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One Construct or Two? Knowledge Management, University Entrepreneurship, And A Brief Validated Measure

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Abstract

Research on higher education in Latin America increasingly combines questionnaire measures of knowledge management and of student entrepreneurship in structural models that posit influence relationships between them, yet rarely verifies a precondition of such models: that the constructs be empirically distinguishable. This study assessed the dimensional structure, reliability, and convergent and discriminant validity of an eighty-item, seven-dimension instrument designed to measure both variables, using responses from 1,092 students of private universities in Northern Lima, Peru, most of whom were employed and had prior entrepreneurial experience. Competing factor models were compared at the item level, and reliability, average variance extracted, and heterotrait-monotrait ratios were estimated. The hypothesized seven-factor structure did not substantively outperform a single-factor model; all twenty-one latent correlations among dimensions ranged from 0.86 to 0.97; and six of seven dimensions failed the convergent validity criterion despite high composite reliability. The instrument therefore measures essentially one general dimension, here termed knowledge-based entrepreneurial capacity. A fourteen-item short form preserving the content coverage of the original instrument was derived and validated, showing acceptable fit, satisfactory convergent validity, and high reliability. The findings caution against interpreting structural coefficients between closely related self-report measures as substantive effects, and provide researchers and university managers in the region with a parsimonious, freely reusable measurement tool and a reproducible validation protocol.

Keywords: knowledge management; university entrepreneurship; discriminant validity; construct redundancy; scale validation; Latin America

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1. Introduction

Universities across Latin America have embraced a third mission centred on innovation and entrepreneurship, transforming themselves from teaching institutions into actors expected to create, transfer, and commercialize knowledge (Etzkowitz & Leydesdorff, 2000; Gaffaro & Naranjo, 2025). Within this agenda, knowledge management—the organizational processes through which knowledge is created, shared, integrated, and applied (Nonaka & Takeuchi, 1995; Davenport & Prusak, 2000)—has been proposed as a key antecedent of students' entrepreneurial capabilities, on the premise that institutional dynamics of knowledge creation and exchange equip students to identify opportunities and launch ventures (Frolova et al., 2021).

A large empirical literature in the region tests this premise with a recognizable design: long self-report questionnaires administered to a single source at a single point in time, analysed with structural equation models that regress entrepreneurship measures on knowledge management measures. Reported structural coefficients are typically large, and the models are typically declared well-fitting (Chávez Vera et al., 2024; González-Prida et al., 2024). This evidence base, however, rests on a precondition that is almost never tested explicitly: that the predictor-side and criterion-side constructs are empirically distinguishable. When conceptually adjacent scales with uniformly positive wording are answered by the same respondents in the same session, common method variance can inflate their correlations to the point where the constructs no longer discriminate (Podsakoff et al., 2003), and a structural path between them estimates little more than the regression of one dimension on itself.

Psychometrics has long described this risk as the jangle fallacy—assuming that two labels imply two constructs—and, in its contemporary form, as construct proliferation and redundancy (Le et al., 2010; Shaffer et al., 2016). The entrepreneurial-university field, where frameworks and measures multiply rapidly (Guerrero et al., 2024), is particularly exposed. The consequences are not academic niceties: tautological structural models, overestimated effects, and institutional investments justified by spurious evidence.

Clarifying this question matters beyond methodology. In Peru, entrepreneurship is one of the main routes of economic insertion for young people, in a labour market with high informality and a productive fabric dominated by micro and small enterprises. Universities have responded by deploying entrepreneurship courses, incubators, and innovation programmes, frequently justified with the available correlational evidence on the effects of knowledge management and

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entrepreneurial training. If that evidence rests on relationships inflated by measure redundancy, institutional investment decisions and educational policy are being informed by systematically upward-biased estimates. Establishing what the instruments in use actually measure is therefore a requirement both of scientific accumulation and of the responsible allocation of public and private resources in the region's university ecosystems (Guerrero et al., 2024).

This study applies a rigorous validation protocol to a case representative of regional research practice: an eighty-item, seven-dimension instrument measuring knowledge management (three dimensions) and university entrepreneurship (four dimensions), administered to 1,092 students of private universities in Northern Lima, Peru—a population of working students with prior entrepreneurial experience, characteristic of urban-periphery economies marked by self-employment and informality (Amorós et al., 2021). Three research questions guide the analysis. RQ1: Does the hypothesized seven-dimension structure provide empirical separation over more parsimonious two-factor and one-factor models, evaluated at the item level? RQ2: Do the dimensions satisfy contemporary criteria of convergent and discriminant validity? RQ3: If essential unidimensionality is found, can a brief form with satisfactory psychometric properties be derived while preserving content coverage? The contribution is twofold: systematic evidence on construct redundancy in one of the most studied variable pairs of the regional agenda, and a validated fourteen-item measure—knowledge-based entrepreneurial capacity (KEC-14)—together with a fully reproducible verification protocol.

2. Literature Review

2.1. Knowledge management and entrepreneurship in the entrepreneurial university

Knowledge management theory consolidated around the SECI model, which describes knowledge creation as continuous conversion between tacit and explicit knowledge through socialization, externalization, combination, and internalization (Nonaka & Takeuchi, 1995). Subsequent work emphasized organizational culture, incentives, and infrastructure as enabling conditions for knowledge sharing (Davenport & Prusak, 2000; Wang & Noe, 2010) and the mechanisms of knowledge transfer across units and organizations (Argote et al., 2000). Universities were reconceptualized as knowledge-intensive organizations whose competitive contribution lies in creating, codifying, and diffusing knowledge, a view formalized in the entrepreneurial-university paradigm (Clark, 1998) and the Triple Helix model of university-industry-government interaction (Etzkowitz & Leydesdorff, 2000; Cai & Etzkowitz, 2020). International evidence links entrepreneurial universities to regional competitiveness (Guerrero et al., 2016), institutional entrepreneurial orientation to spin-off creation (O'Shea et al., 2005), and entrepreneurship education to student outcomes (Nabi et al., 2017). In Latin America, Triple Helix dynamics have been documented in low-technology industrial collaboration (Mikhailov & Puffal, 2024), while recent reviews stress that the field faces theory-building challenges, with multiplying constructs and measures that hinder cumulative knowledge (Guerrero et al., 2024).
The translation of these frameworks into questionnaire measurement exhibits recurrent features across the regional literature: long self-report batteries with Likert scales, dimensions defined conceptually around the stages of the knowledge cycle (creation, infrastructure, application, learning), uniformly positive wording, and cross-sectional administration to a single source. Each feature is individually defensible; their combination, however, creates the classic conditions for the inflation of common method variance (Podsakoff et al., 2003) and for conceptually distinguishable dimensions to become empirically redundant. The maturity of measurement in the field compounds the risk: operationalizations based on processes, capabilities, and infrastructures coexist with diffuse boundaries among themselves and with neighbouring constructs, while validation efforts concentrate on internal consistency and exploratory factor analysis, with little attention to discriminant validity between adjacent measures (Guerrero et al., 2024). Findings built on such foundations rest on heterogeneous validity, which is precisely why systematic validation studies—comparing alternative structures, testing discrimination, and refining instruments—constitute primary rather than auxiliary contributions to the field.

2.2. The knowledge management-entrepreneurship link: evidence and warning signs

The Peruvian context offers a particularly informative setting. The country's enterprise structure is dominated by micro and small firms, with high rates of early-stage entrepreneurial activity partly driven by necessity, and the districts of Northern Lima concentrate a young population, frequently of migrant origin, inserted in self-employment economies (Amorós et al., 2021). Private universities in the area have grown by serving a student body that combines study with work and, in a notable proportion, with running their own or family businesses. The locally available evidence depicts university support ecosystems that are still incipient—incubators of intermediate maturity, weak evaluation systems, and training in transversal competencies that students themselves judge insufficient. In this environment, students' entrepreneurial dispositions are formed less in specialized curricular programmes than in everyday work and entrepreneurial experience, with direct consequences for measurement: self-reports about knowledge processes and entrepreneurial capabilities are issued from an integrated life experience, not from differentiated institutional domains.

The hypothesis that knowledge management drives student entrepreneurship is theoretically plausible: socialization and combination processes expose students to opportunities, networks, and competencies that facilitate venture creation (Frolova et al., 2021). The empirical record is less uniform than its reception suggests. A study of Indonesian student entrepreneurs found no significant direct effect of knowledge management on business innovation capabilities, which emerged only when moderated by perceived university support and entrepreneurial resilience (Mustofa & Mulyono, 2024). Studies that do report large direct effects typically share the single-source, cross-sectional self-report design, and sometimes report predictor-criterion correlations of striking magnitude—0.86 between entrepreneurial self-efficacy and intention (González-Prida et al., 2024)—which, once scale unreliability is considered, imply disattenuated correlations approaching unity, the operational criterion of construct redundancy (Le et al., 2010).

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Peruvian evidence based on the theory of planned behaviour shows similar features of design and effect size (Chávez Vera et al., 2024). Such magnitudes are documented warning signs: a substantial share of constructs introduced in organizational research overlaps heavily with existing ones, and systematic proliferation tests are recommended before structural interpretation (Shaffer et al., 2016).

The theoretical mechanisms invoked to ground the relationship are themselves plausible and well articulated. From the SECI perspective, the socialization of tacit knowledge in university communities of practice would expose students to entrepreneurial role models and uncodified know-how; externalization and combination would facilitate the transformation of business intuitions into formal plans; and internalization would consolidate competencies through practice (Nonaka & Takeuchi, 1995; Frolova et al., 2021). From the Triple Helix perspective, university-industry-government articulation would generate the opportunity conditions—financing, mentoring, demand—that convert individual disposition into actual venture creation (Cai & Etzkowitz, 2020; Mikhailov & Puffal, 2024). The problem, then, lies not in the theory but in the empirical inference: for a structural model to corroborate these mechanisms, the measures of antecedent and consequence must capture distinguishable variance, and that condition must be demonstrated, not presumed.

2.3. Discriminant validity, common method bias, and the parceling problem

The contemporary standard for discriminant validity in reflective measurement models is the heterotrait-monotrait ratio of correlations (HTMT), which estimates the disattenuated correlation between two constructs; simulation evidence shows it outperforms the classical Fornell-Larcker criterion, with thresholds of 0.85 (strict) and 0.90 (liberal) and the recommendation to corroborate problematic pairs through nested model comparisons (Henseler et al., 2015; Rönkkö & Cho, 2022; Fornell & Larcker, 1981). Convergent validity requires average variance extracted (AVE) of at least 0.50 alongside composite reliability above 0.70 (Hair et al., 2019). Two further phenomena are central to interpreting the regional literature. First, common method variance—single source, single occasion, homogeneous item format—systematically inflates observed correlations between constructs measured under the same method, and procedural and statistical remedies remain under-adopted in cross-sectional questionnaire research (Podsakoff et al., 2003; Podsakoff et al., 2012). Second, item parceling: aggregating items into composite indicators before estimation mechanically improves fit indices and can camouflage measurement misspecification, which is why parcels are considered inappropriate precisely when the measurement model itself is in question (Bandalos, 2002; Little et al., 2002; Marsh et al., 2013). Excellent fit obtained on parcels is therefore not evidence of measurement validity; rigorous evaluation must be conducted, and reported, at the item level (Kline, 2016). Finally, high reliability is not evidence of construct validity: alpha and composite reliability grow mechanically with scale length and item homogeneity, so a long battery of redundant items will produce excellent reliability coefficients while AVE remains deficient and HTMT excessive—the signature of a highly reliable measure of a single dimension.

3. Methodology

3.1. Design, participants, and ethics

An instrumental, non-experimental, cross-sectional validation design was adopted on primary survey data. Participants were 1,092 students of private universities located in Northern Lima, Peru, recruited through non-probability convenience sampling; formal requests to the national higher-education authority and the national statistics institute confirmed that no sampling frame disaggregating university students by entrepreneurial activity was available, precluding probability sampling. The sample has a distinctive profile: the large majority of participants were employed at the time of the survey and reported prior entrepreneurial experience, a student-worker profile typical of Latin American urban-periphery economies (Amorós et al., 2021). Participation was voluntary and anonymous with informed consent; the protocol was approved by the institutional research ethics committee (approval number withheld for blind review). There were no missing values. The sample size comfortably exceeds the 5:1 case-to-parameter ratio for the most complex model estimated and provides near-unit power for detecting misfit (Kline, 2016).

Data were collected through a structured questionnaire administered during scheduled academic sessions, with standardized instructions emphasizing anonymity, the absence of right or wrong answers, and the exclusively academic use of responses. Completion took approximately 25 to 30 minutes given the length of the battery—a burden that, as the results will show, is itself consequential for response quality. Responses were screened for completeness at collection, which explains the absence of missing values; no responses were excluded a priori on quality grounds, a deliberate decision that allows the prevalence of low-variability response patterns to be documented rather than silently removed, and its implications discussed as a finding in its own right.

3.2. Instrument

The instrument comprised 80 items on five-point Likert scales (1 = strongly disagree; 5 = strongly agree), organized into seven hypothesized dimensions. Knowledge management comprised knowledge creation and innovation dynamics (KCID, 15 items), infrastructure and processes for knowledge management (IPKM, 15 items), and lifelong learning and digital transformation (LLDT, 10 items). University entrepreneurship comprised institutional resources and support (IRS, 10 items), individual and contextual factors (ICF, 5 items), entrepreneurial culture and training (ECT, 15 items), and entrepreneurial competencies and skills (ECS, 10 items). The instrument was developed from the SECI and entrepreneurial-university literatures, with content validity established through expert judgement and a pilot application. All items were positively worded.

In terms of content, the knowledge management dimensions operationalize the knowledge-cycle processes in the university environment: KCID captures student participation in idea generation, formative research, and innovation activities; IPKM assesses the perception of institutional supports—repositories, platforms, processes, and services—that facilitate access to and exchange of knowledge; and

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LLDT captures the disposition toward continuous learning and the appropriation of emerging digital technologies. The entrepreneurship dimensions cover the spectrum of conditions and capabilities identified by the literature: IRS measures perceived institutional resources, incubation, and accompaniment; ICF, motivational and personal-environment factors; ECT, exposure to entrepreneurial culture and curricular and extracurricular training; and ECS, self-assessed competencies to identify opportunities, plan, and manage business initiatives. This correspondence with the SECI and entrepreneurial-university frameworks gives the instrument reasonable content validity; the question this study tests is whether that conceptual architecture finds a counterpart in the empirical structure of responses.

3.3. Analytical procedure

The analysis proceeded in five stages. First, sampling adequacy was evaluated with the Kaiser-Meyer-Olkin index and Bartlett's sphericity test, and dimensionality with Horn's parallel analysis (50 replications, 95th percentile; Horn, 1965), the first-to-second eigenvalue ratio, and the variance share of the first factor. Second, three nested confirmatory factor models were estimated by maximum likelihood on the 80 items: (M1) seven correlated factors as hypothesized; (M2) two correlated factors corresponding to knowledge management (40 items) and entrepreneurship (40 items); (M3) a single general factor. Fit was evaluated with the comparative fit index (CFI), Tucker-Lewis index (TLI), root mean square error of approximation (RMSEA), and chi-square to degrees-of-freedom ratio against conventional criteria (Hu & Bentler, 1999), and models were compared through CFI differences. All models were deliberately estimated at the item level rather than on parcels (Bandalos, 2002; Little et al., 2002; Marsh et al., 2013). Third, reliability (Cronbach's alpha; McDonald's omega for the general factor and the short form), and convergent validity (AVE and composite reliability from the standardized loadings of M1) were estimated. Fourth, discriminant validity was assessed through the full HTMT matrix among the seven dimensions (Henseler et al., 2015) with 0.85 and 0.90 thresholds (Rönkkö & Cho, 2022), complemented by the latent correlations of M1, Harman's single-factor test, and the inspection of low-variability (straightlining) response patterns as diagnostics of method variance (Podsakoff et al., 2003). Fifth, given evidence of essential unidimensionality, a short form was derived by selecting the two items with the highest loadings on the general factor within each of the seven content areas, preserving full domain coverage; the resulting fourteen-item form was re-estimated as a unidimensional model and evaluated for fit, loadings, AVE, omega, and corrected item-total correlations. Analyses were conducted in Python 3.12 (semopy, factor_analyzer); the full analysis code is provided as supplementary material to ensure reproducibility.

4. Results

4.1. Sampling adequacy and dimensionality

The 80-item correlation matrix showed excellent factorability (KMO = 0.982; Bartlett's chi-square ≈ 69,547; $p < .001$). The first eigenvalue (36.86) explained 46.1% of total variance and was ten times the second (3.40; ratio 10.8), a pattern characteristic of a dominant general dimension. Parallel analysis formally retained up to five components above chance, but the disproportionate magnitude of the first factor relative to the remainder (36.86 versus 3.40, 3.11, 1.80, and 1.49) indicates that shared substantive variance concentrates overwhelmingly in one dimension. The mean inter-item correlation across all 80 items was 0.45 (range 0.27-0.72), including pairs formed by items from theoretically distinct variables, and the alpha of the full battery reached 0.985—an extreme value that is itself indicative of content redundancy.

4.2. Competing measurement models

Table 1 presents the fit of the three competing models estimated at the item level. None reached conventional good-fit thresholds, as is expected with 80 indicators; the decisive evidence is the comparison among them. The seven-factor model (CFI = 0.739) barely outperformed the two-factor model (CFI = 0.725) and the single-factor model (CFI = 0.711). The total difference between treating the data as seven distinct constructs or as one was ΔCFI = 0.028: the hypothesized multidimensional structure, with 21 additional covariance parameters, provides no substantive empirical separation over the single-dimension hypothesis (RQ1).

Table 1. Fit of competing item-level confirmatory factor models (N = 1,092)

Model	χ^2/df	CFI	TLI	RMSEA
M1: Seven correlated factors	6.83	0.739	0.730	0.073
M2: Two factors (KM; entrepreneurship)	7.09	0.725	0.718	0.075
M3: One general factor	7.41	0.711	0.703	0.077

Note. Maximum likelihood estimation on all 80 items. CFI = comparative fit index; TLI = Tucker-Lewis index; RMSEA = root mean square error of approximation.

The logic of this comparison deserves emphasis, because it is the most direct test available for the question at stake. If the seven dimensions captured distinct constructs, the seven-factor model—which freely estimates 21 inter-factor covariances and assigns each item to its specific dimension—should fit substantially better than a model forcing all 80 items onto one factor; the cost in parsimony would be repaid in fit. Conversely, if a single dimension underlies the responses, freeing those additional parameters buys almost nothing. The observed ΔCFI of 0.028 across the full span from one to seven factors falls far below any conventional criterion for preferring the more complex model and contrasts sharply with the near-saturated fit that the same data yield when the model is estimated on aggregated indicators—the comparison that motivates the parceling discussion in Section 5.2.

4.3. Reliability and convergent validity

Table 2 reports reliability and convergent validity by dimension. All seven dimensions showed high internal consistency (alpha 0.845-0.936; composite reliability 0.846-0.936). Convergent validity, however, was insufficient: six of seven AVE values fell below the 0.50 threshold (range 0.471-0.524), with standardized loadings between 0.59

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and 0.79. This combination—high reliability with deficient AVE—is the signature of long, redundant scales whose items share broad general variance while contributing little dimension-specific variance (Hair et al., 2019). The high reliability derives from scale length and item homogeneity, not from well-defined specific constructs (RQ2).

Table 2. Reliability and convergent validity by dimension

Dimension	Items	α	CR	AVE
KCID: Knowledge creation and innovation dynamics	15	0.933	0.933	0.481
IPKM: Infrastructure and processes for KM	15	0.936	0.936	0.494
LLDT: Lifelong learning and digital transformation	10	0.904	0.905	0.488
IRS: Institutional resources and support	10	0.908	0.908	0.497
ICF: Individual and contextual factors	5	0.845	0.846	0.524
ECT: Entrepreneurial culture and training	15	0.930	0.930	0.471
ECS: Entrepreneurial competencies and skills	10	0.907	0.907	0.494

Note. α = Cronbach's alpha; CR = composite reliability; AVE = average variance extracted, computed from the standardized loadings of the seven-factor item-level model. Only ICF meets AVE ≥ 0.50.

4.4. Discriminant validity

Discriminant validity failed across the board (Table 3). HTMT values among the seven dimensions ranged from 0.862 to 0.974 (mean 0.912); twelve of the 21 pairs exceeded the liberal 0.90 threshold and all 21 exceeded the strict 0.85 threshold. The latent correlations of M1 confirmed the pattern, ranging from 0.86 to 0.97. The most severe violations occurred within knowledge management (IPKM-LLDT: HTMT = 0.974; KCID-IPKM: 0.964), but correlations between dimensions of theoretically distinct variables were equally incompatible with discrimination (ECT-IPKM: 0.921; LLDT-IRS: 0.911). Notably, the matrix does not exhibit the block structure—high correlations within each variable, moderate ones between variables—that two higher-order constructs would produce; it shows uniform, elevated saturation throughout, consistent with the single dominant dimension of Section 4.1. At the aggregate level, the correlation between knowledge management and entrepreneurship composite scores was 0.916, which approaches unity once corrected for attenuation.

Table 3. Heterotrait-monotrait (HTMT) ratio matrix

	KCID	IPKM	LLDT	IRS	ICF	ECT	ECS
KCID	—	0.964	0.931	0.893	0.880	0.911	0.862
IPKM		—	0.974	0.896	0.900	0.921	0.893
LLDT			—	0.911	0.902	0.924	0.887
IRS				—	0.930	0.933	0.883
ICF					—	0.945	0.872
ECT						—	0.936
ECS							—

Note. Computed on observed inter-item correlations (N = 1,092). Values above 0.85/0.90 indicate compromised discriminant validity; 12 of 21 pairs exceed 0.90 and all exceed 0.85.

4.5. Common method variance and response quality

Two complementary observations sharpen the diagnosis. First, the violations are not attributable to a few problematic items: standardized loadings were uniformly moderate-to-high (0.59-0.79) across all 80 items, so no small subset of weak indicators drives the pattern, and item-level purification—removing low-loading items—cannot restore discrimination that the latent structure does not contain. Second, the within-variable and between-variable HTMT distributions overlap almost completely: the mean HTMT among knowledge management dimensions (0.957) and among entrepreneurship dimensions (0.916) is statistically indistinguishable in practical terms from the mean between variables (0.898). Discriminant validity thus fails at both levels of the hypothesized hierarchy—among first-order dimensions and between the two higher-order variables—ruling out the rescue strategy of collapsing dimensions into two correlated higher-order factors, whose two-factor counterpart (M2) indeed fit no better than the single-factor model.

Harman's single-factor test showed the first unrotated factor explaining 46.1% of total variance, immediately adjacent to the 50% heuristic for substantial method contamination. Response-pattern inspection further revealed that 25.8% of participants (282 of 1,092) answered all 80 items with a within-person standard deviation below 0.5 scale points, and 14 participants gave the identical response to every item—patterns consistent with acquiescence and straightlining, which uniformly inflate inter-item correlations. These diagnostics are not conclusive in isolation, but they converge with the remaining evidence toward a general dimension inflated by the measurement design (Podsakoff et al., 2012).

A sensitivity analysis assessed whether the unidimensional structure of the KEC-14 is robust to the exclusion of low-variability respondents. After removing the 282 participants (25.8%) with within-person standard deviation below 0.5, the unidimensional model retained acceptable fit in the filtered sample (N = 810; CFI = 0.928; TLI = 0.915;

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RMSEA = 0.090), with reliability and convergent validity remaining satisfactory (α = 0.940; ω = 0.940; AVE = 0.532). A bifactor model with one general factor and two orthogonal group factors (knowledge management, university entrepreneurship) provided formal indices of essential unidimensionality: explained common variance (ECV) = 0.865 and omega hierarchical (ωh) = 0.924 in the filtered sample (ECV = 0.891 and ωh = 0.941 in the full sample), both well above the thresholds of 0.60 and 0.70, respectively, recommended by Rodriguez et al. (2016) and Reise et al. (2013). The general factor thus accounts for the vast majority of reliable variance regardless of straightlining prevalence, and the correlation between the KEC-14 and the full 80-item composite remained high (r = 0.899 in the filtered sample versus 0.920 in the full sample). These results confirm that the substantive conclusion—essential unidimensionality—is not an artefact of response-pattern homogeneity.

4.6. The KEC-14 short form

Given the essentially unidimensional structure, a parsimonious measure of the general construct—knowledge-based entrepreneurial capacity (KEC)—was derived under RQ3 by selecting the two highest-loading items on the general factor within each of the seven original content areas, preserving full domain coverage in a fourteen-item form. The unidimensional KEC-14 model showed acceptable fit (CFI = 0.943; TLI = 0.932; $\chi^2/df = 9.55$; RMSEA = 0.089), standardized loadings between 0.606 and 0.815, satisfactory convergent validity (AVE = 0.599), and high reliability (α = ω = 0.954), with corrected item-total correlations between 0.603 and 0.792 (Table 4). The slightly elevated RMSEA reflects the combination of few degrees of freedom and high loadings, a known circumstance in which CFI and TLI are more informative. For applied use, the KEC-14 is scored as the simple mean of its items; its correlation with the 80-item total score was 0.92, indicating that the short form preserves most of the information of the full instrument at one sixth of the response burden. The two items with relatively lower loadings (0.63 and 0.61) contribute non-redundant content from the individual-factors and competencies areas and comfortably exceed conventional retention thresholds.

As preliminary interpretive guidance for applied users, mean scores can be read against the response anchors of the original scale, and institutional baselines should be established locally on first administration; given the convenience sampling, the present sample's distribution should not be treated as a normative reference. The supplementary material includes the scored dataset and a worked example of the computation, so that adopting institutions can verify their implementation against the published results before deployment.

Table 4. Psychometric properties of the KEC-14 short form (N = 1,092)

Item	Content area	λ	Item-total r
KM1	Knowledge creation and innovation	0.743	0.727
KM2	Knowledge creation and innovation	0.794	0.771
KM3	Infrastructure and processes	0.796	0.771
KM4	Infrastructure and processes	0.802	0.785
KM5	Lifelong learning and digital transformation	0.815	0.792
KM6	Lifelong learning and digital transformation	0.811	0.784
UE1	Institutional resources and support	0.805	0.783
UE2	Institutional resources and support	0.804	0.780
UE3	Individual and contextual factors	0.796	0.785
UE4	Individual and contextual factors	0.626	0.622
UE5	Entrepreneurial culture and training	0.803	0.779
UE6	Entrepreneurial culture and training	0.798	0.775
UE7	Entrepreneurial competencies and skills	0.796	0.779
UE8	Entrepreneurial competencies and skills	0.606	0.603

Note. λ = standardized loading of the unidimensional model; item-total r = corrected item-total correlation. Global fit: CFI = 0.943; TLI = 0.932; RMSEA = 0.089. AVE = 0.599; α = ω = 0.954. Full item wording is provided as supplementary material.

5. Discussion

5.1. Theoretical implications

The results are unequivocal and convergent: in this sample, knowledge management and university entrepreneurship, as operationalized, are not two constructs but one. The first implication concerns the interpretation of the literature that estimates structural effects between them with single-source cross-sectional designs. When the disattenuated predictor-criterion correlation approaches unity, the structural coefficient and the explained variance derived from it do not inform an influence between distinct phenomena; they reflect the regression of a dimension on itself. This does not imply that the substantive relationship between knowledge processes and entrepreneurial activity is non-existent—evidence from designs with behavioural criteria and institutional moderators suggests it exists and is conditioned (Mustofa & Mulyono, 2024)—but that the dominant regional designs are saturated with common variance and cannot identify it. Reread in this light, the very large correlations reported by prior regional studies between adjacent cognitive-attitudinal constructs (González-Prida et al., 2024; Chávez Vera et al., 2024) appear less as anomalies of particular instruments than as a structural feature of the design family.

The second implication joins the construct-proliferation debate (Le et al., 2010; Shaffer et al., 2016; Guerrero et al., 2024). The case illustrates the full mechanism: rich conceptual frameworks translate into plausible dimensional taxonomies; taxonomies are operationalized into long batteries of closely worded items; and simultaneous single-source administration produces data in which conceptual distinctions

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find no empirical counterpart. The jangle fallacy originates not in the theory but in the measurement chain. Substantively, the identified general construct merits positive interpretation: in a sample of working students with prior entrepreneurial experience, it is theoretically coherent that perceptions of institutional knowledge processes and self-assessed entrepreneurial capabilities form one integrated evaluative disposition—a knowledge-based entrepreneurial capacity—rather than separate domains. For this profile, learning, managing knowledge, and undertaking ventures are facets of a single everyday practice, which connects with the view of the entrepreneurial university as an integrated ecosystem (Clark, 1998; Guerrero et al., 2016). The integration of knowledge management and entrepreneurship in the university context has also been documented in this journal and allied outlets: knowledge management processes are intertwined with research and innovation in university groups (Páez et al., 2016; Arboleda & Plazas Tenorio, 2024), university-industry collaboration in Latin American entrepreneurial universities faces organizational rather than conceptual barriers (Puerta Sierra & Jasso, 2020), and organizational culture for technological cooperation between research institutes and firms reinforces the same knowledge-entrepreneurship nexus observed here (Parolin et al., 2020). These findings suggest that instruments for such contexts should model that integration explicitly rather than presuppose separation.

For theory building in innovation management, the episode carries a generalizable lesson. The entrepreneurial-university literature has expanded through the accretion of frameworks—ecosystems, orientations, capabilities, cultures—each generating its own measurement apparatus, and recent reviews explicitly identify this proliferation as an obstacle to cumulative knowledge (Guerrero et al., 2024). The present results show what the obstacle looks like at the data level: distinctions that organize the literature conceptually can be entirely absent from the covariance structure that questionnaires actually produce. Progress therefore requires treating measurement validation not as a preliminary formality but as a substantive research activity in which theories are genuinely at risk—where finding that two constructs collapse is publishable, informative, and consequential for the framework that posited them. Fields that institutionalize such tests accumulate; fields that do not, accumulate citations.

A potential objection concerns the relationship between the knowledge-based entrepreneurial capacity identified here and the well-established construct of entrepreneurial self-efficacy (ESE). The distinction is both conceptual and operational. ESE, as defined in the social-cognitive tradition (Bandura, 1997), captures an individual's confidence in performing specific entrepreneurial tasks—opportunity recognition, resource mobilization, venture launch—and is typically measured with items referencing perceived ability (e.g., "I am confident I can..."). KEC, by contrast, integrates institutional and contextual elements that ESE excludes: perceived quality of knowledge-management infrastructure, university support ecosystems, organizational culture for innovation, and digital-transformation readiness. Whereas ESE is an intra-individual appraisal of competence, KEC reflects the student's integrated evaluation of the institutional-individual nexus through which entrepreneurial capacity is actually formed in the university context. The two constructs therefore occupy different levels of analysis and answer different research questions: ESE asks "Do I believe I can?", KEC asks "Does my university environment, combined with my own capacities, equip me to create value from knowledge?" The distinction matters for policy: interventions that raise ESE (e.g., motivational workshops) need not improve the institutional knowledge processes that KEC captures, and vice versa. Future research should directly examine the discriminant validity of KEC-14 against established ESE scales (e.g., McGee et al., 2009) to confirm empirically what the content analysis suggests.

5.2. Methodological implications

Two clarifications protect the interpretation from misreadings. The finding does not assert that knowledge management and entrepreneurship are conceptually identical, nor that their distinction is theoretically useless: the claim is strictly about measurement under a particular design family, and the generative question—how university knowledge processes feed entrepreneurial activity—remains open and important. Nor does the finding reduce to the trivial observation that related constructs correlate: correlations of 0.86 to 0.97 among all 21 latent pairs, AVE below 0.50 in six of seven dimensions, and a one-factor model statistically equivalent to the hypothesized structure jointly exceed, by a wide margin, what conceptual relatedness alone would produce, and meet the operational definitions of redundancy established in the literature (Le et al., 2010; Rönkkö & Cho, 2022). The appropriate reading is conditional: under long, homogeneous, single-source self-report batteries, these constructs collapse; whether they separate under better designs is an empirical question this study cannot answer but makes unavoidable.

Four operational recommendations follow for regional research practice. First, report the full HTMT matrix and single-factor model comparisons as a precondition for any structural model relating adjacent self-report constructs; the computational cost is trivial and the interpretive benefit decisive (Rönkkö & Cho, 2022). Second, evaluate and report measurement-model fit at the item level: in the present case, estimation on aggregated indicators would have produced excellent fit indices—as is arithmetically expected when reducing 80 items to a handful of parcels—whereas item-level fit (CFI = 0.739) reveals the true state of the measurement model, empirically confirming the warnings of the parceling literature (Bandalos, 2002; Marsh et al., 2013). Third, incorporate response-quality screening and procedural remedies against method bias—temporal or source separation, reversed items, straightlining detection—given that a quarter of the sample exhibited minimal-variability response patterns (Podsakoff et al., 2012). Fourth, in instrument design, prefer shorter scales with maximally differentiated items, behavioural anchors over agreement with general statements, and, where feasible, objective indicators such as verified incubator participation or formalized ventures.

5.3. Practical implications for Latin America

For applied research and university management in the region, the KEC-14 offers a brief, reliable measure of knowledge-based entrepreneurial capacity with verified convergent validity (AVE = 0.599 in the full sample; AVE = 0.532 after excluding low-variability respondents,

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both exceeding the 0.50 threshold), providing initial evidence that the abbreviated version preserves the convergent properties of the parent instrument and is suitable for institutional diagnostics, evaluation of entrepreneurship-training programmes, and monitoring of university ecosystems at one sixth of the original response burden. Its brevity enables longitudinal and evaluative uses that an eighty-item battery makes impractical: repeated administration across the student trajectory and pre-post designs for specific interventions, addressing the evaluation deficit documented for Latin American university incubators. For policymakers and institutional leaders, the finding that knowledge and entrepreneurship perceptions form one integrated disposition suggests that compartmentalized interventions—knowledge-management programmes on one side, entrepreneurship programmes on the other—may artificially segment an experience that students live as unitary, supporting the articulation of teaching, research, and outreach in integrated ecosystems (Gaffaro & Naranjo, 2025). For journal editors and reviewers in the region, the protocol used here—item-level model comparison, full HTMT reporting, method diagnostics, open code—can serve as a screening checklist that would materially raise the evidential standard of the field.

Concrete usage guidance maximizes the tool's value. The KEC-14 is scored as the simple mean of its items in the original response metric, given unidimensionality and homogeneous loadings; the loss relative to factor scoring is negligible. Administration takes under five minutes, enabling integration into routine institutional surveys without dedicated sessions. Its unidimensional structure simplifies comparison across cohorts, campuses, and institutions, provided future studies establish the corresponding measurement invariance; until then, within-institution longitudinal monitoring is the safest application. Because the instrument and the analysis code are openly available, institutions can replicate the validation on their own data before adoption—an exercise that doubles as a diagnostic of response quality in their survey processes, given the straightlining prevalence documented here. Finally, the protocol's screening logic extends beyond this instrument: any Latin American research group combining adjacent perception scales can run the item-level model comparison and HTMT matrix in minutes before committing to a structural narrative.

5.4. Limitations and future research

Four limitations bound the conclusions. Convenience sampling restricted to private universities in one urban area precludes generalization; replication with probability and multi-site samples is needed. The cross-sectional single-source design cannot separate trait from method variance; designs with temporal separation, multiple informants, or behavioural indicators are the indicated route to estimating the substantive knowledge-entrepreneurship relationship free of method contamination. The KEC-14 was derived and validated in the same sample, implying a risk of capitalization on chance; its structure requires confirmation in independent samples, together with measurement invariance testing across sex, age, and employment status, and predictive validation against external criteria. Finally, Harman's test and straightlining indicators are imperfect diagnostics of method bias; marker-variable or explicit method-factor designs are warranted (Podsakoff et al., 2012). Whether, with shorter instruments, heterogeneous wording, and procedural separation, the theoretical dimensions of knowledge management and entrepreneurship would recover empirical discrimination remains an open question—precisely the research agenda this study motivates.

6. Conclusions

This study provides systematic, fully reproducible evidence that an instrument representative of regional research practice—80 items and seven dimensions measuring knowledge management and university entrepreneurship—measures, in a large sample of Peruvian working students, one general dimension: the multidimensional structure does not outperform a single-factor model, convergent validity fails in six of seven dimensions, and discriminant validity fails in all 21 pairs. Structural models linking these variables under equivalent designs should therefore be interpreted with great caution, as their coefficients largely reflect shared construct and method variance. As a constructive alternative, the study delivers the KEC-14, a brief, unidimensional, reliable measure of knowledge-based entrepreneurial capacity with satisfactory convergent validity, and a reproducible verification protocol whose routine adoption would strengthen the evidence base on which entrepreneurial-university theory and policy are built in Latin America. The message is constructive rather than sceptical: that two labels do not correspond to two constructs under a given design does not close the substantive question of how university knowledge processes feed student entrepreneurship—it reformulates it, and equips the field with a diagnosis, a tool, and a protocol to pursue it.

Three boundary conditions frame the contribution. The evidence concerns one instrument, one design family, and one population; it does not license the inference that all knowledge management or entrepreneurship measures are redundant everywhere, but it does shift the burden of proof: in contexts and designs similar to those studied here—long positively worded batteries, single-source cross-sectional administration, populations for whom knowledge and enterprise are an integrated daily practice—distinguishability must be demonstrated before structural claims are advanced. The KEC-14 inherits these boundaries: it is validated for diagnostic and monitoring purposes in comparable populations, and its use as a criterion or predictor in explanatory models should await independent confirmation and invariance evidence. Within those boundaries, the study replaces an unverified assumption with a tested answer, an unusable instrument with a usable one, and an opaque analytic practice with an open, reproducible protocol.

Data Availability Statement

The anonymized dataset and the complete Python analysis code that reproduce all results reported in this article are deposited in an open repository (DOI withheld for blind review) and are provided to reviewers as supplementary material.

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