals excluding zero, in every robustness specification (Table 7, Panel A). Multiple imputation reproduced the primary estimates almost exactly, and the latent-variable model, which corrects for measurement error, produced the same pattern. After covariate adjustment, the indirect association was smaller (ab = .163) and the direct association virtually unchanged. No covariate was significantly associated with intention, whereas grade point average was positively associated with competence (b = .707, p < .001). When the four access items and the eight literacy-oriented X1 items were entered together, their composites correlated .82; the access items had no reliable unique association with intention (b = .091, HC3 p = .147), whereas the literacy-oriented items retained a small one (b = .170, p = .014). The direct association therefore cannot be attributed specifically to material access rather than to the broader digital readiness that the X1 items jointly reflect.

Because more than a third of respondents already operated an online business, the model was estimated separately by venture status (Panel B). In students without a business, for whom the intention items most plausibly describe a plan to start a venture, both components were clearly positive (ab = .181; c′ = .260). In students with a business, the indirect component was somewhat larger (ab = .240) and the direct component smaller but still above zero (c′ = .159, 95% CI [.016, .292]). Interaction tests did not show that venture status modified any path (all HC3 p > .17). Students with a business reported slightly lower access readiness than those without (3.74 versus 3.91, d = −0.26, p = .024), but their intention was the same (3.35 versus 3.34, p = .880).

All five orderings of the three variables reproduced the observed covariances exactly, and each produced a significant indirect association (Panel C). The data therefore do not favour the focal ordering over its alternatives. For example, competence could equally be treated as the predictor, with a smaller indirect component through access readiness. The focal ordering rests on the theoretical rationale in Section 2.4, not on the data.

4.7. Discussion

In this single programme, perceived digital access readiness was associated with digital entrepreneurial intention through a component shared with competence and through a direct component of similar size. The pattern was stable across missing-data treatments, sample definitions, X1 specifications, estimators, covariates, and venture-status groups. Two findings limit what this means. The access items could not be separated from basic digital-literacy items, and the covariance structure does not identify the ordering of the variables.

Alshebami et al. (2025) concluded that female students benefited from access to technology only when they possessed digital literacy. The present results agree with part of that account, since about half of the association was shared with capability, but a direct component of similar size remained. Several explanations for the difference are possible, and the design cannot choose among them. *Population:* the earlier study examined female students in Saudi

Arabia, whereas this study examined a mixed-gender Indonesian programme. *Operationalisation:* the earlier mediator was digital literacy, whereas here literacy-type items fell within the predictor and the mediator was entrepreneurial competence; different allocations of literacy content can by themselves change how an association is divided. *Estimator:* measurement error in a composite mediator tends to understate indirect and overstate direct components, but the latent-variable model gave the same pattern, so this explanation seems unlikely on its own. *Institutional and cultural context* may also differ. *Access conditions:* where basic access is widespread, remaining variation may reflect latitude to experiment; this study did not measure access conditions, and platform use is an imperfect proxy. A test of this last possibility would require objective access measures across institutions or regions and a pre-specified multi-group comparison or moderated mediation test (Hayes, 2015).

Competence made the larger relative predictive contribution, consistent with evidence that digital competence, self-efficacy, and digital capital are associated with digital entrepreneurial intention (Bachmann et al., 2024; Balgiu et al., 2024; Kivuyo et al., 2025; Lam et al., 2025; Mir et al., 2023). The LMG decomposition describes how explained variance is shared between two correlated self-reports in one sample; it should not be used to rank investments in capability or infrastructure.

The venture-status results address a conceptual concern about the outcome. For students without a business, the intention items most plausibly measure nascent intention; for students with a business, they may capture continuation or growth intention. Scalar invariance indicates that the items relate to the latent variable in the same way in both groups, so mean and path comparisons are technically justified. Invariance does not, however, show that the construct means the same thing in both groups. Item wording such as planning steps "to start a digital business in the future" fits nascent intention better than continuation intention. The near-identical intention means of the two groups may reflect this ambiguity.

Theoretically, the results are consistent with treating access readiness as an enabling condition that is related to, but not exhausted by, capability beliefs, as in decomposed accounts of perceived behavioural control (Taylor & Todd, 1995; Ajzen, 2002). Because the TPB constructs themselves were not measured, the results cannot show that access operates through controllability beliefs, nor whether it adds to attitude, subjective norms, and perceived behavioural control. Practically, the findings suggest two propositions for testing rather than conclusions for resource allocation: that structured practice in digital-venture tasks would raise competence and, through it, intention, and that reducing device and connectivity constraints would be associated with higher intention independently of competence. Both require experimental or time-lagged evaluation, and intention itself is not behaviour (Gieure et al., 2020).

5. Conclusion and Suggestion

In a near-census of one Indonesian office administration education programme, perceived digital access readiness was associated with digital entrepreneurial intention both through a component shared with digital entrepreneurial competence and directly, and competence made the larger relative predictive contribution. These results held in students with and without an existing online business. They are limited to one programme and to cross-sectional self-reports; the access measure could not be separated from basic digital literacy, and alternative orderings of the variables fit the data equally well. Within these limits, the data do

not match a pattern in which capability accounts for the entire access–intention association. Programme staff may treat capability development and access support as complementary, while recognising that neither has been shown to cause changes in intention.

6. Limitations and Future Research

First, the construct-content limitation is central to interpretation. The four-item access specification was a post-data-collection refinement, the items are self-reports, and they were inseparable from basic digital-literacy items. Future studies should measure access with indicators anchored in observable resource conditions, such as device ownership and adequacy, broadband stability, data affordability, frequency of network interruptions, and platform availability, alongside a separate measure of digital literacy.

Second, cross-sectional data cannot identify the ordering of the variables. Reverse and reciprocal relationships are plausible, and all orderings fitted equally well. A time-lagged design measuring access at T1, competence at T2, and intention or venture behaviour at T3, or an intervention study, is needed to test whether competence transmits an effect of access (Maxwell & Cole, 2007).

Third, convergent validity is adequate but not strong. AVE was below .50 under ML for all constructs, and for intention also under the polychoric solution, and the Fornell–Larcker criterion for intention relative to competence was met only marginally in the polychoric solution. Shorter scales with less redundant items should be developed and validated in independent samples.

Fourth, the model is TPB-informed but omits attitude, subjective norms, perceived controllability, and formally defined self-efficacy, and it leaves 58.7% of intention variance unexplained. A comparative model including access, digital competence, attitude, subjective norm, self-efficacy, controllability, and intention would show whether access contributes beyond the conventional TPB predictors. Family entrepreneurial background, risk propensity, start-up capital, and entrepreneurship education are further candidates (Wardoyo et al., 2025).

Fifth, all variables were self-reported on one occasion. Procedural remedies and diagnostic tests reduce, but do not remove, concern about common-method variance (Podsakoff et al., 2012). Sixth, the study covers one programme at one university, and nonrespondents could not be compared with respondents. Finally, nascent and continuation intention were not measured separately. Future research should distinguish nascent digital entrepreneurial intention among non-entrepreneurs from continuation or growth intention among existing student entrepreneurs.

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Declaration of AI and AI-assisted technologies in the writing process

During the preparation of this work, the author used Claude (Anthropic) to support statistical analysis, drafting, and language editing. After using this tool, the author reviewed and edited the content as needed and takes full responsibility for the content of the publication.

Declaration of interest and data availability

The author declares no conflict of interest. The anonymised dataset and analysis scripts are available from the corresponding author on reasonable request.

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Appendix

Table A1. Item-level statistics (n = 344)

Item	Content (abridged translation)	M	SD	CITC	λ
X1	Perceived digital access readiness and original X1 items				
AKS1	Easy access to a digital device for daily activities	3.89	0.83	.621	.725
AKS2	Easy access to digital platforms at any time	3.96	0.84	.572	.683
AKS3	Own devices are adequate for activities	3.78	0.85	.558	.678
JAR1	Stable internet connection	3.76	0.85	.529	.618
JAR2†	Resolve connection problems independently	3.60	0.91	.643	.691
JAR3†	Use networks to extend relationships	3.85	0.87	.577	.620
KOM1†	Communicate effectively and politely online	3.58	0.89	.595	.653
KOM2†	Understand etiquette of digital interaction	3.66	0.90	.648	.738
KOM3†	Convey ideas clearly through digital channels	3.55	0.88	.619	.663
INF1†	Find relevant information online	3.66	0.83	.568	.613
INF2†	Filter and verify information	3.79	0.88	.596	.649
INF3†	Manage digital data neatly and securely	3.68	0.90	.594	.634
X2	Digital entrepreneurial competence (wording in S1)				
DK1	Digital initiative	3.73	0.91	.644	.671
DK2	Digital initiative	3.68	0.91	.705	.731
DK3	Digital initiative	3.57	0.92	.669	.690
DK4	Digital initiative	3.75	0.93	.674	.701
DK5	Digital initiative	3.57	0.90	.696	.724
DK6	Digital initiative	3.54	0.94	.733	.758
DK7	Digital initiative	3.53	0.94	.660	.681
EK1	E-commerce self-efficacy	3.60	0.92	.729	.755
EK2	E-commerce self-efficacy	3.48	0.94	.723	.752
EK3	E-commerce self-efficacy	3.50	0.87	.662	.686
EK4	E-commerce self-efficacy	3.60	0.88	.698	.718
EK5	E-commerce self-efficacy	3.38	0.91	.616	.639
EK6	E-commerce self-efficacy	3.70	0.83	.637	.661
EK7	E-commerce self-efficacy	3.32	0.97	.719	.748
EK8	E-commerce self-efficacy	3.49	0.89	.622	.647
Y	Digital entrepreneurial intention (wording in S1)				
Y1	Intention	3.46	0.88	.586	.627
Y2	Intention	3.39	0.85	.569	.604
Y3	Intention	3.44	0.90	.629	.672
Y4	Intention	3.25	0.85	.628	.670
Y5	Intention	3.40	0.91	.609	.641
Y6	Intention	3.22	0.88	.597	.642
Y7	Intention	3.54	0.88	.617	.665
Y8	Intention	3.22	0.89	.612	.657
Y9	Intention	3.43	0.88	.540	.571

Item	Content (abridged translation)	M	SD	CITC	λ
Y10	Intention	3.25	0.87	.612	.645
Y11	Intention	3.12	0.83	.593	.639
Y12	Intention	3.36	0.87	.570	.603

Notes: CITC = corrected item-total correlation within the item's scale; λ = standardised ML CFA loading in model M1. † Literacy-oriented X1 items excluded from the focal composite; their CITC and λ refer to the eight-item set in model M6.

Source: Data processed (2026).