Shaping Future Learning Through Digital-Skills Profiling

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Structure

- Theoretical foundation
- Research gap & problem
- Measurement approach
- Analytical strategy
- Data & instrument
- Model estimation & selection
- Results & implications

Main Issue

[Labor market demands]

↑

[Students heterogeneity] ? [Uniform curricula]

↓

[System underperformance]

- Growing mismatch between graduates' digital skills and labor market demands
- Digital skills often treated as uniform, ignoring student heterogeneity
- One size fits all curricula limit effectiveness

Recognizing variability in digital competence

- Digital competence is central to employability and resilience
- Students differ widely in:
  - Prior experience
  - Educational background
- Effective curriculum reform requires evidence based profiling

Aim of the Study

Identify **meaningful digital-skills profiles** among university students to inform **targeted and differentiated curriculum design**

Objectives

Compare profiling using LPA based on:

- **Scale scores**
- **ICM-CFA factor scores**
- **Bifactor ESEM (B-ESEM) factor scores**

The importance of the study

Clear need for **robust assessment**

to enable evidence-based digital skills integration

(Laanpere, 2019; Montenegro-Rueda & Fernández-Batanero, 2024; Siddiq et al., 2016)

Theoretical Background

(The foundation for more advanced modeling approaches)

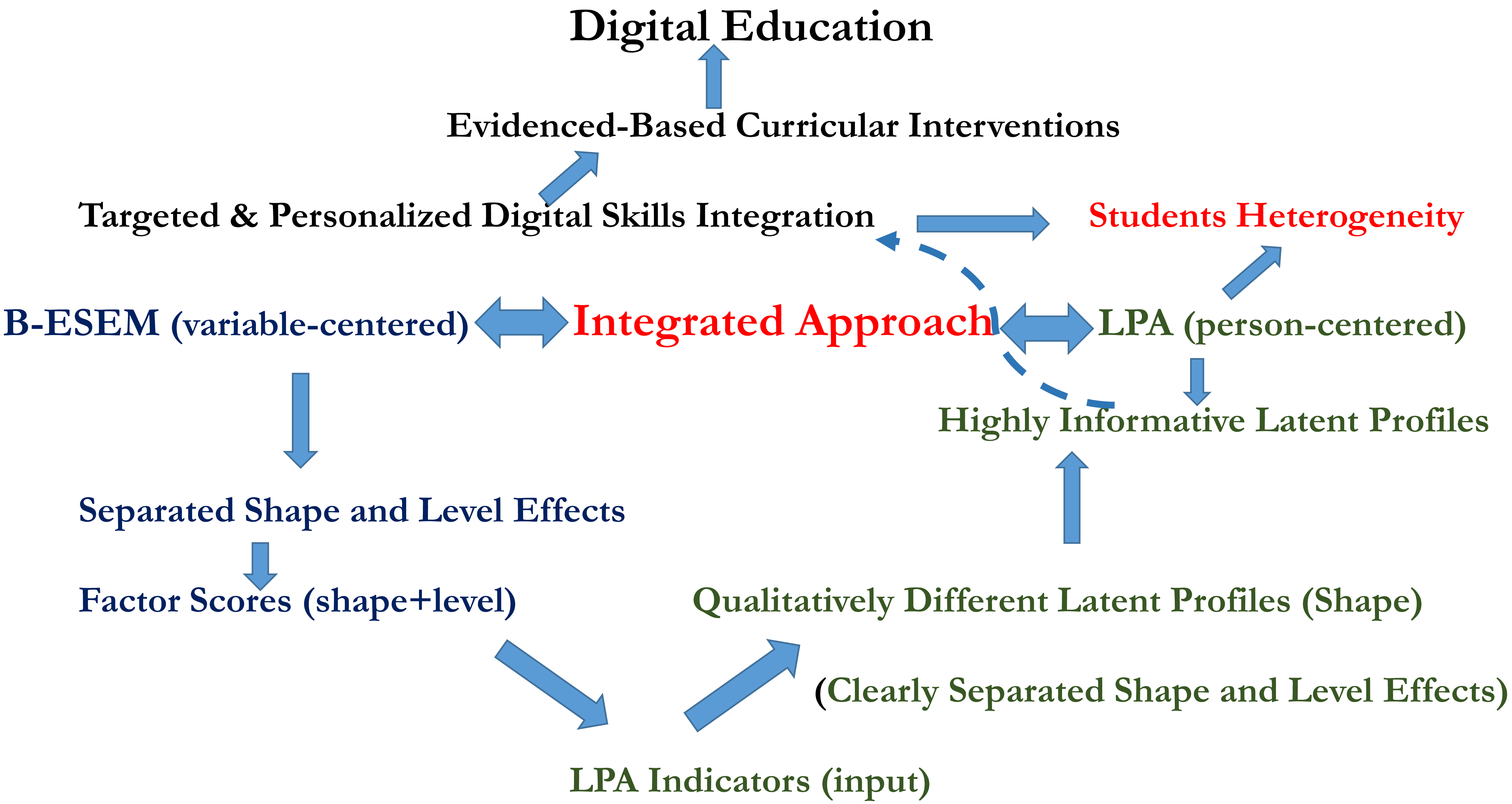
Digital skills are:

- Multidimensional
- Hierarchically structured

DigComp: general competence + domain specific skills

Profiling must capture level and shape differences (highly informative !!!)

(Morin & Marsh, 2015; Morin et al., 2016, 2017)


Digital Education
Evidenced-Based Curricular Interventions
Targeted & Personalized Digital Skills Integration
Students Heterogeneity
B-ESEM (variable-centered)
Integrated Approach
LPA (person-centered)
Highly Informative Latent Profiles
Separated Shape and Level Effects
Factor Scores (shape+level)
Qualitatively Different Latent Profiles (Shape)
(Clearly Separated Shape and Level Effects)
LPA Indicators (input)

An integrated variable-centered and person-centered modeling approach

Latent Profile Analysis (LPA)

$$f(\mathbf{y}_i \mid \boldsymbol{\theta}) = \sum_{c=1}^{C} \boldsymbol{\gamma}_c f_c(\mathbf{y}_i \mid \boldsymbol{\mu}_c, \boldsymbol{\Sigma}_c)$$

Latent Profile Analysis (LPA) - widely used in psychology and education to identify unobserved subgroups that cannot be detected through variable-centered approaches.

Extracted profiles should be qualitatively (shape) different from one another

(Morin & Marsh, 2015)

Variable-centered approach

Person-centered analyses should be systematically preceded by a comprehensive examination of the psychometric multidimensionality of the indicators used in LPA.

(Morin et al., 2016, 2017)

- **Scale scores:**
  - Ignore measurement error
  - Capture mainly overall level
- **ICM CFA:**
  - Restrictive (zero cross loadings)
  - Shape and level effects are not properly disaggregated from one another
- **B-ESEM:**
  - Models general + specific skills
  - Preserves multidimensional and hierarchical structure

Digital skills
Why B-ESEM + LPA

- B-ESEM separates:
  - Overall digital competence
  - Domain specific strengths/weaknesses
- LPA identifies homogeneous student profiles
- Combined approach (B-ESEM+LPA) enables:
  - Richer interpretation
  - Greater policy relevance

Examination of the psychometric multidimensionality of scale indicators used in LPA

CFA → Restrictive

ESEM → Cross-loadings allowed

Bifactor CFA → General + specific (restricted)

Bifactor ESEM → Most accurate (flexible + hierarchical)

B-ESEM consistently outperforms traditional ICM-CFA, ESEM, and hierarchical models when modeling multidimensional constructs.

(Morin et al., 2016)

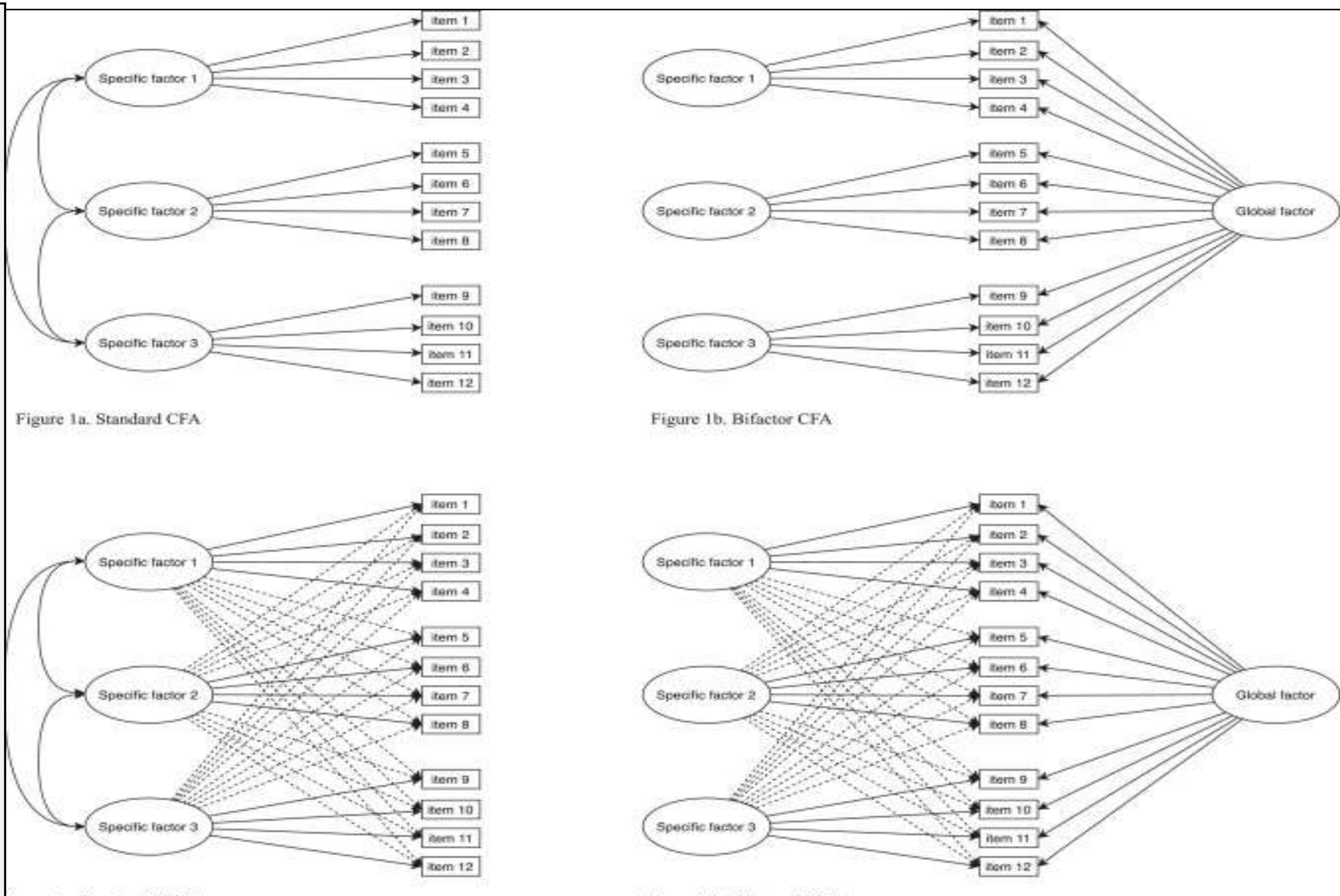


Figure 1a. Standard CFA

Figure 1b. Bifactor CFA

Figure 1c. Standard ESEM

Figure 1d. Bifactor ESEM

Source: Alamer (2022)

Method

Study Procedure

- **Sample:** 599 university students (MC simulation)
- **Instrument:** Short yDSI (Helsper et al., 2020)

(24 items, 4 domains: TO, INP, CI, CCP)

Analysis:

B-ESEM for measurement

LPA for profiling

Mplus 8.11

WLSMV for B-ESEM

MLR for LPA

Model Estimation & Selection

- **2–7 profile LPA models** (MLR; 1000 starts)
- **Free means & variances across profiles**
- **Selection based on**:

    AIC, BIC, SABIC, entropy

    Class size, aLMR, BLRT

Profile Solutions Compared

Three profiling strategies:

- ❖ Sum scores → level based profiles
- ❖ ICM CFA scores → limited differentiation
- ❖ B-ESEM scores → quantitative (level) + qualitative (shape) patterns

Main Results

Optimal Profile Solutions Across Indicator Sets

❖ **Sum scores → 3 profiles** (“low–medium–high” only)

✓ **Best balance of fit, parsimony & interpretability**

❖ **ICM CFA scores → 5 profiles** (small gains, still level-driven)

✓ **Supported by fit, entropy, aLMR/BLRT**

✓ **Captures advanced & very low skill groups**

❖ **B-ESEM scores → 5 profiles** **(reveals hidden qualitative differences)**

✓ **Optimal based on fit, stability & substantive interpretability**

Main Results

❖ **B-ESEM based LPA produced the most informative profiles**

✓ Identified both:

- Overall competence differences
- Domain specific skill configurations

✓ Superior interpretability and classification quality

The informative superiority of LPA based on B-ESEM factor scores

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

LPA based on ICM-CFA factor scores (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 (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

Discussion

- ✓ Digital competence heterogeneity is systematic
- ✓ Modeling choices strongly shape conclusions
- ✓ B-ESEM factor scores avoids misleading simplification

Implications for Curriculum Design

- Move beyond uniform digital skills training

- Design:

  - ✓ Remedial pathways for low skill students

  - ✓ Advanced pathways for high skill profiles

- Prioritize INP and CCP development

Implications for FOE Community

- ❑ Supports:
  - ✓ Personalized learning
  - ✓ Adaptive curricula
  - ✓ Efficient resource allocation
- ❑ Aligns with FOE goals:
  - ✓ Innovation
  - ✓ Equity
  - ✓ Future ready graduates

Conclusion

- B-ESEM based LPA offers diagnostic precision
- Captures both level and shape of digital competence
- Provides strong empirical basis for:
  - Targeted curricula
  - Evidence based digital education policy

Thank you
for your attention!