

Graph-Enhanced Knowledge Tracing for Explainable Learner Modeling: A Systematic Literature Review

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Abstract. Knowledge Tracing (KT) has become a central approach for modeling students' evolving knowledge states, but conventional sequence-based KT models offer limited representation of relationships among skills, concepts, and assessment indicators, reducing their interpretability for monitoring mastery and learning progression. This study systematically reviews how graph-based and knowledge graph-enhanced KT models have been developed, integrated, and evaluated to support skill mastery, learning outcome monitoring, and assessment-related interpretation. A PRISMA-based Systematic Literature Review was conducted using Scopus and IEEE Xplore, covering publications indexed from 2015 to 2025. From 116 initial records, 20 studies satisfied the eligibility criteria for active graph-enhanced KT and were included in the synthesis corpus, comprising 8 core (40.0%) and 12 supporting (60.0%) studies. Six major integration families were identified, including GCN/GNN-based, Knowledge Graph/ontology-enhanced, heterogeneous or multiplex graph, attention-over-graph, Q-matrix/concept map-based KT, and graph-supported recommendation. Graph-enhanced KT can enrich learner-state representation, support skill and mastery interpretation, and strengthen explainable learner modeling, particularly among core studies. However, active graph-KT integration remains limited, and issues of construct validity, cross-domain generalization, fairness, and deployment-oriented evaluation remain underexplored.

Keywords: Knowledge Tracing, Knowledge Graph, Graph Neural Networks, Q-matrix, Learning Analytics, Explainable AI in Education

1. INTRODUCTION

Artificial intelligence-based information systems are increasingly used to support data-driven decision-making in digital learning environments. By processing learner interaction data from digital learning platforms, intelligent tutoring systems, and adaptive learning environments, these systems can support learner modeling, performance prediction, personalized feedback, adaptive recommendation, and academic decision support [1][2][3]. Such data include sequential evidence such as exercise responses, correctness labels, learning time, hints, and assessment outcomes, which can be used to infer how students acquire and retain knowledge over time [4][5][6].

In this context, Knowledge Tracing (KT) has become a key approach in educational data mining because it models learners' latent knowledge states from temporal interaction data and predicts future learning performance [6][7][8]. Building on this foundation, early KT approaches represent mastery through probabilistic state transitions, while Deep Knowledge Tracing and its variants use neural architectures to capture complex temporal learning patterns from student-item interaction sequences [9][10].

As part of intelligent learning information systems, KT transforms temporal learner interaction records into actionable insights regarding knowledge states, learning progression, and potential learning needs. Although KT models have improved the prediction of learner performance, many sequence-driven approaches still have limitations in representing explicit relationships among knowledge components, skills, exercises, and concepts [11][12][13]. Student responses are rarely limited to isolated items; instead, they often reflect mastery of related skills, prerequisite concepts, or broader knowledge components [14][8]. Therefore, predictions based only on sequential correctness may be insufficient for interpreting skill mastery, concept mastery, learning progression, and assessment-related decision-making [15][16]. This limitation is critical for decision-oriented learning information systems because teachers, academic managers, and adaptive learning platforms require not only prediction scores but also interpretable evidence explaining which skills, concepts, or assessment indicators contribute to a learner's mastery state.

Recent studies have addressed this issue by integrating graph-based knowledge structures into KT models. These structures include knowledge graphs, concept graphs, skill graphs, course maps, Q-matrices, prerequisite graphs, topology graphs, ontologies, and heterogeneous student-exercise-concept networks [17][18][19]. In graph-enhanced KT, graph structures may serve as input representations, graph encoders, feature-propagation mechanisms, state-update supports, prediction components, or recommendation constraints. For example, graph neural and graph convolutional KT models leverage concept-question-skill relations to improve learner-state estimation, while ontology-enhanced and knowledge graph-enhanced KT models use structured semantic relations to improve interpretability and knowledge representation [20][11][17]. From an informatics perspective, these graph structures function as a knowledge representation layer that connects raw learner interaction data with interpretable educational entities, such as questions, skills, concepts, learning outcomes, and competency indicators.

Graph-enhanced KT is also relevant for skill mastery and learning outcome monitoring, as educational assessment requires links among items, skills, concepts, and indicators of learning progression. Q-matrix-based approaches connect items to knowledge components, while concept-map-based approaches use prerequisite relations to support continuous tracking of student knowledge development [18][10]. In addition, other studies incorporate learning transfer, cognitive diagnosis, knowledge structure, and difficulty information to capture changes in mastery across related tasks and concepts [21][22][23]. These approaches show that graph-based and structure-aware KT can provide richer learner representations by linking observed performance with interpretable constructs such as skills, concepts, mastery levels, and assessment indicators.

Explainability is also an important issue in graph-enhanced KT. In practical learning information systems, model outputs must be understandable to stakeholders who use them for diagnosis, intervention, recommendation, and monitoring. Graph-based representations can support explainability by showing how learner responses are connected to skills, concepts, prerequisite relations, and learning outcomes. Attention mechanisms, ontology structures, and knowledge graph paths can also provide evidence for why a model estimates a certain mastery state or recommends a specific learning action. Therefore, graph-enhanced KT has the potential to bridge predictive learner

modeling and explainable learning analytics by making learner-state estimation more transparent, traceable, and useful for decision support.

For clarity, this review defines graph-enhanced KT as any KT or learner-state modeling approach in which a graph-based structure (e.g., knowledge graph, concept graph, skill graph, Q-matrix, or ontology) is technically integrated into the model's representation, inference, or interpretation of student knowledge, as distinct from graph-supported recommendation or descriptive educational knowledge graphs not computationally linked to knowledge-state inference. It is further distinguished from Cognitive Diagnosis (static mastery profiles), broader Learner Modeling (e.g., affect or engagement), and Educational Recommendation (selecting content rather than estimating knowledge).

Explainability is likewise operationalized rather than treated as a single construct: evidence ranges from visualization and attention-weight inspection to validated explanation quality assessed with teachers or experts, and is treated as indicative unless a study reports an explicit usefulness evaluation. Relative to prior reviews, which have generally examined KT architectures, educational XAI, or knowledge-graph construction as separate strands, this review synthesizes their intersection, examining how graph-based structures are technically integrated into KT pipelines and relate to skill-mastery interpretation and explainable, decision-oriented learner modeling.

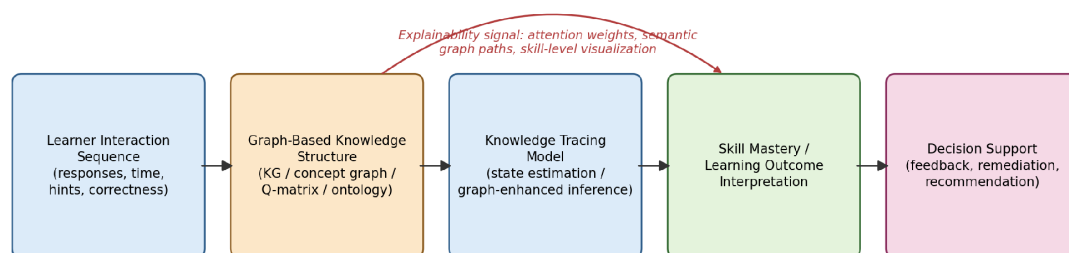


Figure 1. Conceptual framework

Despite growing interest in graph-enhanced KT, the literature remains fragmented across model families, graph types, integration mechanisms, and educational interpretations. Some studies use GNN or GCN architectures as the main inference mechanism [11][24], while others use heterogeneous networks, ontologies, concept maps, course maps, or Q-matrices as supporting representations [25][26]. Moreover, the integration stage also varies: graph information may be used in the input representation, state transition,

attention layer, output interpretation, or recommendation mechanism [27][28]. This diversity makes it difficult to determine which graph integration strategies are dominant and how model outputs can be interpreted in relation to skill mastery, concept mastery, learning progression, or assessment structures.

Unlike previous reviews that mainly discuss knowledge tracing models, graph-based learning analytics, or explainable artificial intelligence in education separately, this review focuses on the intersection of graph-enhanced KT, skill-mastery interpretation, and explainable learner modeling. Its central contribution is to synthesize graph integration mechanisms, graph roles within KT pipelines, and the operationalization of skill mastery, while also identifying informatics-oriented research gaps related to interpretability, construct validity, fairness, cross-domain generalization, and deployment readiness. Therefore, this review not only summarizes existing KT studies but also clarifies how graph-based knowledge representation can support more explainable and decision-oriented learner modeling systems.

This review contributes to the information systems and informatics literature in three ways. First, it provides a taxonomy of graph-enhanced KT model families and integration mechanisms. Second, it maps how graph-based structures support skill mastery, competency, learning outcomes, and assessment-related interpretation. Third, it identifies open research gaps for developing explainable, valid, fair, and deployable learner modeling systems. Together, these contributions position the review as a synthesis of graph-enhanced KT for decision-oriented learner modeling and explainable learning analytics.

2. METHODS

2.1 Review Design

This study used a Systematic Literature Review (SLR) to synthesize research on graph- and knowledge graph-enhanced Knowledge Tracing (KT) for skill mastery, learning outcome monitoring, and assessment-related interpretation. The review followed the PRISMA 2020 framework [56] to ensure transparency in study identification, screening, eligibility assessment, and inclusion.

The review process consisted of eight stages: (1) formulating research questions, (2) designing the search strategy, (3) identifying candidate studies, (4) applying inclusion and exclusion criteria, (5) selecting eligible studies, (6) assessing study quality, (7) extracting data, and (8) synthesizing the evidence.

Screening and eligibility decisions were documented systematically to maintain transparency. Each record was screened against the inclusion and exclusion criteria, with borderline cases re-examined against the full text before a final decision. Screening and eligibility assessment were carried out by a single reviewer (the author), applying the criteria consistently throughout the process; for borderline classification decisions, particularly at the corpus-classification stage, the author consulted with the co-authors to check consistency of interpretation against the inclusion and exclusion criteria, although this consultation supported reflective validation rather than constituting an independent second screening of the full record set. This single-reviewer design carries an inherent risk of individual interpretive bias in borderline eligibility decisions.

2.2 Scope of Review and Research Questions

Structured educational knowledge in this review refers to graph-based representations used to model relationships among learning entities, including knowledge graphs, concept graphs, skill graphs, prerequisite graphs, Q-matrices, curriculum graphs, topology graphs, ontologies, and heterogeneous learning interaction graphs. These structures were considered relevant when they were technically integrated into KT or learner modeling processes, or when they were analytically used to support learner-state interpretation, rather than merely presented as conceptual descriptions or visual illustrations.

Four research questions guided the review:

- 1) RQ1. What families of knowledge tracing models are employed in studies that integrate graph-based knowledge structures, and what assumptions do they make regarding the representation and dynamics of student knowledge?
- 2) RQ2. How are knowledge graphs or graph-based structures integrated into knowledge tracing models in terms of mechanisms and pipeline stages?
- 3) RQ3. How are skill mastery, competency, and learning outcomes operationalized in graph-enhanced knowledge tracing studies, particularly

through item–skill, question–concept, skill–competency, or assessment mapping?

- 4) RQ4. What are the main limitations and open research gaps concerning construct validity, cross-domain generalizability, interpretability, fairness, and real-world deployability of graph-enhanced knowledge tracing models?

2.3 Data Sources and Search Strategy

The literature search was conducted in Scopus and IEEE Xplore on 18 November 2025, covering publications indexed from 2015 to 2025. These databases were selected for their strong indexing of computer science, AI, educational data mining, learning analytics, and adaptive learning research. Coverage was intentionally restricted to these two databases; ACM Digital Library and Web of Science were not searched due to institutional access constraints at the time of the review, a limitation that is revisited in the Conclusion together with its implications for coverage of ACM-, EDM-, LAK-, AAAI-, IJCAI-, CIKM-, and KDD-affiliated venues. Backward and forward citation snowballing was not performed; this is likewise disclosed as a scope limitation rather than an unresolved task, since extending the search would constitute new data collection beyond the scope of this revision.

The search strategy was constructed based on three conceptual blocks representing the core constructs of the study: (i) knowledge tracing and student modeling, (ii) structured knowledge representation using graphs, and (iii) outcome-based learning and assessment. Different query structures were used for IEEE Xplore and Scopus to accommodate the search syntax and indexing characteristics of each database.

For IEEE Xplore, the following query was used:

("knowledge tracing" OR "knowledge state" OR "mastery prediction") AND ("knowledge graph" OR "prerequisite graph" OR "skill graph" OR "Q-matrix") AND ("learning outcome" OR "outcome-based" OR competency OR "mastery level")

Applied filters (IEEE Xplore): Content Type = Journals and Conferences; Year = 2015–2025. An Open Access filter was deliberately not applied, since it is not a scientific relevance criterion.

For Scopus, a broader query was used to improve recall:

TITLE-ABS-KEY (*"knowledge tracing" OR "student modeling" OR "learner modeling"*)
 AND (*"knowledge graph" OR "concept graph" OR "skill graph" OR "prerequisite graph"*
OR "curriculum graph" OR "competency graph" OR "domain model" OR "Q-matrix") AND
 (*"learning outcome" OR "outcome-based" OR CLO OR PLO OR competency OR "mastery level" OR rubric OR assessment*)

Applied filters (Scopus): Subject Area = Computer Science, Engineering, and Social Sciences; Year = 2015–2025; Language = English.

2.4 Eligibility Criteria

The inclusion and exclusion criteria were applied to ensure that the selected studies were aligned with the scope of the review. The inclusion criteria are presented in table 1.

Table 1. Inclusion Criteria

Code	Inclusion Criteria
I1	The study discusses sequence-based student modeling, particularly knowledge tracing or equivalent learner-state modeling from temporal learning data.
I2	The study explicitly integrates a graph-based knowledge structure, such as a knowledge graph, concept graph, skill graph, prerequisite graph, Q-matrix, ontology, or heterogeneous graph.
I3	The study is situated in an educational or digital learning context and uses real learning interaction data or public educational datasets.
I4	The study operationalizes student knowledge, skill mastery, knowledge components, competency, learning progression, or learning outcome in a way that supports interpretation of model outputs.
I5	The study is a primary research article published in a peer-reviewed journal or conference proceeding and provides sufficient methodological detail.

The exclusion criteria were used to eliminate studies that lacked technical graph integration, sequence-based learner modeling, educational relevance, or sufficient methodological detail. These criteria were not intended to remove studies that used graph-related structures as supporting representations, interpretation tools, or

recommendation components. However, studies were excluded when graph structures were mentioned only conceptually, without technical, analytical, or interpretive use. The exclusion criteria are presented in table 2.

Table 2. Exclusion Criteria

Code	Exclusion Criteria
E1	The study only mentions graph structures conceptually or visually without technical integration into modeling, inference, prediction, or recommendation.
E2	The study does not involve sequence-based student modeling or knowledge-state tracking.
E3	The study is outside the education domain or does not use real learning data.
E4	The study does not allow model outputs to be interpreted in relation to skills, concepts, knowledge components, mastery, competency, or assessment.
E5	The study is not a primary research article, such as an editorial, short abstract, conceptual proposal, poster, tutorial, or incomplete report.

2.5 Study Selection Procedure

The identification stage yielded 116 records, comprising 62 from Scopus and 54 from IEEE Xplore. After removing 4 duplicate records, 112 unique records were screened based on titles, abstracts, and keywords. The screening focused on relevance to Knowledge Tracing, graph-based knowledge representation, learner modeling, mastery prediction, and assessment-related interpretation.

During the retrieval stage, 5 reports could not be accessed in full text, leaving 48 full-text reports for eligibility assessment. The eligibility assessment applied the predefined inclusion and exclusion criteria, focusing on whether each study involved sequence-based learner modeling or Knowledge Tracing, technically integrated graph-based knowledge structures, used educational learning data, and allowed interpretation of model outputs in relation to skills, concepts, mastery, competency, or assessment indicators.

After full-text assessment, 28 reports were excluded because they did not jointly satisfy the full set of eligibility criteria, including reports showing sequence-based knowledge tracing without a technically integrated graph structure, or a graph-related structure without sequence-based learner-state modeling. The remaining 20 reports satisfied all baseline inclusion criteria I1–I5 in full and were formally included in the synthesis corpus. Combining the title, abstract-stage exclusions ($n = 59$) with the full-text-stage exclusions ($n = 28$) yields a total of 87 excluded reports. The overall selection process is shown in Figure 2.

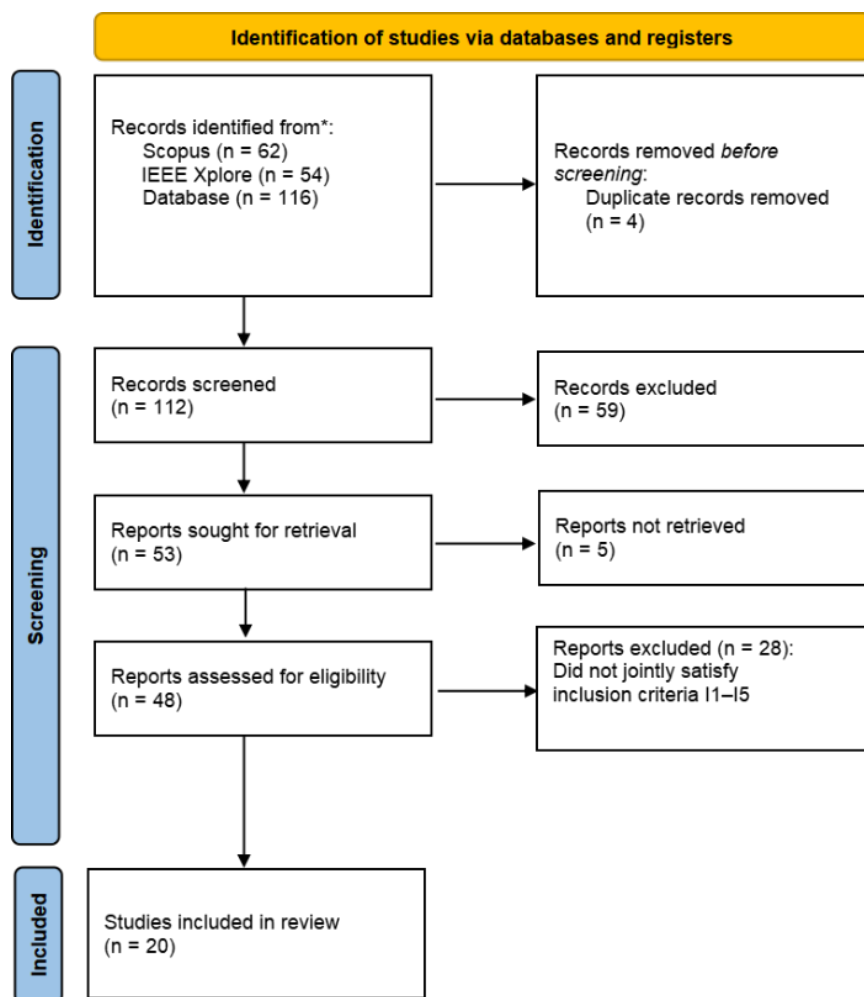


Figure 2. PRISMA flow diagram of the study selection process

2.6 Corpus Classification

The 20 studies that satisfied all eligibility criteria in full, including a binary reading of I1 (sequence-based KT) and I2 (technically integrated graph structure), were classified into

core and supporting studies based on the depth of graph integration and the centrality of sequence-based Knowledge Tracing within each study's model. Core studies actively integrated graph-based structures into KT models as the main computational or representational mechanism. Supporting studies used graph-related structures such as Q-matrices, concept maps, course maps, or state graphs together with sequence-based KT, but not always as the primary inference mechanism. The classification of the final corpus is presented in Table 3.

Table 3. Final Corpus Classification

Category	Number	Description	Role
Core	8 (40,0%)	Studies that actively integrate graph-based structures into KT models	Main evidence for RQ1 and RQ2; together with Supporting studies, forms the basis for the RQ4 gap analysis.
Supporting	12 (60,00%)	Studies using graph-related structures such as Q-matrices, concept maps, course maps, or state graphs, but not always as the primary inference mechanism.	Supporting evidence for RQ1–RQ3; together with Core studies, forms the basis for the RQ4 gap analysis.

2.7 Quality Assessment

Quality assessment was conducted to evaluate methodological clarity, relevance, and analytical usefulness. Each study was assessed using seven criteria, scored from 0 to 2, where 0 = not reported, 1 = partially reported, and 2 = clearly reported. The maximum possible quality score was 14, based on the seven criteria shown in table 4.

Table 4. Quality Assessment Criteria

Code	Criterion
QA1	The study clearly states its research objective and contribution.
QA2	The study provides sufficient detail on the KT model, graph structure, or integration mechanism.

Code	Criterion
QA3	The study clearly describes the dataset, learning context, or educational domain.
QA4	The study explains how student knowledge, skill mastery, concept mastery, or learning progression is represented.
QA5	The study uses appropriate evaluation metrics for KT, prediction, recommendation, diagnosis, or assessment interpretation.
QA6	The study compares the proposed model with relevant baselines or alternatives.
QA7	The study discusses limitations, interpretability, generalization, implementation, or future work.

After each study was evaluated using the criteria in table 4, the total quality score was calculated to determine the methodological strength of the evidence. The interpretation of the quality scores is presented in table 5.

Table 5. Quality Score Interpretation

Score Range	Quality Level	Interpretation	Role in Synthesis
11-14	High	The study provides clear objectives, sufficient methodological detail, appropriate evaluation, and relevant findings.	Used as strong evidence in the main synthesis.
7-10	Moderate	The study is relevant but has partial limitations in reporting, evaluation, or methodological explanation.	Used as supporting evidence in the synthesis.
4-6	Low	The study provides limited methodological or empirical detail but may offer useful contextual information.	Used only as contextual or peripheral evidence.
0-3	Very Low	The study lacks sufficient relevance, methodological clarity, or extractable information.	Excluded from the synthesis.

Corpus classification and quality assessment were treated as complementary: the former determined each study's relevance to the review questions, the latter the strength of evidence it contributed.

2.8 Data Extraction

Data were extracted using a structured matrix covering study identity, KT model family, graph type, graph integration stage, dataset or learning context, skill or assessment mapping, evaluation metrics, main findings, reported limitations, and corpus category. The extraction fields were aligned with the research questions. Model family and student knowledge assumptions were used to answer RQ1. Graph type and integration stage were used to answer RQ2. Dataset, assessment mapping, and interpretation target were used to answer RQ3. Reported limitations and future research directions were used to answer RQ4.

Due to differences in model architectures, graph types, datasets, and evaluation metrics, this review employed RQ-guided narrative and thematic synthesis rather than a meta-analysis. The synthesis grouped studies according to KT model family, graph integration mechanism, assessment-related interpretation, and reported limitations. Thematic patterns were then identified to construct the taxonomy of graph-enhanced KT, map graph roles within KT pipelines, analyze how skill mastery and learning outcomes were operationalized, and identify research gaps related to construct validity, cross-domain generalization, interpretability, fairness, and deployability. The data extraction and synthesis framework is presented in table 6.

Table 6. Data Extraction and Synthesis Framework

Extraction Field	Description	Related RQ	Synthesis Output
Study identity	Author, year, publication venue, and study type.	General mapping	Descriptive overview of selected studies.
KT model family	Type of KT or learner-state modeling approach used in the study.	RQ1	Classification of KT model families and assumptions about student knowledge

Extraction Field	Description	Related RQ	Synthesis Output
			representation and dynamics.
Graph type	Knowledge graph, concept graph, skill graph, Q-matrix, ontology, heterogeneous graph, or related structure.	RQ2	Mapping of graph-based knowledge representation types.
Graph integration stage	Input representation, graph encoder, state update, attention mechanism, output interpretation, recommendation layer, or decision-support layer.	RQ2	Mapping of graph integration mechanisms and pipeline stages.
Dataset or learning context	Public KT benchmark dataset, LMS, ITS, programming learning, assessment data, or recommendation-oriented educational data.	RQ3	Analysis of educational data contexts and learning evidence.
Skill or assessment mapping	Item-skill, question-concept, skill-competency, mastery, learning outcome, or assessment-related mapping.	RQ3	Analysis of skill mastery, learning outcomes, competency, and assessment-related interpretation.
Evaluation metrics	Predictive, recommendation, interpretability, or assessment-related evaluation metrics.	RQ3/RQ4	Comparison of evaluation focus across selected studies.
Main findings	Key reported findings related to graph-enhanced KT, learner modeling, skill mastery, or explainability.	RQ1-RQ4	Cross-study thematic synthesis.

Extraction Field	Description	Related RQ	Synthesis Output
Reported limitations	Validity, interpretability, fairness, generalization, deployment, or future work.	RQ4	Gap and limitation matrix covering construct validity, cross-domain generalization, interpretability, fairness, and deployability.
Corpus category	Core, supporting, or peripheral.	All RQs	Evidence grouping for core, supporting, and contextual synthesis.

3. RESULTS AND DISCUSSION

This section presents the results of the systematic review based on the final corpus of 20 formally included studies (core and supporting). The results are organized according to the research questions and synthesis outputs. The presentation includes a descriptive overview of selected studies, publication and topic trends, dataset distribution, taxonomy of graph-enhanced Knowledge Tracing (KT) integration, evaluation metrics and reported benefits, operationalization of skill and assessment-related interpretation, mapping of selected studies based on review criteria, research gap and limitation matrix, and research question coverage. Unless otherwise noted, the categorical breakdowns in Tables 7 through 11 are multi-label rather than mutually exclusive, since a single study may be counted under more than one dataset context, integration family, evaluation metric, benefit type, or interpretation category.

3.1. Descriptive Overview of Selected Studies

The final review corpus consisted of 20 formally included studies, classified by relevance to graph-enhanced KT into 8 core (40.0%) and 12 supporting (60.0%) studies. Core studies actively integrate graph-based structures into KT models; supporting studies involve KT

and graph-related structures without the graph always serving as the primary inference mechanism.

This distribution indicates that graph-enhanced KT remains an emerging, methodologically fragmented area: only 8 of the 20 formally included studies meet the strongest definition of active graph-enhanced KT, while most supporting studies use graph-related structures as priors, guides, or interpretation tools rather than central inference components—showing that graph-enhanced KT should not be treated as a single homogeneous model family.

3.2. Publication Trend

The annual distribution of the 20 formally included studies is shown in Figure 3. The reviewed studies were published between 2015 and 2025, with no eligible publications recorded between 2015 and 2018; activity increased sharply from 2024 onward, rising from 6 studies in 2024 to 9 in 2025, consistent with the recent emergence of GCN and GNN-based, knowledge-graph-enhanced, ontology-enhanced, dynamic-graph, and heterogeneous-graph KT.

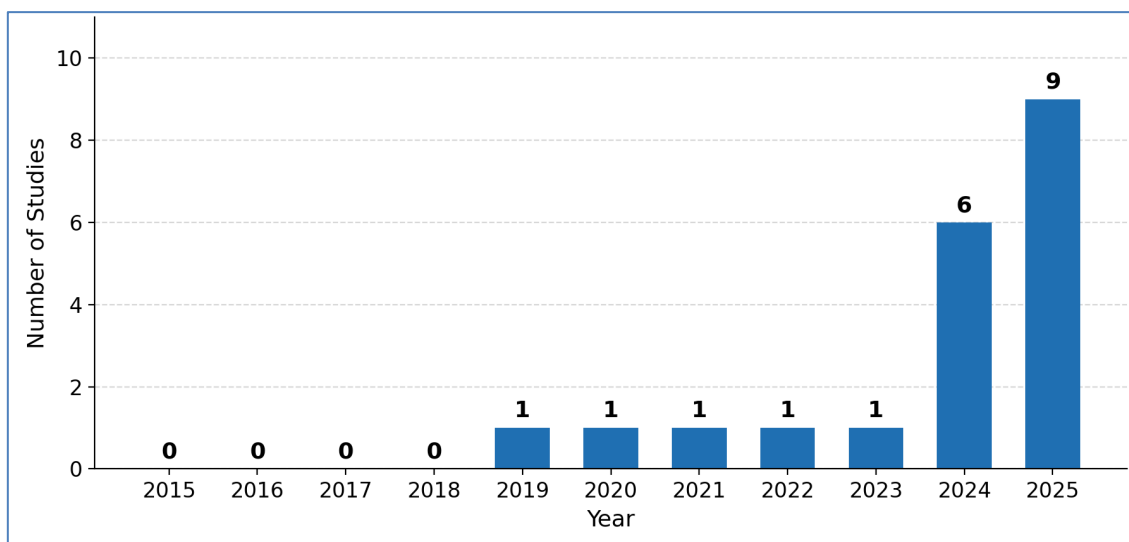


Figure 3. Annual publication trend of the 20 selected studies

The topic trend of the 20 formally included studies is shown in figure 4. The figure summarizes the thematic development of the reviewed corpus based on the topic categories identified during data extraction and synthesis.

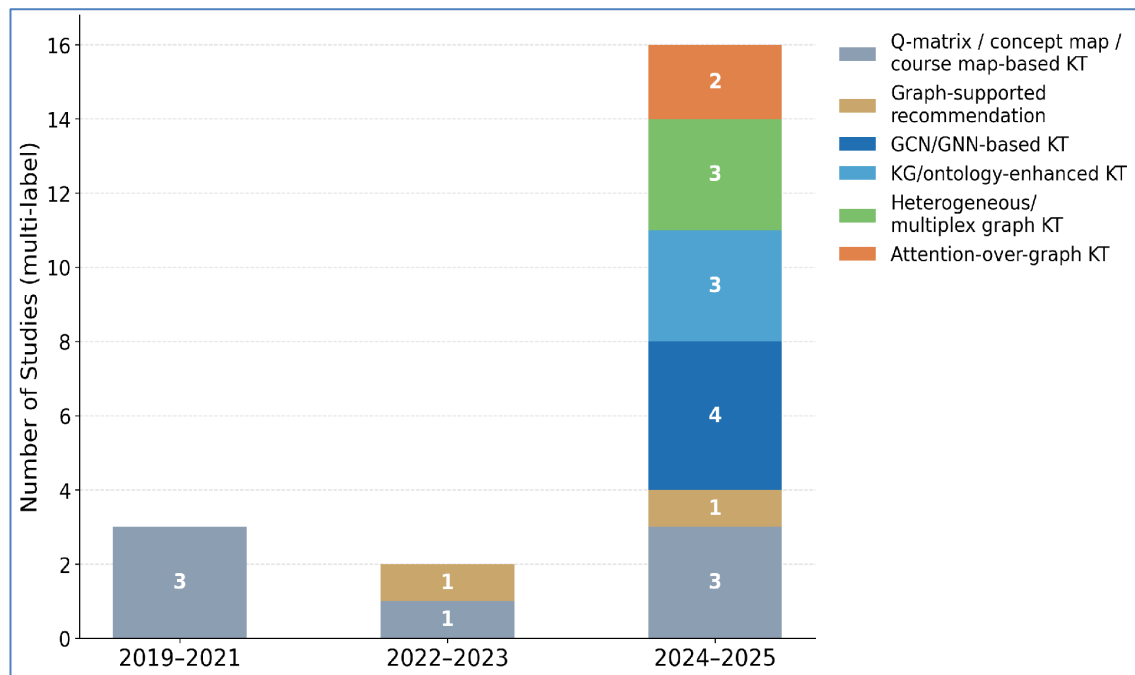


Figure 4. Trend topics in graph-enhanced knowledge tracing research

Figure 4 shows that earlier studies were mainly associated with open learner modeling, Q-matrix or factorization-based KT, and knowledge structure modeling; from 2021 onward, studies increasingly addressed concept/course map KT, assessment or recommender contexts, and graph-supported recommendation; and the most recent period (2024–2025) shows stronger attention to KG/ontology-enhanced KT, GCN/GNN-based KT, dynamic or hierarchical graph KT, and heterogeneous or multiplex graph KT—indicating a shift from graph as a descriptive/supporting representation toward graph as an active component in learner-state estimation, attention modeling, and recommendation.

3.3. Dataset and Educational Context Distribution

The selected studies used diverse educational data sources: most KT-centered studies relied on student interaction data, while others used programming learning data, e-learning logs, ITS records, robotics learning data, or assessment-oriented educational data, as summarized in Table 7.

Table 7. Dataset and Educational Context Distribution

Data Source / Context	Description	Related Studies
Public KT benchmark datasets	Used to evaluate KT prediction, learner-state modeling, and graph-enhanced KT.	[11][29][30][31][17][32][24]
Programming learning data	Used for programming KT, answer-sequence modeling, and programming knowledge graph representation.	[27]
ITS / e-learning logs	Used for student modeling, concept mastery tracking, adaptive learning, and learner-state monitoring.	[21][33][34][35]
Question-skill / item-concept datasets	Used to connect student responses to skills, concepts, or knowledge components.	[10][11][24][26][32][34]
Recommendation-oriented educational data	Used for exercise recommendation, learning resource recommendation, and learning path recommendation.	[28][35]
Assessment-oriented educational data	Used for learning progress monitoring, assessment interpretation, or educational decision support.	[27]

Table 7 shows that most studies operationalize learning evidence through relationships among learners, items, questions, skills, and concepts, linking student performance to knowledge components or mastery indicators; however, the diversity of datasets—differing in educational domain, interaction structure, and evaluation objective—makes direct quantitative comparison difficult and is why this review used narrative and thematic synthesis rather than meta-analysis, focusing on model families, graph integration mechanisms, interpretation targets, and reported limitations.

3.4. Taxonomy of Graph-Enhanced KT Integration

The synthesis identified six main families of graph-enhanced KT integration, based on model family, graph role, and integration mechanism, because the reviewed corpus includes models beyond Deep Knowledge Tracing (DKT), this review uses the broader term graph-enhanced KT.

Table 8. Taxonomy of Graph-Enhanced KT Integration

Model / Integration Family	Main Integration Logic	Article	Graph Role
GCN / GNN- based KT	Graph structures are used as the main computational mechanism for representation learning or learner-state update.	[11][24][32] [20]	Active graph backbone
KG / ontology- enhanced KT	Knowledge graph or ontology encodes semantic relations among concepts, exercises, learners, or knowledge points.	[17][26][27]	Explicit semantic structure
Heterogeneous / multiplex graph KT	Multiple node and relation types are modeled to represent complex learning interactions.	[25][36][30]	Multi-relational graph
Attention over graph	Graph information is combined with attention mechanisms to improve KT prediction or feature fusion.	[17][37]	Graph-supported attention
Q-matrix / concept map / course map- based KT	Graph-like structures map items to skills, concepts, or prerequisite relations.	[21][34][29] [31][33][10] [38]	Structural prior or guide
Graph- supported recommendation	Graph structures support exercise recommendation, resource recommendation, or learning path decision-making.	[28][39]	Recommendation or decision layer

Table 8 shows that graph integration occurs at different depths: in core studies, graph structures are active computational components (GCNs, GNNs, ontologies, dynamic/hierarchical graphs, multiplex heterogeneous graphs); in supporting studies, they more often serve as structural priors, mappings, or representation supports; and in peripheral studies, graph or KT components mostly operate at the application or decision-support layer. This confirms graph-enhanced KT is not a single methodological category—studies using graph as a mapping or auxiliary representation mainly support interpretability, while those integrating graphs into representation learning or state-update mechanisms are more likely to influence predictive performance and learner-state estimation.

To complement table 8, figure 5 visually summarizes the six graph-enhanced KT integration families and their relative graph roles, providing a quick-reference overview of the taxonomy.

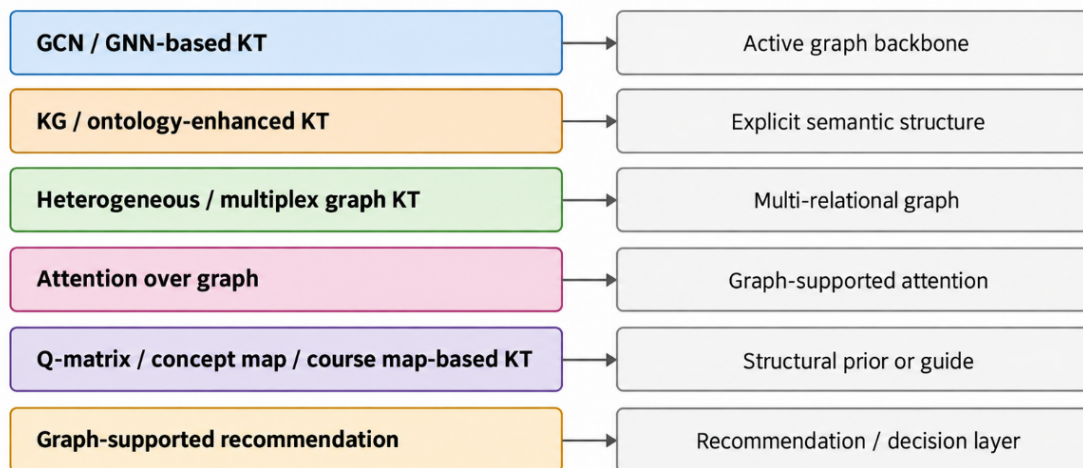


Figure 5. Taxonomy of the six graph-enhanced KT integration families

3.5. Evaluation Metrics and Reported Improvements

Evaluation methods varied by objective: KT-centered studies mainly used predictive metrics, recommendation-oriented studies used ranking metrics, and studies on

explainability, learner modeling, or assessment interpretation used qualitative or application-specific evidence.

Table 9. Evaluation Metrics Used in Selected Studies

Evaluation Focus	Common Metrics / Evidence	Article
KT prediction	AUC, accuracy, RMSE, MAE, prediction loss	[20][36][37][29] [30][11][16][24][32]
Graph representation quality	Ablation analysis, representation robustness, graph completion quality	[11][26][32][24]
Recommendation quality	Precision, Recall, F1-score, Hit Rate, NDCG, diversity, novelty	[28][39]
Mastery / skill interpretation	Mastery level, concept mastery, skill proficiency, learning progression	[10][33][21][34][37]
Explainability / assessment interpretation	Explanation usefulness, interpretability, expert validation, learner reflection	[26][40]
Practical learning effect	Learning gain, usage, engagement, improvement rate	[34]

Table 9 shows predictive performance remains the most common evaluation focus, particularly in KT-centric studies, while recommendation-oriented studies broaden evaluation with ranking metrics (Precision, Recall, F1-score, Hit Rate, NDCG); evaluation of assessment, explanation, fairness, and deployment-oriented usefulness is less consistently represented—revealing a gap between the claimed interpretability benefits of graph-enhanced KT and actual evaluation practice. The reported benefits of graph-enhanced KT are summarized in table 10.

Table 10. Summary of Reported Benefits

Benefit Type	Description	Evidence Base
Improved prediction performance	Graph-enhanced KT models generally improve learner response prediction compared with conventional KT baselines.	Core and selected supporting studies

Benefit Type	Description	Evidence Base
Richer learner-state representation	Graph structures help represent relations among skills, concepts, questions, knowledge components, and learners.	Core and supporting studies
Better skill and mastery interpretation	Q-matrix, concept map, ontology, and knowledge graph structures support interpretation of model outputs at skill or concept level.	Supporting and selected core studies
Enhanced recommendation relevance	Graph-based representations support exercise, resource, or learning path recommendation based on learner mastery and difficulty.	Supporting and peripheral studies
Improved explainability	Ontology, concept maps, and explainable recommendation mechanisms support more interpretable learner modeling.	Core, supporting, and peripheral studies
Support for learning progression analysis	Some studies model mastery change, forgetting, learning transfer, or progression across related concepts.	Supporting studies

Table 10 shows that graph-enhanced KT contributes not only to prediction performance but also to learner-state representation, skill-level interpretation, recommendation relevance, explainability, and learning-progression analysis, though core studies provide stronger evidence for active graph integration while supporting/peripheral studies mainly support interpretation, recommendation, or assessment applications—indicating that graph-enhanced KT’s value is multidimensional and future evaluation should consider both computational performance and educational interpretability.

3.6. Operationalization of Skill, Outcome, and Assessment-Related Interpretation

To answer RQ3 more explicitly, the selected studies were examined for how they operationalized skill mastery, learning progression, competency, or assessment-related

interpretations. The operationalization varied across studies and was not limited to one mapping structure. The results are summarized in Table 11.

Table 11. Operationalization of Skill, Outcome, and Assessment-Related Interpretation

Operationalization Type	Description	Article
Question-skill / item-skill mapping	Learner responses are linked to skills or knowledge components for mastery prediction.	[11][24][20][10]
Knowledge point / concept mapping	Knowledge states are represented through relations among concepts or knowledge points.	[17][27][26][25][32]
Q-matrix-based mapping	Items are mapped to latent skills or knowledge components using Q-matrix structures.	[21][10][34][36]
Concept map / prerequisite mapping	Concept relations or prerequisite paths guide interpretation of learning progression.	[29][33]
Exercise/resource recommendation mapping	Learner state is used to select exercises, resources, or paths based on mastery, difficulty, or learning need.	[39][28]
Assessment / explainability mapping	Model outputs support assessment interpretation, explanation, learner reflection, or decision support.	[26][41]

Table 11 shows that most studies interpret learning at the level of skills, concepts, knowledge components, mastery states, or assessment indicators; core studies connect graph structures more directly to KT inference, while supporting/peripheral studies often contribute through mapping, recommendation, assessment, or explanation. Explainability

is mainly supported through structured mappings and semantic relations—Q-matrix/item-skill mappings support skill-level interpretation, while ontologies and knowledge graphs provide semantic paths linking responses to concepts or outcomes—but only a limited number of studies explicitly evaluate explanation quality, fairness, or deployment usefulness, suggesting explainability is often implied through graph structure rather than systematically validated. After identifying the main forms of operationalization for skills, outcomes, and assessments, the next step is to show how each selected study meets the review criteria. Table 12 maps the selected studies according to KT, KG/graph structure, educational data, and outcome or skill interpretation.

3.7. Mapping of Selected Studies Based on Review Criteria

The mapping shows that all 20 formally included studies satisfy the four review criteria (KT, graph-based structure, educational data, and outcome/skill interpretation) in full. However, the depth of graph integration still varies across studies: core studies use graph structures as active components in KT inference, while supporting studies use graph-related structures as supporting representations, interpretation tools, or decision-support mechanisms.

Table 12. Mapping of Selected Studies Based on Review Criteria

ID	KT	Graph / KG	Education Data	Outcome / Skill	Focus
[11]	Yes	Yes	Yes	Yes	GCN + self-supervised learning for knowledge point representation in KT
[17]	Yes	Yes	Yes	Yes	KG, GCN, and attention-based KT architecture
[27]	Yes	Yes	Yes	Yes	KG-based programming KT using KC-exercise relations
[26]	Yes	Yes	Yes	Yes	Ontology-enhanced explainable KT

ID	KT	Graph / KG	Education Data	Outcome / Skill	Focus
[32]	Yes	Yes	Yes	Yes	Hierarchical graph and GCN-based KT
[24]	Yes	Yes	Yes	Yes	Dynamic question-skill graph for KT
[20]	Yes	Yes	Yes	Yes	Multi-path GNN for dynamic KT
[25]	Yes	Yes	Yes	Yes	Multiplex heterogeneous network for KT
[36]	Yes	Yes	Yes	Yes	Heterogeneous interaction graph for KT
[37]	Yes	Yes	Yes	Yes	Graph attention for KT improvement
[21]	Yes	Yes	Yes	Yes	Q-matrix as prior structure for knowledge proficiency tracking
[34]	Yes	Yes	Yes	Yes	KT and Q-matrix for robotics learning evaluation
[29]	Yes	Yes	Yes	Yes	Course map and prerequisite- aware KT
[39]	Yes	Yes	Yes	Yes	Semantic-enhanced KG for KT- based exercise recommendation
[30]	Yes	Yes	Yes	Yes	Short- and long-term knowledge state graph representation
[33]	Yes	Yes	Yes	Yes	Concept map-based continuous student KT
[10]	Yes	Yes	Yes	Yes	Q-matrix-based factorization- machine KT
[38]	Yes	Yes	Yes	Yes	Dual-centric KT with concept relation graph
[28]	Yes	Yes	Yes	Yes	Knowledge concept graph for personalized exercise recommendation

ID	KT	Graph / KG	Education Data	Outcome / Skill	Focus
[31]	Yes	Yes	Yes	Yes	Q-matrix-based individualized and group-similarity mastery update in KT

Notes: "Yes" indicates the criterion is clearly satisfied; "No" indicates the criterion is not satisfied.

Table 12 shows that all 20 core and supporting studies satisfy the four review criteria in full, since only studies jointly satisfying I1 (KT) and I2 (graph integration) were formally included in the synthesis corpus. Within the 20 formally included studies, the remaining source of variation is the depth of graph integration, not whether the four criteria are met at all.

3.8. Research Gap and Limitation Matrix

The synthesis of model families, graph roles, datasets, evaluation metrics, and operationalization patterns reveals several open gaps in graph-enhanced KT research. These gaps are related to graph integration depth, construct validity, cross-domain generalization, interpretability, fairness, and deployment readiness. The research gap and limitation matrix is presented in Table 13.

Table 13. Research Gap and Limitation Matrix

Gap Dimension	Evidence from Results	Interpretation
Graph integration depth	Of the 20 formally included studies, 8 were classified as core and 12 as supporting.	Full technical integration between graph structures and KT remains limited.
Construct validity	Studies use different mappings, such as KG, ontology, Q-matrix, concept map, course map, and item-skill relations.	The link between latent knowledge states and educational constructs is not consistently validated.

Gap Dimension	Evidence from Results	Interpretation
Cross-domain generalization	Studies use heterogeneous datasets from KT benchmarks, programming learning, ITS, recommendation, and assessment contexts.	Findings may not generalize uniformly across learning domains.
Interpretability	Some studies use ontology, KG, attention, or concept maps, but explanation quality is not consistently evaluated.	Interpretability remains uneven and is often implied through graph structure rather than explicitly validated.
Fairness	Fairness rarely appears as an explicit evaluation focus in the reviewed studies.	Fairness remains underexplored in graph-enhanced KT.
Deployment readiness	Most studies are benchmark-oriented, model-oriented, or application-specific.	Real-world implementation and decision-support validation remain limited.

Table 13 shows that the strongest development in graph-enhanced KT lies in predictive modeling, graph-based learner representation, and structural mapping. However, the reviewed corpus provides weaker evidence for construct validation, fairness evaluation, and real-world deployment. This indicates that graph-enhanced KT is progressing technically, but its educational and decision-support value still requires more systematic validation.

These gaps are important for future research in information systems and informatics. Graph-enhanced KT should not only aim to improve prediction scores but also to demonstrate how graph-based knowledge representation can produce valid, interpretable, fair, and deployable learner-modeling systems. This is especially relevant to intelligent learning information systems that support academic decision-making, personalized learning, and the diagnosis of skill mastery.

3.9. Research Question Coverage

To ensure that the Results section directly addresses the research questions, Table 14 maps each RQ to the corresponding result components and evidence base.

Table 14. Research Question Coverage

Research Question	Supporting Result Components	Evidence Base	How the RQ Is Answered
RQ1: KT model families and assumptions	Descriptive overview and taxonomy of graph-enhanced KT integration	Tables 8 and 12	The studies are classified into GCN/GNN-based KT, KG/ontology-enhanced KT, heterogeneous graph KT, Q-matrix/concept-map-based KT, and graph-supported recommendation.
RQ2: Graph integration mechanisms and pipeline stages	Taxonomy and study-level graph role mapping	Tables 8 and 12	Graph roles are identified as active graph backbone, semantic structure, attention support, Q-matrix prior, concept map guide, state graph, or recommendation layer.
RQ3: Skill mastery, competency, learning outcome, and assessment mapping	Dataset distribution, evaluation metrics, benefits, and operationalization of skill/outcome interpretation	Tables 7, 9, 10, 11, and 12	The results show how studies operationalize skill, concept, mastery, learning progression, competency, and assessment-related interpretation.
RQ4: Limitations and open research gaps	Corpus classification, evaluation limitations, and gap matrix	Tables 9, 10, 12, and 13	The results identify gaps in graph integration depth, construct validity, cross-domain generalization, interpretability, fairness, and deployment readiness.

Table 14 confirms that the Results section addresses all research questions. RQ1 and RQ2 are answered through the descriptive overview, taxonomy, and study-level mapping. RQ3 is answered through dataset distribution, evaluation evidence, reported benefits, and operationalization of skill or assessment interpretation. RQ4 is answered through the research gap and limitation matrix, supported by the corpus classification and evaluation patterns. Overall, the Results show that graph-enhanced KT has developed from structure-aware learner modeling toward more explicit graph-based inference and interpretation. Nevertheless, the reviewed corpus also shows that technical integration, construct validity, explainability evaluation, fairness, and deployment readiness remain uneven across studies. These findings provide the basis for the discussion of theoretical, methodological, and practical implications in the next section.

3.10. Discussion

The results of this review indicate that graph-enhanced KT is developing as an important extension of conventional sequence-based learner modeling. Traditional KT mainly estimates student knowledge states from temporal learner–item interactions, whereas graph-enhanced KT introduces structured relations among skills, concepts, questions, knowledge components, and learning resources. This shift shows that learner modeling is moving from sequence-only prediction toward more structure-aware and interpretable representations of learning processes.

The reviewed studies show that graph integration occurs at different depths. Some studies use graph structures as static mappings, priors, or representation supports, while core studies integrate graphs more directly into KT inference through GCNs, GNNs, ontologies, dynamic graphs, hierarchical graphs, heterogeneous graphs, attention mechanisms, or state-update processes [8][11][42]. This distinction is important because not all studies that mention graphs qualify as full graph-enhanced KT. Full graph-enhanced KT requires graph structures to contribute directly to learner-state estimation, prediction, interpretation, or decision support. Graph-enhanced KT also supports interpretation at the level of skills, concepts, knowledge components, mastery states, and learning progression. Question–skill, item–skill, Q-matrix, concept map, knowledge graph, and ontology-based mappings help connect learner responses to educational constructs [38][43].

The evaluation pattern across the reviewed corpus shows that graph-enhanced KT research remains dominated by predictive metrics such as AUC, accuracy, RMSE, MAE, and prediction loss [44]. Recommendation-oriented studies also use Precision, Recall, F1-score, Hit Rate, and NDCG, but interpretability, fairness, construct validity, and deployment-oriented evaluation remain less consistently examined. This reveals an evaluation gap: graph-enhanced KT is often motivated by explainability and educational decision support, but its validation still relies mainly on prediction performance.

From an information systems perspective, graph-enhanced KT can serve as a knowledge representation and decision-support layer in intelligent learning systems. Linking learner interaction data with skills, concepts, assessment indicators, and mastery structures can support personalized feedback, remedial learning, resource recommendations, learning path planning, and academic decision-making. Nevertheless, full graph-KT integration, construct validation, cross-domain generalization, fairness, and real-world deployment remain open challenges. Future research should integrate graph structures more directly into KT inference and evaluate graph-enhanced KT not only through predictive metrics but also through interpretability, skill-mastery validity, fairness, learning-progression analysis, and deployment in real learning environments.

Beyond the evaluation gap noted above, several issues deserve closer attention. First, explainability claims should be treated cautiously: attention weights, semantic paths, or concept mappings improve the traceability of a model's internal representation, but do not by themselves establish that the resulting explanations are useful or trustworthy—this requires validation with teachers, learners, or domain experts, not just the presence of a graph structure. Second, educational validity remains open: strong predictive performance does not guarantee that estimated mastery corresponds to actual learning outcomes, curriculum competencies, or assessment rubrics, and few studies establish this correspondence empirically. Third, most reported improvements are presented as raw metric gains without statistical-significance testing, making it hard to judge whether graph-based enhancements are substantive or marginal. Fourth, graph construction is not risk-free: knowledge graphs, Q-matrices, and concept maps depend on expert input and design choices that can introduce noise, bias, or domain-dependency. Fifth, fairness risks are largely unaddressed—biased skill maps, unequal learning histories, and demographic differences could propagate into biased mastery predictions, yet fairness

auditing is rarely reported. Finally, real-world deployment faces barriers beyond accuracy: data sparsity, curriculum alignment, teacher trust, dashboard usability, learner data privacy, and the computational cost of graph-based inference at scale. Addressing these issues is essential for graph-enhanced KT to move from benchmark-oriented research toward dependable, decision-oriented learner modeling.

4. CONCLUSION

This systematic literature review synthesized 20 formally included studies (8 core, 40.0%; 12 supporting, 60.0%) to examine how graph- and knowledge graph-enhanced Knowledge Tracing (KT) models support skill mastery, learning outcome monitoring, and assessment-related interpretation. The findings show that graph-enhanced KT is developing from conventional sequence-based learner modeling toward more structure-aware approaches that incorporate relationships among learners, exercises, skills, concepts, knowledge components, and learning resources, organized into six integration families: GCN/GNN-based KT, KG/ontology-enhanced KT, heterogeneous or multiplex graph KT, attention-over-graph KT, Q-matrix/concept map-based KT, and graph-supported recommendation. Graph-based structures can enrich learner-state representation, support skill and mastery interpretation, and strengthen explainable learner modeling, particularly among the core studies where graph integration is technically active rather than incidental.

The review's main contribution to the field is diagnostic rather than purely descriptive: it shows that active graph-KT integration remains limited relative to the broader body of KT and graph-adjacent literature, and that claims of explainability and decision-oriented support in this subfield are largely a synthesis aim rather than a property validated with teachers, learners, or domain experts. Most reviewed studies still report predictive metrics only, leaving interpretability, fairness, and deployment-oriented outcomes underexamined. This reframes graph-enhanced KT for the information systems field as a promising but empirically under-tested knowledge-representation and decision-support layer, rather than an already-proven alternative to conventional KT.

Future research should prioritize four directions. First, standardized benchmarks and shared Q-matrices or skill maps are needed to make findings across studies comparable.

Second, fairness testing should be built into evaluation protocols to detect biased skill maps or demographic disparities in mastery prediction. Third, graph structures should be integrated more explicitly into KT pipelines — as structural priors, encoders, attention components, state-update mechanisms, or interpretation layers — rather than added as auxiliary features. Fourth, graph-enhanced KT should be evaluated beyond predictive metrics, through interpretability validated with real stakeholders, skill-mastery validity, learning-progression analysis, and deployment testing in real learning platforms. Practically, adaptive learning systems, intelligent tutoring systems, and educational platforms stand to benefit from graph-enhanced KT by linking learner responses to skills, concepts, and mastery indicators to support exercise recommendation, remedial learning, and progress monitoring. Standardized datasets containing learner interaction logs, item–skill mappings, concept relations, and mastery indicators would further improve comparability and accelerate development in this direction.

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