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ORIGINAL ARTICLE

Factors Influencing Pre-Service Natural Science Teachers' Competence in Using Digital Learning Resources: The Mediating Role of Personal Readiness

Gai Thi Tran[1],
Hang Diem Thi Nguyen[1,+],
Dung Van Ha[2]
Truong Nhat Van Ho[3]

[1]Vinh University, Nghe An, Vietnam;
[2]Hanoi Metropolitan University, Hanoi, Vietnam;
[3]Master's Student (Cohort 31), Vinh University, Nghe An, Vietnam
[+]*Corresponding author* ● *Email: hangntd@vinhuni.edu.vn*

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ABSTRACT
This study examines factors associated with pre-service Natural Science teachers' competence in using digital learning resources (DLRC) and tests the mediating role of personal readiness. A cross-sectional survey of 330 pre-service teachers was analyzed using partial least squares structural equation modeling. Pedagogical support showed the strongest direct relationship with DLRC ($\beta = 0.384$, $p < 0.001$), followed by personal readiness ($\beta = 0.308$, $p < 0.001$) and technological support ($\beta = 0.231$, $p < 0.001$). Pedagogical support, technological support, and the digital environment and policies were positively associated with personal readiness. Significant indirect effects through readiness were observed for pedagogical support ($\beta = 0.102$), technological support ($\beta = 0.097$), and the digital environment and policies ($\beta = 0.057$). The model explained 33.6% of the variance in personal readiness and 49.6% in DLRC. The findings identified DLRC as a resource-focused component of professional digital competence and suggest that pedagogical design, accessible technology, institutional conditions, and teacher students' readiness should be developed in coordination.

1. INTRODUCTION

In the context of rapid digital transformation and the development of artificial intelligence, digital learning materials have become a crucial resource for promoting innovation in teaching methods and improving the quality of teacher training. Digital learning materials encompass not only text, images, videos, and electronic lectures but also open educational resources, learning management systems, simulations, virtual experiments, and AI-powered content. The DigCompEdu framework identifies the selection, creation, adaptation, management, and sharing of digital resources as a core area of a teacher's digital competence (Redecker & Punie, 2017). The widespread use of AI also necessitates that learners know how to verify information, protect personal data, comply with copyright, and take responsibility for the digital content they use (Miao & Holmes, 2023; Vuorikari et al., 2022).

For science education students, the competence in using digital learning resources (DLRC) is particularly important. The integrated nature of Physics, Chemistry, Biology, and Natural Sciences subjects requires future teachers to flexibly utilize simulations, virtual experiments, scientific videos, visual data, and specialized software to organize discovery and problem-solving activities. However, access to technology does not equate to the ability to use learning materials effectively and responsibly. Studies show that the digital competence of teacher students remains uneven and is influenced by the training program, faculty support, technological conditions, and educational environment (Dolezal et al., 2025; Zhang et al., 2026). These conditions can only be translated into practical competence when students possess motivation, self-study ability, critical thinking, and foundational technological skills.

Although prior studies have examined pre-service teachers' broad digital competence, less is known about the specific competence required to evaluate, organize, adapt, create, and responsibly use digital learning resources in Natural Science teacher education. Existing frameworks define relevant competency domains, but empirical evidence remains limited regarding how pedagogical support, technological support, and institutional digital conditions jointly operate and whether personal readiness transmits their associations with this competence. Addressing this gap, the study examines the relationships of pedagogical support, technological support, and the digital environment and policies with pre-service Natural Science teachers' competence in using digital learning resources (DLRC), and tests the mediating role of personal readiness. The analysis uses 330 valid responses and PLS-SEM. The study contributes by operationalizing DLRC as a context-specific component of professional digital competence and by testing an explanatory mechanism that connects institutional conditions with personal readiness.

2. LITERATURE REVIEW

Digital transformation highlights the need for pre-service teachers to develop professional digital competence. Digital resources now include text, images, video, e-lectures, learning management systems, simulations, virtual experiments, open educational resources, and AI-generated content. Their educational use requires more than technical operation: learners must search for, evaluate, organize, create, adapt, and use resources safely, ethically, and in alignment with pedagogical purposes (Miao & Holmes, 2023; Vuorikari et al., 2022). In this study, Digital Learning Resource Competence (DLRC) is treated not as an entirely new or general digital-competence construct, but as a context-specific component of pre-service teachers' professional digital competence. It focuses on the purposeful and responsible use of digital resources for learning and future teaching, corresponding closely to the "Digital Resources" area of DigCompEdu while incorporating the critical, ethical, and AI-related requirements of contemporary Natural Science education (Redecker & Punie, 2017; Falloon, 2020). This narrower scope distinguishes DLRC from broad digital competence, which also encompasses communication, assessment, learner empowerment, and professional engagement. For prospective Natural Science teachers, DLRC is especially salient because Physics, Chemistry, Biology, and Integrated Natural Science depend on visualization, simulation, data analysis, and experimentation. The framework of Technological Pedagogical Content Knowledge (TPACK) further indicates that effective resource use emerges from the integration of technological, pedagogical, and subject-matter knowledge rather than from access to tools alone (Mishra & Koehler, 2006). Prior research claims that pre-service teachers' digital competence is shaped by program integration, instructor modelling, authentic practice, and institutional support (Tondeur et al., 2012; Instefjord & Munthe, 2017; Gudmundsdottir & Hatlevik, 2018; Dolezal et al., 2025). However, these studies provide limited evidence on whether personal readiness mediates the relationships between external support conditions and the resource-focused competence examined here.

2.1. Digital learning resources and DLRC

Digital learning materials are resources that contain content, information, or learning activities created, stored, distributed, and used through digital technology. Digital learning materials can take many forms, including electronic text, images, audio, video, e-lectures, question banks, simulations, virtual experiments, educational games, scientific data, open educational resources, and AI-powered content. Unlike traditional documents, digital learning materials can integrate multimedia, update quickly, be widely shared, reused, and flexibly adapted to learners' goals, content, and characteristics. However, exploiting digital learning materials also places demands on reliability, copyright, data security, and accountability when using AI-generated content (Miao & Holmes, 2023; Redecker & Punie, 2017).

In science education, digital learning materials are highly visual, interactive, and simulated. Physical phenomena, chemical processes, or biological structures which are difficult to observe directly can be represented using 3D models, videos, virtual experiments, and simulation software. Digital learning materials also allow students to change parameters, observe results, collect data, and test hypotheses in a safe environment. These features support discovery learning, problem-solving, experimentation, and STEM education. However, scientific learning materials must be accurate, well-founded, and appropriate to the lesson objectives and the learners' level. Therefore, prospective teachers not only need to know how to search for learning materials but also to evaluate, adapt, and integrate them into teaching activities. The DigCompEdu framework views the selection, creation, adaptation, management, protection, and sharing of digital resources as a core area of a teacher's digital competence (Redecker & Punie, 2017). In Vietnam, Circular No. 02/2025/TT-BGDĐT identifies relevant competency domains, including data and information exploitation, digital content creation, safety, problem-solving, and AI application. Circular No.

18/2026/TT-BGDĐT further specifies requirements for teachers through competencies in organizing teaching and learning in a digital environment, information and data skills, digital content creation, professional development, and responsible AI application (Ministry of Education and Training, 2025, 2026).

In brief, Digital Learning Resource Competence (DLRC) is defined here as a context-specific component of professional digital competence: the ability of pre-service teachers to search for, evaluate, organize, integrate, create, adapt, share, and use digital learning resources effectively, safely, ethically, and responsibly for learning and future teaching. It operationalizes the resource-focused domain of DigCompEdu in Natural Science teacher education rather than proposing a wholly independent digital-competence framework (Redecker & Punie, 2017; Falloon, 2020).

DLRC encompasses knowledge, practical skills, critical judgement, and professional responsibility. For conceptual clarity, its indicators represent four connected aspects:

First, identifying and evaluating digital learning resources: This component reflects the ability to identify learning resource needs according to learning or teaching objectives; select appropriate sources and keywords; and assess the reliability, accuracy, timeliness, and relevance of the resources. For AI-generated content, students need to compare it with scientific sources and not treat AI results as a default, definitive source of knowledge.

Second, organizing and integrating digital learning resources: This component refers to the ability to classify, store, manage, and retrieve learning resources; select resources appropriate to the content, methods, and characteristics of learners; and integrate learning resources into lesson plans and learning activities. In science education, integration must ensure a link between learning materials and activities such as observation, experimentation, data analysis, and problem-solving.

Thirdly, creating and adapting digital learning materials: This component reflects the ability to create, edit, combine, and convert learning materials into different formats. Students can use digital tools, simulation software, and AI to design videos, infographics, lectures, models, or tests. Learning materials need to be adapted to learners' goals, levels, needs, and accessibility, rather than simply copying or reusing them as is.

Fourth, professional development and digital responsibility: This component emphasizes the ability to share, collaborate, evaluate, and improve learning materials based on feedback; adhere to copyright, cite sources, and protect personal data; and use AI transparently, safely, and responsibly. This dimension connects competence in digital learning materials with professional ethics and the continuous professional development of future teachers.

2.2. Theoretical foundation of the research model

The research model integrates the Digital Competency Framework for Vietnamese Learners, the Digital Competency Framework for Teachers, DigCompEdu, and an ecological approach to competency development. Combining these platforms enables the justification of digital learning resource utilization competence from two perspectives: teacher students' current competencies as learners and the professional competencies they need to develop as future teachers.

First, the Digital Competency Framework for Learners, issued under Circular No. 02/2025/TT-BGDĐT, comprises six competency domains: data and information exploitation; communication and collaboration in the digital environment; digital content creation; safety; problem-solving; and artificial intelligence application. The framework emphasizes searching, evaluating, managing, and using information; creating content; ensuring safety; solving problems; and using AI ethically. It provides the basis for identifying the fundamental digital competencies students need during their studies and when utilizing digital learning materials (Ministry of Education and Training, 2025). Secondly, Circular No. 18/2026/TT-BGDĐT stipulates the Digital Competency Framework for teachers and educational administrators, comprising six domains with 20 component competencies. For teachers, the domains focus on organizing teaching and learning in a digital environment; testing and evaluation; empowering learners; digital technology skills; professional development; and applying artificial intelligence. This framework shifts the focus from simply using technology to designing, organizing, and improving educational activities using technology. Therefore, it serves as a professional basis for identifying the requirements that teacher education students need to gradually develop before participating in teaching (Ministry of Education and Training, 2026). Thirdly, the DigCompEdu Teacher Digital Competency Framework provides an international benchmark for the model. DigCompEdu comprises six domains and 22 component competencies, with the digital resource domain emphasizing the ability to select, create, adapt, manage, protect, and share resources. It also affirms that teachers' digital competence is demonstrated not only through technological operational skills but also through the ability to integrate technology into teaching, assessment, learner support, and professional development (Redecker & Punie, 2017).

These competency frameworks define the content of DLRC but do not by themselves explain variation among teacher students. An educational-ecological perspective suggests that competence is associated with interactions between individual characteristics and training conditions. Pedagogical support provides authentic requirements, instructor modelling, and opportunities to practise resource selection and integration; technological support provides access to infrastructure, platforms, software, and databases; and the digital environment and policies provide institutional orientation, a culture of sharing, and development opportunities. This conceptual selection is consistent with evidence that systematic curriculum integration, instructor modelling, authentic practice, and institutional conditions are associated with pre-service teachers' professional digital competence (Tondeur et al., 2012; Instefjord & Munthe, 2017; Gudmundsdottir & Hatlevik, 2018). External resources, however, may be less effectively used when students have limited motivation, self-regulation, critical thinking, or foundational technological skills.

Personal readiness (PR) is therefore proposed as the mechanism linking external support conditions with DLRC. It reflects motivation, self-directed learning and time management, critical thinking, and foundational digital skills. These personal resources enable students to recognize learning opportunities, evaluate information, experiment with tools, and apply digital resources to professional tasks. The model consequently tests both direct associations and indirect associations through PR.

2.3. Hypothesis development and research model

The research model consists of three independent variables, one mediating variable, and one dependent variable. The independent variables are pedagogical support, technological support, and the digital environment/policies. The mediating variable is personal readiness. The dependent variable is digital learning resource utilization competence (DLRC). The variables are denoted as follows:

Table 1. Symbols for variables in the model

Role	Factor	Symbol
Independent variable	Pedagogical support	PS
Independent variable	Technology support	TS
Independent variable	Digital environment and policies	ES
Intermediate variable	Personal readiness	PR

2.3.1. Pedagogical Support

Pedagogical support (PS) reflects the extent to which instructors and courses require, guide, and provide opportunities for students to use digital learning materials. The PS factor is measured by four observed variables:

PS1: Instructor requirements for using digital learning materials;

PS2: Application of project-based learning, STEM education, and active learning methods;

PS3: Course design requiring students to utilize digital learning materials;

PS4: Assessment and evaluation using videos, websites, reports, or digital products.

Instructor modelling, authentic technology-rich tasks, and opportunities to design digital products are associated with pre-service teachers' motivation, self-directed learning, and professional digital competence (Tondeur et al., 2012; Instefjord & Munthe, 2017; Dolezal et al., 2025). Pedagogically designed tasks also require students to search, evaluate, create, and integrate resources in subject-specific contexts. Therefore:

H1: Pedagogical support (PS) has a positive impact on personal readiness (PR) of science education students. In addition, technology-based learning tasks create opportunities for students to directly search for, evaluate, create, and integrate learning materials into their teaching activities. Therefore:
H5: Pedagogical support (PS) has a positive impact on the ability of science education students to utilize digital learning materials (DLRC).

2.3.2. Technology support (TS)

Technological support (TS) reflects the availability, stability, and usefulness of the infrastructure, platforms, and technological resources in the training institution. The TS factor is measured by four observed variables:

TS1: Internet/Wi-Fi speed and stability;

TS2: LMS ease of use and usefulness;

TS3: School-provided learning materials and databases;

TS4: Learning materials and databases provided by the school.

Reliable infrastructure and usable platforms can reduce access barriers, support experimentation, and promote self-directed learning and repeated practice with digital resources. Nevertheless, technology contributes to professional competence most effectively when connected to pedagogical and subject-matter knowledge (Mishra & Koehler, 2006; Gudmundsdottir & Hatlevik, 2018). Therefore:

H2: Technological support (TS) has a positive impact on the personal readiness (PR) of science education students.

Access to the Internet, LMS, digital libraries, and specialized software also helps students organize, adapt, and create learning materials. Therefore:

H6: Technological support (TS) has a positive impact on the digital learning resource utilization competence (DLRC) of science education students.

2.3.3. Digital Environment and Policies (ES)

Digital environment and policies reflect support for institutional orientation, digital culture, and capacity-building activities within the training institution. The ES factor is measured by three observed variables:

ES1: Policies promoting digital transformation and the use of digital learning materials;

ES2: The environment for sharing and exchanging learning materials among students;

ES3: Training programs or workshops on digital skills.

Institutional orientation, a culture of resource sharing, and structured digital-skills development signal expectations and provide learning opportunities. Prior synthesis indicates that coherent institutional and program-level conditions are important for preparing pre-service teachers to integrate technology (Tondeur et al., 2012; Zhang et al., 2026). Therefore:

H3: Digital environment and policies (ES) have a positive influence on personal readiness (PR) of natural science education students.

In the proposed model, ES does not directly impact DLRC. The influence of ES is assumed to be transformed through PR.

2.3.4. Personal Readiness (PR)

Personal readiness is the degree of student preparation in terms of motivation, self-study ability, critical thinking, and fundamental technological skills. PR is a mediating variable and is measured by four observed variables:

PR1: Motivation and passion for learning;

PR2: Self-study ability and time management;

PR3: Critical thinking ability;

PR4: Basic computer and internet skills.

Students with stronger motivation, self-directed learning, critical judgement, and foundational digital skills are better positioned to seek, verify, adapt, and apply digital resources. These capacities connect broad digital competence with responsible professional practice (Falloon, 2020; Dolezal et al., 2025). Therefore:

H4: Personal readiness (PR) positively influences DLRC of natural science education students.

2.3.5. Digital Resource Utilization Competence (DLRC)

DLRC is the ability to search, evaluate, organize, integrate, create, adapt, and use digital learning materials effectively, safely, and responsibly. DLRC is the dependent variable, measured by eight observed variables:

DLRC1: Searching for learning materials suitable for learning or teaching objectives;

DLRC2: Assessing the reliability, accuracy, and relevance of learning materials;

DLRC3: Organizing, storing, and managing digital learning materials;

DLRC4: Integrating digital learning materials into teaching plans and activities;

DLRC5: Creating or editing learning materials using digital tools;

DLRC6: Adapting learning materials to learner characteristics and needs;

DLRC7: Sharing, collaborating, and using learning materials in accordance with copyright and privacy regulations;

DLRC8: Verifying and transparently using AI-generated content. DLRC is the model's output, directly influenced by PS, TS, and PR, and indirectly influenced by PS, TS, and ES through PR.

2.3.6. The Mediating Role of Personal Readiness (PR)

External support conditions are expected to be associated with DLRC partly through students' capacity to recognize and use relevant opportunities. Personal readiness may therefore transmit the relationships of pedagogical support, technological support, and the digital environment and policies with DLRC. This expectation is consistent with the ecological view of competence development and with evidence that both individual and program-level conditions shape pre-service teachers' digital competence (Tondeur et al., 2012; Zhang et al., 2026). Therefore:

H7a: Personal readiness (PR) mediates the relationship between pedagogical support (PS) and DLRC (DLRC).

Indirect relationship: PS→PR→DLRC

H7b: Personal readiness (PR) plays a mediating role in the relationship between technological support (TS) and DLRC (DLRC).

Indirect relationship: TS→PR→DLRC

H7c: Personal readiness (PR) acts as a mediator in the relationship between the digital environment-policy (ES) and the DLRC (DLRC).

Indirect relationship: ES→PR→DLRC

2.3.7. Research model

Based on the hypotheses developed above, the proposed research model illustrates the direct effects of PS, TS, and PR on DLRC, as well as the indirect effects of PS, TS, and ES through PR. The hypothesized relationships among the constructs are presented in Figure 1.

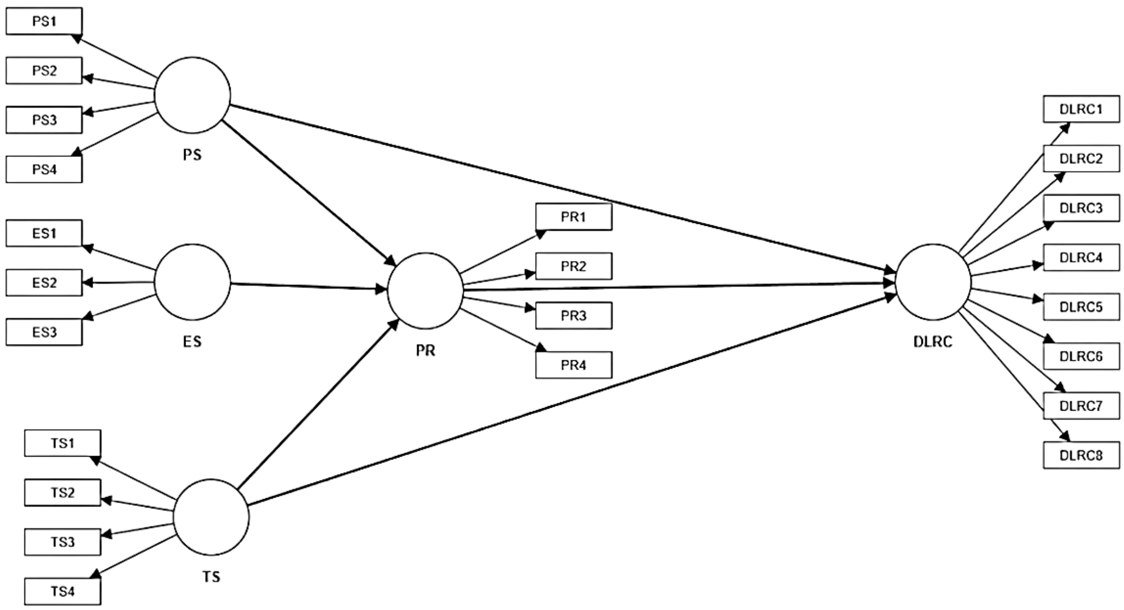

Figure 1. Proposed research model

3. MATERIALS AND METHODS

3.1. Research Design

This cross-sectional study employed a quantitative explanatory and predictive design. The proposed model was informed by the Digital Competence Framework for Educators (DigCompEdu), which specifies the professional and pedagogical digital competencies expected of educators, including prospective teachers (Redecker & Punie, 2017). It was also contextualized using the Digital Competency Framework for Vietnamese Learners, which reflects the digital knowledge, skills, attitudes, and responsibilities required within the Vietnamese education system (Ministry of Education and Training, 2025). An educational-ecological perspective was incorporated to explain digital competence as an outcome associated with the interaction between individuals' personal resources and the pedagogical, technological, and institutional conditions in which they learn and develop professionally. PLS-SEM was employed to estimate the proposed direct and indirect relationships and to assess the model's explanatory and predictive performance (Hair et al., 2022). Given the cross-sectional and self-reported nature of the data, the estimated structural paths are interpreted as statistical associations consistent with the proposed theoretical model rather than as evidence of causal effects.

3.2. Research Subjects and Sample

The target population comprised pre-service teachers enrolled in Physics Education, Chemistry Education, Biology Education, or Natural Science Education programs at participating Vietnamese universities. Participants were recruited through a convenience sampling procedure, with representation sought across institution, major, academic year, and gender. The analytical sample included 330 respondents who met the eligibility criterion of enrolment in one of the four target programs and provided usable responses for all model indicators. The same 330 cases were used in every PLS-SEM analysis reported in this article. This size was adequate for estimating the measurement and structural models and the specified indirect effects (Hair et al., 2022). The non-probability recruitment procedure is acknowledged as a limitation to generalizability.

3.3. Data Collection Tools and Methods

The questionnaire was developed through a theory-driven comparison of the Digital Competency Framework for Vietnamese Learners and the Digital Resources area of DigCompEdu (Ministry of Education and Training, 2025; Redecker & Punie, 2017). Items for DLRC were adapted to the learning and prospective teaching tasks of Natural Science students, including the use of scientific data, simulations, virtual experiments, specialized software, and AI-generated content. The support and readiness indicators were contextualized from the conceptual domains identified in prior teacher-digital-competence research (Tondeur et al., 2012; Instefjord & Munthe, 2017; Dolezal et al., 2025). All items were measured on a five-point Likert scale from 1 (strongly disagree) to 5 (strongly agree). The reported measurement model contains the final set of 23 indicators; no separate 55-item DLRC scale was analyzed.

The model comprises five latent variables measured by 23 indicators: pedagogical support (PS, 4 indicators), technological support (TS, 4), digital environment and policies (ES, 3), personal readiness (PR, 4), and DLRC (8). DLRC is the outcome variable, PR is the mediator, and PS, TS, and ES are the predictor variables.

3.4. Data Analysis Method

Data were processed using SPSS 26 and SmartPLS 4 following Hair et al. (2022). First, the reflective measurement model was assessed using indicator loadings, Cronbach's alpha, rho_A, composite reliability, AVE, HTMT, and the Fornell-Larcker criterion. Second, the structural model was evaluated using VIF, bootstrapped path coefficients, 95% confidence intervals, R^2, f^2, and Q^2. Indirect effects were assessed by bootstrapping; mediation was inferred when the indirect-effect confidence interval excluded zero. This procedure evaluates model quality and predictive relevance without treating the observed associations as proof of causality.

4. RESULTS AND DISCUSSION

4.1. Data analysis

4.1.1. Assessing Reliability and Convergent Validity

Table 2. Reliability and Convergent Validity of the Scale

Factors	Indicator number	External load	Cronbach's Alpha	(rho_A)	(rho_C)	AVE
DLRC	8	0.802-0.861	0.935	0.935	0.946	0.687
ES	3	0.874-0.913	0.872	0.879	0.921	0.796
PR	4	0.862-0.901	0.905	0.907	0.933	0.778
PS	4	0.837-0.913	0.905	0.906	0.934	0.778
TS	4	0.822-0.879	0.867	0.869	0.910	0.716

Table 2 presents the measurement-model results. Indicator loadings ranged from 0.802 to 0.913 and exceeded the recommended threshold of 0.708. Cronbach's alpha ranged from 0.867 to 0.935, rho_A from 0.869 to 0.935, and composite reliability from 0.910 to 0.946. These values indicate satisfactory internal consistency without requiring indicator removal (Hair et al., 2022).

The AVE values ranged from 0.687 to 0.796, all greater than 0.50. This indicates that each structure explains at least 68.7% of the variance of the corresponding indicators. Thus, all five scales met the requirements for reliability and convergent validity (Hair et al., 2022).

In particular, DLRC achieved the highest reliability, with rho_C = 0.946. ES achieved the highest AVE of 0.796, indicating that the three ES indicators effectively reflected the concepts of digital environment and policy. Although DLRC had the lowest AVE, its value of 0.687 still significantly exceeded the 0.50 threshold.

4.1.2. Assessing Discriminant Value

Table 3. Discriminant validity according to HTMT criteria

Factors	DLRC	ES	PR	PS	TS
DLRC	-				
ES	0.416	-			
PR	0.621	0.355	-		
PS	0.613	0.197	0.473	-	
TS	0.493	0.276	0.484	0.238	-

Table 3 reports the HTMT assessment. Values ranged from 0.197 to 0.621 and were below the conservative threshold of 0.85, supporting discriminant validity (Henseler et al., 2015; Hair et al., 2022). The largest value, between PR and DLRC (0.621), is theoretically plausible because readiness is expected to be associated with competence, yet the two constructs remain empirically distinct.

Table 4. Discriminant validity according to the Fornell-Larker criterion

Factors	DLRC	ES	PR	PS	TS
DLRC	**0.829**				
ES	0.375	**0.892**			
PR	0.572	0.318	**0.882**		
PS	0.565	0.173	0.429	**0.882**	
TS	0.444	0.239	0.429	0.211	**0.846**

Table 4 shows that the square root of each construct's AVE (0.829-0.892) exceeded its correlations with the other constructs. Together with the HTMT results, the Fornell-Larcker criterion supports discriminant validity and permits assessment of the structural model.

4.1.3. Multicollinearity assessment

Multicollinearity among forecast variables was assessed through the Variance Inflation Factor (VIF). The results showed that the VIFs of the structural model ranged from 1.064 to 1.437, all below the 3 threshold, indicating no significant multicollinearity among the independent variables. Specifically, the VIFs of the paths to PR ranged from 1.064 to 1.095, and those to DLRC from 1.227 to 1.437. Therefore, the path coefficients can be estimated reliably and are not significantly biased by excessive correlation among forecast variables.

Table 5. Multicollinearity statistics of the structural model

Relationship between factors	VIF
ES → PR	1.079
PS → PR	1.064
TS → PR	1.095
PR → DLRC	1.437
PS → DLRC	1.227
TS → DLRC	1.227

4.1.4. Testing Direct Effects

The hypotheses about direct effects were tested using bootstrapping. The 95% confidence intervals of all path coefficients did not contain zero values, and all p-values were less than 0.001. Therefore, all six hypotheses about direct effects were accepted. The results showed that PS had the strongest positive influence on PR with $\beta=0.330$, $t=7.072$, $p<0.001$. TS had a nearly equivalent influence on PR with $\beta=0.315$, $t=6.976$, $p<0.001$. ES also had a positive effect on PR, but to a lesser extent, with $\beta = 0.185$, $t = 4.008$, $p < 0.001$. For DLRC, PS is the strongest direct predictor variable with $\beta=0.384$, $t=9.334$, $p<0.001$. This is followed by PR with $\beta=0.308$, $t=7.282$, $p<0.001$, and TS with $\beta=0.231$, $t=5.577$, $p<0.001$. The results confirm that DLRC is not only dependent on technological conditions but is more strongly influenced by how instructors design tasks, organize learning activities, and evaluate digital products. Simultaneously, PR plays a crucial role in transforming supportive conditions into students' actual competencies.

4.1.5. Structural Testing of the Research Model

The results of the structural testing of the research model are shown in Figure 2 below:

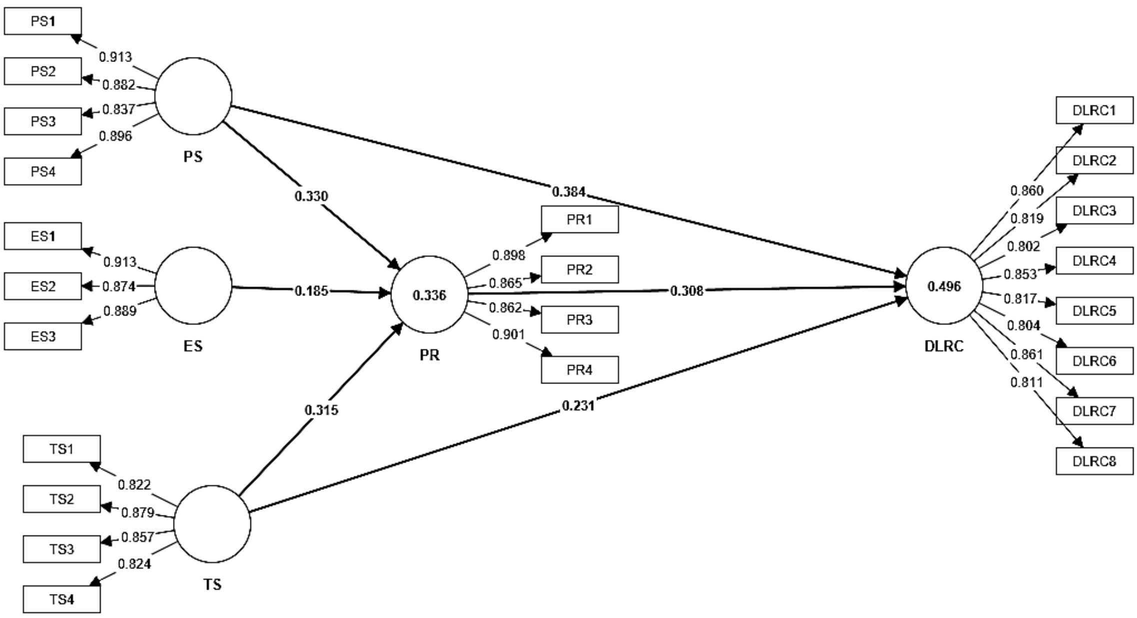

Figure 2. Testing the structural model using PLS-SEM

Table 6. Results of testing direct impacts

Hypothesis	Relationship between factors	β	STDEV	t	p	CI 95%	Conclusion
H1	PS → PR	0.330	0.047	7.072	<0.001	[0.236; 0.419]	accept
H2	TS → PR	0.315	0.045	6.976	<0.001	[0.228; 0.403]	accept
H3	ES → PR	0.185	0.046	4.008	<0.001	[0.096; 0.278]	accept
H4	PR → DLRC	0.308	0.042	7.282	<0.001	[0.225; 0.392]	accept
H5	PS → DLRC	0.384	0.041	9.334	<0.001	[0.303; 0.462]	accept
H6	TS → DLRC	0.231	0.041	5.577	<0.001	[0.148; 0.312]	accept

4.1.6. Testing the mediating role of personal readiness

The mediating role of PR was assessed through specific indirect effects. Bootstrapping results showed that all three indirect effects were statistically significant, and the 95% confidence intervals did not contain zero values. The indirect effect of PS on DLRC through PR was β=0.102 (t=5.117, p<0.001). Since PS has a direct effect on DLRC and both effects are in the same direction, PR serves as an additional mediator in the PS → DLRC relationship. Similarly, the indirect effect TS → PR → DLRC reached β=0.097, t=4.830, p<0.001. Since the direct TS → DLRC curve remains significant and directional, PR also serves as an additional mediator in the relationship between technology support and DLRC. For ES, the indirect ES → PR → DLRC effect reaches β=0.057, t=3.257, p=0.001. The results show that the digital environment and policies influence DLRC by reinforcing personal readiness.

Table 7. Results of mediating impact testing

Hypothesis	Indirect effect	β	STDEV
H7a	PS → PR → DLRC	0.102	0.020
H7b	TS → PR → DLRC	0.097	0.020
H7c	ES → PR → DLRC	0.057	0.018

Based on Table 7, the total impact of TS is 0.329, while the total impact of ES on DLRC is 0.057. The results show that PR acts as a mediator in all three relationships. The indirect impact of PS on DLRC is the strongest (β=0.102), followed by TS (β=0.097) and ES (β=0.057). The low STDEV values, from 0.018 to 0.020, indicate stable estimation results. Thus, H7a, H7b, and H7c are all supported.

Table 8. Direct, indirect, and total impact on DLRC

Factors	Direct effect	Indirect impact through PR	Total impact
PS	0.384	0.102	0.485
TS	0.231	0.097	0.329
ES	Not specified	0.057	0.057
PR	0.308	-	0.308

From Table 8, the results show that PR does not completely replace the effects of PS and TS but acts as a supplementary mechanism. For ES, the model only establishes an indirect path through PR. Therefore, the results confirm the indirect-effect mechanism but are insufficient to conclude that it entirely mediates, without testing the competing model that includes the ES → DLRC path.

4.1.7. Explanatory Ability and Scale of Effect

Table 9 presents the coefficient of determination (R^2) and the adjusted coefficient of determination (Adjusted R^2) of the dependent variables in the research model. According to Hair et al. (2022), R^2 reflects the degree to which the independent variables explain the dependent variable; the higher the value, the better the model's explanatory power. The coefficient of determination, R^2, is used to assess the explanatory power of the predictor variables for the endogenous variables. The results show that PS, TS, and ES explain 33.6% of the variance in PR (R^2 = 0.336). The adjusted R^2 value is 0.330, indicating that the model explains a moderate amount of variation in personal readiness. PR, PS, and TS explain 49.6% of the variance in DLRC (R2 = 0.496), with an adjusted R2 of 0.491. This is a moderate to fairly moderate level of explanation in educational and behavioral research.

Table 9. Coefficients of determination of endogenous variables

Endogenous variables	(R^2)	(R^2) adjustment	Level of explanation
PR	0.336	0.330	Average
DLRC	0.496	0.491	Average to above average

The f^2 effect size indicates that PS has the largest effect on DLRC, with $f^2 = 0.238$, corresponding to an average effect size. PR has an effect size of f^2=0.131, close to the average; TS has a small effect size with f^2=0.087. For PR, PS has the largest effect size ($f^2 = 0.154$), followed by TS ($f^2 = 0.137$). ES has a small effect size ($f^2 = 0.048$).

4.1.8. Predictive Power of the Model

From Table 10, predictive relevance was evaluated using the Blindfolding method through the Q^2 index. The results in Table 10 show that the Q^2 values for PR and DLRC are 0.257 and 0.337, respectively. Both values are greater than 0, confirming that the model has predictive power for endogenous variables. At thresholds of 0.02, 0.15, and 0.35, corresponding to small, medium, and large forecasting capabilities, respectively, PR achieved a medium forecasting level. DLRC also reached a medium forecasting level but approached the large forecasting threshold.

Table 10. Predictive relevance Q^2 values

Endogenous variables	SSO	SSE	(Q2=1-SSE/SSO)	Level of forecast
PR	1.320.000	980.475	0.257	Medium
DLRC	2.640.000	1.751,148	0.337	Average, near high

The exogenous variables PS, TS, and ES, with Q^2=0, are normal because they are not predicted by any other variables in the model. Overall, the research model meets the requirements for reliability, convergent validity, discriminant validity, multicollinearity, explanatory power, and predictive power. PS is the factor with the strongest overall influence on DLRC, followed by TS and PR. At the same time, PR plays a crucial bridging role in transforming pedagogical support, technology, and the digital policy environment into the capacity of science education students to utilize digital learning resources.

4.2. Discussion

The findings indicate that DLRC is associated with both training conditions and personal readiness. The model explained 49.6% of the variance in DLRC and demonstrated predictive relevance ($Q^2 = 0.337$). Pedagogical support had the largest total association with DLRC ($\beta = 0.485$), comprising a direct relationship ($\beta = 0.384$) and an indirect relationship through PR ($\beta = 0.102$). Its medium effect size ($f^2 = 0.238$) further suggests that pedagogical design is more consequential in the model than access to technology alone. This pattern accords with research emphasizing instructor modelling, authentic practice, and systematic curriculum integration in the development of pre-service teachers' professional digital competence (Tondeur et al., 2012; Instefjord & Munthe, 2017; Gudmundsdottir & Hatlevik, 2018). It also supports the DigCompEdu proposition that digital resources obtain educational value through purposeful pedagogical use (Redecker & Punie, 2017).

Technological support was positively associated with DLRC (total effect $\beta = 0.329$; direct effect $\beta = 0.231$; indirect effect through PR $\beta = 0.097$), although its effect size was smaller than that of pedagogical support ($f^2 = 0.087$). Reliable internet, LMS access, digital libraries, simulations, and specialized software appear to provide enabling conditions, but the comparison of coefficients suggests that infrastructure alone is insufficient. This interpretation is consistent with TPACK and prior teacher-education research, which position technology as one component of integrated professional knowledge and practice (Mishra & Koehler, 2006; Tondeur et al., 2012).

PR was positively associated with DLRC ($\beta = 0.308$; $f^2 = 0.131$) and carried significant indirect effects for all three external conditions. For PS and TS, significant direct and indirect paths indicate complementary partial mediation. For ES, the tested model included no direct ES→DLRC path; the evidence therefore supports only an indirect association through PR ($\beta = 0.057$), not a demonstrated direct effect or full mediation. These results suggest that motivation, self-directed learning, critical thinking, and foundational digital skills may help students use the opportunities provided by programs and institutions (Falloon, 2020; Dolezal et al., 2025).

Theoretically, the study specifies DLRC as a resource-focused component of professional digital competence and provides evidence for personal readiness as an explanatory mechanism between external support conditions and DLRC. Practically, the statistical pattern suggests two levels of action. In the short term, programs can prioritize assessed digital-product tasks, instructor modelling, guided resource evaluation, and workshops on copyright and responsible AI; these actions align with the comparatively large PS→DLRC relationship. At the institutional level, universities can maintain reliable LMS and specialist software access, develop shared resource repositories, and align digital policies with sustained readiness-building activities; these measures reflect the TS relationships and the indirect ES→PR→DLRC pathway. These recommendations are directions supported by observed associations, not experimentally verified interventions.

5. CONCLUSION

This study examines factors associated with pre-service Natural Science teachers' competence in using digital learning resources and the mediating role of personal readiness. Pedagogical support demonstrates the strongest total relationship with DLRC, followed by technological support, while personal readiness is directly associated with DLRC and transmitted part of the relationships from external support conditions. The digital environment and policies are related to DLRC only indirectly through PR in the tested model. These findings extend resource-focused professional digital competence research by connecting pedagogical, technological, and institutional conditions with a personal readiness mechanism.

The model explained 33.6% of the variance in PR and 49.6% of the variance in DLRC and demonstrated predictive relevance for both endogenous constructs. For teacher education, the results suggest prioritizing authentic, assessed digital-resource tasks and instructor modelling while maintaining accessible infrastructure, shared repositories, and readiness-building support. Because these recommendations derive from cross-sectional associations, their effectiveness should be evaluated through longitudinal or intervention studies.

Limitations of the study include the non-probability convenience sampling procedure, the restriction to Natural Science teacher-education programs, reliance on self-reported perceptions, and the cross-sectional design, all of which limit generalizability and causal inference. The use of a single questionnaire also creates a risk of common method bias, and the study did not include behavioral traces or performance-based assessments of DLRC. In addition, the model examines only a limited set of pedagogical, technological, institutional, and personal factors. Future studies should use probability or multi-stage sampling, report and compare institutional subgroups, combine self-reports with authentic performance tasks or platform data, assess common method variance explicitly, and test the model longitudinally or experimentally with additional factors.

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