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Contextual Role of Digital Literacy in Impactful Learning and Work Readiness: A Comparative Study of Elementary Teacher Education and Information Technology Students

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Abstrak

Penelitian ini menganalisis determinan pembelajaran berdampak pada mahasiswa Pendidikan Guru Sekolah Dasar (PGSD) dan kesiapan kerja pada mahasiswa Teknologi Informasi (TI), serta membandingkan peran literasi digital di kedua konteks. Studi komparatif dua model terpisah ini menggunakan desain kuantitatif *ex post facto* pada 222 mahasiswa PGSD Universitas Muhammadiyah Muara Bungo (total sampling) dan 321 mahasiswa TI di tiga perguruan tinggi swasta Provinsi Jambi (survei daring), dilengkapi tahap kualitatif pada 15 mahasiswa PGSD. Analisis menggunakan PLS-SEM (SmartPLS 4.1.1.4) dan analisis tematik. Pada mahasiswa PGSD, keterampilan mendesain pembelajaran (β=0,347; p=0,002) dan pengetahuan pedagogis konten (β=0,344; p<0,001) menjadi prediktor utama pembelajaran berdampak, diikuti literasi digital (β=0,205; p=0,018); ketiganya positif dan signifikan (R^2=0,700). Seluruh partisipan wawancara memprioritaskan penguasaan konten daripada teknologi. Pada mahasiswa TI, literasi digital merupakan prediktor dominan kesiapan kerja (efek langsung β=0,542; f^2=0,576; p<0,001). Efek tidak langsung melalui motivasi kerja juga signifikan (β=0,197; p<0,001), sehingga efek total mencapai 0,739 dengan mediasi parsial. Model menjelaskan 86,2% varians kesiapan kerja. Perbandingan ini menunjukkan bahwa literasi digital menjadi penentu utama pada bidang berbasis teknologi, tetapi bersifat pelengkap pada bidang pedagogis; perannya kontekstual, bukan universal. Temuan mendukung *Pedagogy Primacy Theory*, sehingga kurikulum perlu proporsional sesuai kompetensi inti bidang keilmuan.

Kata Kunci: Literasi Digital; Pembelajaran Berdampak; Kesiapan Kerja; Motivasi Kerja; Kontekstualitas.

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Abstract

This study analyzes determinants of impactful learning among Primary School Teacher Education (PGSD) students and of work readiness among Information Technology (IT) students, and compares the role of digital literacy across both contexts. Two separate models were estimated using a quantitative ex post facto design on 222 PGSD students (total sampling) at Universitas Muhammadiyah Muara Bungo and 321 IT students (online survey) at three private universities in Jambi, complemented by interviews with 15 PGSD students. PLS-SEM (SmartPLS 4.1.1.4) and thematic analysis were used. Among PGSD students, instructional design skills (β=0.347; p=0.002) and pedagogical content knowledge (β=0.344; p<0.001) were the main predictors of impactful learning, followed by digital literacy (β=0.205; p=0.018); all were positive and significant (R^2=0.700). Interviewees prioritized content knowledge over technology. Among IT students, digital literacy dominated work readiness (direct effect β=0.542; f^2=0.576; p<0.001). The indirect effect via work motivation was significant (β=0.197; p<0.001), yielding a total effect of 0.739 (partial mediation). The model explained 86.2% of work readiness variance. Digital literacy is thus the primary determinant in technology-based fields but complementary in pedagogical fields; its role is contextual, not universal. The findings support the Pedagogy Primacy Theory, so curricula should align with each discipline's core competencies.

Keywords**:** *Digital Literacy; Impactful Learning; Work Readiness; Work Motivation; Contextuality.*

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INTRODUCTION

The digitalization of higher education is advancing rapidly across nearly every field of study (Selwyn, 2016), and it has fostered a common assumption among policymakers that digital literacy is a 21st-century competency to be prioritized uniformly across all study programs. This assumption is open to question on both conceptual and empirical grounds. Digital literacy is the ability to understand and process information in digital formats rather than mere technical proficiency Gilster (1997), so its value depends on what is done with that information in a particular professional setting. Consistent with this, Tondeur et al., (2017) show that generic competency frameworks applied across academic contexts tend to overlook differences in professional, demands, and Buckingham, (2015) argues that digital literacy should be understood contextually instead of as a competency that is dominant everywhere. Whether its weight actually differs across fields, however, has rarely been tested directly.

In the learning context, the evidence suggests that digital literacy does not operate on its own. Pre-service teachers show an uneven pattern of digital competency, with consistent weakness in pedagogical integration compared with basic usage Zeng et al., (2025), and digital literacy gaps among higher education students are shaped more by digital infrastructure and educator readiness than by individual capacity (Ndibalema 2025). Meanwhile, effective teaching is classically attributed to pedagogical competencies: the integration of content and pedagogical knowledge Shulman (1986) and

the systematic, staged design of learning (Gagne et al., 2005). Taken together, these studies imply that the contribution of digital literacy to learning depends on pedagogical and institutional conditions, yet pedagogical content knowledge, instructional design skills, and digital literacy have largely been examined separately, so their relative weight in producing impactful learning remains unclear.

The work context presents a seemingly opposite picture. Digital literacy has been identified as one of the strongest predictors of employability competency in technical fields Potgieter et al., (2023) as a dominant factor in career intentions among Generation Z Lam et al., (2025) and as the area where graduates' competencies diverge most from workplace expectations (Zhou et al., 2025). These studies establish that digital competency matters for work readiness, but they say little about how it does so. Self-determination theory offers a plausible mechanism, in which competence-supporting experiences foster motivation that bridges competence and actual readiness (Ryan & Deci, 2020), yet whether digital literacy and technology-based entrepreneurial ability shape work readiness directly, through work motivation, or both has not been examined within a single model.

The two bodies of evidence are therefore inconsistent: digital literacy appears secondary to pedagogy in teacher education but dominant in technically oriented fields. Our preliminary studies reproduce this inconsistency. Among Elementary Teacher Education (PGSD) students at Universitas Muhammadiyah Muara Bungo, pedagogical content knowledge, digital literacy, and learning design skills together explained most of the variation in impactful learning, but learning design skills and pedagogical content knowledge showed nearly equal strength and consistently outperformed digital literacy, and students who had completed their School Field Introduction (PLP) said they prioritized pedagogy over technology. Among Information Technology students, by contrast, digital literacy was the most dominant predictor of work readiness.

Existing research cannot resolve this inconsistency because each study examines a single context, outcome, and model. When populations, outcomes, instruments, and analytic procedures all differ, a contrast between teacher education and technical fields cannot be attributed to the discipline itself. Among the studies reviewed here, none compares the role of digital literacy across a pedagogically humanistic field and a technically industrial field using the same competency and the same analytic procedure, and evidence from Indonesian higher education is particularly scarce. The proposition that competency demands differ by field therefore remains an assertion rather than an empirically tested claim. This study addresses that gap by analyzing the influence of pedagogical content knowledge, digital literacy, and learning design skills on impactful learning among PGSD students; the influence of digital literacy and technology-based entrepreneurial ability on work readiness through work motivation among Information Technology students;

and the role of digital literacy across these two contexts.

This study is novel in three respects. It compares the same competency across two contrasting higher education contexts under one PLS-SEM procedure, so that differences can be attributed to context rather than to method. It examines the relative weight of digital literacy against pedagogical competencies in one context and its direct and motivation-mediated effects in the other, supported by focus group interviews that explain the pattern in the pedagogical context. Finally, it formulates a theoretical proposition that the role of digital literacy is contextual, determined by whether it is a core competency of the target profession, which underlies the Pedagogy Primacy Theory and the Subject Specific Deep Learning Pedagogy framework proposed here.

RESEARCH METHOD

Research Design

This study is a comparative multi-context study consisting of two separate structural models estimated on two independent samples, not a single pooled model. The models are analyzed separately because their outcome constructs differ: impactful learning for Elementary Teacher Education (PGSD) students and work readiness for Information Technology (IT) students. They are combined in one study because both position digital literacy as a predictor, use 5-point Likert-scale perception instruments, and are estimated with the same procedure (PLS-SEM in SmartPLS 4.1.1.4) under the same decision criteria. The comparison is therefore made at the level of results, by contrasting the path coefficient, significance, and effect size of digital literacy in each model alongside qualitative evidence; no multigroup test was conducted because the outcomes differ.

A quantitative ex post facto design was applied to both groups. For the PGSD group, a sequential explanatory mixed-methods design was used: a questionnaire survey (12 August to 12 September 2025) was followed by a focus group interview (6 October 2025) to explain the quantitative results. For the IT group, an associative quantitative survey design was used to examine the influence of technology-based entrepreneurial ability and digital literacy on work readiness through work motivation.

Population and Sample

PGSD *group.* The population comprised all active students of the PGSD Study Program at Universitas Muhammadiyah Muara Bungo (N = 222). Because the population was limited and accessible, total sampling was used (Sugiyono, 2016): all 222 students were included, so no stratification or random selection was applied (Table 1). The focus group involved 15 students selected through purposive sampling based on three criteria: (a) enrolled in the eighth semester; (b) having passed the microteaching, learning planning, and instructional design courses; and (c) having completed School Field Introduction 2 (PLP 2).

Table 1. Population and sample of the PGSD group

Stage	Institution	Population	Sample	Technique
Survey	Universitas Muhammadiyah Muara Bungo	222	222	Total sampling
Focus group	Universitas Muhammadiyah Muara Bungo	–	15	Purposive sampling

IT *group*. Respondents were active students of IT-related programs at three private universities in Jambi Province: Universitas Muhammadiyah Muara Bungo, Universitas Merangin, and Universitas Nurdin Hamzah. Four programs were covered: Information Technology Education, Informatics Engineering, Information Systems, and Information Technology. The inclusion criteria were active enrollment in one of these programs and being in the fourth, sixth, or eighth semester, because students at these stages have completed most core courses and have gained practical and project experience relevant to work readiness. The online questionnaire yielded 321 responses, all of which were analyzed. Table 2 shows the sample distribution by study program and semester. Because the sample was obtained through an online survey, generalization beyond these institutions should be made with caution.

Table 2. Sample distribution of the IT group

Stratum	Category	Sample (n)	Percentage (%)
Study program	Information Technology Education	143	44.6
	Informatics Engineering	95	29.6
	Information Systems	58	18.1
	Information Technology	25	7.8
Semester	Fourth	103	32.1
	Sixth	141	43.9
	Eighth	77	24.0
Total		321	100

Instruments and Data Collection

Data were collected online through Google Forms using 5-point Likert-scale questionnaires developed from the indicators of each variable. The PGSD model was analyzed with 18 retained items: pedagogical content knowledge (3 items), digital literacy (5), learning design skills (5), and impactful learning (5). The IT model comprised technology-based entrepreneurial ability, digital literacy, and work motivation (five indicators each) and work readiness (six indicators). For the PGSD group, the questionnaire link was distributed through the study program's communication group. Data were exported to Microsoft Excel and imported into SmartPLS 4.1.1.4. All retained indicators had outer loadings above 0.70, indicating validity and reliability.

Data Analysis

Quantitative data for both models were analyzed with PLS-SEM. The measurement model was evaluated through convergent validity (outer loading > 0.70), discriminant validity (HTMT and the Fornell-Larcker criterion), and construct reliability (Cronbach's alpha and composite reliability). The structural model was evaluated through

the coefficient of determination (R^2), predictive relevance (Q^2, blindfolding), effect size (f^2), and path coefficients tested by bootstrapping. Model fit was assessed with SRMR (threshold < 0.08) and NFI. A hypothesis was accepted when the t-statistic was ≥ 1.96 and p ≤ 0.05 (Hair & Alamer, 2022). Focus group data were analyzed through thematic coding to identify supporting and inhibiting factors. Finally, the digital literacy path coefficients, significance, and effect sizes of the two models were compared to address the central research question on the contextuality of digital literacy's role.

RESULTS AND DISCUSSION

RESULTS

Elementary Teacher Education (PGSD) Students

The PGSD model involved 222 respondents. Across the 18 items, means ranged from 4.018 to 4.252 (1–5 scale), standard deviations from 0.701 to 0.804, and skewness and kurtosis fell within ±1. Variable means were 4.11 (pedagogical content knowledge, PCK), 4.03 (digital literacy, LD), 4.04 (learning design skills, KMP), and 4.27 (impactful learning, PB). *Measurement model.* All loadings exceeded 0.70 (0.773–0.937), Cronbach's alpha and composite reliability exceeded 0.70, and AVE exceeded 0.50 for all constructs (Table 1). Discriminant validity was met: all HTMT values were below 0.90 (highest 0.883) and each square root of AVE exceeded the corresponding inter-construct correlations (Table 2).

Table 3. Measurement model of the PGSD model

Construct	Items	Outer loading	Cronbach's α	CR (rho_a)	CR (rho_c)	AVE
PCK	3	0.901 – 0.918	0.899	0.900	0.937	0.832
LD	5	0.773 – 0.899	0.917	0.921	0.938	0.753
KMP	5	0.895 – 0.928	0.951	0.952	0.962	0.836
PB	5	0.888 – 0.937	0.953	0.954	0.964	0.842

Table 4. Discriminant validity of the PGSD model (HTMT above diagonal; Fornell Larcker below diagonal; AVE on diagonal)

	PCK	LD	KMP
PCK	**0.912**	0.841	0.883
LD	0.763	**0.868**	0.867
KMP	0.818	0.811	**0.915**
PB	0.784	0.749	0.795

Structural model. Model fit was good (SRMR = 0.035 for both saturated and estimated models; NFI = 0.921). The model explained 70.0% of the variance in impactful learning (R^2 = 0.700; adjusted R^2 = 0.696) with strong predictive relevance (Q^2 = 0.686) (Table 5).

Table 5. Model fit and explanatory power of the PGSD model

Indicator	Value	Criterion
SRMR (saturated / estimated)	0.035 / 0.035	< 0.08
NFI	0.921	> 0.90
d_ULS / d_G	0.213 / 0.264	–

Indicator	Value	Criterion
Chi-square	353.09	–
R^2 (adjusted R^2) of PB	0.700 (0.696)	–
Q^2 predict of PB (RMSE; MAE)	0.686 (0.566; 0.404)	> 0

Tested individually, PCK (β = 0.784; t = 22.262), LD (β = 0.749; t = 19.185), and KMP (β = 0.795; t = 22.346) each predicted PB (all p < 0.001). When entered simultaneously, all three remained positive and significant, but KMP (β = 0.347) and PCK (β = 0.344) were stronger than LD (β = 0.205) (Table 4). The coefficient of LD fell from 0.749 to 0.205 as pedagogical predictors were added, which indicates that most of its apparent influence overlaps with PCK and KMP. Effect sizes for predictor combinations are reported in Table 5.

Table 6. Path coefficients of the PGSD model

Model	Path	β	SE	t	P
PCK + LD	PCK → PB	0.509	0.069	7.375	< 0.001
	LD → PB	0.360	0.070	5.156	< 0.001
LD + KMP	LD → PB	0.305	0.093	3.394	< 0.001
	KMP → PB	0.548	0.094	6.113	0.001
PCK + KMP	PCK → PB	0.406	0.091	4.528	< 0.001
	KMP → PB	0.463	0.094	5.063	< 0.001
Simultaneous	**PCK → PB**	**0.344**	0.089	3.868	< 0.001
	LD → PB	**0.205**	0.086	2.377	0.018
	KMP → PB	**0.347**	0.112	3.107	0.002

Table 7. Effect size (f^2) of predictor combinations on PB

Combination	f^2
PCK + LD	0.246
PCK + KMP	0.201
LD + KMP	0.201
PCK + LD + KMP	0.087

Qualitative findings. Focus group interviews with 15 students who had completed PLP produced three categories. Supporting factors were field practice experience, intrinsic motivation, lecturer role modeling, campus technology facilities, and microteaching opportunities. Inhibiting factors were limited school infrastructure, unequal technology access, the risk of technical disruption, and limited digital competency. Moderating factors were a balanced learning approach, prioritization of content knowledge, and learning from field experience. All interviewees stated that they prioritized content knowledge over technology use.

Information Technology Students

The IT model involved 321 respondents: Information Technology Education (44.6%), Informatics Engineering

(29.6%), Information Systems (18.1%), and Information Technology (7.8%), in the fourth (32.1%), sixth (43.9%), and eighth (24.0%) semesters. *Measurement model.* All loadings exceeded 0.70 (0.764–0.897), and reliability and convergent validity were satisfactory for all constructs (Table 6). Discriminant validity, however, was not fully established. HTMT exceeded 0.90 for digital literacy–work readiness (0.962) and work motivation–work readiness (0.943), and the correlations between these pairs (0.899 and 0.867) exceeded the √AVE of digital literacy (0.877) and work motivation (0.843) (Table 7). Work readiness therefore overlaps empirically with digital literacy and work motivation, and results involving these paths are interpreted with caution.

Table 8. Measurement model of the IT model

Construct	**Items**	**Outer loading**	**Cronbach's α**	**CR (rho_a)**	**CR (rho_c)**	**AVE**
Technopreneurship (TP)	5	0.764 – 0.856	0.872	0.874	0.908	0.663
Digital literacy (LD)	5	0.866 – 0.897	0.925	0.926	0.944	0.770
Work motivation (WM)	5	0.809 – 0.874	0.898	0.899	0.925	0.711
Work readiness (WR)	6	0.867 – 0.889	0.941	0.941	0.953	0.727

Table 9. Discriminant validity of the IT model (HTMT above diagonal; Fornell-Larcker below diagonal; AVE on diagonal)

	TP	**LD**	**WM**	**WR**
TP	**0.814**	0.883	0.886	0.867
LD	0.794	**0.877**	0.895	**0.962**
WM	0.785	0.818	**0.843**	**0.943**
WR	0.788	**0.899**	**0.867**	**0.879**

Note. Bold off-diagonal values indicate HTMT > 0.90 or an inter-construct correlation exceeding AVE.

Structural model. SRMR was 0.055 (< 0.08), while NFI was 0.842, below the 0.90 benchmark; SRMR is therefore used as the primary fit indicator. The model explained 86.2% of the variance in work readiness (adjusted R^2 = 0.861) and 71.9% of work motivation (adjusted R^2 = 0.717), with strong predictive relevance (Q^2 = 0.820 and 0.712) (Table 10).

Table 10. Model fit and explanatory power of the IT model

Indicator	**Value**	**Criterion**
SRMR (saturated / estimated)	0.055 / 0.055	< 0.08
NFI	0.842	> 0.90
d_ULS / d_G	0.704 / 0.556	–
Chi-square	1040.29	–
R^2 (adjusted R^2) of WR	0.862 (0.861)	–
R^2 (adjusted R^2) of WM	0.719 (0.717)	–

Indicator	Value	Criterion
Q^2 predict of WR (RMSE; MAE)	0.820 (0.428; 0.326)	> 0
Q^2 predict of WM (RMSE; MAE)	0.712 (0.541; 0.417)	> 0

In the full model, digital literacy had the largest direct effect on work readiness (β = 0.542; f^2 = 0.576), followed by work motivation (β = 0.374; f^2 = 0.285), while the direct effect of technopreneurship was negligible (β = 0.063; f^2 = 0.009) (Table 9). Digital literacy also strongly predicted work motivation (β = 0.526; f^2 = 0.363), as did technopreneurship (β = 0.367; f^2 = 0.177). Work motivation partially mediated the effect of digital literacy: the indirect effect was 0.197 (SE = 0.036; t = 5.395; p < 0.001), giving a total effect of 0.739. Technopreneurship influenced work readiness mainly through work motivation (indirect effect = 0.137; SE = 0.035; t = 3.960; p < 0.001; total effect = 0.200). When each predictor was tested alone, the coefficients were higher (Table 10), because bivariate coefficients do not control for the other predictors and therefore should not be read as direct effects in the full model.

Table 11. Path coefficients and effects of the IT full model

Path	β	f^2	Category
LD → WR (direct)	0.542	0.576	Large
LD → WM → WR (indirect)	0.197	–	–
LD → WR (total)	0.739	–	–
WM → WR	0.374	0.285	Medium
TP → WR (direct)	0.063	0.009	Small
TP → WM → WR (indirect)	0.137	–	–
TP → WR (total)	0.200	–	–
LD → WM	0.526	0.363	Large
TP → WM	0.367	0.177	Medium

Table 12. Bivariate path coefficients and mediation tests of the IT model

Hypothesis	Path	β	SE	t	p
H1	TP → WR	0.791	–	33.371	< 0.001
H2	LD → WR	0.899	–	59.689	< 0.001
H3	TP → WM	0.786	–	33.171	< 0.001
H4	LD → WM	0.819	–	28.379	< 0.001
H5	WM → WR	0.868	0.015	56.523	< 0.001
H6	TP → WM → WR	0.137	0.035	3.960	< 0.001
H7	LD → WM → WR	0.197	0.036	5.395	< 0.001
H8	TP, LD, WM → WR (R^2)	0.862			

Comparison of the Two Models

Table 13. Role of digital literacy in the two contexts

Aspect	PGSD	IT
Field orientation	Pedagogical-humanistic	Technical-industrial
Dependent variable	Impactful learning	Work readiness

Digital literacy β (full model, direct)	0.205 (third of three predictors)	0.542 (largest direct predictor)
Digital literacy t / p	2.377 / 0.018	–
Bivariate β	0.749	0.899
Indirect / total effect	–	0.197 / 0.739
Strongest predictors	KMP (0.347), PCK (0.344)	LD (0.542), WM (0.374)
R^2	0.700	0.862
Discriminant validity	Fully met	Not met for LD–WR and WM–WR

DISCUSSION

Pedagogical competencies outweigh digital literacy among PGSD students

Learning design skills (β = 0.347) and pedagogical content knowledge (β = 0.344) were stronger predictors of impactful learning than digital literacy (β = 0.205), and the coefficient of digital literacy shrank from 0.749 when tested alone to 0.205 once the pedagogical predictors were included. This shrinkage matters more than the ranking itself. It suggests that most of what appears to be the influence of digital literacy is shared with pedagogical competencies (interconstruct correlations of 0.76–0.82), so digital literacy contributes to impactful learning mainly when it is embedded in how content is taught and designed. This reading is consistent with Glister (1997) view of digital literacy as the ability to understand and process information, not merely to operate tools, and with Shulman (1986) argument that teaching quality depends on integrating content and pedagogical knowledge, while Gagne et al., (2005) describe instructional design as the step that turns content into staged learning experiences. Under these theories, a pre-service teacher's ability to transform content and design learning is the more proximal determinant of impact on pupils.

Prior studies support this pattern. Zeng et al., (2025) found that pre-service teachers' digital competence is weakest in pedagogical integration, so digital skill alone does not guarantee that technology improves teaching. Ndibalema (2025) showed that digital literacy gaps in higher education stem more from infrastructure and educator readiness than from individual capacity, which matches the inhibiting factors our interviewees named: limited school infrastructure, unequal technology access, and technical disruption. Studies that place digital competence first, such as Potgieter et al., (2023) and Zhou et al., (2025), differ from our PGSD result, but they examine employability and workplace expectations rather than teaching quality. The difference therefore probably reflects what is being predicted, not a contradiction. Two features of our sample may also have amplified the pedagogical emphasis. The interviewees were eighth-semester students who had just completed field practice, when classroom realities are most salient, and mean scores on all constructs were high (4.03–4.27), which leaves little room to separate predictors. The implication is that PGSD curricula should strengthen content-pedagogy integration and design skills first, and teach digital literacy within lesson-design and field practice rather than as a stand-alone competency. Whether digital

literacy works indirectly through pedagogical content knowledge, as the shrinking coefficient hints, was not tested here and merits a mediation model.

Digital literacy matters more for work readiness among IT students

Digital literacy had the largest direct effect on work readiness (β = 0.542) and also acted indirectly through work motivation (0.197), for a total effect of 0.739. The mechanism is best explained by self-determination theory Ryan & Deci (2020) when students master the digital competencies at the core of their profession, they experience competence and autonomy, which sustains motivation and in turn readiness for work. The partial mediation indicates that digital literacy shapes readiness both by building capability directly and by strengthening the drive to apply it.

The result agrees with Potgieter et al., (2023), who identified digital competence among the strongest predictors of employability in technical fields, and with Zhou et al., (2025) who documented a gap between graduates' digital competencies and employers' expectations. It extends them by testing a motivational pathway that these studies did not model. Two considerations qualify the strength of the finding. First, digital literacy and work readiness overlapped empirically (HTMT = 0.962; correlation above the square root of AVE), so part of the strong association may reflect conceptual closeness: in digital workplaces, digital literacy is itself a component of readiness. Second, all constructs were self-reported by the same respondents, which can inflate associations. These factors suggest the size of the effect should be read as an upper bound, even though its direction and rank among predictors are plausible. For IT programs, the implication is to treat digital literacy as a core curricular priority and to pair it with motivation-building experiences such as industry internships and mentoring, since motivation carries part of the effect.

Technopreneurship works mainly through motivation

The direct effect of technology-based entrepreneurial ability on work readiness was negligible (β = 0.063; f^2 = 0.009), whereas its indirect effect through work motivation was clear (0.137). This pattern suggests that entrepreneurial ability becomes useful for employment readiness only when it energizes students to act on it. It is compatible with the competence-to-motivation logic of self-determination theory Ryan & Deci (2020) and with Lam et al., (2025), who connect digital competence to entrepreneurial intention through a social cognitive process in which belief in one's abilities drives action. The difference is the outcome: they study entrepreneurial intention, whereas we study readiness for employment, where entrepreneurial skills may matter less than the motivation to enter and persist in work. Program designers should therefore not expect entrepreneurship courses alone to raise work readiness unless they also build motivation, for example through project-based, industry linked activities.

The role of digital literacy is contextual

The contrast between the two models, third of three predictors for PGSD students and largest direct predictor for IT students, is best explained by how central digital literacy

is to each field's core professional competency. Teaching quality is judged by what pupils learn, which depends on pedagogical transformation of content (Shulman, 1986; Gagne et al., 2005), whereas readiness for IT work is judged largely by competence in digital tools and environments. This is consistent with Buckingham (2015) argument that digital literacy should be understood in context rather than as uniformly dominant, and it motivates the proposed Pedagogy Primacy Theory and the Subject Specific Deep Learning Pedagogy framework: where the profession centers on human development, content and pedagogy form the foundation, learning design translates that foundation into practice, and digital literacy supports it.

This interpretation should be held with care. The two models have different outcomes and were not compared with a formal multigroup test, so the contrast shows that the rank of digital literacy differs across the models, not that field of study alone causes the difference. Differences in outcome construct, sampling (total sampling at one university versus an online survey across three), and the discriminant validity problem in the IT model could each contribute. What the findings do justify is a more cautious claim than the assumption that digital literacy should be prioritized uniformly Selwyn (2016) curriculum policy should weight digital literacy according to its place in each field's core competencies, strengthening pedagogical content knowledge and design skills in teacher education and positioning digital literacy as a core priority in IT programs. Institutions can reinforce this through partnerships with the world of work that match each field's demands.

Limitations and future research

This study used cross-sectional, self reported data, two separately estimated models with different outcomes, a single institution PGSD sample, and an IT sample obtained through an online survey, which limits generalization. Discriminant validity between work readiness and both digital literacy and work motivation was not fully established. Future studies could apply the same outcome measure in both fields and use multigroup analysis, add objective or employer-rated measures of work readiness, and test whether pedagogical content knowledge mediates the effect of digital literacy on impactful learning

CONCLUSION

This study examined the role of digital literacy in two higher education contexts. Among Elementary Teacher Education (PGSD) students, pedagogical content knowledge, digital literacy, and learning design skills all positively and significantly predicted impactful learning, but learning design skills ($\beta = 0.347$) and pedagogical content knowledge ($\beta = 0.344$) were stronger than digital literacy ($\beta = 0.205$). Among Information Technology students, digital literacy had the largest direct effect on work readiness ($\beta = 0.542$) and a further indirect effect through work motivation (0.197), which indicates partial mediation. Technology-based entrepreneurial ability influenced work readiness mainly through work motivation, with a negligible direct effect.

Comparing the two models shows that digital literacy ranks third among PGSD predictors but first among IT predictors, so its role is contextual rather than universal and depends on how central it is to each field's core competencies. Because the two models have different outcomes and the IT model shows overlap between digital literacy and work readiness, this conclusion should be read as a pattern to be tested further, not as a causal effect of field alone. Curriculum policy should therefore weight digital literacy by field: pedagogical content knowledge and learning design skills first in teacher education, and digital literacy together with motivation-building experiences in IT programs.

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