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Aligning technological, pedagogical, and critical competencies for AI integration in teacher education: a dependency-based framework

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ABSTRACT

Artificial intelligence (AI) is increasingly reshaping teacher education, yet previous research has shown that its integration often remains fragmented, technocentric, and weakly connected to pedagogical and critical dimensions. This study examines structural limitations in AI integration and proposes a dependency-based framework for aligning technological, pedagogical, and critical competencies in preservice teacher preparation. A sequential mixed-methods design was used. The qualitative phase analyzed 16 documents, including teacher education syllabi and peer-reviewed studies, through hybrid thematic analysis. The quantitative phase examined perceived competency patterns among 194 preservice teachers enrolled in a general didactics course. The documentary analysis identified four recurrent limitations: technocentric orientation, curricular fragmentation, insufficient teacher preparation, and weak incorporation of ethical and critical perspectives. The empirical results showed an uneven competency profile, with higher technological competence (M=4.28, SD=0.39) than pedagogical competence (M=3.74, SD=0.30) and critical competence (M=3.13, SD=0.28). Inferential analysis confirmed statistically significant differences among the three dimensions, $\chi^2(2, N=194)=368.29$, $p<0.001$, with a very large effect size (Kendall's W=0.95). The main contribution is the concept of structural imbalance, which explains AI integration as competency misalignment rather than isolated skill deficiency. The proposed framework contributes to educational evaluation by offering a criterion for assessing whether AI-related competencies are coherently aligned to support pedagogically meaningful and ethically responsible practice.

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1. INTRODUCTION

Artificial intelligence (AI) has become a defining element of contemporary educational change. Adaptive learning systems, intelligent tutoring, learning analytics, and generative AI tools are increasingly used to personalize instruction, support feedback processes, and inform data-based decision-making in educational institutions [1]–[5]. These developments have expanded the possibilities of educational evaluation and research by generating new forms of evidence about learning processes, teacher decision-making, and curriculum design.

In teacher education, however, the rapid incorporation of AI has created a persistent tension between technological adoption and pedagogical preparation. Preservice teachers are often introduced to digital tools before they have developed sufficient capacity to transform those tools into coherent instructional strategies. Prior studies on digital competence and teacher preparation show that access to technology does not automatically produce pedagogically meaningful use, especially when professional learning remains focused on operational skills rather than instructional reasoning and reflective practice [6]–[9].

Several theoretical frameworks provide important foundations for understanding technology integration in education. The technological pedagogical content knowledge (TPACK) framework emphasizes the interaction among technology, pedagogy, and content, while digital competence frameworks identify professional capacities required for educational technology use [10]–[12]. More recent AI literacy and digital competence evaluation models extend this discussion by emphasizing technical understanding, critical evaluation, ethical awareness, and evidence-based assessment of competence [13], [14].

Despite these contributions, existing approaches do not fully explain why teacher education programs may produce preservice teachers who feel confident using AI tools but remain less prepared to design instruction with AI or evaluate ethical and social risks. Previous literature has mainly identified the competencies required for AI or digital technology use in education, but it has provided less explanation of how uneven development across competency domains constrains meaningful AI integration. This unresolved problem is particularly relevant because AI tools are often introduced as efficiency-enhancing resources rather than as components of educational practice requiring curricular coherence, pedagogical judgment, and critical responsibility [15]–[18].

This study addresses this problem by introducing the concept of structural imbalance. Structural imbalance refers to the misalignment between technological, pedagogical, and critical competencies in AI integration. The novelty of this study lies in conceptualizing AI integration not as the accumulation of separate competencies, but as a problem of structural alignment among technological, pedagogical, and critical dimensions. The concept is grounded in the assumption that these competencies do not operate as separate or additive domains; instead, they function as an interdependent system in which weakness in one dimension constrains the educational value of the others. This perspective is consistent with recent debates on responsible AI, teacher agency, and the need to connect AI literacy with pedagogical decision-making [19]–[23].

Accordingly, this study aims to analyze the current state of AI integration in teacher education, identify structural limitations in existing approaches, and develop a dependency-based framework that explains the relationships between technological, pedagogical, and critical competencies. The contribution of the study is threefold. First, it defines structural imbalance as an evaluative category for analyzing AI integration in teacher education. Second, it proposes a dependency-based model in which competency alignment is treated as a condition for effective AI integration. Third, it provides preliminary empirical evidence from preservice teachers to examine the consistency of the proposed framework within an authentic educational context [24], [25].

2. METHOD

2.1. Research design

A sequential explanatory mixed-methods design was adopted to examine AI integration in teacher education. The qualitative phase was conducted first to identify recurrent structural patterns in curricula and related literature. The quantitative phase then examined whether similar patterns appeared in preservice teachers' perceived competencies. This design was selected because the study is exploratory and seeks to connect conceptual development with initial empirical evidence rather than to establish causal effects.

The integration of phases was planned analytically. Findings from the documentary analysis informed the organization of the competency dimensions used in the empirical assessment. The quantitative results were then interpreted in relation to the qualitative categories to determine whether the observed competency profile was consistent with the structural limitations identified in the documentary corpus.

2.2. Qualitative documentary analysis

The qualitative phase consisted of a documentary analysis of materials related to AI integration in teacher education. The corpus was selected through purposive sampling and included two document types: academic syllabi from teacher education programs and peer-reviewed scientific publications on AI in education. A total of 16 documents were analyzed, comprising six syllabi and 10 scientific articles. Documents were included when they met three criteria: implementation or publication between 2020 and 2025, explicit relevance to AI integration in teacher education, and sufficient conceptual or curricular detail for analytical coding.

The analysis followed a hybrid inductive-deductive thematic procedure. First, open coding was used to identify recurring ideas, practices, and gaps associated with AI integration. Second, axial coding was

applied to establish relationships among codes and to group them into broader categories. Third, selective coding was used to consolidate the categories into four analytical dimensions: technocentric orientation, curricular fragmentation, deficits in teacher preparation, and absence of critical and ethical perspectives.

To enhance trustworthiness, the analysis used data triangulation across syllabi and scientific publications, theoretical triangulation through comparison with established competency frameworks, and iterative review of categories by the research team. Coding decisions were recorded in an analytical matrix linking documentary evidence with emerging categories. A subset of the corpus was independently reviewed by two members of the research team to examine coding consistency. Disagreements in category interpretation were resolved through discussion until consensus was reached. This procedure strengthened the dependability, transparency, and reproducibility of the qualitative phase.

2.3. Quantitative empirical assessment

The quantitative phase examined perceived competency development among 194 preservice teachers enrolled in a General Didactics course during the second academic period (PII) of 2025. Participants were distributed across six parallel class groups within the same teacher education program. The participants had a mean age of 21.4 years (SD=1.8). Regarding gender distribution, 120 participants (62%) identified as female and 74 participants (38%) as male. This context was considered appropriate for an initial empirical assessment because it represented a natural educational setting in which AI-related activities could be incorporated into regular instructional processes.

The intervention was implemented over one academic semester and included three aligned components. The technological component focused on the operational use of AI tools for instructional support. The pedagogical component required students to connect AI use with lesson planning, learning objectives, and assessment strategies. The critical component involved guided reflection on ethical, social, and contextual implications of AI, including issues related to data use, bias, transparency, and teacher responsibility.

Data were collected using a structured questionnaire with Likert-scale items ranging from 1 to 5. The instrument assessed three dimensions: technological competence, pedagogical competence, and critical competence. The items were developed from the conceptual framework of the study and reviewed by five external experts in educational technology and teacher education to assess clarity, relevance, and coherence. Expert judgment supported content validity, while internal consistency analysis indicated robust and acceptable reliability across all three dimensions, yielding specific Cronbach's alpha coefficients of $\alpha=0.87$ for the technological dimension, $\alpha=0.81$ for the pedagogical dimension, and $\alpha=0.79$ for the critical dimension. Because the instrument was used in an exploratory context, the findings should be interpreted as preliminary evidence of perceived competence rather than as definitive measurement of performance.

2.4. Data analysis and integration

Quantitative data were analyzed using descriptive and inferential statistics. Descriptive analysis included means, standard deviations, medians, minimum and maximum values, and percentage distributions across competency levels. Given that the three competency dimensions were measured in the same group of participants and were based on Likert-scale responses, the Friedman test was used to examine whether statistically significant differences existed among technological, pedagogical, and critical competencies. Kendall's W was reported as an effect size to estimate the magnitude of the observed imbalance. Post hoc pairwise comparisons were conducted using Wilcoxon signed-rank tests with Bonferroni correction to identify differences between specific competency dimensions.

In addition, a structural imbalance index (SII) was calculated as a complementary descriptive indicator. The SII was defined as the difference between the highest and lowest mean scores across the three dimensions. The normalized SII was obtained by dividing this gap by the possible Likert-scale range ($5-1=4$). This procedure provided an interpretable indicator of competency misalignment and complemented the inferential comparison among dimensions.

Qualitative and quantitative findings were integrated through methodological triangulation. The structural patterns identified in the documentary analysis were compared with the empirical competency profile. This integration made it possible to examine whether the quantitative pattern of higher technological competence and lower pedagogical and critical competence was consistent with the qualitative evidence of technocentric and fragmented AI integration.

2.5. Ethical considerations and methodological scope

The study followed ethical principles of voluntary participation, anonymity, confidentiality, and academic integrity. Participants were informed about the academic purpose of the assessment, and responses were analyzed in aggregate form. The study did not attempt to establish causal effects. Its scope was

exploratory and focused on developing and initially supporting a conceptual framework that requires further validation through longitudinal, experimental, and structural modeling approaches.

Participants in this study were students enrolled in the general didactics course of the education program, taught by the corresponding author during the study period. Their participation was voluntary, and they were fully informed about the academic and research purpose of the assessment before providing their responses. No identifying information was collected, and data were analyzed in aggregate form to protect participant confidentiality.

3. RESULTS AND DISCUSSION

3.1. Documentary findings

The documentary analysis identified four recurrent limitations in AI integration within teacher education. The first limitation was technocentric orientation. Across syllabi and scientific publications, AI was frequently presented as a set of tools for automation, content generation, and data processing. Less attention was given to instructional design, pedagogical reasoning, and the relationship between AI-supported resources and learning outcomes.

The second limitation was curricular fragmentation. AI-related content was commonly located in isolated modules or elective activities, with limited evidence of progression across the curriculum. This organization restricted the development of integrated competencies because technological knowledge was not systematically connected to pedagogical application or critical reflection.

The third limitation was insufficient teacher preparation. Although the analyzed documents referred to general digital competence, fewer documents addressed specific AI-related capacities such as prompt evaluation, AI-supported instructional planning, interpretation of algorithmic outputs, and adaptation of AI tools to diverse learning contexts.

The fourth limitation was the weak incorporation of critical and ethical perspectives. Issues such as data privacy, algorithmic bias, transparency, accountability, and the social consequences of AI were generally treated as peripheral topics rather than as central components of teacher education. Together, these findings indicate that current approaches tend to develop operational familiarity with AI while providing less support for pedagogical and critical alignment.

3.2. Empirical competency patterns

The empirical results showed an uneven distribution of perceived competencies across the three dimensions of the proposed framework. Table 1 presents the descriptive statistics for technological, pedagogical, and critical competence. The technological dimension reached the highest mean score (M=4.28, SD=0.39), followed by the pedagogical dimension (M=3.74, SD=0.30) and the critical dimension (M=3.13, SD=0.28). This pattern indicates that preservice teachers perceived themselves as more competent in the operational use of AI tools than in pedagogical integration and critical evaluation.

Table 1. Descriptive statistics of competency development (n=194)

Dimension	Mean	SD	Median	Min.	Max.	Interpretation
Technological competence	4.28	0.39	4.30	3.10	5.00	High
Pedagogical competence	3.74	0.30	3.70	3.10	4.30	Moderate
Critical competence	3.13	0.28	3.10	2.50	3.70	Moderate-low

Note: scores are based on a 5-point Likert scale, where higher values indicate higher perceived competence. Interpretation categories were defined as: low (1.00–2.49), moderate (2.50–3.99), and high (4.00–5.00).

To determine whether these differences were statistically significant, a Friedman test was conducted because the three competency dimensions were measured in the same group of participants using Likert-scale responses. The results showed statistically significant differences among technological, pedagogical, and critical competencies, $\chi^2(2, N=194)=368.29$, $p<0.001$, with a very large effect size (Kendall's W=0.95). This finding indicates a strong and systematic imbalance across the three competency dimensions.

Post hoc pairwise comparisons using Wilcoxon signed-rank tests with Bonferroni correction confirmed that technological competence was significantly higher than pedagogical competence (mean difference=0.54, 95% CI [0.51, 0.57], $p<0.001$) and critical competence (mean difference=1.15, 95% CI [1.11, 1.18], $p<0.001$). Pedagogical competence was also significantly higher than critical competence (mean difference=0.61, 95% CI [0.59, 0.63], $p<0.001$). These results provide inferential support for the existence of structural imbalance in AI competency development among preservice teachers.

Table 2 presents the distribution of students across high, medium, and low competency levels. The percentage pattern complements the inferential results by showing that technological competence was more

frequently reported at a high level than pedagogical or critical competence. The distribution reveals that 72% of students reached a high level in the technological dimension, compared with 48% in the pedagogical dimension and 31% in the critical dimension. Conversely, the proportion of students in the low category increased from 5% in technological competence to 13% in pedagogical competence and 27% in critical competence. This pattern suggests that preservice teachers perceived themselves as more capable of using AI tools than of integrating them into teaching or evaluating their ethical and contextual implications.

To make the magnitude of the imbalance more explicit, Table 3 presents the mean-gap analysis and SII. The SII complements the Friedman test by providing an interpretable measure of competency misalignment. The normalized SII of 0.288 indicates that the gap between the highest and lowest competency dimensions represented 28.8% of the possible scale range. Although this index does not establish causal dependency among dimensions, it supports the interpretation that competency development was unevenly distributed. These findings extend previous literature by showing that the problem is not only the limited development of AI-related competence, but the uneven configuration of technological, pedagogical, and critical competencies within teacher education.

Table 2. Comparative distribution of competency levels

Dimension	High (%)	Medium (%)	Low (%)
Technological competence	72	23	5
Pedagogical competence	48	39	13
Critical competence	31	42	27

Note: percentages represent the proportion of students classified into competency levels based on Likert-scale responses.

Table 3. Mean-gap analysis and SII

Indicator	Value	Interpretation
Technological–pedagogical gap	0.54	Moderate gap
Pedagogical–critical gap	0.61	Moderate gap
Technological–critical gap	1.15	Substantial gap
SII	1.15	Difference between maximum and minimum means
Normalized SII	0.288	28.8% of the possible scale range

Note: SII=highest mean−lowest mean. The normalized SII was calculated using the possible Likert-scale range (5−1=4).

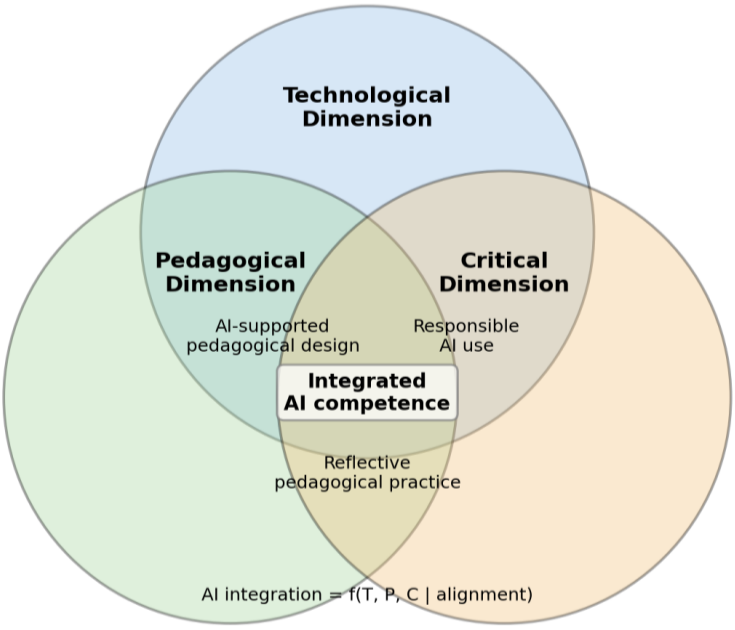
3.3. Dependency-based framework for AI integration

Based on the qualitative and quantitative findings, this study proposes a dependency-based framework for AI integration in teacher education. The framework is organized around three core dimensions. The technological dimension refers to operational knowledge and skills for using AI systems. The pedagogical dimension refers to the ability to integrate AI into instructional design, learning processes, and assessment. The critical dimension refers to ethical, reflective, and contextual understanding of AI use.

The model differs from additive competency approaches because it assumes that effective AI integration depends on the alignment among dimensions. In functional terms, the relationship can be expressed as AI integration = f(T, P, C | alignment), where T represents technological competence, P represents pedagogical competence, and C represents critical competence. This expression is conceptual rather than statistically validated. It indicates that the educational value of AI depends not only on the presence of each competency, but on the degree to which the competencies are aligned.

Figure 1 shows the three dimensions as overlapping domains. The intersection between technological and pedagogical dimensions represents AI-supported pedagogical design. The intersection between technological and critical dimensions represents responsible AI use. The intersection between pedagogical and critical dimensions represents reflective pedagogical practice. The central intersection represents integrated AI competence, which emerges when all three dimensions are developed in a balanced and coherent way.

The framework therefore interprets structural imbalance as a constraint on AI integration. For example, preservice teachers may use AI tools to generate lesson plans, but if they do not align those plans with learning objectives or evaluate the accuracy and bias of AI-generated content, the resulting practice remains pedagogically weak and ethically vulnerable. In this sense, the least developed dimension limits the effectiveness of the others.



Note: integrated AI competence emerges from the alignment of technological, pedagogical, and critical dimensions.

Figure 1. Dependency-based framework for AI integration in teacher education

3.4. Theoretical contribution and comparison with existing frameworks

The proposed framework extends existing research by shifting attention from competency possession to competency alignment. Prior studies have documented technocentric approaches to AI in education and have shown that technology use is often prioritized over pedagogical transformation [26], [27]. These studies provide valuable evidence that AI adoption in education is frequently driven by operational efficiency, automation, and digital tool use. However, they provide less explanation of how technological emphasis interacts with pedagogical and critical dimensions in teacher education.

The present study advances this discussion by interpreting technocentrism as part of a broader structural imbalance that affects how competencies are organized and developed. In this sense, the contribution is not limited to confirming that technological competence tends to be stronger than other dimensions. Rather, the study shows that this difference forms part of an uneven competency configuration in which technological, pedagogical, and critical dimensions are not equally developed.

The framework also differs from multidimensional models that classify competencies into separate categories. TPACK, digital competence frameworks, and AI literacy models are useful for identifying what teachers need to know, but they provide less explanation of how weakness in one domain can constrain the educational use of another. The dependency-based perspective adds an explanatory mechanism: AI integration depends on the interdependence and alignment of technological, pedagogical, and critical dimensions.

This distinction is relevant for educational evaluation. If evaluation focuses only on whether preservice teachers can use AI tools, it may overestimate readiness for AI-supported teaching. A dependency-based evaluation approach would examine whether technological competence is accompanied by pedagogical design capacity and critical judgment. Therefore, the framework offers a more comprehensive basis for assessing AI readiness in teacher education programs.

In summary, existing literature has mainly established that AI integration in education requires technological competence, digital literacy, pedagogical knowledge, and ethical awareness. The present study adds a different contribution by showing that these dimensions should not be evaluated as isolated or additive components. The originality of the proposed framework lies in its focus on structural alignment: AI integration is interpreted as limited by the misalignment among technological, pedagogical, and critical competencies. This provides a more specific evaluative criterion for teacher education programs because it shifts assessment from whether preservice teachers possess AI-related skills to whether those skills are coherently aligned for pedagogically meaningful and ethically responsible practice.

3.5. Practical implications for teacher education

The findings have implications for curriculum designers, teacher educators, accreditation agencies, and educational policymakers. Curriculum designers should avoid distributing AI content across isolated modules and should instead organize AI learning experiences progressively across teacher preparation programs. A coherent curriculum should connect tool use with lesson design, assessment, inclusion, data responsibility, and ethical reflection.

Teacher educators should design learning activities that require students to justify why, when, and how AI is used in instructional contexts. For example, assignments may require preservice teachers to use AI to support lesson planning, compare AI-generated materials with curricular objectives, identify potential bias or inaccuracies, and redesign outputs according to student needs. This type of activity develops technological, pedagogical, and critical competencies simultaneously.

Accreditation agencies and policymakers can use the framework to evaluate whether teacher education programs prepare future teachers for responsible AI integration. Rather than measuring AI integration only through infrastructure or tool availability, quality assurance processes should examine the alignment between digital resources, pedagogical preparation, ethical guidelines, and assessment practices. This orientation is consistent with broader international concerns about the social implications of AI and the need for responsible educational innovation [28]–[32].

The model is also context-sensitive. Institutional resources, national policies, digital infrastructure, faculty expertise, and student access to technology may influence how competency alignment develops. Therefore, the framework should not be applied as a rigid universal checklist. It should be adapted to local educational systems while preserving the central evaluative principle: effective AI integration requires balanced development across technological, pedagogical, and critical dimensions.

The originality of these recommendations lies in their evaluative orientation. Rather than focusing only on access to AI tools or additional training in digital skills, the framework proposes that teacher education programs should be assessed according to the balance and alignment among technological, pedagogical, and critical competencies. This provides a practical criterion for curriculum review, instructional design, and accreditation processes. In this sense, the recommendations are significant because they move AI integration beyond tool adoption toward a more coherent model of responsible teacher preparation.

3.6. Limitations and future research

Several limitations should be considered. First, the empirical component relied on self-reported perceptions, which may not fully represent actual classroom performance. Second, although the Friedman test provided inferential evidence of significant differences among competency dimensions, the one-group exploratory design limits causal inference and does not allow the dependency relationships proposed in the framework to be interpreted as causal effects. Third, although expert review supported content validity and internal consistency was acceptable, broader construct validation is needed. Fourth, the study was conducted in a specific institutional context, which may limit transferability.

Future research should validate the proposed framework using longitudinal designs, experimental comparisons, performance-based assessments, and structural equation modeling. Such studies would make it possible to examine whether the dependency relationships proposed here can predict instructional quality, ethical decision-making, and sustained AI integration in diverse teacher education contexts. Future work should also examine how critical pedagogy, teacher agency, and institutional change can strengthen responsible AI integration [33]–[35].

4. CONCLUSION

This study examined AI integration in teacher education and identified structural limitations that constrain its effective implementation. The qualitative findings showed that current approaches are often characterized by technocentric orientation, curricular fragmentation, insufficient teacher preparation, and weak incorporation of critical and ethical perspectives. The empirical findings showed a similar pattern of imbalance, with stronger technological competence than pedagogical and critical competence among preservice teachers. Inferential analysis confirmed statistically significant differences among the three competency dimensions, providing initial statistical support for the notion of structural imbalance.

In response, the study proposed a dependency-based framework that conceptualizes AI integration as an interdependent process. The framework argues that technological competence alone is insufficient unless it is aligned with pedagogical design and critical awareness. This perspective shifts the focus from the accumulation of competencies to their structural alignment. The framework contributes to educational evaluation by providing a basis for identifying imbalances in teacher education programs and for designing

more coherent curriculum structures. It also offers practical guidance for teacher educators, curriculum designers, accreditation agencies, and policymakers seeking to support responsible AI integration.

The evidence presented in this study should be considered preliminary because of the exploratory design, self-reported data, and context-specific sample. Future research should empirically validate the model across different educational systems using longitudinal, experimental, performance-based, and structural modeling approaches. Overall, the study highlights that meaningful AI integration in teacher education depends on the balanced alignment of technological, pedagogical, and critical competencies.

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C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

The authors declare that they have no conflicts of interest.

DATA AVAILABILITY

The data supporting the findings of this study are available from the corresponding author, [WLSA], and may be provided upon receipt of a reasoned and justified request.

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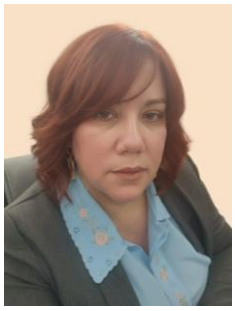
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