Shaping Future Learning through Digital-Skills Profiling

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Abstract

In contemporary knowledge societies, higher education institutions face a growing misalignment between the digital competence that graduates possess and the levels required by an increasingly digitalized labor market. Effective curriculum reform requires a theoretically coherent and methodologically rigorous understanding of digital skills as a construct and the heterogeneity with which these skills are distributed across student populations. Although digital skills are widely acknowledged as multidimensional and hierarchically structured, as reflected in conceptual frameworks such as DigComp, empirical studies addressing heterogeneity continue to rely on scale scores or factor scores derived from restrictive measurement models (e.g., Independent Cluster Model Confirmatory Factor Analysis, ICM-CFA), which fail to adequately capture the coexistence of global and specific dimensions and their interrelationships. Recent methodological advances emphasize the need to model digital skills using bifactor Exploratory Structural Equation Modeling (B-ESEM) and to use factor scores from such models as indicators in Latent Profile Analysis (LPA). This approach enables the clear disaggregation of level and shape differences, allowing for more meaningful, substantive, and interpretable student profiles. The present study aims to identify homogeneous subgroups of university students based on multidimensional digital skill patterns using LPA based on B-ESEM factor scores, and to contrast this approach with LPA solutions based on scale scores and ICM-CFA factor scores. Findings highlight the superior informational richness and classification accuracy of the B-ESEM-based profile solution, with meaningful implications for differentiated, targeted, and personalized curriculum design in higher education.

Keywords: *digital skills, curriculum design, latent profile analysis, bifactor-ESEM, higher education*

1. Introduction

European higher education systems face a growing mismatch between graduates' skills and the demands of increasingly digitalized labor markets. In response, digital competence is now widely regarded by policymakers as a foundational requirement for employability, economic resilience, and civic participation. Rapid technological change, driven by automation, artificial intelligence, data intensification, and hybrid work models, has made the effective use of digital information and tools essential across sectors.

Despite this recognition, digital skills remain unevenly integrated into higher education curricula. Treating them as optional or peripheral limits graduates' preparedness for contemporary work environments. At the same time, students differ substantially in their existing digital competencies due to variation in prior education, socioeconomic background, discipline, and learning trajectories. Uniform curricular solutions therefore risk inefficiency, either failing to support lower-skilled students or under-challenging more advanced ones.

From a policy perspective, effective curriculum reform requires evidence on how digital competencies are structured within student populations. Specifically, it is necessary to identify meaningful profiles that capture both overall levels of digital competence and distinct patterns of strengths and weaknesses across skill domains. Such knowledge enables targeted interventions, more efficient allocation of educational resources, and better alignment between higher education outcomes and labor market needs.

Established policy frameworks, particularly DigComp [1], conceptualize digital competence as a multidimensional construct comprising interrelated domains, alongside an overarching general competence. However, conventional measurement approaches often inadequately represent this structure, producing biased estimates that limit the value of subsequent analyses. When used for student profiling, such measures tend to capture only broad level differences, providing limited guidance for targeted policy action.

Recent advances show that pairing strong measurement models with person-centered methods produces more actionable insights. B-ESEM captures overall and domain-specific digital skills, and LPA transforms these results into clear competence profiles. This integrated approach strengthens the policy usefulness of digital-skills data and directly supports informed curriculum design.

2. Digital Skills as a Multidimensional and Hierarchical Construct

Contemporary conceptualizations define digital skills as a multidimensional construct extending beyond technical proficiency to include cognitive, communicative, creative, and evaluative capacities. This view mirrors the embedding of digital technologies in learning, employment, and professional practice.

The European Commission’s DigComp framework formalizes this view by identifying several interrelated domains of digital competence. These domains function in a complementary manner, with competencies such as information literacy, communication, content creation, and safety mutually reinforcing one another.

This interdependence implies a hierarchical structure, consisting of an overarching level of general digital proficiency alongside domain-specific competencies that capture distinct patterns of strengths and weaknesses. Accurately representing this structure is essential for informing policy-relevant analyses and for designing targeted, efficient curriculum interventions.

2.1. Measurement Models for Capturing the Multidimensional Structure of Digital Skills

Accurately assessing digital skills requires measurement models capable of representing multidimensional item behavior. Traditional confirmatory factor analysis (CFA), grounded in the Independent Cluster Model [2], constrains cross-loadings to zero, despite substantial evidence that items often reflect multiple skill domains. For complex constructs such as digital skills, this assumption produces oversimplified representations and systematically biases parameter estimates [3, 4]. When true cross-loadings are suppressed, construct-relevant variance is misallocated, typically inflating factor correlations and distorting construct definitions [5].

This limitation highlights the need for models that explicitly account for multidimensional item structure. Exploratory structural equation modeling (ESEM) [6] addresses this issue by allowing theoretically guided cross-loadings under confirmatory control, better capturing the inherent overlap among digital skill domains. However, both CFA and ESEM lack the capacity to model hierarchical structures, leaving the coexistence of general and domain-specific competencies unrepresented.

Bifactor CFA models overcome this limitation by estimating a general factor alongside specific domain factors, enabling a clearer partitioning of shared and domain-specific variance [7]. Integrating bifactor modeling with ESEM yields bifactor ESEM (B-ESEM), which simultaneously models cross-loadings and hierarchical structure, offering a comprehensive framework for representing interconnected digital skills [8].

Methodological research recommends comparing CFA, ESEM, bifactor CFA, and B-ESEM to detect construct-relevant multidimensionality [9]. B-ESEM improves the validity of digital skills measurement by clearly separating general proficiency from specific skill domains.

Importantly, factor scores derived from B-ESEM provide a robust foundation for person-centered analyses, enabling the identification of student profiles that reflect both overall digital competence and distinct domain-level configurations.

2.2. Latent Profile Analysis

Latent Profile Analysis (LPA) [10] is a person-centered statistical methodology designed to identify homogeneous subgroups within a heterogeneous population based on individuals’ scores on multiple continuous indicators. Unlike traditional cluster analysis, LPA is model-based and probabilistic, offering robust fit indices, classification accuracy measures, and replication tests that validate the extracted classes.

LPA equation is: $f(\mathbf{y}_i \mid \boldsymbol{\theta}) = \sum_{c=1}^{C} \boldsymbol{\gamma}_c f_c(\mathbf{y}_i \mid \boldsymbol{\mu}_c, \boldsymbol{\Sigma}_c)$, where, $f(\mathbf{y}_i \mid \boldsymbol{\theta})$, as the distribution of a set of scores y_i, given model parameters $\boldsymbol{\theta}$, is a function of the proportion of class c, $\boldsymbol{\gamma}_c$, and the class specific distribution, $f_c(\mathbf{y}_i \mid \boldsymbol{\mu}_c, \boldsymbol{\Sigma}_c)$, given its mean $\boldsymbol{\mu}_c$ and covariance metrics, $\boldsymbol{\Sigma}_c$.

Latent Profile Analysis (LPA) is widely used in psychology and education to identify unobserved subgroups that cannot be detected through variable-centered approaches. In educational research, LPA has been applied to motivation, engagement, well-being, and, more recently, students' digital behavior and digital competence.

Digital-skills LPA studies differ considerably in their use of item-level or aggregated indicators. While [11] is transparent about indicator choice, this clarity is often lacking elsewhere [12], hindering interpretation and comparison.

Despite their convenience, scale scores do not account for measurement error or reflect the underlying latent structure of digital competence. As a result, LPA based on scale scores tends to yield profiles driven primarily by overall level differences (e.g., low, medium, high), offering limited insight into domain-specific skill patterns. Methodological research therefore emphasizes that person-centered analyses should be grounded in robust variable-centered models that accurately represent construct multidimensionality [13].

Using factor scores derived from ICM-CFA only partially addresses this issue, as these scores remain constrained by restrictive assumptions, including zero cross-loadings. Such limitations can distort profile solutions and obscure meaningful qualitative differences. In contrast, bifactor ESEM generates factor scores that explicitly separate general and domain-specific components while preserving cross-domain information.

When B-ESEM factor scores are used in LPA, resulting profiles capture both level and shape differences, yielding richer and more interpretable classifications. This approach has been successfully applied in occupational and educational psychology to model complex psychological constructs [5, 14]. However, no published research has yet applied B-ESEM–based LPA to digital skills, despite their clearly demonstrated hierarchical and multidimensional structure.

Purpose of the Study*:* Addressing this gap, the present approach identifies digital-skills profiles that capture both overall competence and distinct domain-level patterns. These differentiated profiles offer direct value for policy and practice, enabling targeted, adaptive, and evidence-based curriculum interventions. As such, B-ESEM–based LPA represents a significant methodological advance for digital-skills assessment and curriculum development.

This study demonstrates these advantages by showing that B-ESEM–derived profiles are psychometrically robust, theoretically coherent, and practically actionable, offering a strong foundation for more responsive and effective digital-skills curricula in higher education.

3. Method

3.1. Participants and Procedure

An online survey was administered via Google Forms to students across four faculties at Fan S. Noli University of Korça as part of a university-funded digital skills project. The sample included 599 students (69.3% female; *M* age = 22.09, *SD* = 5.75). Ethical approval was obtained from relevant institutional authorities, and participation was voluntary and anonymous.

The survey comprised socio-demographic items and the 24-item short Youth Digital Skills Indicator (yDSI; Helsper et al., 2020). The instrument was translated and culturally adapted through expert review. A preliminary test–retest evaluation with 30 students, administered three weeks apart, demonstrated good temporal stability (Spearman's ρ ≈ .80).

3.2. Sample Size

Prior research suggests that 300–500 cases are adequate for stable Latent Profile Analysis solutions [15]. ESEM-based Monte Carlo simulations demonstrated adequate estimation quality, with standard error bias below 5% and MSE below .02 at *n* = 350. The final sample exceeded this threshold, supporting robust parameter estimation.

3.3. Measure

Students' digital skills were assessed using the validated 24-item Youth Digital Skills Indicator (yDSI) [16], covering four functional domains: Technical–Operational (TO), Information Navigation–Processing (INP), Communication–Interaction (CI), and Content Creation–Production (CCP). The problem-solving and safety domains were excluded due to conceptual overlap. Items were rated on a 0–5 scale; "prefer not to answer" responses were treated as missing. The yDSI shows strong psychometric validity across multiple EU countries.

3.4. Data Analysis

All analyses were conducted in Mplus 8.11 (Muthén & Muthén). Three sets of LPA indicators were used: (a) summed scale scores for the four yDSI domains, (b) standardized factor scores from an ICM-CFA model, and (c) standardized factor scores from a bifactor ESEM model, identified in prior work as the best-fitting structure [17] among the CFA/ESEM configurations recommended for comparison [9]. Models were estimated using WLSMV, recommended for ordinal indicators and samples above 200 [18].

For each indicator set, two- to seven-profile LPA models were estimated using MLR with 1,000 random starts, 200 initial iterations, and 100 final optimizations, allowing means and variances to vary across profiles. Model selection followed standard multi-criteria guidelines [19], drawing on AIC, BIC, SABIC, entropy, smallest class percentage, and the adjusted Lo–Mendell–Rubin (aLMR) and Bootstrap Likelihood Ratio Tests (BLRT). BIC favored simpler models [20], entropy ≥ .80 signaled good accuracy [21], and classes <5% were viewed as potentially spurious unless theoretically meaningful [22]. The aLMR was interpreted cautiously due to instability, and the BLRT due to its sensitivity to minor likelihood improvements [23].

4. Results

4.1. Latent Profile Analysis Based on yDSI Sum Scores

LPA using the four yDSI sum-score indicators showed improved fit from the two- to five-class models, as indicated by decreasing AIC, BIC, and aBIC values (Table 1). Entropy remained high (.865–.914), with the three-class model showing the strongest classification (.914). The aLMR test supported only the two- and three-class solutions, whereas the BLRT remained significant across models but was interpreted cautiously due to its tendency to over-extract classes.

Table 1. *Fit Indices from Three Person-Centered Models*

Models	LL	nfp	SF	AIC	BIC	aBIC	Entropy	aLMR p-value	BLRT p-value
Model 1. LPA based on scale sum scores									
2 Profiles	-7383.508	17	1.3181	14801.016	14875.736	14821.766	.865	.0000	< .0001
3 Profiles	**-7082.979**	26	1.5598	14217.958	14332.235	14249.692	.914	.0008	< .0001
4 Profiles	-6916.025	35	1.5974	13902.049	14055.884	13944.768	.897	.0726	< .0001
5 Profiles	-6850.340	44	1.8198	13788.680	13982.071	13842.384	.897	.6260	< .0001
6 Profiles	-6801.404	53	1.7129	13708.807	13941.756	13773.496	.820	.6067	< .0001
7 Profiles	-6804.605	62	1.8033	13733.210	14005.716	13808.884	.893	1.0000	1.0000
Model 2. LPA based on ICM-CFA factor scores									
2 Profiles	-2800.148	17	1.1581	5634.297	5709.016	5655.046	.883	< .0001	< .0001
3 Profiles	-2366.445	26	1.3939	4784.890	4899.166	4816.624	.910	.0280	< .0001
4 Profiles	-2080.184	35	1.4657	4230.368	4384.202	4273.087	.949	.0021	< .0001
5 Profiles	-1874.478	44	1.4850	3836.957	4030.348	3890.661	.952	.0004	< .0001
6 Profiles	-1770.228	53	1.5150	3646.455	3879.404	3711.144	.951	.0466	< .0001
7 Profiles	-1773.546	62	1.3859	3671.092	3943.598	3746.765	.942	.1868	< .0001
Model 3. LPA based on B-ESEM factor scores									
2 Profiles	500.417	21	1.0873	-958.833	-866.533	-933.202	.956	< .0001	< .0001
3 Profiles	762.746	32	1.2774	-1461.492	-1320.844	-1422.435	.938	.0004	< .0001
4 Profiles	1039.443	43	1.4486	-1992.885	-1803.889	-1940.402	.927	.0119	< .0001
5 Profiles	1249.863	54	1.4580	-2391.726	-2154.382	-2325.817	.952	.0045	< .0001
6 Profiles	1039.443	65	0.9583	-1948.885	-1663.193	-1869.550	.944	.1109	1.0000
7 Profiles	1039.443	76	0.8196	-1926.885	-1592.845	-1834.124	.948	.1103	1.0000

Notes. LL = Model loglikelihood; nfp = number of free parameters; SF: scaling factor of the robust Maximum Likelihood estimator; AIC = Akaïke Information Criterion; BIC = Bayesian Information Criterion; ABIC = sample-size Adjusted BIC; ALMR: Adjusted Lo-Mendell-Rubin Likelihood Ratio Test; BLRT = Bootstrap Likelihood Ratio Test

Although the five-class model produced the lowest information criteria, it yielded fragmented (Table 2) and substantively weak classes, including very small groups and a non-significant aLMR.

Table 2. *Final class proportions for the latent classes based on estimated posterior probabilities for the three alternative models*

Model 1. LPA based on sum scores							
2 Profiles	.40690	.59310					
3 Profiles	.35467	.53461	.11073				
4 Profiles	.07689	.10870	.42045	.39395			
5 Profiles	.08140	.04759	.39141	.10759	.37201		
6 Profiles	.03250	.13954	.26008	.13636	.32402	.10750	
7 Profiles	.00712	.13363	.37338	.05719	.31624	.00498	.10746
Model 2. LPA based ICM-CFA factor scores							
Classes	C1	C2	C3	C4	C5	C6	C7
2 Profiles	.31781	.68219					
3 Profiles	.24331	.56366	.19303				
4 Profiles	.25466	.12797	.03829	.57908			
5 Profiles	.07524	.22520	.53816	.03829	.12311		
6 Profiles	.02666	.12218	.22081	.06268	.52938	.03840	
7 Profiles	.03170	.50304	.20718	.03829	.00334	.09585	.12060
Model 3. LPA based on B-ESEM factor scores							
2 Profiles	.73174	.26826					
3 Profiles	.20519	.27867	.51614				
4 Profiles	.22098	.41851	.26259	.09792			
5 Profiles	.03657	.34839	.30011	.09791	.21702		
6 Profiles	.41851	.09792	.22098	.00000	.26259	.00000	
7 Profiles	.26259	.41851	.00000	.00000	.22098	.09792	.00000

Thus, only the three- and four-class models were considered viable (Table 3).

In the three-class solution, Class 1 (35.47%) showed uniformly low digital skills; Class 2 (53.46%) showed moderate but even skill levels; and Class 3 (11.07%) showed high skills, especially in CI and CCP.

In the four-class solution, three classes differed only in magnitude, and the additional class did not offer conceptual distinction, with one class mean not reaching statistical significance.

Balancing fit indices, parsimony, aLMR results, class size, and interpretability, the three-class model provided the most coherent and theoretically meaningful representation of heterogeneity in digital skills based on yDSI sum scores.

4.2. Latent Profile Analysis Based on ICM-CFA Factor Scores

LPA based on the four ICM-CFA factor scores showed improving fit from the two- to five-class models, with decreasing AIC, BIC, and aBIC values and consistently high entropy (.883–.952). The aLMR test supported solutions up to five classes but not beyond, while the BLRT remained significant across all models (Table 1).

Among the three-, four-, and five-class solutions (Table 3), the three-class model reflected only quantitative differences: a very low-skill class (24.33%), a moderate-skill class (56.37%), and a high-skill class (18.87%), all showing uniform patterns across dimensions. However, the lowest-skill class had a non-significant mean, limiting its distinctiveness.

The four-class solution largely replicated the three-class structure but introduced a small (3.83%) subgroup with exceptionally high INP and CCP scores, representing a distinct high-performing group.

The five-class model added a meaningful low-performing subgroup (7.52%) with deficits across all domains, including TO dimension. All latent means were statistically significant, and the remaining classes aligned closely with those in the four-class solution.

Considering statistical fit, aLMR and BLRT support, high entropy, and the substantive value of distinguishing both an advanced and a very low-performing subgroup, the five-class solution provided the most informative representation of heterogeneity in the ICM-CFA factor scores.

4.3. Latent Profile Analysis Based on Bifactor ESEM Factor Scores

Using bifactor ESEM factor scores, the LPA incorporated both a general digital-skills dimension (quantitative variation) and four specific dimensions capturing qualitative differences across domains. Fit indices improved steadily from the two- to five-class models, with decreasing AIC, BIC, and aBIC values and high entropy (.927–.956). The aLMR and BLRT test supported up to five classes, while nonsignificant results for larger solutions, along with fragmented and near-empty classes (Table 2), indicated over-extraction.

Table 3. *Standardized latent class means for the competing profiles across the three approaches*

LPA based on scale sum scores										
3 Profiles										
Means	C1	p-value	C2	p-value	C3	p-value				
TO	2.356	.000	5.901	.000	15.120	.000				
INP	2.703	.000	5.241	.000	11.584	.000				
CI	2.330	.000	6.864	.000	85.721	.000				
CCP	2.586	.000	5.859	.000	45.747	.000				
4 Profiles										
Means	C1	p-value	C2	p-value	C3	p-value	C4	p-value		
TO	4.196	.000	15.264	.000	7.352	.000	3.142	.000		
INP	2.878	.000	11.601	.000	6.147	.000	3.559	.000		
CI	3.778	.000	88.818	.004	8.380	.000	2.932	.000		
CCP	3.672	.000	47.125	.000	7.274	.000	3.045	.000		
5 Profiles										
Means	C1	p-value	C2	p-value	C3	p-value	C4	p-value	C5	p-value
TO	4.282	.000	13.340	.000	3.540	.000	15.301	.000	8.002	.000
INP	2.794	.000	6.664	.000	3.722	.000	11.570	.000	6.614	.000
CI	3.082	.000	6.999	.000	3.174	.000	91.281	.230	9.138	.000
CCP	3.592	.000	7.816	.019	3.140	.000	48.009	.064	7.942	.000
LPA based on ICM-CFA factor scores										
3 Profiles										
Means	C1	p-value	C2	p-value	C3	p-value				
TO	-2.171	.000	0.057	.787	2.800	.000				
INP	-2.252	.000	0.092	.614	2.231	.003				
CI	-2.490	.000	0.130	.474	2.292	.000				
CCP	-2.426	.000	0.109	.518	2.335	.007				
4 Profiles										
Means	C1	p-value	C2	p-value	C3	p-value	C4	p-value		
TO	-2.083	.000	3.487	.000	1.193	.017	0.246	.005		
INP	-2.166	.000	3.035	.000	67.514	.003	0.236	.015		
CI	-2.392	.000	4.154	.004	26.442	.000	0.270	.004		
CCP	-2.327	.000	4.204	.000	78.746	.002	0.237	.016		
5 Profiles										
Means	C1	p-value	C2	p-value	C3	p-value	C4	p-value	C5	p-value
TO	-8.213	.000	-1.852	.000	0.341	.000	1.193	.017	3.640	.000
INP	-4.503	.000	-2.248	.000	0.356	.000	67.508	.003	3.125	.000
CI	-5.455	.000	-2.027	.000	0.379	.001	26.441	.000	4.461	.000
CCP	-6.401	.000	-2.642	.000	0.369	.000	78.745	.002	4.347	.000
LPA based on B-ESEM factor scores										
4 Profiles										
Means	C1	p-value	C2	p-value	C3	p-value	C4	p-value		
G	1.148	.000	-1.350	.000	0.748	.000	1.978	.001		
TO	11.018	.000	29.643	.000	69.238	.000	5.820	.000		
INP	0.423	.000	-0.155	.031	-0.515	.000	1.000	.000		
CI	10.996	.000	27.908	.000	87.791	.000	13.967	.000		
CCP	-0.024	.787	-0.020	.773	-0.015	.878	0.315	.053		
5 Profiles										
Means	C1	p-value	C2	p-value	C3	p-value	C4	p-value	C5	p-value

G	-34.353	.004	0.441	.000	-1.987	.000	1.978	.001	0.996	.000
TO	170.760	.008	51.487	.000	43.076	.000	5.818	.000	10.771	.000
INP	-1.805	.000	-0.427	.000	-0.100	.217	1.001	.000	0.496	.000
CI	101.058	.002	62.818	.000	35.534	.000	13.976	.000	11.231	.000
CCP	-0.121	.614	0.000	.999	-0.025	.763	0.315	.053	-0.037	.679

Both the four- and five-class models showed significant latent means. The four-class model demonstrated strong fit, high entropy (.927), significant aLMR and BLRT values, and no classes below 5%. In this solution, 41.85% of students scored below average on the general factor, while nearly 10% showed stronger general and specific digital skills (Table 3).

The five-class model achieved the lowest information criteria and excellent entropy (.952), but included a small class (3.63%), below recommended stability thresholds. Despite its size, this class provided meaningful insight by illustrating how severe INP deficits can substantially depress overall digital competence. The remaining classes were interpretable, distinct, and adequately sized.

Balancing statistical fit, class stability, and substantive interpretability, the five-class bifactor ESEM solution was identified as the optimal profile structure.

5. Discussion

This study compared three latent profile analysis (LPA) strategies for identifying heterogeneity in students' digital competence: (a) yDSI sum scores, (b) ICM-CFA factor scores, and (c) bifactor ESEM factor scores. Although all approaches produced statistically adequate solutions, the B-ESEM–based LPA generated the most informative and educationally meaningful profiles because it simultaneously captured *overall digital skill levels* and *qualitative differences across specific domains*. This dual perspective provides a depth of interpretation not attainable with sum scores or ICM-CFA models.

Limitations of Sum Score and ICM-CFA Approaches: LPAs based on yDSI sum scores and ICM-CFA factor scores primarily detected *quantitative* variation, producing "low–medium–high" profiles with minimal differentiation across TO, INP, CI, and CCP. While statistically acceptable, these solutions reflect a single continuum of ability and offer limited insight for targeted curriculum design.

The ICM-CFA approach added nuance by identifying two small but meaningful subgroups: a high-performing group distinguished by strong INP and CCP skills, and a vulnerable group with very low competence across all domains. While these findings support differentiated teaching, the profiles did not reveal qualitative patterns because the ICM-CFA model constrains both cross-domain relationships and hierarchical structure.

Advantages of the B-ESEM–Based LPA: The B-ESEM approach substantially improved profile interpretability by modeling both the general digital-skills factor and domain-specific qualitative variation. Controlling for overall ability exposed meaningful differences in INP and CCP that were masked in the previous models. The resulting profiles combined level and shape differences, offering deeper insight into how students' strengths and weaknesses interact.

Notably, B-ESEM revealed that strategic (INP) and creative (CCP) skills exert disproportionate influence on overall competence. Students with severe INP deficits displayed sharply lower general scores, while profiles with strong CCP performance showed elevated digital proficiency. These distinctions, central for curriculum design, are uniquely identifiable through B-ESEM.

Why the B-ESEM Approach Is Optimal: The B-ESEM–based LPA offered the strongest combination of statistical fit, class stability, conceptual clarity, and policy relevance. It simultaneously captured quantitative differences in students' overall digital competence and qualitative variation across the four specific dimensions, producing distinct and interpretable subgroups that reflect realistic digital-skill configurations. Although two classes in the ICM-CFA and B-ESEM solutions fell below the conventional 5% threshold, both yielded meaningful substantive insights, suggesting that such cutoffs should not be applied rigidly when small groups represent genuine educational needs.

Implications for Targeted and Differentiated Curriculum Design

The B-ESEM profiles provide direct guidance for evidence-based curriculum improvement. The identification of INP and CCP as key differentiators among high-performing students suggests curricula should incorporate activities that strengthen information evaluation, synthesis, complex problem-solving, and creative content production. These components align closely with contemporary digital-literacy frameworks.

Conversely, the detection of a subgroup lacking foundational digital skills highlights the need for remedial, scaffolded instruction focused on operational tasks, safety practices, and structured digital routines. Without such support, these students risk marginalization in digital learning environments and future labor markets.

Because B-ESEM profiles include both level and shape information, they offer a strong foundation for tiered, adaptive, and personalized curriculum pathways. Institutions can design differentiated learning trajectories that match students' strengths, address specific deficits, and allocate resources strategically. This stands in clear contrast to "one-size-fits-all" curricula that overlook substantial within-population variability.

6. Conclusion

By comparing three modeling strategies, this study demonstrates that B-ESEM–based LPA provides the most powerful method for uncovering meaningful digital-skills heterogeneity. By separating general competence from specific qualitative dimensions, B-ESEM offers diagnostic precision that raw scores and ICM-CFA models cannot achieve.

The identification of INP and CCP as critical drivers of overall digital ability, and the detection of both high-performing and at-risk subgroups, provides actionable evidence for curriculum modernization. These insights support institutional strategies that embed digital skills in a differentiated, targeted, and personalized manner. Accordingly, the B-ESEM approach not only advances methodological practice but also provides a strong empirical basis for equitable and responsive digital-skills policy and curriculum design within higher education.

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