Are Functional and Critical Digital Skills Distinct? Evidence from Set Bifactor-ESEM Using the yDSI among Students

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Abstract

This study investigated the structural validity of students' digital skills by comparing eight competing measurement models, including Confirmatory Factor Analysis (CFA), Exploratory Structural Equation Modeling (ESEM), and bifactor-ESEM variants, using data from a sample of 603 university students. All models aimed to assess both critical and functional digital skills, providing a comprehensive evaluation of the multidimensional structure of digital competence. Model performance was evaluated using robust fit indices: χ^2, RMSEA, CFI, TLI, and SRMR. The Set bifactor-ESEM model demonstrated superior fit (χ^2 (368) = 729.47, RMSEA = .040 [90% CI: .036–.045], CFI = .994, TLI = .992, SRMR = .022), outperforming both traditional CFA and Full bifactor-ESEM models. Examination of the latent structure highlighted distinct patterns across the two digital skill domains. Critical skills adhered to a predominantly unidimensional configuration anchored by the general factor, whereas functional skills exhibited a clearly multidimensional structure informed by their specific subdomains. The general factors of the two layers were only weakly correlated (r = .29), despite being statistically significant. Two subcomponents tied to strategic and creative digital skills showed a significant cross-set association. In contrast, the majority of factor correlations obtained from the full ESEM model were statistically non-significant (e.g., CIC–TO: r = .025, p = .894; CIC–INP: r = .067, p = .606), highlighting the empirical separation of critical and functional skills. These findings suggest that digital skills are best conceptualized as a layered construct, comprising interrelated but structurally distinct domains. Implications for assessment design, educational interventions, and theoretical modeling are discussed.

Keywords: *digital competence; yDSI; critical digital literacy; Set bifactor-ESEM; WLSMV; higher education*

1. Introduction

In an increasingly digitalized society, acquiring digital competence is essential for meaningful participation in social, economic, and civic life. Established frameworks such as DigComp [1] and the cross-nationally validated youth Digital Skills Indicator (yDSI) [2] conceptualize digital competence as a multidimensional construct that spans information, communication, content creation, safety, and problem-solving. A core feature of these frameworks is the distinction between functional and critical digital skills. Functional skills involve procedural and task-oriented digital practices, whereas critical skills encompass evaluative, reflective, and harm-mitigating capacities essential for informed digital engagement [3].
The short yDSI scale reflects this structure through two heterogeneous item sets: functional skills are measured through behavioral self-report items, while critical skills rely on knowledge-based items. With this design, some overlap among items is expected within each layer, yet overlap between layers is deliberately restricted to maintain their conceptual separation.
Integrating these components into the core of educational curricula is increasingly regarded as a priority [4]. Still, to shape curricula that genuinely support students, it is important to understand more precisely how functional and critical skills work together.
Given the multidimensionality of digital competence, appropriate methodological models are needed to capture its internal structure accurately.

2. Methodological Overview of Competing Latent Variable Techniques

For hierarchical constructs, bifactor specifications are often recommended to separate general (G) and specific (domain-level) sources of variance. Bifactor-ESEM [5] extends this logic with ESEM's flexibility, and Set bifactor-ESEM further constrains the space of cross-loadings to within-set relations, providing a principled compromise among fit, parsimony, and interpretability. Meta-analytic evidence indicates that bifactor-ESEM models generally yield superior fit and more defensible parameters for complex educational constructs [6].

Exploratory Factor Analysis (EFA) is a data-driven method for identifying latent dimensions without imposing prior structural constraints. All items freely load on all factors, with oblique rotations used to obtain interpretable patterns. EFA is valuable for probing dimensionality and detecting cross-loadings when theory is limited, but it is not confirmatory and does not provide global fit indices for hypothesis testing. Consequently, it is less suitable when specific item–factor relationships are theoretically expected [7].
Independent Cluster Model CFA (ICM-CFA) specifies that each item loads on a single factor, with all cross-loadings fixed to zero.
This strict structure provides strong confirmatory control and allows the use of global fit indices. The model is highly parsimonious and straightforward to interpret, making it suitable when constructs are clearly separable and cross-loadings are negligible. However, the zero cross-loading assumption is often unrealistic for multidimensional constructs, leading to inflated factor correlations and compromised discriminant validity, as frequently observed in digital competence research [7].
Full ESEM integrates the flexibility of EFA with the hypothesis-testing capabilities of SEM. All non-target cross-loadings are freely estimated, typically under target rotation to approximate the intended structure. This approach generally achieves better fit and more realistic factor correlations than CFA, accommodating construct-relevant multidimensionality without post hoc modifications. Lower parsimony and the presence of numerous cross-loadings can complicate interpretation, particularly when theoretical guidance is weak [6], [7].
In *full Bifactor-CFA*, each item loads on a general factor (G) and one specific factor, while all cross-loadings remain fixed to zero. This structure separates general and domain-specific variance, making it informative for hierarchical constructs. The prohibition of cross-loadings can lead to misfit or biased estimates when multidimensional cross-loadings are plausible [5], [8].
Full Bifactor-ESEM combines bifactor logic with ESEM flexibility, allowing items to load on G and cross-load on multiple specific factors. It offers the most comprehensive representation of hierarchical, multidimensional constructs and often reduces bias in loadings and correlations relative to CFA. This approach is highly parameterized, necessitating large sample sizes and a strong theoretical foundation; it may also present estimation challenges [5], [6].
In *Set CFA (Second-Order or Set-Restricted Confirmatory Factor Analysis*), items are organized into theoretically defined sets (e.g., functional vs. critical), with cross-loadings between sets fixed to zero. Within each set, standard CFA constraints are applied. This structure preserves the a priori conceptual distinction between item types, supporting model parsimony and interpretability. However, cross-loadings within each set remain constrained to zero, which may lead to inflated factor correlations and biased estimates of specific factors [9].
Set-ESEM (Set Exploratory Structural Equation Modeling) permits cross-loadings within theoretically defined item sets (e.g., within functional or within critical items), while constraining cross-set cross-loadings to zero. This approach typically employs target rotation and strikes a balance between model realism and parsimony. Compared to CFA, it reduces inflation of factor correlations, and unlike full ESEM, it avoids over-permissiveness by preserving the theoretical structure of item types. Set-ESEM is particularly well-suited for modeling item heterogeneity but requires clear theoretical justification for the definition of item sets. However, it is less flexible than full ESEM when cross-set cross-loadings are substantively meaningful. [7], [9].
Set bifactor-ESEM extends Set-ESEM by adding a general factor. Items load on G and on set-specific factors, with cross-loadings allowed only within sets. It is ideal for hierarchical structures with heterogeneous item formats (e.g., functional behavioral items vs. critical knowledge items), capturing both general and specific variance while preserving theoretical separation between sets, enhancing discriminant validity and interpretability. Set bifactor-ESEM is more complex than Set-CFA or Set-ESEM. It requires adequate sample size, strong theory, and careful rotation specification [5], [9].

2.1. Why Set-Level Modeling Is Well-Suited to the yDSI

Digital competence is increasingly conceptualized as a multidimensional construct comprising both foundational operational abilities and higher-order evaluative capacities. Empirical and conceptual work reinforces a functional–critical distinction within this construct: Study [3] shows that functional skills support engagement with digital platforms, whereas critical skills guide judgment and strategic responses in complex digital environments. Another study [10] similarly classifies functional and critical literacies as distinct yet complementary categories within broader digital literacy models. The yDSI formalizes this dual-layer structure by explicitly separating functional and critical aspects across its four skills domains, and its mixed item formats (behavioral vs. knowledge) justify set-level constraints that

prevent cross-set contamination while allowing for within-set cross-loadings [2]. This measurement architecture aligns directly with Set-ESEM specifications and, for hierarchical modeling, with Set-bifactor ESEM, which enables estimation of a general digital competence factor spanning both sets while preserving domain-specific and set-specific variance [5], [9].
Meta-analytic work indicates that bifactor-ESEM families often provide superior fit and more trustworthy parameters than their CFA counterparts for educational constructs that are simultaneously general and domain-specific [6]. A study [11] identified a bifactor-ESEM solution as the most suitable representation of teachers' ICT competence beliefs, with a clear separation between the general factor and domain-specific components such as safety and collaboration.
The aim of this study is to determine whether functional and critical digital skills are represented as distinct yet interconnected domains of digital competence through the empirical modeling of the correlational structure of yDSI indicators using advanced analytic approaches, including the Set bifactor ESEM model. Alternative modeling strategies are compared to identify the most parsimonious and theoretically coherent representation of digital competence. Through the clarification of the relationship between functional and critical skill layers, the theoretical understanding of digital competence is refined, and more robust, evidence-based assessment and curriculum development in higher education are supported, ensuring that both skill sets are addressed in a balanced and pedagogically meaningful manner.

3. Method

3.1. Participants and Procedure

Data were collected from students at *Fan S. Noli University of Korça*, located in southeastern Albania. Participation was voluntary and anonymous, and responses were submitted via an online questionnaire, in full compliance with ethical standards approved by the Rector and university's Ethics Council.
The measurement instrument was based on the short version of the Youth Digital Skills Indicator (yDSI) [2] and included two sets. The first consisted of 24 items measuring functional digital skills across four dimensions: Technical and Operational Skills (TO), Information Navigation and Processing Skills (INP), Communication and Interaction Skills (CI), and Content Creation and Production Skills (CCP). These items were rated on a six-point Likert scale ranging from 0 (*I do not understand what you mean by this*) to 5 (*Very true of me*), with an additional option (*I do not want to answer*) coded as 99 and treated as missing value.
The second set comprised 9 items assessing critical digital skills across three dimensions: Information Navigation and Processing (INPC), Communication and Interaction (CIC), and Content Creation and Production (CCPC). These items used a four-category response format: 1 (*Definitely not true*), 2 (*Definitely true*), 3 (*I'm not sure*), and 99 (*I do not want to answer*), with the latter also treated as missing value. A total of 603 students participated (M_{age} = 22.07; *SD* = 5.72; years; 69.3% female). The sample size closely approximated the recommended minimum of 630 participants, as calculated using Soper's (2025) a priori sample size calculator for structural equation modeling [12]. This estimate was based on an anticipated effect size of 0.15, a desired statistical power of 0.80, and a model structure involving four latent and 24 observed variables.

3.2. *Data Analysis*

All models were estimated in Mplus (Muthén & Muthén) v. 8.11, using the Weighted Least Squares Mean and Variance adjusted (WLSMV) estimator, which is well-suited for ordinal data. WLSMV treats variables as categorical, uses polychoric correlations, and provides robust parameter estimates and standard errors even when normality assumptions are violated [7]. It is particularly effective for scales with five or fewer response categories and performs reliably with sample sizes over 200 [13], [14].
To assess the structural validity of digital competence, eight competing models were tested, including Full ICM-CFA, Full ESEM, Full bifactor-CFA, Full bifactor-ESEM, Second-order Set ICM-CFA**,** Set-ESEM**,** Set bifactor-CFA**,** and Set bifactor-ESEM.
Model fit was evaluated using χ^2, CFI, TLI, RMSEA (with 90% confidence interval), and SRMR, following established guidelines [15]. Thresholds for acceptable to excellent fit were defined as CFI/TLI ≥ .90/.95, RMSEA ≤ .08/.05, and SRMR ≤ .08. Given the chi-square test's sensitivity to sample size and model complexity, it was interpreted in conjunction with other indices [16].

4. Results

4.1. Model Fit Evaluation

Among the competing models, the Set bifactor-ESEM model (M8) demonstrated the most balanced and superior fit: χ^2 (368) = 729.47, RMSEA = .040 (90% CI: .036–.045), CFI = .994, TLI = .992, and SRMR = .022 (Table 1). These values meet or exceed conventional thresholds for excellent model fit.

Table 1. *Model fit for competing measurement models*

	Models	χ^2	df	RMSEA	90% CI	CFI	TLI	SRMR
M1	Full ICM-CFA	1362.968	474	.056	.052 .059	.986	.984	.044
M2	Full ESEM	716.867	318	.046	.041 .050	.994	.990	.021
M3	Full Bifactor-CFA	1426.246	462	.059	.055 .062	.985	.983	.043
M4	Full Bifactor-ESEM	621.322	292	.043	.039 .048	.995	.991	.019
M5	Set ICM-CFA 2 order	1317.458	487	.053	.050 .057	.987	.986	.045
M6	Set ESEM	940.023	402	.047	.043 .051	.992	.989	.025
M7	Set Bifactor-CFA	1482.861	482	.059	.055 .062	.984	.983	.051
M8	Set Bifactor-ESEM	729.468	368	.040	.036 .045	.994	.992	.022

Note. χ^2 - Chi-square; df - degrees of freedom; TLI - Tucker-Lewis Index; CFI - Comparative Fit Index; RMSEA - Root Mean Square Error of Approximation [90%CI]; SRMR - Standardized Root Mean Square Residual

Compared to other models, Set Bifactor-ESEM outperformed both traditional CFA-based models and fully exploratory ESEM variants (see Table 2).

Table 2. *Fit Index Differences Supporting Model Selection Based on Parsimony and Structure*

Model Comparison	$\Delta\chi^2$	Δdf	ΔRMSEA	ΔCFI	ΔTLI	ΔSRMR	Meet criteria
M2-M1	-646.101	-156	-.010	.008	.006	-.023	Yes
M3-M1	63.278	-12	.003	-.001	-.001	-.001	No
M4-M2	-95.545	-26	-.003	.001	.001	-.002	No/Yes
M6-M2	223.156	84	.001	-.002	-.001	.004	Yes
M6-M5	-377.435	-85	-.006	.005	.003	-.020	Yes
M7-M5	165.403	-5	.006	-.003	-.003	.006	No
M8-M4	108.146	76	-.003	-.001	.001	.003	No/Yes
M8-M7	-753.393	-114	-.019	.010	.009	-.029	Yes

For instance, the Set Bifactor-CFA model (M7) yielded higher RMSEA (.059) or SRMR (.051), and lower CFI (.984) or TLI (.983), indicating poorer fit and inflated error. When comparing Set Bifactor-ESEM (M8) with Full Bifactor-ESEM (M4), M8 showed better performance on RMSEA (.040 vs. .043) and TLI (.992 vs. .991), two indices that penalize for lack of parsimony. Although M4 slightly outperformed M8 on CFI (.995 vs. .994) and SRMR (.019 vs. .022), this pattern is identical to the findings reported by Marsh et al. (2011). They noted that Full-ESEM models may achieve slightly better fit on certain indices due to increased flexibility, but this often reflects capitalizing on chance, especially when the difference in chi-square is proportional to the difference in degrees of freedom.

4.2. Latent Structure and Factor Correlations

The Set Bifactor-ESEM model revealed low correlations between the general factors representing functional and critical digital skills (r = .29–.30), providing strong empirical support for their distinctiveness (Figure 1). In contrast, the Set Bifactor-CFA model produced substantially higher G-factor correlations (r ≈ .77), suggesting inflated overlap likely due to the restrictive assumption of zero cross-loadings. These findings reinforce the realism and flexibility of ESEM-based approaches in modeling multidimensional constructs. In the context of the Set B-ESEM solution, statistically significant cross-set correlations were detected solely among the INP and CCP sub-dimensions.

The choice of the best-fitting model reflects not only statistical fit but also adherence to theory, interpretability of parameter estimates, and parsimony, tempered by sample size considerations. When CFA and ESEM models yield similar fit and factor correlations, CFA may be preferred for its simplicity, especially in small samples. However, when ESEM models demonstrate substantially better fit and more clearly differentiated factors, they should be preferred.

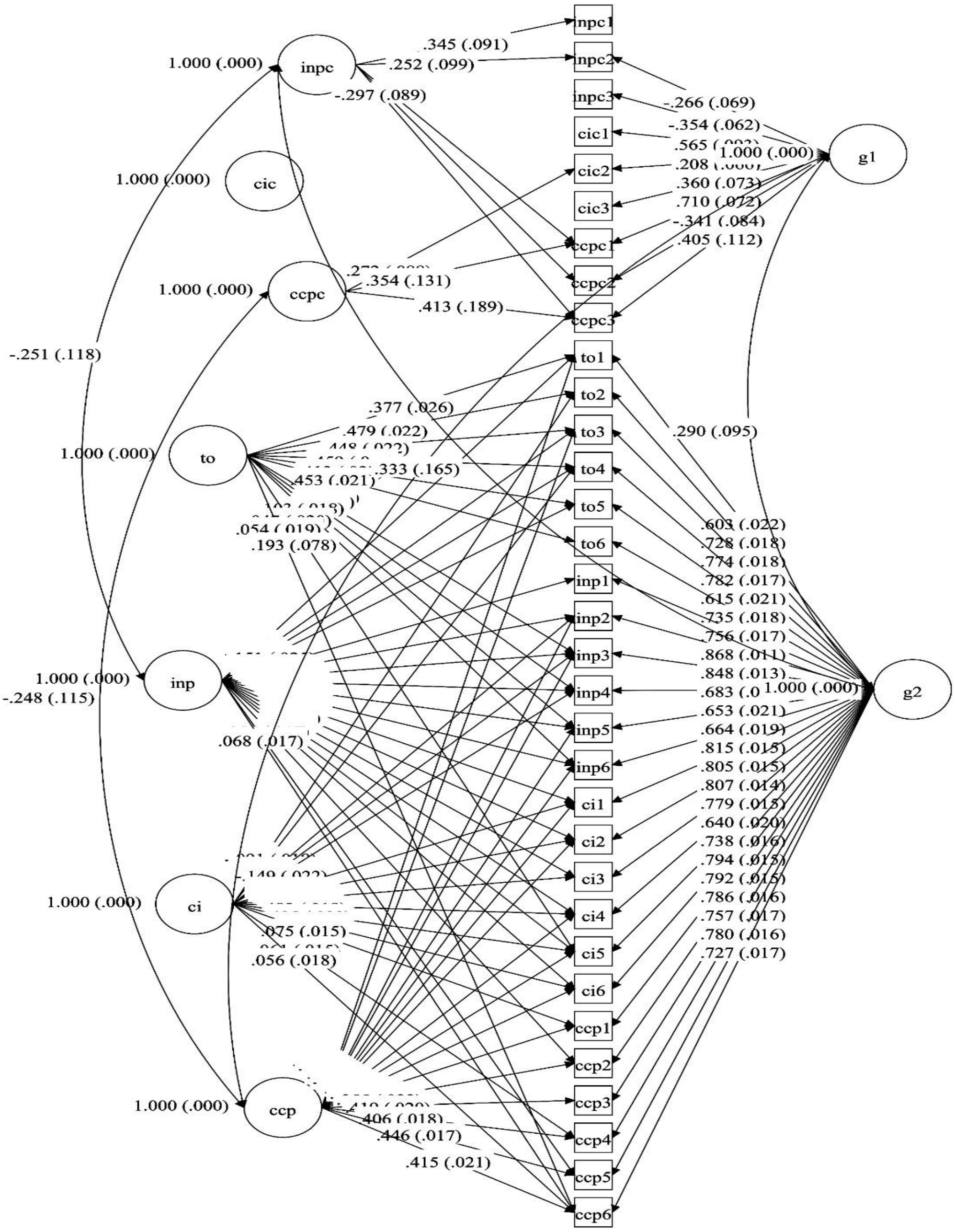

Figure 1. *Standardized loadings (only statistically significant) of Set B-ESEM*

4.3. Structural Differentiation between Skill Domains

A closer inspection of item-level loadings revealed differential structural behavior between the two skill sets:

- For critical digital skills, the Set bifactor-ESEM model showed a dominance of the general factor, with most items loading significantly on G and relatively weak or non-significant loadings on their designated sub-factors. This pattern supports a unidimensional structure for critical skills under the constraints of the Set B-ESEM framework.
- For functional digital skills, the same model exhibited a more nuanced structure, where items loaded meaningfully on both the general factor and their respective sub-factors (e.g., TO, INP, CI, CCP). This indicates a multidimensional configuration, with both general and domain-specific influences contributing to item responses.

In contrast, the Full bifactor-ESEM model revealed a more integrated structure across both domains. Specific factor loadings were stronger and more interpretable, and cross-loadings were present across

items, suggesting a multidimensional latent structure overall. However, the general factor was less dominant for critical items, and the clarity of unidimensionality was reduced.
In summary, the Set bifactor-ESEM (Set B-ESEM) model offers the most accurate and theoretically sound representation of digital competence in this study. It confirms the hypothesized structure, reduces model bias, and adheres to best practices in multidimensional modeling by balancing statistical rigor with conceptual clarity.
The evidence supporting this conclusion includes:

- Low general factor (G-factor) correlations, indicating limited overlap across domains.
- Superior model fit of Set B-ESEM compared to alternatives.
- Distinct behavior across different item sets, reinforcing the need for a nuanced approach.

Together, these findings demonstrate that functional and critical digital skills are distinct yet interrelated domains, best captured through a parsimonious bifactor-ESEM framework, such as Set B-ESEM (see Table 3).

Table 3. *Modeling Approaches for Multidimensional Constructs: A Conceptual Comparison*

Model	Cross-loadings allowed	General factor included	Parsimony	Interpretability	Typical use case	Key advantage
Full ICM-CFA	No	No	High	Limited (rigid)	Simple, clean structures	Most parsimonious
Full ESEM	Yes (all)	No	Low	Complex	Multidimensional constructs	Realistic item behavior
Set-ESEM	Yes (within sets)	No	Moderate	Balanced	Distinct item sets (domains/methods)	Fit + structure preserved
Set B-ESEM	Yes (within sets)	Yes	Moderate	High	Hierarchical + item-type heterogeneity	General + specific variance, minimal bias

5. Discussion

This study aimed to evaluate the structural validity of digital competence by comparing eight competing measurement models, with particular focus on the bifactor-ESEM framework. The findings provide compelling evidence for the superiority of the Set bifactor-ESEM model, both in terms of statistical fit and theoretical interpretability. More importantly, the results offer nuanced insights into the distinctiveness between critical and functional digital skills, which has important implications for digital competence theory and assessment.
Structural Validity and Model Selection: The Set bifactor-ESEM model demonstrated excellent fit across all indices, outperforming both traditional CFA models and fully exploratory ESEM variants. Its balance between parsimony and flexibility allowed for a more realistic representation of the latent structure, avoiding the inflation of factor correlations commonly observed in ICM-CFA models. The low G-factor correlations ($r = .29–.30$) between critical and functional sets further support the hypothesis that these are distinct but related constructs, rather than manifestations of a single underlying dimension.
Within the Set B-ESEM model, a statistically significant association between functional and critical digital skills was identified only for the INP and CCP sub-dimensions. This pattern indicates that strengthening strategic (INP) and creative (CCP) functional digital skills may contribute to enhanced development of the corresponding critical digital skills linked to these domains. Such findings highlight the importance of supporting both layers of competence in an integrated manner, particularly in areas where functional proficiency has the potential to reinforce higher-order critical capacities.
Domain-Specific Structural Patterns: A key contribution of this study lies in the *differential structural behavior* observed across the two skill domains:

- For critical digital skills, the Set bifactor-ESEM model revealed a pronounced general-factor dominance: item loadings clustered on G, while specific-factor loadings were weak or non-significant. Such a configuration indicates that critical skills function as a unified construct, likely reflecting an overarching evaluative or judgment-based competency.
- Functional digital skills, however, exhibited a differentiated structure: items loaded substantively on their sub-factors while still contributing to the general factor. This pattern underscores the domain-specific and task-oriented nature of functional competence.

Emerging evidence supports this functional–critical distinction. Study [3] showed that functional and critical digital skills are mobilized differently in real-world civic action, reinforcing their conceptual separation. In contrast, the Full bifactor-ESEM specification in this study blurred these boundaries: although it increased specific-factor variance and enabled cross-loadings, it reduced the coherence of the general factor, especially for critical skills, highlighting a trade-off between flexibility and theoretical clarity.

Implications for Theory and Practice

These findings have several theoretical and practical implications:

1. *Clarifying the multidimensional architecture of digital competence:* The differentiated structure observed in Set bifactor-ESEM supports the conceptual separation between critical and functional digital skills, aligning with frameworks that treat digital competence as a multidimensional construct (e.g., [1], [3], [17]). This distinction helps refine existing frameworks by positioning functional skills as domain-specific operational abilities and critical skills as higher-order evaluative capacities grounded in reflective judgment.
2. *Strengthening construct validity through appropriate modeling:* Findings showing differential model performance (Set bifactor-ESEM vs. Full bifactor-ESEM) highlight the importance of choosing modeling structures that respect theoretical boundaries. The dominance of a general factor in the critical domain supports a unidimensional conceptualization, while the multidimensionality of functional skills confirms their domain-embedded nature. Theoretically, this suggests that digital competence is not a uniform construct but a hierarchical configuration that needs tailored representation.
3. *Advancing measurement theory in digital education research:* The results underscore that flexibility in measurement (e.g., allowing extensive cross-loadings) may undermine interpretability when constructs are expected to remain distinct. Theoretical work in digital competence should therefore prioritize models that balance complexity with conceptual clarity, ensuring that measurement aligns with pedagogically meaningful distinctions.
4. *Designing curricula that target both functional and critical layers:* Programs should intentionally integrate learning outcomes that build both:

- Functional skills: operational, technical, and domain-specific competencies (e.g., navigating platforms, managing information, producing content).
- Critical skills: evaluation, reflective judgment, bias recognition, ethical and safety-related reasoning.

  Curricula must avoid treating digital competence as a monolithic skill and instead develop structured progression from functional to critical capacities.

5. *Supporting adaptive, evidence-based program design:* The hierarchical nature of digital competence indicates that:

- Foundational functional skills should be taught early (baseline operational literacy).
- Critical skills should be embedded across the curriculum as transversal competences.

  This ensures students gradually move from tool-use proficiency to reflective digital citizenship and informed decision-making

6. Conclusion

This study provides empirical evidence that functional and critical digital skills form distinct yet interconnected layers of digital competence. Using Set bifactor-ESEM, we demonstrated that critical skills are best represented as a largely unidimensional construct, dominated by a general evaluative factor, whereas functional skills retain a multidimensional configuration aligned with domain-specific operational tasks. These structural differences reinforce contemporary theoretical work emphasizing the layered nature of digital competence and highlight the importance of selecting modeling approaches that respect established conceptual boundaries.

The results show that the Set bifactor-ESEM model provides a clearer and more interpretable structure of digital competence than more flexible alternatives. Although the Full bifactor-ESEM specification increased specific-factor variance, it weakened the coherence of the general factor, especially in the critical domain. Set bifactor-ESEM therefore emerges as the most theoretically aligned framework for digital-skills assessment. These insights, in turn, support curricula that balance operational competence with evaluative digital judgment, reflecting the layered architecture of digital competence.

Overall, the findings enhance theoretical clarity around digital competence, validate more precise modeling strategies, and inform the development of curricula that better prepare students for evolving digital demands.

Limitations and Future Directions

While the Set bifactor-ESEM model provided the best representation of the data, its structure is partially constrained by theoretical assumptions. Future research should explore hybrid models that allow for partial cross-loadings while preserving interpretability. Additionally, longitudinal designs could help determine whether the structural distinction between critical and functional skills holds over time and across developmental stages.

The study relied on data collected from students at a single institution, a factor that may limit the generalizability of the findings.

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