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Assessing Mathematics Pre-Service Teachers' Content Knowledge and Pedagogical Content Knowledge through a Diagnostic Computer-Based Test

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ABSTRACT

Content Knowledge (CK) and Pedagogical Content Knowledge (PCK) are core components of mathematics teachers' competence, yet they are rarely measured simultaneously through technology-based diagnostic assessment. This study measures and profiles the CK and PCK of mathematics pre-service teachers using a diagnostic Computer-Based Test (CBT). A quantitative descriptive-correlational design was applied to 30 purposively selected pre-service teachers. Each construct was measured with 25 multiple-choice items whose content validity was established by expert judgment and whose reliability was confirmed before use (KR-20 = 0.81 for CK; 0.79 for PCK). Data were analyzed with descriptive statistics, Pearson correlation, and simple linear regression after assumption checks. Mean CK (50.00%) and PCK (52.67%) were both below the 75% mastery threshold, with 60% of students in the low category; specialized content knowledge and knowledge of content and curriculum were the weakest dimensions. CK and PCK correlated strongly and positively ($r = 0.72$; $p < 0.001$), with CK accounting for about 52% of the variance in PCK as a predictive, non-causal association. The CBT generated actionable diagnostic profiles at the dimension and indicator levels. These findings support using diagnostic CBT to guide data-driven curriculum reform integrating content mastery and pedagogical capacity.

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1. INTRODUCTION

The quality of a nation's mathematics education depends heavily on teachers' professional competence. Cross-national studies have shown that mathematics teachers' professional knowledge, comprising Content Knowledge (CK) and Pedagogical Content Knowledge (PCK), is a primary predictor of instructional effectiveness and students' academic achievement [1], [2]. The 2022 PISA results placed Indonesian students' mathematics literacy 68th out of 81 countries, below the OECD average, indicating a fundamental problem in the quality of mathematics instruction [3]. This condition is inseparable from the quality of professional knowledge formed in teacher education institutions, so ensuring an adequate professional-knowledge profile of pre-service teachers becomes a strategic imperative [4], [5].

Theoretically, the Mathematical Knowledge for Teaching (MKT) framework distinguishes CK, comprising common, specialized, and horizon content knowledge, from PCK, which encompasses knowledge of content and students, content and teaching, and content and curriculum [6], [7]. Systematic reviews affirm that PCK is the most frequently studied yet the most difficult component to measure consistently because of its contextual and multidimensional nature [8], [9]. Studies in Indonesia show that the professional knowledge of mathematics pre-service teachers varies widely across institutions and curricula, with a notable weakness in the PCK aspect [10], [11]. Similar findings have been reported in cross-national contexts [12], [13].

Alongside the rapid digitalization of education, competency-evaluation systems are now shifting massively from traditional approaches toward technology-based assessment. Various studies indicate that CBT is often more valid and reliable than conventional examination methods [14], [15]; however, its use to objectively measure both the content knowledge and the pedagogical content knowledge of pre-service teachers simultaneously remains very limited because of the complexity of these constructs [16], [17]. The potential of CBT to generate diagnostic feedback based on learning analytics has also not been optimally exploited [18], even though interactive digital feedback has been shown to improve mathematical understanding [19], [20].

The urgency of this study is heightened in the context of Indonesia's uneven higher-education digital transformation [21], which is not yet supported by adequate standardization of assessment systems [22]. Measuring teacher competence in the digital era is required to produce data that are actionable for study-program managers and policymakers [23]. A number of studies affirm that CK and PCK are relatively independent constructs that require different intervention pathways [24], [25], and that teacher effects on student achievement are substantial [26]. Taken together, however, this body of work remains fragmented: CK and PCK are rarely measured simultaneously with a single validated instrument, the diagnostic potential of CBT is seldom exploited at the indicator level, and the evidence is concentrated in a few well-studied national settings, leaving a clear gap for integrated, technology-based diagnosis of both constructs.

Building on this gap, the present study makes three specific contributions rather than a general claim to novelty. Theoretically, it provides empirical evidence on how CK and PCK co-vary at low overall proficiency, showing that their interdependence persists even when neither reaches mastery, an insight that refines, rather than merely applies, the MKT and COACTIV frameworks [6], [25], [27]. Methodologically, it operationalizes a CBT that produces layered, indicator-level diagnostic profiles for both constructs simultaneously, addressing the scarcity of validated instruments that jointly diagnose CK and PCK [28], [29]. Practically, it demonstrates how such diagnostic data can be translated into targeted curriculum and instructional decisions. By drawing on an underrepresented context, the study also contributes comparative evidence to the international literature on teacher knowledge rather than a purely local application of CBT [12], [30]. Accordingly, the study aims to: (1) measure and profile pre-service teachers' CK and PCK; (2) identify strengths and weaknesses at the dimension and indicator levels; and (3) demonstrate how diagnostic profiles can inform instructional intervention.

2. METHOD

This study employed a quantitative approach with a descriptive-survey and correlational design. The population comprised students of the Mathematics Education study program at a teacher education institution who were in their fifth and seventh semesters. A sample of 30 students was determined through purposive sampling with the inclusion criteria: (1) active students who had adequately completed mathematics-content and pedagogy courses; and (2) willing to take the entire series of CBT tests. Given the limited sample size, all data were analyzed as a single intact group (n = 30) and were not directed toward inter-semester comparison.

Research setting and participants. The research was conducted in the odd semester of the 2024/2025 academic year in the Mathematics Education study program of a state Islamic teacher education institution in Indonesia. Participants were selected using total (saturated) purposive sampling: all 30 students who met the inclusion criterion, having completed the core mathematics-content and pedagogy courses, were included, so that the sample comprised the entire eligible cohort rather than a probability sample. The sample size (n = 30) therefore reflects the actual number of eligible students at the single participating institution and suits the study's diagnostic, exploratory aim of profiling CK and PCK in depth; it is nonetheless acknowledged as a constraint on statistical power and on the generalizability of the correlational and regression results, as elaborated in the Discussion.

The operationalization of the variables comprised two main constructs. CK was defined as mastery of the mathematics content to be taught, measured through 25 multiple-choice items; PCK was defined as the ability to integrate content knowledge with pedagogical strategies, also measured through 25 multiple-choice items. Scores were converted into percentages of achievement relative to the ideal maximum score. The CBT instrument was designed to generate layered diagnostic reports, namely the total score, achievement per dimension, achievement per indicator, and an individual achievement profile for each student. Each item was mapped to a specific indicator and dimension (see the notes below Table 1) so that the CBT system could produce achievement per dimension and per indicator for all students at once, as well as their individual diagnostic profiles. The composition of the instrument is presented in Table 1. The multiple-choice format was chosen to enable fully automated, standardized, and scalable scoring across all participants and indicators at once, a prerequisite for the layered diagnostic reporting; its rationale and limitations are elaborated under 'Item format'.

Table 1. Composition of CBT Instrument Items by MKT Dimension

Domain	Dimension	Number of Items
CK	Common Content Knowledge CCK)	7
CK	Specialized Content Knowledge (SCK)	14
CK	Horizon Content Knowledge (HCK)	4
PCK	Knowledge of Content and Students (KCS)	10
PCK	Knowledge of Content and Teaching (KCT)	9
PCK	Knowledge of Content and Curriculum (KCC)	6
Total		50

Notes on dimension codes and indicator coverage (based on the developed CK and PCK instruments). **CK – CCK** (Common Content Knowledge, items 1–7): understanding basic concepts (e.g., lines and angles), performing calculations and measurements accurately, and applying mathematical concepts in everyday life. **CK – SCK** (Specialized Content Knowledge, items 8–21): explaining concepts and principles, analyzing and connecting mathematical objects, proving properties, building models, and solving complex mathematical problems. **CK – HCK** (Horizon Content Knowledge, items 22–25): connecting school mathematics with advanced academic mathematics and with other disciplines. **PCK – KCS** (Knowledge of Content and Students, items 1–10): analyzing students' preconceptions and understanding as well as predicting and analyzing students' misconceptions, errors, and difficulties. **PCK – KCT** (Knowledge of Content and Teaching, items 11–19): selecting and organizing learning materials, selecting sources, strategies, and techniques, and selecting and analyzing representations for presenting material. **PCK – KCC** (Knowledge of Content and Curriculum, items 20–25): designing content and topic combinations, applying standards and curricula, and designing instruments to measure students' abilities.

Instrument development and content validity. The CBT instrument was developed through a systematic procedure. First, a test blueprint was constructed by mapping each item to a specific MKT dimension and indicator (Table 1). Second, the draft items were reviewed by three experts—two mathematics-education lecturers and one educational-assessment specialist—to establish content validity; the level of expert agreement was quantified using Aiken's V, and items with $V \geq 0.80$ were retained while the remaining items were revised or replaced. Third, the revised items were trialed and analyzed empirically before being administered in the present study. To illustrate the item format, each CK item presented a mathematical task with four to five options, whereas each PCK item was framed as a short classroom scenario or a sample of student work followed by options representing alternative pedagogical decisions. The complete test blueprint and sample items are available from the authors upon reasonable request.

Reliability and item analysis. Based on the item analysis, the instrument demonstrated adequate psychometric quality. Internal-consistency reliability computed with the Kuder–Richardson formula (KR-20) reached 0.81 for the CK test and 0.79 for the PCK test, both within the acceptable-to-good range. The item difficulty indices ranged from 0.20 to 0.87 (a balanced mix of easy, medium, and hard items), and the discrimination indices were largely satisfactory ($D \geq 0.30$); only items meeting the validity, difficulty, and discrimination criteria were retained in the final CBT.

Item format. Multiple-choice items were chosen because the CBT was designed for automated, standardized, and scalable diagnosis across many participants and indicators simultaneously. To capture pedagogical reasoning rather than mere recall, the PCK items were built around short classroom scenarios, samples of student work, and instructional-decision situations, with distractors constructed from typical student misconceptions and common teaching errors. It is nevertheless acknowledged that the multiple-choice format cannot fully capture the depth of pedagogical reasoning that open-ended or performance-based tasks would reveal, a limitation revisited in the Discussion.

The analysis techniques comprised descriptive and inferential analyses. Descriptive analysis produced the mean (M), standard deviation (SD), minimum, maximum, median, and percentage of achievement at the total, dimension, indicator, and individual levels, as well as a three-level categorization (High, Medium, Low). The categorization used the following cut-off points: High (≥ 75%), Medium (60–74.99%), and Low (< 60%), where the 75% mark represents the ideal mastery criterion adopted in this study. Inferential analysis was conducted through two techniques: (1) Pearson correlation to test the CK–PCK relationship and the corresponding inter-dimension relationships (CCK–KCS, SCK–KCT, HCK–KCC) at $\alpha = 0.05$; and (2) simple linear regression with CK as the predictor and PCK as the criterion. Prior to the inferential tests, the underlying assumptions were examined, namely the normality of the CK and PCK distributions (Shapiro–Wilk), the linearity of their relationship, the absence of influential outliers, and homoscedasticity; all assumptions were adequately met, so that the parametric analyses were appropriate.

All scoring, achievement computation, correlation, and linear regression were performed using Microsoft Excel through standardized formulas (including CORREL, SLOPE, INTERCEPT, and RSQ) so that every figure can be traced back to the raw data. The study also observed standard research-ethics principles: participation was entirely voluntary, informed consent was obtained from all respondents before data collection, and the participants' anonymity and confidentiality were maintained throughout the recording, processing, and reporting of data by using codes instead of names, with the individual-profile example presented under the pseudonym Student 1.

3. RESULTS AND DISCUSSION

3.1. Results

This section reports the findings of the data analysis in the following order: respondent characteristics, descriptive statistics, the distribution of achievement categories, dimension- and indicator-level achievement, the correlation and regression results, and an individual diagnostic profile. The 30 respondents were fifth- and seventh-semester students of the Mathematics Education study program who had completed the core mathematics-content and pedagogy courses; all of them completed the full series of CK and PCK tests through the CBT system.

Overall, students' professional-knowledge achievement had not yet reached the ideal competency threshold (≥ 75%). The mean CK score was 50.00% (SD = 10.16), PCK 52.67% (SD = 23.96), and the combined Professional Knowledge (PK) score 51.33% (SD = 16.04). The complete descriptive statistics are presented in Table 2.

Table 2. Descriptive Statistics of CK, PCK, and Professional Knowledge Scores (n = 30)

Variable	Mean (%)	SD	Min	Max	Median
Content Knowledge (CK)	50.00	10.16	24	68	52.00
Pedagogical Content Knowledge (PCK)	52.67	23.96	8	96	54.00
Professional Knowledge (PK)	51.33	16.04	26	78	50.00

Table 2 shows that the mean PCK is slightly higher than CK (a difference of 2.67 points), an interesting pattern indicating that pedagogical-transformation capacity slightly exceeds content mastery. The large standard deviation of PCK (SD = 23.96) and the much smaller one for CK (SD = 10.16) reflect substantial heterogeneity in knowledge profiles, with score ranges of 24–68% for CK and 8–96% for PCK. The distribution of Professional Knowledge categories is presented in Table 3.

Table 3. Distribution of Professional Knowledge Categories (n = 30)

Category	Frequency (f)	Percentage (%)
High	0	0.00
Medium	12	40.00
Low	18	60.00
Total	30	100.00

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All students (100%) were in the Low or Medium category, with 60.00% in the Low category and 40.00% in the Medium category, and no student reached the High category. This indicates that the majority of pre-service teachers have not attained an optimal level of professional-knowledge mastery. Achievement per dimension is presented in Table 4 and Figure 1.

Table 4. Average Achievement per CK and PCK Dimension

Domain	Dimension	Items	Mean (%)	SD
CK	CCK	7	73.33	20.47
CK	SCK	14	36.91	24.16
CK	HCK	4	55.00	35.60
PCK	KCS	10	54.07	33.18
PCK	KCT	9	57.50	26.14
PCK	KCC	6	46.25	32.30

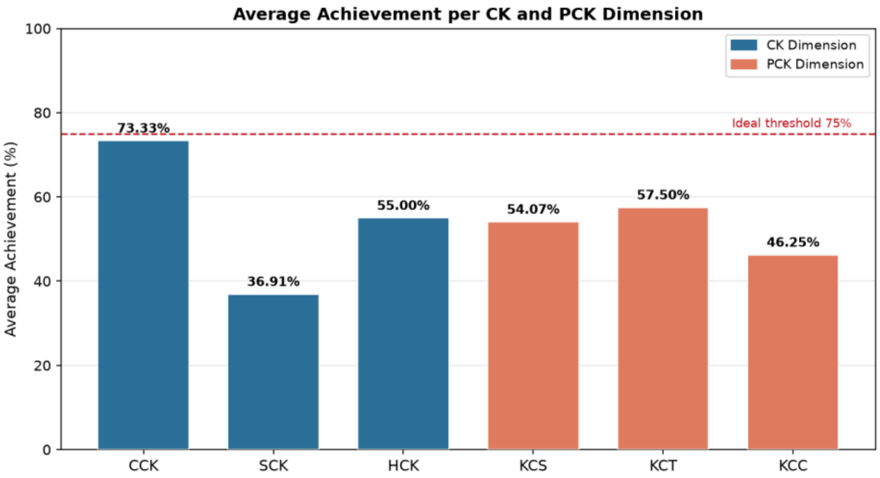

Figure 1. Average Achievement per CK and PCK Dimension

In the CK domain, the CCK dimension was the highest (73.33%) and SCK the lowest (36.91%); in the PCK domain, KCT was the highest (57.50%) while KCC was the lowest of all six dimensions (46.25%). Diagnostically, the low SCK and KCC signal a weak ability to relate content to the structure and organization of the curriculum—an area that needs to be prioritized in intervention. Achievement at the indicator level is presented in Table 5 and visualized in Figure 2.

Table 5. Average Achievement per CK and PCK Indicator

Domain	Indicator	Mean (%)
CK	CCK1	86.67
CK	CCK2	80.00
CK	CCK3	46.67
CK	SCK1	63.33
CK	SCK2	46.67
CK	SCK3	43.33
CK	SCK4	20.00
CK	SCK5	23.33
CK	SCK6	30.00
CK	SCK7	33.33
CK	HCK1	53.33
CK	HCK2	56.67
PCK	KCS1	58.33
PCK	KCS2	48.33

Domain	Indicator	Mean (%)
PCK	KCS3	58.33
PCK	KCS4	51.67
PCK	KCS5	53.33
PCK	KCT1	55.00
PCK	KCT2	66.67
PCK	KCT3	60.00
PCK	KCT4	36.67
PCK	KCC1	51.67
PCK	KCC2	43.33
PCK	KCC3	45.00

Notes on indicator codes (based on the CK and PCK instruments). CK indicators — **CCK1**: understanding basic school-mathematics concepts, such as lines, angles, sequences, and basic statistics (items 1–3); **CCK2**: performing calculations and measurements accurately (items 4–5); **CCK3**: applying mathematical concepts in everyday life (items 6–7); **SCK1**: explaining academic mathematical concepts and principles (items 8–9); **SCK2**: analyzing mathematical objects (items 10–11); **SCK3**: connecting mathematical properties and objects (items 12–13); **SCK4**: proving mathematical properties or theorems (items 14–16); **SCK5**: applying proof strategies (item 17); **SCK6**: building and constructing mathematical models (items 18–19); **SCK7**: solving complex mathematical problems (items 20–21); **HCK1**: connecting school mathematics with advanced academic mathematics (items 22–23); **HCK2**: connecting mathematics with other disciplines (items 24–25). PCK indicators — **KCS1**: analyzing students' preconceptions (items 1–2); **KCS2**: identifying students' level of understanding (items 3–4); **KCS3**: predicting students' misconceptions (items 5–6); **KCS4**: identifying sources of students' learning difficulties (items 7–8); **KCS5**: analyzing students' literacy issues and errors (items 9–10); **KCT1**: organizing and sequencing learning materials (items 11–12); **KCT2**: selecting learning sources, strategies, and techniques (items 13–14); **KCT3**: selecting representations and illustrations for presenting material (items 15–17); **KCT4**: analyzing the weaknesses and strengths of representations (items 18–19); **KCC1**: composing content and topic combinations (items 20–21); **KCC2**: applying standards and curricula (items 22–23); **KCC3**: designing instruments to measure students' abilities (items 24–25).

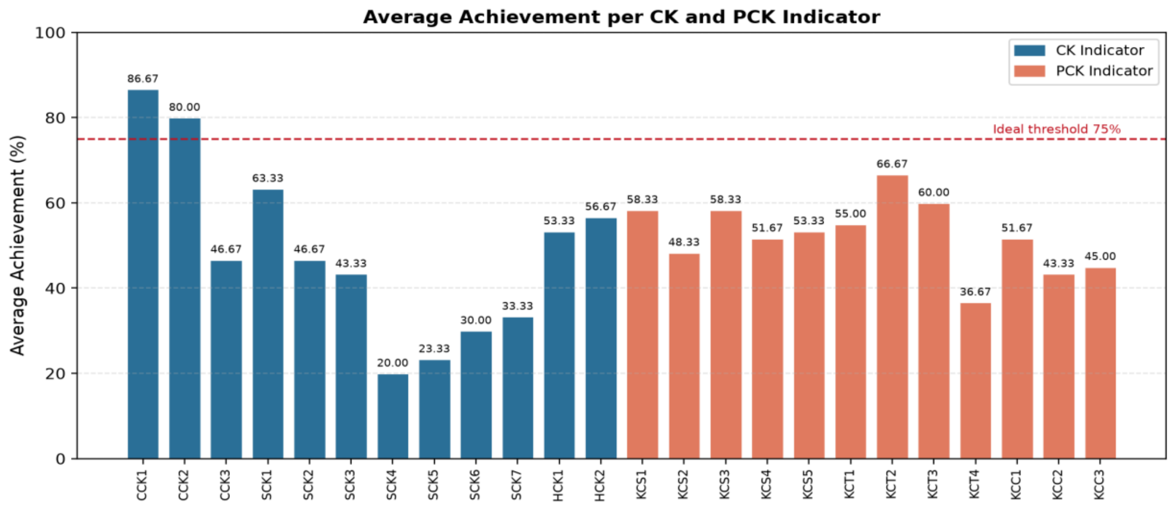

Figure 2. Average Achievement per CK and PCK Indicator

Figure 2 visualizes the average achievement of each indicator exactly as listed in Table 5. The range of achievement across indicators spans 20.00% to 86.67%. The highest achievement is on the CK indicator CCK1 (86.67%; understanding basic school-mathematics concepts), which is fundamental and therefore the most widely mastered by students. Conversely, the lowest overall achievement is on indicator SCK4 (20.00%; proving mathematical properties or theorems), the skill with the highest cognitive demand in the CK domain, followed by SCK5 (23.33%; applying proof strategies) and SCK6 (30.00%; building and constructing mathematical models). The pattern in the SCK dimension declines gradually with complexity, from explaining concepts and principles (SCK1; 63.33%), analyzing and connecting mathematical objects (SCK2 46.67%; SCK3 43.33%), solving complex problems (SCK7; 33.33%), to the most difficult modeling and proving (SCK6 30.00%; SCK5 23.33%; SCK4 20.00%), a pattern consistent with cognitive load theory. Because each dimension's achievement remains the mean of its constituent indicators, for example, KCS (54.07%) is the mean of KCS1–KCS5 and CCK (73.33%) is the mean of CCK1–CCK3—this pattern maps precisely which items and indicators are the sources of weakness, so that lecturers can design remediation targeted at concrete rather than generic weaknesses. The results of the Pearson correlation test are presented in Table 6.

Table 6. Pearson Correlation between Domains and between Parallel Dimensions

Relationship	r	p	Interpretation
CK – PCK	0.72	< 0.001	Strong
CCK – KCS	0.42	< 0.05	Moderate
SCK – KCT	0.54	< 0.01	Moderate
HCK – KCC	0.86	< 0.001	Very strong

The strong positive correlation between CK and PCK ($r = 0.72$; $p < 0.001$) confirms that the two domains are constructively interdependent, reinforced by the correlations between parallel dimensions, especially HCK–KCC ($r = 0.86$) and SCK–KCT ($r = 0.54$). The predictive relationship of CK on PCK was tested through simple linear regression (Table 7 and Figure 3).

Table 7. Results of the Simple Linear Regression of CK on PCK

Parameter	Value
Slope (b)	1.708
Intercept (a)	−32.734
Coefficient of determination (R^2)	0.5245
Pearson r	0.72
Equation	PCK = 1.708 × CK − 32.734

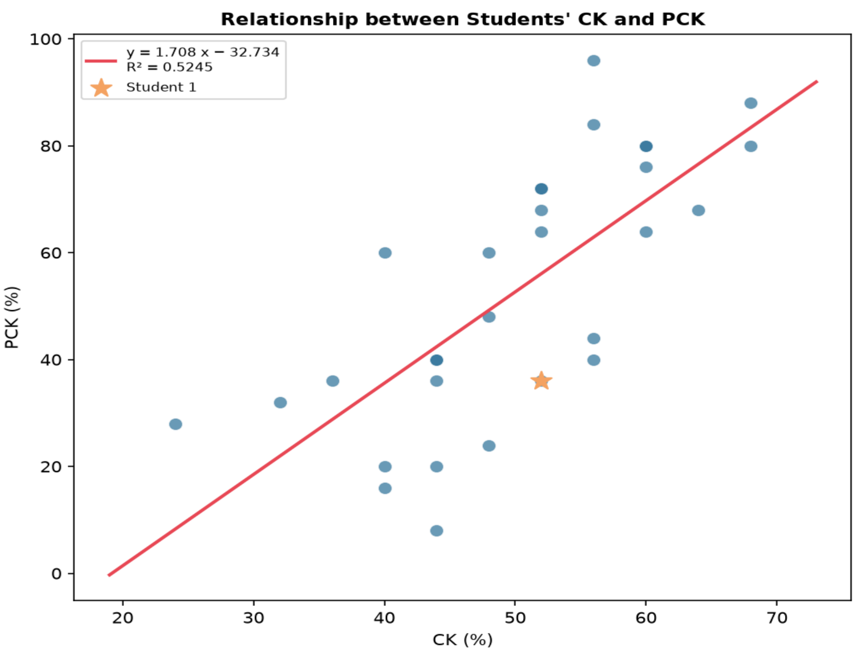

Figure 3. Scatter Plot and Regression Line of the CK–PCK Relationship

The equation PCK = 1.708 × CK − 32.734 with $R^2 = 0.52$ indicates that about 52% of the variance in PCK is statistically associated with CK. Because the design is correlational, this relationship should be interpreted as a predictive association rather than a causal effect; the remaining 48% of the variance signals that PCK does not form automatically from content mastery but requires an explicit pedagogical learning pathway.

The CBT also breaks aggregate achievement down into individual diagnostic profiles automatically. To illustrate this capability, rather than to draw general conclusions from a single case, Table 8 and Figure 4 summarize the profile of one participant (pseudonym Student 1), and Figures 5 and 6 show anonymized screenshots of the corresponding diagnostic report generated by the CBT. Such reports are produced automatically for every participant.

Table 8. Individual Achievement Profile of Student 1 Compared with the Class Average

Domain	Student 1 Score (%)	Class Average (%)	Difference	Category
Content Knowledge (CK)	52.00	50.00	+2.00	Low
Pedagogical Content Knowledge (PCK)	36.00	52.67	−16.67	Low

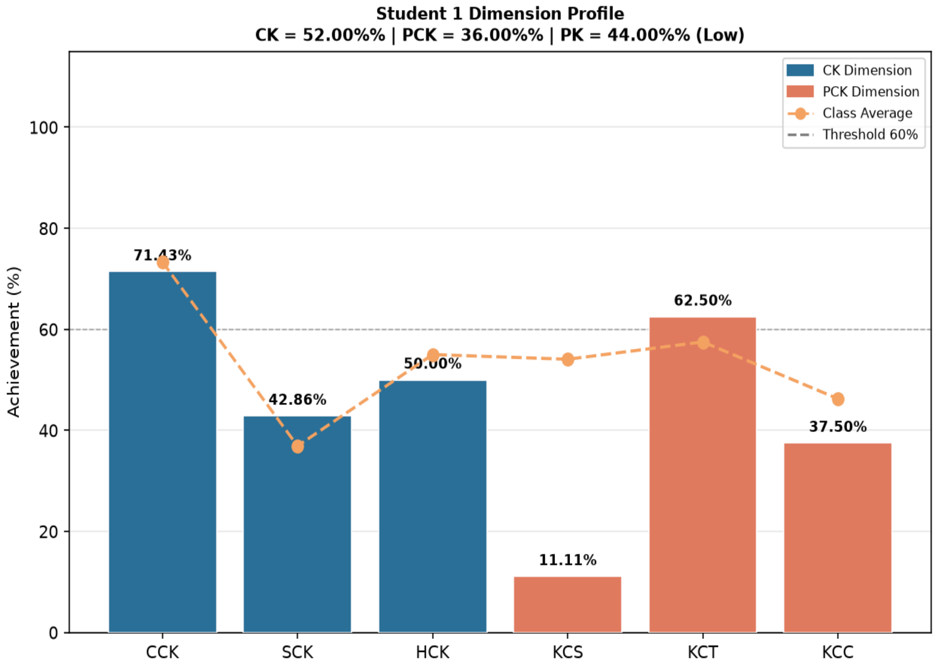

Figure 4. CK and PCK Achievement Profile of Student 1 Compared with the Class Average

As an illustrative example, Student 1 answered 13 of 25 CK items and 9 of 25 PCK items correctly, falling into the Low category for both domains, with CK slightly above and PCK well below the class average. Anonymized screenshots of the report are shown in Figures 5 and 6, with no identifiable student information displayed. This single case is used only to demonstrate the diagnostic output of the CBT and is not intended as a basis for general interpretation.

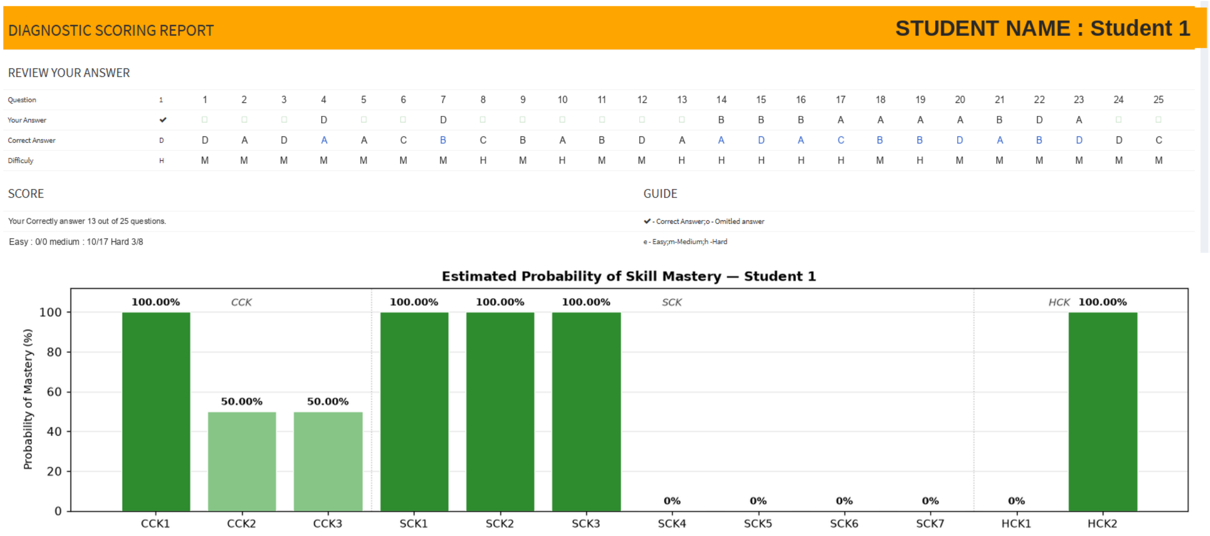

Figure 5. CBT Diagnostic Scorecard for the CK Domain for Student 1 (original system screenshot)

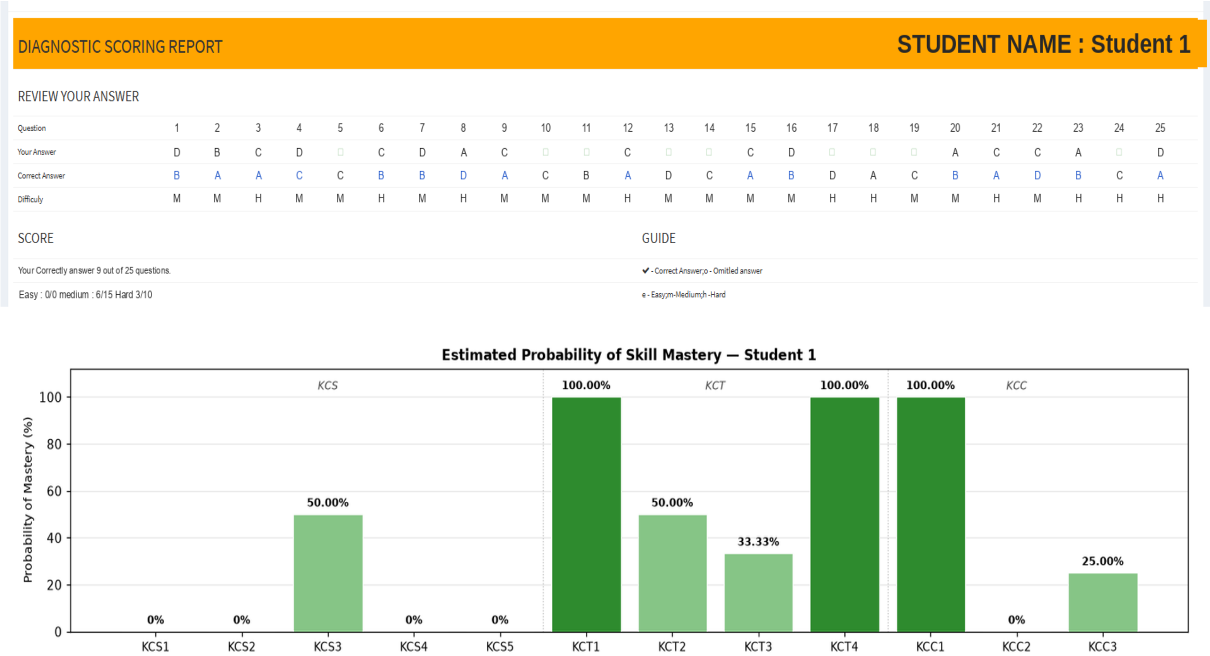

Figure 6. CBT Diagnostic Scorecard for the PCK Domain for Student 1 (system screenshot)

Figures 5 and 6 reveal diagnostic functions of the CBT that are more difficult to implement efficiently in conventional paper-based tests. In addition to recapping correct/incorrect answers per item along with their difficulty level, a combination of the Medium (M) and Hard (H) categories according to the item analysis of the instrument, the system presents an Estimated Probability of Skill Mastery graph that maps Student 1's mastery probability for each skill indicator (CCK1–HCK2 for CK and KCS1–KCC3 for PCK), complete with a mapping of sample items to each indicator. Thus, the CBT does not merely provide a final score but directly identifies which indicators have been mastered and which remain weak, in Student 1's case, several indicators show a mastery probability close to zero, so that lecturers can follow up with specific and immediate remediation. It is this automation of scoring, standardization of reporting, and diagnostic depth that affirms the added value of the CBT in assessing the professional knowledge of mathematics pre-service teachers.

At the indicator level, the same report pinpoints exactly which indicators a student has and has not mastered. For Student 1, for example, several higher-order indicators, advanced reasoning and proof within SCK, and knowledge of students within KCS registered no mastery, whereas basic content indicators were fully mastered. This illustrates how indicator-level diagnosis can guide individualized remediation far more precisely than dimension averages alone, without implying that this individual profile generalizes to the cohort.

Summary of key findings. In sum, both CK (50.00%) and PCK (52.67%) fell below the 75% mastery threshold; 60.00% of the students were in the low category and none reached the high category; SCK (36.91%) and KCC (46.25%) were the weakest dimensions; CK and PCK were strongly and positively associated ($r = 0.72$; $p < 0.001$); and the CBT was able to decompose these results down to the indicator and individual-student levels, as illustrated by the profile of Student 1.

3.2. Discussion

Interpreted against the study's objectives, three points stand out. First, neither CK nor PCK reached the mastery threshold, and contrary to the common assumption that content mastery precedes and exceeds pedagogical knowledge, PCK was marginally higher than CK; this pattern resonates with Shulman's argument that transforming content into teachable form is a distinct challenge [7] and with the MKT framework's treatment of CK and PCK as related but non-identical constructs [6]. Second, the weakest areas lay in advanced specialized content within CK and in knowledge of curriculum within PCK, echoing the COACTIV model's claim that these facets critically shape the quality of instructional planning [2], [25]. Third, CK achievement was far more homogeneous than PCK, suggesting that pedagogical capacity develops more unevenly across pre-service teachers, consistent with reviews describing PCK as the most context-dependent and hardest-to-cultivate component [8], [9].

The pattern of correlations indicates that stronger mastery in particular content dimensions tends to co-occur with the corresponding pedagogical capacity, yet content mastery accounts for only part of the variation in PCK, consistent with evidence that pre-service teachers in developing contexts often show comparatively weaker PCK because curricula emphasize content coverage over pedagogical transformation [1], [10]. Rather than forming automatically from content knowledge, PCK appears to require explicit, dedicated learning experiences. The profile of Student 1 is consistent with this interpretation but is treated here only as an illustrative example, not as evidence in its own right.

These results are broadly consistent with prior Indonesian studies reporting that the professional knowledge of mathematics pre-service teachers is generally moderate and uneven, with PCK frequently emerging as the more fragile component [10], [11]. The finding that PCK was marginally higher than CK is noteworthy and can be interpreted cautiously: the PCK items, which draw on familiar classroom situations, may be more accessible to students than the CK items, which demand advanced and abstract mathematical reasoning; moreover, the far larger dispersion of PCK ($SD = 23.96$) indicates that this apparent advantage is unevenly distributed across the cohort. The particularly low

SCK (36.91%) is plausibly linked to teacher-education curricula that emphasize procedural and elementary content over advanced mathematical reasoning—such as formal proof, mathematical modeling, and complex problem solving—so that the more cognitively demanding indicators (SCK4–SCK7) remain underdeveloped [24], [25].

Theoretically, the study offers a specific insight rather than a mere application of existing models: in a low-proficiency, underrepresented setting, CK and PCK remain strongly interdependent even though neither reaches mastery and PCK can slightly exceed CK. This qualifies the intuitive assumption that CK necessarily leads PCK and suggests that, at early proficiency levels, the two constructs may develop in tandem rather than strictly sequentially—extending the MKT and COACTIV frameworks to conditions from which they were not originally derived [6], [25], [27]. Methodologically, the study contributes a CBT model that jointly diagnoses CK and PCK down to the indicator level, addressing the scarcity of instruments that do so simultaneously [22], [28]. In policy terms, the finding that no student reached the high category provides empirical grounds for data-driven rather than assumption-driven curriculum reform [5], [23], a concern underscored by Indonesia's recent international assessment results [3].

Positioned this way, the CBT functions not merely as an examination tool but as a diagnostic-assessment ecosystem that yields rich, decomposable cognitive data actionable for program managers [23], [30]. Several limitations should nonetheless temper these conclusions and caution against generalizing beyond the single institution and the 30 participants studied here: (a) the small sample size, which limits statistical power and generalizability; (b) the total-purposive, single-institution sampling; (c) the bivariate scope, which does not model other determinants simultaneously; (d) the reliance solely on quantitative CBT data, without syllabus and document analysis, classroom observation, or interviews that could triangulate and explain why students underperformed; (e) the limited external evidence of the instrument's validity and reliability beyond the internal analyses reported here; and (f) the multiple-choice format, which cannot fully capture the reasoning that open-ended or performance-based tasks would reveal. In practical terms, these findings imply that teacher-education curricula should allocate explicit, assessed learning time to advanced specialized content (formal proof, mathematical modeling, and complex problem solving) and to knowledge of students and curriculum. They should embed diagnostic CBT within course cycles so that indicator-level weaknesses are identified early and addressed through targeted, evidence-based remediation. Future research should employ larger multi-institution and longitudinal samples, mixed-methods designs that add qualitative triangulation, and multivariate models to strengthen internal and external validity.

CONCLUSION AND RECOMMENDATIONS

This study set out to measure and profile the CK and PCK of mathematics pre-service teachers through a diagnostic CBT. On average, both constructs remained below the mastery threshold, with the majority of students in the low category and none in the high category; the weakest areas were advanced specialized content within CK and knowledge of curriculum within PCK, while CK and PCK were strongly and positively associated. Theoretically, the study clarifies that CK and PCK can remain interdependent and PCK can slightly exceed CK, even at low overall proficiency; methodologically, it demonstrates a

CBT capable of layered, indicator-level diagnosis of both constructs; and practically, it provides a standardized, efficient means of generating actionable competence profiles for teacher education. These conclusions should be read in light of the study's limitations, namely a small, single-institution, purposively selected sample analyzed with bivariate, multiple-choice-based methods. Overall, the central message is that diagnostic computer-based assessment can meaningfully advance the monitoring and development of mathematics pre-service teachers' professional knowledge, provided its profiles are used to inform evidence-based curriculum and instructional reform.

Recommendations. The following recommendations are offered as literature-informed, potentially effective alternatives suggested by, rather than directly proven by, the present findings, and they should be validated in future studies.

For lecturers. Remedial instruction may target not only the weakest dimensions (SCK within CK and KCC within PCK) but also the weakest indicators identified in Table 5. In the CK domain, priority may be given to strengthening mathematical proof, proving properties or theorems (SCK4) and applying proof strategies (SCK5) through scaffolded proof practice, analysis of proof errors, and habituation to deductive argumentation, followed by mathematical modeling (SCK6) and complex problem solving (SCK7) via problem-based learning. In the PCK domain, the focus may fall on analyzing the strengths and weaknesses of representations (KCT4), applying standards and curricula (KCC2), and designing measurement instruments (KCC3) through case-based learning, analysis of teaching videos, and curriculum-document study.

For teacher education institution curriculum managers. The results encourage integrating a diagnostic CBT, capable of mapping achievement down to the indicator and individual levels, into the study program's quality-assurance cycle, and rebalancing the curriculum so that advanced mathematical reasoning and pedagogical-content competence receive as much emphasis as procedural content mastery.

For future researchers. Future studies may use larger, multi-institution, and longitudinal samples, mixed-methods designs that add qualitative triangulation (syllabus analysis, classroom observation, and interviews), and multivariate models involving additional determinants (such as academic background, learning motivation, and quality of teaching) to strengthen external validity and to explain the causes of the observed weaknesses. A further agenda is to develop and empirically test enhancements to the CBT itself, automatic item-level feedback with worked explanations, direct links to remedial materials for each weak indicator, and adaptive item delivery. So that, once validated, the system can function not only as a diagnostic tool but also as an integrated learning-support environment.

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REFERENCES

[1] X. Yang and G. Kaiser, "The impact of mathematics teachers' professional competence on instructional quality and students' mathematics learning outcomes," *Curr. Opin. Behav. Sci.*, vol. 48, p. 101225, Dec. 2022, doi: 10.1016/j.cobeha.2022.101225.

[2] S. Krauss *et al*., "Pedagogical content knowledge and content knowledge of secondary mathematics teachers," *J. Educ. Psychol.*, vol. 100, no. 3, pp. 716–725, Aug. 2008, doi: 10.1037/0022-0663.100.3.716.

[3] OECD, *PISA 2022 Results (Volume I): The State of Learning and Equity in Education*. In PISA. OECD Publishing, 2023. doi: 10.1787/53f23881-en.

[4] International Association for the Evaluation of Educational Achievement, *Policy, practice, and readiness to teach primary and secondary mathematics in 17 countries: findings from the IEA Teacher Education and Development Study in Mathematics (TEDS-M).* Amsterdam: IEA, 2012.

[5] H. Qian and P. Youngs, "The effect of teacher education programs on future elementary mathematics teachers' knowledge: a five-country analysis using TEDS-M data," *J. Math. Teach. Educ.*, vol. 19, no. 4, pp. 371–396, Aug. 2016, doi: 10.1007/s10857-014-9297-0.

[6] D. Loewenberg Ball, M. H. Thames, and G. Phelps, "Content Knowledge for Teaching: What Makes It Special?," *J. Teach. Educ.*, vol. 59, no. 5, pp. 389–407, Nov. 2008, doi: 10.1177/0022487108324554.

[7] L. S. Shulman, "Those Who Understand: Knowledge Growth in Teaching," *Educ. Res.*, vol. 15, no. 2, pp. 4–14, Feb. 1986, doi: 10.3102/0013189X015002004.

[8] M. Grigaliūnienė, E. Lehtinen, L. Verschaffel, and F. Depaepe, "Systematic Review of Research on Pedagogical Content Knowledge in Mathematics: Insights from a Topic-Specific Approach," *ZDM – Math. Educ.*, vol. 57, no. 4, pp. 777–794, Aug. 2025, doi: 10.1007/s11858-025-01684-1.

[9] F. Depaepe, L. Verschaffel, and G. Kelchtermans, "Pedagogical content knowledge: A systematic review of the way in which the concept has pervaded mathematics educational research," *Teach. Teach. Educ.*, vol. 34, pp. 12–25, Aug. 2013, doi: 10.1016/j.tate.2013.03.001.

[10] S. Y. Ningsih, Turmudi, and D. Juandi, "Pedagogical content knowledge (PCK) profile of prospective teachers in mathematics learning," *J. Phys. Conf. Ser.*, vol. 1521, no. 3, p. 032057, Apr. 2020, doi: 10.1088/1742-6596/1521/3/032057.

[11] S. Fiangga, S. Khabibah, S. M. Amin, and R. Ekawati, "A Learning Design Analysis of the Pre-service Teachers' Mathematics Pedagogical Content Knowledge," *J. Phys. Conf. Ser.*, vol. 1899, no. 1, p. 012153, May 2021, doi: 10.1088/1742-6596/1899/1/012153.

[12] X. Yang, B. Schwarz, and I. K. C. Leung, "Pre-service mathematics teachers' professional modeling competencies: a comparative study between Germany, Mainland China, and Hong Kong," *Educ. Stud. Math.*, vol. 109, no. 2, pp. 409–429, Feb. 2022, doi: 10.1007/s10649-021-10064-x.

[13] J. Njiku, "Pre-service teachers manifested mathematics pedagogical content knowledge: The role of the teaching practicum," *Pedagog. Res.*, vol. 10, no. 1, p. em0229, Jan. 2025, doi: 10.29333/pr/15647.

[14] A. J. Boevé, R. R. Meijer, C. J. Albers, Y. Beetsma, and R. J. Bosker, "Introducing Computer-Based Testing in High-Stakes Exams in Higher Education: Results of a Field Experiment," *PLOS ONE*, vol. 10, no. 12, p. e0143616, Dec. 2015, doi: 10.1371/journal.pone.0143616.

[15] C. Y. Piaw, "Replacing Paper-based Testing with Computer-based Testing in Assessment: Are we Doing Wrong?," *Procedia - Soc. Behav. Sci.*, vol. 64, pp. 655–664, Nov. 2012, doi: 10.1016/j.sbspro.2012.11.077.

[16] A. Berry, P. Friedrichsen, and J. Loughran, Eds., *Re-examining pedagogical content knowledge in science education*. In teaching and learning in science series. London, New York: Routledge, 2015. doi: 10.4324/9781315735665.

[17] M. Schmid, E. Brianza, and D. Petko, "Self-reported technological pedagogical content knowledge (TPACK) of pre-service teachers in relation to digital technology use in lesson plans," *Comput. Hum. Behav.*, vol. 115, p. 106586, Feb. 2021, doi: 10.1016/j.chb.2020.106586.

[18] L. Maas, M. J. S. Brinkhuis, L. Kester, and L. Wijngaards-de Meij, "Cognitive Diagnostic Assessment in University Statistics Education: Valid and Reliable Skill Measurement for Actionable Feedback Using Learning Dashboards," *Appl. Sci.*, vol. 12, no. 10, p. 4809, May 2022, doi: 10.3390/app12104809.

[19] A. Barana, M. Marchisio, and M. Sacchet, "Interactive Feedback for Learning Mathematics in a Digital Learning Environment," *Educ. Sci.*, vol. 11, no. 6, p. 279, Jun. 2021, doi: 10.3390/educsci11060279.

[20] S. Rezat, "How automated feedback from a digital mathematics textbook affects primary students' conceptual development: two case studies," *ZDM – Math. Educ.*, vol. 53, no. 6, pp. 1433–1445, Nov. 2021, doi: 10.1007/s11858-021-01263-0.

[21] L. N. Yaqin, L. D. Prasojo, N. A. Haji-Othman, N. Yusof, and A. Habibi, "Addressing the Digital Divide in Indonesian Higher Education: Insights, Implications, and Potential Solutions," in *From Digital Divide to Digital Inclusion*, Ł. Tomczyk, F. D. Guillén-Gámez, J. Ruiz-Palmero, and A. Habibi, Eds., in Lecture Notes in Educational Technology. Singapore: Springer Nature Singapore, 2023, pp. 291–307. doi: 10.1007/978-981-99-7645-4_13.

[22] Naila Rajiha and S. Rini, “Computer-Based Standardized Testing (CBT) Summative Assessment: One Institution Experience,” *JISAE J. Indones. Stud. Assess. Eval.*, vol. 9, no. 1, pp. 1–7, Jan. 2023, doi: 10.21009/jisae.v9i1.33233.

[23] G. Kaiser and J. König, “Competence Measurement in (Mathematics) Teacher Education and Beyond: Implications for Policy,” *High. Educ. Policy*, vol. 32, no. 4, pp. 597–615, Dec. 2019, doi: 10.1057/s41307-019-00139-z.

[24] T. Kleickmann *et al.*, “Teachers’ Content Knowledge and Pedagogical Content Knowledge: The Role of Structural Differences in Teacher Education,” *J. Teach. Educ.*, vol. 64, no. 1, pp. 90–106, Jan. 2013, doi: 10.1177/0022487112460398.

[25] J. Baumert and M. Kunter, “The COACTIV Model of Teachers’ Professional Competence,” in *Cognitive Activation in the Mathematics Classroom and Professional Competence of Teachers*, M. Kunter, J. Baumert, W. Blum, U. Klusmann, S. Krauss, and M. Neubrand, Eds., Boston, MA: Springer US, 2013, pp. 25–48. doi: 10.1007/978-1-4614-5149-5_2.

[26] B. Rowan, R. Correnti, and R. J. Miller, “What Large-Scale, Survey Research Tells Us about Teacher Effects on Student Achievement: Insights from the Prospects Study of Elementary Schools,” *Teach. Coll. Rec. Voice Scholarsh. Educ.*, vol. 104, no. 8, pp. 1525–1567, Aug. 2002, doi: 10.1111/1467-9620.00212.

[27] S. Blömeke, J.-E. Gustafsson, and R. J. Shavelson, “Beyond Dichotomies: Competence Viewed as a Continuum,” *Z. Für Psychol.*, vol. 223, no. 1, pp. 3–13, Jan. 2015, doi: 10.1027/2151-2604/a000194.

[28] E. Mohammadpour and Y. Maroofi, “A performance-based test to measure teachers’ mathematics and science content and pedagogical knowledge,” *Heliyon*, vol. 9, no. 3, p. e13932, Mar. 2023, doi: 10.1016/j.heliyon.2023.e13932.

[29] T. Clark and H. Endres, “Computer-based diagnostic assessment of high school students’ grammar skills with automated feedback – an international trial,” *Assess. Educ. Princ. Policy Pract.*, vol. 28, no. 5–6, pp. 602–632, Nov. 2021, doi: 10.1080/0969594X.2021.1970513.

[30] G. A. Nortvedt and N. Buchholtz, “Assessment in mathematics education: responding to issues regarding methodology, policy, and equity,” *ZDM*, vol. 50, no. 4, pp. 555–570, Aug. 2018, doi: 10.1007/s11858-018-0963-z.