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A GRAPH-BASED INTELLIGENT TUTORING SYSTEM FOR ADAPTIVE KNOWLEDGE MODELING AND RETENTION IN DYNAMIC LEARNING CONTEXTS

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Chapter 1
Introduction

By the twenty-first century, technological knowledge, while increasingly accessible through digitalization, has also become overwhelmingly abundant and, in many cases, internally inconsistent due to the coexistence of parallel and sometimes contradictory truths. This unprecedented complexity poses challenges to professionals that do not have historical precedent. In the field of information technology, traditional means of knowledge acquisition, such as textbooks, whether printed or digital, are playing a diminishing role. For example, Gyula Obádovics' "Mathematics" (first published in 1956) remains relevant today, reflecting the stability of foundational scientific knowledge. In contrast, Barnabás Bártfai's "Windows 8 and 8.1 for Everyone", published in 2013, has already become obsolete, as the release of Windows 10 introduced fundamental changes to both interface and internal architecture of the operating system. This example illustrates how technological knowledge can have an increasingly short lifespan, highlighting the growing need for adaptive and evolving frameworks of knowledge representation and learning.

1.1 Motivation and objectives

Having worked as a software developer for over 25 years, I have firsthand experience with the rapid pace of technological change, as well as the challenges posed by the coexistence of parallel and sometimes contradictory knowledge. As a university instructor, I am also faced with the difficulty of determining which content to teach students in a manner that remains relevant over time, particularly as the demand for highly qualified professionals continues to grow in certain sectors. At the same time, the presence of intelligent automation in the workplace is increasing. Although research has established that engaging in meaningful work is a key determinant of human mental well-being [39], the scope of such opportunities appears to be narrowing due to the rise of intelligent automation [38].

This paradoxical situation raises the critical question: how must human education evolve to effectively address these challenges? Education has long been one of the most studied domains. More than 30 years ago, a new research field: Artificial Intelligence in Education (AIEd) emerged in academia. AIEd adopts an interdisciplinary approach, integrating artificial intelligence with pedagogy, psychology, and neuroscience to support the development of learning tools that are personalized, effective, flexible, and engaging. Research in AIEd encompasses both traditional classroom settings and workplace learning, with the aim of enhancing formal education and lifelong learning opportunities.

In light of these ongoing socio-technological developments, I have concluded that amidst the unfolding Fourth Industrial Revolution, humanity increasingly needs the support of AIEd. The advent of AI Large Language Models (LLMs), such as ChatGPT [1], capable of executing complex tasks and engaging in natural language interaction, has created an entirely new situation. These models enable the construction of computer systems that can communicate with ordinary human users in an everyday language. In practical terms, this implies that every learner could potentially have access to a virtual teaching assistant capable of guiding them through emerging technologies and providing explanations tailored to their understanding. Nevertheless, it is essential to preserve the central role of the human educator, because, as discussed in the historical overview, learning is not just the transfer of knowledge, but also a deeply social process, one that encompasses moral guidance, interpersonal interaction, and the shared experience of growth within a community.

Consequently, in my research, the following objectives and requirements were defined:

- Develop a model for dynamically representing curricula capable of accommodating rapid domain changes and parallel, potentially conflicting truths.
- Create personalized learning experiences and provide effective support for educators, without diminishing the central role of the educator.

[1] OpenAI, available:https://openai.com/chatgpt

- Establish a framework to help educators track student progress and learning outcomes.
- Design a framework to systematically oversee, manage, and develop curricula.
- Define a method for representing the learners' knowledge states in an accurate and actionable manner.
- Implement a prototype system based on the proposed model and frameworks.
- Propose an approach to generalize learning by enabling and promoting AI-driven knowledge sharing.

In addition to the specific research questions addressed in this dissertation, the research is guided by the following overarching research question (ORQ):

ORQ: How can an intelligent tutoring framework be designed to support adaptive, personalized, and sustainable learning in fast-evolving knowledge domains while preserving the central role of educators?

1.2 Literature review and theoretical background

Over the past decades, several canonical ITS architectures have been proposed to formalize the internal structure and interaction of these systems.

- Tutoring integrated Expert Systems (ES): these systems integrate expert knowledge and are often web-oriented, facilitating the automated formation of a unified ontological space of knowledge and skills [31].
- Agent-based architectures: these architectures utilize intelligent agents to perform various functions within the ITS, enhancing adaptability and personalization [19].
- Emotion Machine based architectures: adaptations of the Emotion Machine (EM) model, which incorporate multiple layers of "thinking" and dynamic agent activity, promoting learner-driven content creation [37].
- Competency-Based Learning (CBL) models: the focus shifts from time spent learning (e.g., "seat time" or course duration) to the demonstration

of mastery over specific, pre-defined knowledge, skills, and dispositions (competencies) [16].

- Generalized Intelligent Framework for Tutoring (GIFT): an open, modular architecture supporting authoring, delivery, instruction, and evaluation of adaptive instruction [34].

In general, an ITS is made up of six major components:

1. Domain knowledge model: Stores the knowledge about the subject matter to be taught. It is essential to provide accurate and relevant instructional content [28].

2. Learner model: represents the system's understanding of the student's knowledge, preferences, and learning progress. This model is crucial for personalizing the learning experience [23].

3. Tutoring module: manages the instructional strategies and interactions with the learner. It adapts teaching methods according to the needs and progress of the student [32].

4. User Interface module: facilitates interaction between the student and the system. It ensures that the system is user-friendly and accessible [33].

5. Communication module: handles the communication between different components of the ITS, ensuring seamless integration and operation [24].

6. Pedagogical model: designs and implements teaching strategies, combining the interests of the student, the capabilities of the tutor, and the characteristics of the subject [24].

These components were originally designed for static or slowly evolving domains, where the structure and content of knowledge remain relatively stable over time. Consequently, the classical ITS architecture provides limited support for rapidly changing or dynamically evolving knowledge environments, such as those found in computer science, software engineering, or other technologies-driven fields.

To effectively operate in dynamic domains, each of the traditional ITS subcomponents must be re-envisioned. The Domain Model must be capable of representing evolving knowledge structures, supporting temporal and version-dependent relationships, and maintaining parallel truths.

The Learner Model must adapt to knowledge that may change or become obsolete while still maintaining an accurate estimation of learner competence over time.

The Pedagogical Model must incorporate mechanisms to recommend updated learning paths as the domain evolves, ensuring continuity between past and current knowledge states.

The User Interface Model must facilitate transparent communication of these changes, helping learners understand how domain evolution impacts their learning trajectory.

Although some research efforts have begun to address aspects of temporal or dynamic knowledge modeling, for example, in adaptive hypermedia systems or lifelong learning frameworks, comprehensive solutions that integrate time dependency and domain evolution across all ITS components remain scarce. This gap highlights the need for a new generation of intelligent tutoring architectures capable of managing dynamic domains holistically rather than through isolated updates.

Finally, Bridging the gap between AI systems and ITS requires generalizing the concept of teaching so that every AI system, regardless of its domain, inherently operates as a tutoring entity capable of supporting human learning alongside task execution.

Chapter 2

Implicit knowledge sharing in AI systems

Current AI systems lack integrated mechanisms to foster user learning during real-time interaction. Explanations, while valuable for building trust, do not constitute teaching. Similarly, ITS solutions offer effective pedagogy, but remain external systems rather than being embedded within everyday AI tools. As a result, a void persists precisely where learning could and should occur.

To address this gap, this chapter proposes a novel framework that embeds an implicit tutoring mechanism directly into AI systems through the introduction of the Knowledge-Sharing-Bridge (KSB). The KSB converts conventional AI agents into hybrid entities that can serve two purposes: to execute tasks and to instruct users.

2.1 High Level Design principles guiding the KSB framework

XAI, while improving transparency, focuses on explanation rather than active teaching. This gap necessitated a framework that seamlessly embeds teaching functionality into AI systems. The development of the KSB framework was guided by the following core design principles:

- Intelligence Augmentation (IA) over AI: The framework prioritizes improving human intelligence and autonomy rather than replacing it.

- Implicit learning over explicit training: Learning should occur in the flow of using technology, reducing barriers such as cost, time, and motivation.
- Universality and accessibility: The KSB is designed to be integrated into any AI system, regardless of the domain, enabling lifelong learning for all users.
- Transparency and trust: By explaining and reporting decisions, AI can foster a more trusted relationship with users.

2.2 Rationale behind KSB subcomponents

The KSB framework, depicted in Figure 2.1, was designed using a High Level Design (HLD) process, defining the overall architecture and subcomponent interactions. The inclusion of the four subcomponents *Explain*, *Report*, *Control*, and *Teach*, as well as the remaining components, was guided by the need to facilitate user learning.

- **Explain**: Integrates XAI techniques to make the AI's decisions interpretable. This supports cognitive understanding and enhances user trust. It is not enough to provide low level explanation; it is advisable to translate the explaining result into a human understandable format. For instance, in a legal environment explainability means legal explanation.
- **Report**: Offers statistical and performance feedback to users, helping them track system behavior and identify improvement areas in their own interaction or decision-making. To prepare thoughtful decisions in terms of AI control it is crucial to monitor the working of the system as well as to follow the communication between the user and the AI agent. The system must enable users to analyze their interactions, which necessitates the inclusion of the Report subsystem in the KSB. Established metrics already exist for evaluating AI agents (e.g., success rate, accuracy), and it can be anticipated that additional measures will emerge in response to the increasing demand for control.
- **Control**: Empowers users with configurable options that promote autonomy and self-regulation, aligning with principles from self-directed learning. To implement controllability, AI developers must put a set of rules into force in the Control subsystem so that the external users can intervene in the working of the system in a predetermined way.

To avoid demonization of AI technology there must be much larger control possibility provided to the users than today, however it means a great challenge to the system's security. Therefore, to avoid malicious interactions, careful implementation of the Control subsystem regarding security issues is crucial.

- **Teach**: Provides personalized, context-sensitive instructional content, enabling users to develop procedural knowledge on how to replicate or modify the AI-driven task. In a healthy synergy, AI learns from humans and humans learn from AI. Teach is the subsystem that facilitates human learning by providing premeditated feedback in a teaching manner. As opposed to the Explain subsystem, where the aim is to understand the AI's response, the Teach subsystem provides information how to learn the skills of the AI agent. For example, if a legal document is being rejected by the AI-classifier agent the Explain subsystem can point on to the key factors why the document was rejected, while the Teach subsystem gives information how the document needs to be constructed to get it accepted.
- **Internal gateway**: Having an internal gateway makes it possible to scale the internal components of the KSB so that can be extended and customized. Either by adding more components or more instances from existing components the internal gateway can encapsulate the communication and can realize internal security features that protect the subcomponents from malicious impacts. By providing private API the system can be integrated seamlessly into various AI systems.
- **User interface and the integration layer**: Users are communicating the AI agent using the user interface (UI). In the proposed framework the UI must be extended for the user to be able to interact with the KSB and to access learning materials, get explanation, realize control or to query statistical information. These functionalities can be implemented separately from the core AI functionality making it possible to apply advanced learning capabilities. The integration layer provides public API to implement the core functionality as well as to access the KSB functionalities behind the gateway. It ensures seamless integration with various AI systems and platforms, adhering to industry standards.
- **Core AI functionality**: The proposed model is describing a simplified AI agent that consists of the trained AI model as well as a pro-

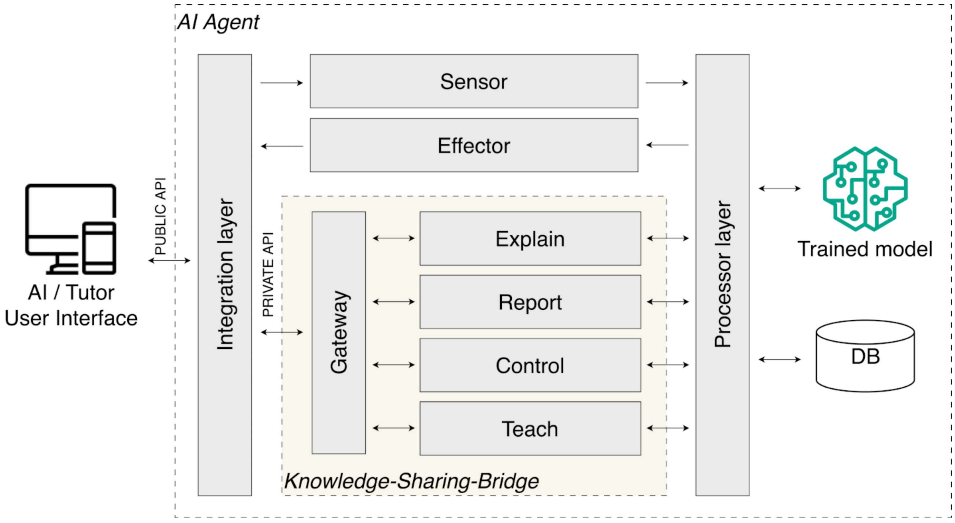


Figure 2.1: KSB framework

cessor layer that implements the business logic of the system. Usually the input/output is realized by the sensor and effector subcomponents. Furthermore, it is important to mention that the system always need a database (DB) where the core functionality related data, user related information or system settings are stored. In the proposed model the KSB related data is also located in this database.

Together, these modules transform AI from a static decision maker into a dynamic educational agent that can provide support to users in real time, enabling skill development and knowledge enhancement. The inclusion of KSB in general AI systems introduces a new model of **continuous implicit learning (CIL)**.

2.3 Experiment with the prototype AV module

The purpose of the Answer Validator (AV) is to automatically evaluate a textual response from a customer service employee. AV is a simple language-model-based AI system that acts as a virtual customer service trainer. The prototype KSB was implemented as part of the AV module.

The experiment with the university student group revealed several important insights. Figure 2.2 demonstrates that enabling the KSB component significantly reduced the performance gap between high- and low-performing stu-

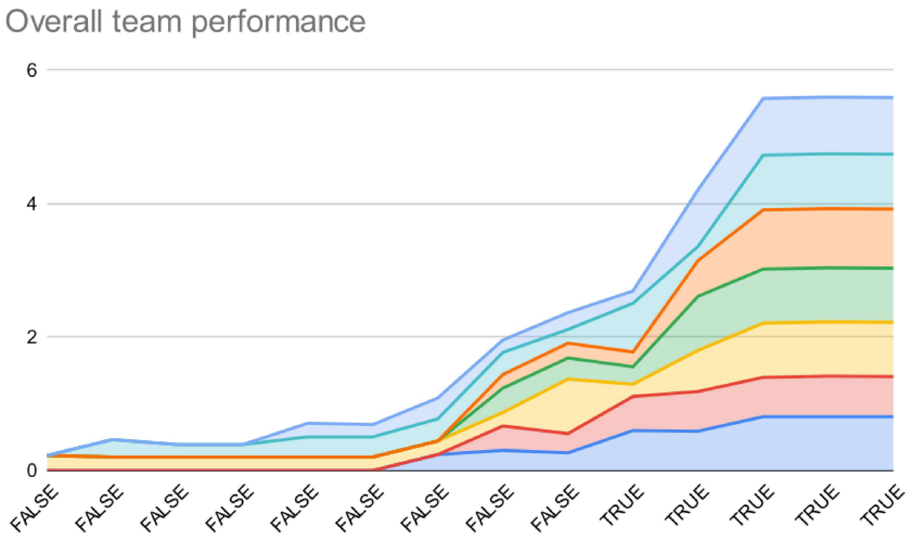


Figure 2.2: Evolving team performance over time (Colors representing individual learners)

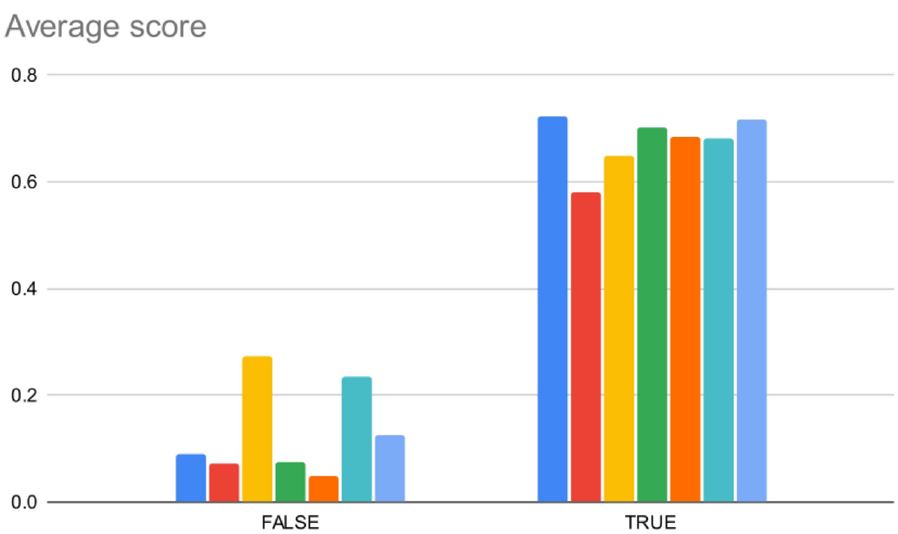


Figure 2.3: Evolving individual performance over time (Colors representing individual learners)

dents. This suggests that KSB subcomponents support personalized learning by adapting to user needs and helping weaker users catch up, thus promoting more equitable outcomes across a group. Figure 2.3 further indicates that all users, regardless of the initial skill level, benefited from the interactive feedback of the KSB, ultimately improving the quality of their responses.

2.4 Thesis 1.

I introduced the Knowledge-Sharing-Bridge framework that embeds an implicit tutoring mechanism directly into Artificial Intelligence systems, which consists of four major subcomponents: *Explain*, *Report*, *Control*, and *Teach*. The modules *Explain* and *Teach*, supported by a dedicated Explainable Artificial Intelligence engine, demonstrate the feasibility of combining explainability with pedagogical guidance. The framework shows potential for applications across domains where human-AI collaboration is critical, including education, corporate training, and technical support. The framework incorporates structured knowledge representations, such as word clouds, that make complex decision logic more transparent, accessible, and pedagogically meaningful. The prototype implementation provides empirical support for the hypothesis that a knowledge-sharing component integrated into Artificial Intelligence systems can bridge the gap between passive consumption of technology and active human learning. The results demonstrate that explainability, when coupled with guidance, not only enhances task outcomes but also empowers users by making AI-driven decisions more comprehensible, actionable, and conducive to sustained knowledge retention.

2.5 Author's publications related to the thesis

Q4: [9]
[2], [3], [4]

Chapter 3

Dynamic ITS data model

3.1 General description of the proposed model

This dissertation proposes the Evolving Knowledge Space Graph (EKSG) model. The following description specifies the logical modifications applied to existing models, such as CbKST, to construct the EKSG framework. The network that represents prerequisite relations in CbKST can be displayed in a precedence diagram. The units of study in ontology can be the replacement of question/problem nodes of this precedence diagram. Thus, using prerequisite relations and units of study, a directed graph can be constructed. The resulted graph combines the benefits of ontologies and CbKST. In addition, two important features are added to the proposed model. To cover the requirements of an evolving domain model, time dependency is introduced and the term abstract time is defined. Although the term time-dependent graph is well known and studied [40], it has not yet been incorporated into educational knowledge representations. The second feature is the use of evoking-hooks that evoke certain knowledge elements by external triggers similar to the solution implemented in the FrameNet system [27].

3.2 Abstract time

Definition 1 *The proposed general abstract time in the given domain is an ordered finite set of* ***time instance*** *values that are strongly related to the domain. Formally:*

$$\mathbf{T}^{inst} = t_1^{inst}, t_2^{inst}, \ldots, t_n^{inst} \tag{3.1}$$

where t_i^{inst} is an instance value, and for every $1 \leq i < n : t_i^{inst} < t_{(i+1)}^{inst}$. Here, n is the number of existing instance values.

Definition 2 *Let $\mathbf{T}^{int}$ be a pairwise distinct set of abstract* ***time intervals*** *within the defined domain:*

$$\mathbf{T}^{int} = \mathbf{t}_1^{int}, \mathbf{t}_2^{int}, \ldots, \mathbf{t}_m^{int} \tag{3.2}$$

where $\mathbf{t}_i^{int} = [t_{(p_i)}^{inst}, t_{(k_i)}^{inst}]$ be an abstract time interval where $1 \leq p_i \leq k_i \leq n$ and $t_{(p_i)}^{inst}, t_{(k_i)}^{inst} \in \mathbf{T}^{inst}$ therefore $t_{(p_i)}^{inst} \leq t_{(k_i)}^{inst}$. The following notation is introduced for the maximal interval: $\mathbf{t}_*^{int} = [t_1^{inst}, t_n^{inst}]$.

Definition 3 *Let $\prec$ be the matching relation that works as follows:*
instance match:

$$\prec \subseteq \mathbf{T}^{inst} \times \mathbf{T}^{inst}, \tau \prec t_i^{inst} \doteq \tau = t_i^{inst} \tag{3.3}$$

interval match:

$$\prec \subseteq \mathbf{T}^{int} \times \mathbf{T}^{int}, \tau \prec \mathbf{t}_j^{int} \doteq \exists l (p_j \leq l \leq k_j) : \tau \prec t_l^{inst} \tag{3.4}$$

set of instances match:

$$\tau \prec \{t_{l_1}^{inst}, t_{l_2}^{inst}, \ldots, t_{l_p}^{inst}\}, (l_1 \leq l_2 \leq \cdots \leq l_p) \doteq \exists l_i (\tau \prec t_{l_i}^{inst}) \tag{3.5}$$

set of intervals match:

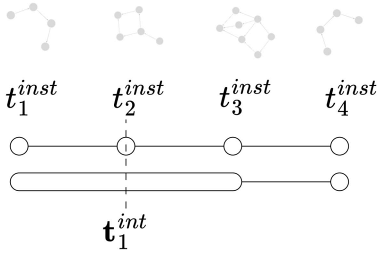
$$\tau \prec \{\mathbf{t}_{l_1}^{int}, \mathbf{t}_{l_2}^{int}, \ldots, \mathbf{t}_{l_k}^{int}\}, (l_1 \leq l_2 \leq \cdots \leq l_k) \doteq \exists l_j (\tau \prec \mathbf{t}_{l_j}^{int}) \tag{3.6}$$

where τ is the time instance that is being examined.

The maximal interval $\mathbf{t}_*^{int}$ is used as the default value when there is no time restriction in the model. Figure 3.1 shows an example abstract timeline in which all three definitions are visualized. The time delay is not interpreted in the proposed model.

3.3 Evoking-hook

Definition 4 *An* ***evoking-hook*** *is a textual element or representation that establishes a connection between the domain item and the corresponding know-*



$t_1^{inst} = v1$
$t_2^{inst} = v2$
$t_3^{inst} = v3$
$t_4^{inst} = v4$
$\mathbf{t}_1^{int} = [v1, v3]$
$\tau = v2$

Figure 3.1: An example abstract timeline that shows different software versions which consists of v1, ..., v4 time instances, where $\tau \prec t_2^{inst}$ and $\tau \prec \mathbf{t}_1^{int}$

ledge unit in the knowledge graph. Evoking-hooks may take different forms, ranging from single words and multiword expressions to longer descriptions or prompts that can be processed, for example, by a large language model.

3.4 The EKSG model

Definition 5 *The proposed **EKSG model** is a labeled acyclic directed graph that can be described in the following way:* $\mathbf{G} = \{\mathbf{U}, \mathbf{R}\}$ *where* $\mathbf{U}$ *is a set of unit nodes representing atomic knowledge, test, and material fragments, and* $\mathbf{R}$ *is a set of relations between the unit nodes.* $\mathbf{U}$ *is a triplet:* $\mathbf{U} = \{\mathbf{U}^K, \mathbf{U}^T, \mathbf{U}^M\}$*, where* $\mathbf{U}^K$ *is a set of **knowledge-units**, which are elements of a certain knowledge domain, represented by a set of four attributes:*

$$\mathbf{U}^K \subseteq \{(n, d, t, e) \mid n \in \mathbf{N}, d \in \mathbf{D}, t \subseteq \mathbf{T}^{int}, e \subseteq \mathbf{E}\} \tag{3.7}$$

where $\mathbf{N}$ *is the set of non-null and unique unit names. The name must reflect the meaning of the unit. The name acts as an external human-readable identifier;* $\mathbf{D}$ *is the set of unique non-null textual descriptions. The purpose of a description is to be able to better delimit the piece of knowledge represented by the unit;* $\mathbf{T}^{int}$ *is a set of abstract time intervals, t may be empty. If t is empty, then there is no time restriction in the model, which means that* $\mathbf{U}^K$ *is valid in all time intervals. If* $\mathbf{T}^{int}$ *contains no values, the model is reduced to a timeless graph;* $\mathbf{E}$ *is an evoking-hook set that may be empty.*

$\mathbf{U}^T$ *is a set of **test-units** which are items of an assessment set. An assessment item can be a question, a problem, or an exercise that is testing whether* *the learner has mastered a certain knowledge-unit. An assessment item is represented by a set of three attributes:*

$$\mathbf{U}^T \subseteq \{(d, m, t) \mid d \in \mathbf{D}, m : \mathbf{S} \rightarrow \{0, 1\}, t \subseteq \mathbf{T}^{int}\} \tag{3.8}$$

where $\mathbf{D}$ *is the set of non-null and unique textual descriptions;* $\mathbf{S}$ *is the set of learners who have completed the test-unit;* m *is a function that gives the information, in a dichotomous manner, if the learner* s_j *has mastered the related knowledge-unit or not. In practice, this information is obtained by presenting the learner with an assessment item, whose response serves as a basis to determine the value of* $m(s_j)$*;* $\mathbf{T}^{int}$ *is the set of time intervals defined as described in 3.7.*

$\mathbf{U}^M$ *is a set of* ***material-units*** *which are holding detailed notes about the knowledge-units. A material-unit is represented by a set of three attributes:*

$$\mathbf{U}^M \subseteq \{(d, n, t) \mid d \in \mathbf{D}, n \in \mathbf{I}, t \subseteq \mathbf{T}^{int}\} \tag{3.9}$$

where $\mathbf{D}$ *is the set of textual descriptions. A material description* d *is non-null and unique;* n *is a detailed note about a specific knowledge-unit;* $\mathbf{I}$ *is the set of all information-material available in the domain in the form of notes. One note can be in many different formats e.g., a hypertext or a multimedia content, etc.;* $\mathbf{T}^{int}$ *is the set of time intervals defined as described in 3.7.*

$\mathbf{R}$ *is a set of directed edges, representing the relations between the units:*

$$\mathbf{R} = \{\mathbf{R}^K, \mathbf{R}^T, \mathbf{R}^M\} \tag{3.10}$$

where $\mathbf{R}^K \subseteq \mathbf{U}^K \times \mathbf{L}^K \times \mathbf{U}^K$ *is a set of ordered triples* $[u^K_{i,t}, l^K_t, u^K_{j,t}]$ *in which* $u^K_{i,t}$ *is a knowledge-unit that is related to another knowledge-unit* $u^K_{j,t}$ *and* l^K_t *is a relation label. The direction of the relation edge is pointing towards* $u^K_{j,t}$*. The relation type between the knowledge-units is determined by the label* $l^K_t \in \mathbf{L}^K$*. Between knowledge-units there are two relation types exist in the proposed model:* $\mathbf{L}^K \subseteq \{PrerequisiteOf_t, IsA_t\}$*. In case of* $PrerequisiteOf_t$ *relation the knowledge represented by* $u^K_{i,t}$ *needs to be acquired before* $u^K_{j,t}$*. In other words,* $u^K_{j,t}$ *depends on* $u^K_{i,t}$*. In case of* IsA_t *relation the knowledge represented by* $u^K_{i,t}$ *is generalized by* $u^K_{j,t}$*.*

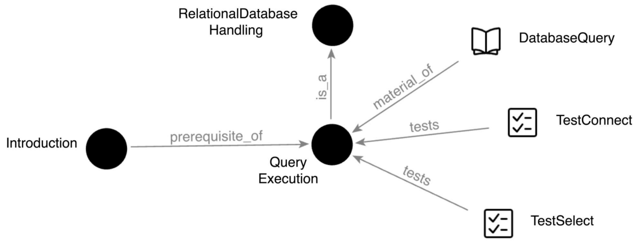


Figure 3.2: An example graph from the databases knowledge domain, that shows the *QueryExecution* KU which has *prerequisite_of* relation to the *Introduction* KU as well as *is_a* relation to the more abstract *RelationalDatabaseHandling* KU. The graph also shows two TUs and one MU connected to *QueryExecution*

$\mathbf{R}^T \subseteq \mathbf{U}^T \times \mathbf{L}^T \times \mathbf{U}^K$ *is a set of ordered triples* $[u^T_{i,t}, l^T_t, u^K_{j,t}]$*, where* $u^T_{i,t}$ *is a test-unit that belongs to one certain knowledge-unit* $u^K_{j,t}$*. The relation type between the knowledge-unit and the test-unit is determined by the label* $l^T_t \in \mathbf{L}^T$*, where* $\mathbf{L}^T \subseteq \{Tests_t\}$ *representing that the actual test-unit* $u^T_{i,t}$ *is testing the mastery level of learner in terms of the connected knowledge-unit* $u^K_{j,t}$*. The edge is pointing towards the knowledge-unit* $u^K_{j,t}$*.*

$\mathbf{R}^M \subseteq \mathbf{U}^M \times \mathbf{L}^M \times \mathbf{U}^K$ *is a set of ordered triples* $[u^M_{i,t}, l^M_t, u^K_{j,t}]$*, where* $u^M_{i,t}$ *is the material-unit that belongs to one certain knowledge-unit* $u^K_{j,t}$*. The relation type between the knowledge-unit and the material-unit is determined by the label* $l^M_t \in \mathbf{L}^M$*, where* $\mathbf{L}^M \subseteq \{MaterialOf_t\}$ *representing that the material-unit* $u^M_{i,t}$ *is a detailed note that explains and teaches the connected knowledge-unit* $u^K_{j,t}$ *to the learner. The edge is pointing towards the knowledge-unit* $u^K_{j,t}$*. Figure 3.2 is visualizing an example graph where the elements of the EKSG model can be observed.*

If the given time interval is empty, the default value is activated, which is t^{int}_*, which means that the model element (node or relation) is valid in all time instances. In case all time restrictions of the model elements are empty, the model reduces to a timeless graph. The fact that the time intervals t may be empty gives the EKSG model great flexibility.

There are several approaches to processing an evolving, time-dependent graph. In the following, the snapshot-based solution is introduced using discrete time-dependent units and time-independent relations.

Definition 6 *Given the* ***snapshot*** $\mathbf{U}^K_\tau = \{u \in \mathbf{U}^K \mid \tau \prec u.t\}$ *(where u.t means: attribute t of object u) contains all knowledge-units in* $\mathbf{G}$ *at time* τ*.*

The same logic can be applied to material-units $\mathbf{U}^M_\tau = \{u \in \mathbf{U}^M \mid \tau \prec u.t\}$ *and test-units* $\mathbf{U}^T_\tau = \{u \in \mathbf{U}^T \mid \tau \prec u.t\}$. *These representations are constituting the* τ*th instance of* $\mathbf{G}$ *graph, therefore these instances can be called snapshots. A snapshot of* $\mathbf{G}$ *at* τ *is denoted by:* $\mathbf{G}_\tau = \{\mathbf{U}^K_\tau, \mathbf{U}^M_\tau, \mathbf{U}^T_\tau, \mathbf{R}\}$. *Consequently, the described EKSG model can be considered as a sequence of static knowledge graphs* $\mathbf{G} = \{\mathbf{G}_1, \mathbf{G}_2, \ldots, \mathbf{G}_\tau, \ldots, \mathbf{G}_k\}$.

3.5 Thesis 2.

I introduced the Evolving Knowledge Space Graph model, which integrates the Knowledge Space Theory with ontological structures, while also incorporating the notion of abstract time, larger-grained knowledge units, and flexible connections to external knowledge representations through evoking-hooks. The Evolving Knowledge Space Graph model enables the representation of evolving domains where multiple parallel truths may coexist (e.g., different software versions) and where knowledge differences and knowledge complexity can be quantified. By integrating these extensions, the Evolving Knowledge Space Graph provides a more realistic and adaptable framework to model knowledge evolution, learner adaptivity, and personalized learning paths in dynamic educational and professional contexts.

3.6 Author's publications related to the thesis

Q3: [7]
[8], [12]

Chapter 4
Dynamic ITS architecture

4.1 The Graph4Learn architecture

To make the theoretical foundations of the EKSG model operational in the G4L ITS, I implemented a working system architecture in which domain knowledge is represented and queried using a graph database. The core structure of the EKSG is a directed graph, where the nodes and edges encode key elements of the instructional model.

In the implemented system, three types of nodes are used to represent and organize information: Knowledge Unit; Material Unit; Test Unit.

In addition to the graph-based representation of domain knowledge, the system also uses a relational database to manage data related to learners and system-level operations. This complementary data storage supports user-specific tracking, personalization, and evaluation processes. The main components stored in the relational database can be seen in Table 4.1.

These data sources are integrated and managed by the central G4L system, which comprises several functional subsystems. These subsystems ensure both the management of user data and the delivery of adaptive learning experiences. The main components can be seen in Table 4.2.

Together, these components form a cohesive system as Figure 4.1 shows, which enables dynamic, personalized learning in rapidly changing knowledge domains. The modular architecture also supports experimentation with various adaptation strategies and predictive models.

Table 4.1: Components stored in the relational database

Component	Description
System configuration data	Including global parameters and system-level settings used by adaptive algorithms and content delivery.
Learner activity logs	Record user interactions with the system.
Teacher related data	Metadata and parameters for prediction algorithms, model configurations, and system-level instructional strategies.

Table 4.2: G4L subsystems

Subsystem	Description
Learner Subsystem	It handles user registration, authentication, and learner profile management. It ensures secure access and interactions with the system.
Teacher Subsystem	It is responsible for learning content selection and knowledge visualization.
Knowledge Retention Subsystem	It operates independently from user-triggered activity and performs scheduled updates of learner knowledge states.

4.2 Graphical representation of knowledge state using an adapted IFL triangle

I used a customized Atanassov intuitionistic fuzzy logic (IFL) interpretation triangle [15] to visualize and model the current knowledge state of individual knowledge units. This representation not only displays directly measured knowledge levels but also supports estimations derived from related units via a predictive algorithm. This approach facilitates customized learning path recommendations based on the learner's current knowledge state.

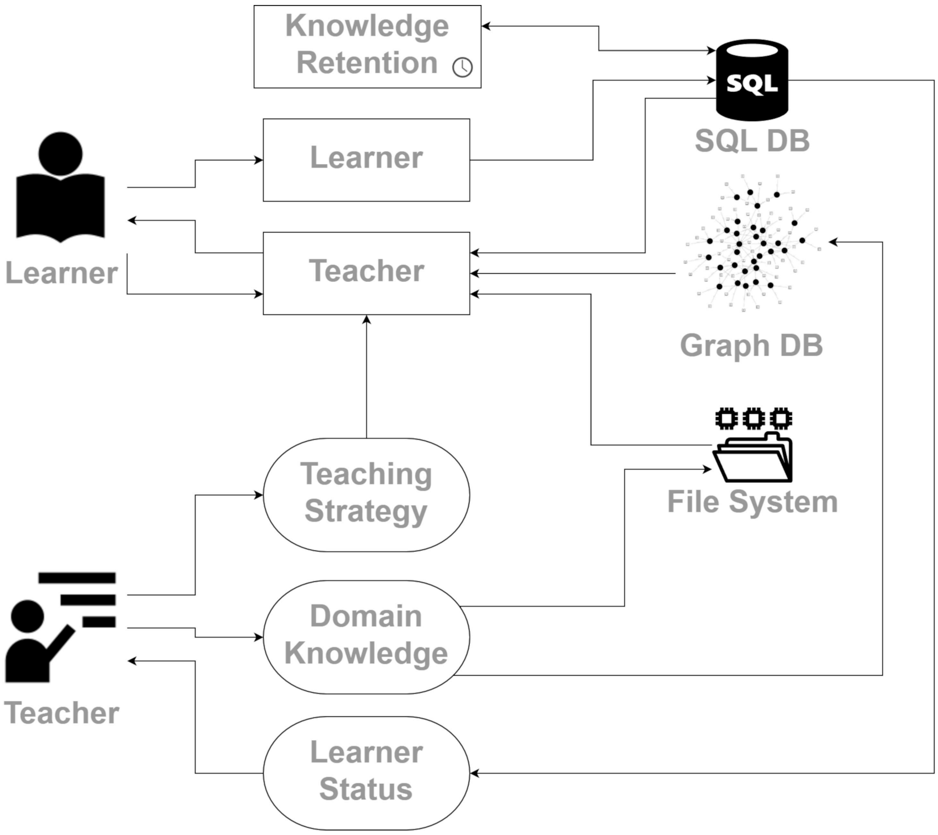


Figure 4.1: The architecture of the G4L system

In my proposed implementation, depicted in Figure 4.2 the horizontal leg of the triangle represents the proportion of correctly answered assessment items, while the vertical leg corresponds to incorrect responses. The actual knowledge state of the learner is denoted by a solid dot within this triangle. The triangle vertices define three epistemic categories: point unknown (origin, marked by "?"), point *does not know* (top of the vertical leg, marked by "✗"), and point *knows* (end of the horizontal leg, marked by "✓"). The estimated knowledge state is shown with a hollow point. Therefore, the triangle is partitioned into three disjoint regions: region **KNOWS**, region **DOES_NOT_KNOW**, and region **UNKNOWN**, by a defined turning point that is visualized by the intersecting dashed lines, classifying the learner's knowledge state.

To facilitate adaptive path recommendation using the Bayesian knowledge propagation algorithm, after each assessment, the algorithm identifies all knowledge units with estimated states outside the KNOWS region. For these units, the algorithm calculates their proximity (P) to the Knows vertex. Units are ranked by ascending proximity, and those closest to the Knows point are

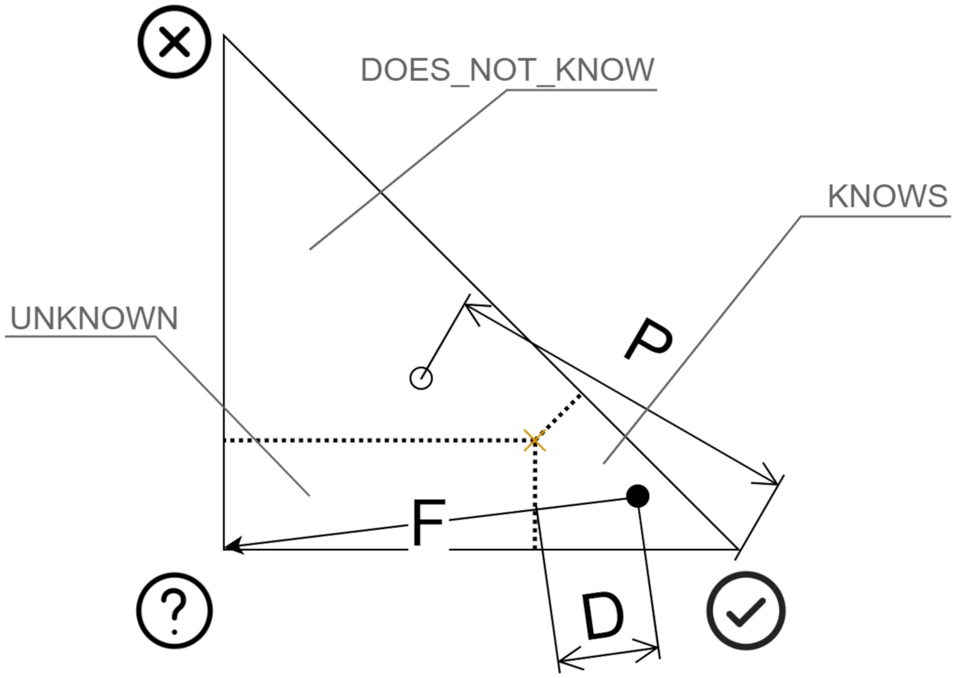


Figure 4.2: The proposed IFL Interpretational Triangle facilitates knowledge state visualization and adaptive path recommendation

recommended for further learning. This strategy prioritizes units that the learner is most likely to master with minimal effort, distinguishing my approach from classical KST. While KST typically selects units from the outer fringe defined by prerequisite relationships [18] and is effective for highly granular knowledge structures [29], my system focuses on medium to large knowledge units common in real-world educational domains with partial content overlap [28]. This justifies my deviation from the traditional adaptive recommendation based on KST.

Forgetting is modeled as a vector shift, represented by a forget (F) arrow, moving the current knowledge point towards the vertex Unknown. The magnitude of this shift is computed using Ebbinghaus's forgetting curve [17], influenced by both the elapsed time and the number of repetitions. To prioritize units for review, the algorithm calculates their decay distance (D), the distance from the current knowledge state point to the threshold beyond which the unit would leave the KNOWS region. Units with the smallest values of D are prioritized for review, reflecting the pedagogical assumption that these are most vulnerable to imminent forgetting.

4.3 Persistent monitoring of the learning process

As Figure 4.1 shows, the EKSG-based G4L architecture supports persistent monitoring of the learning process by storing detailed log records in the database and updating the learner's knowledge state through a dedicated scheduler and knowledge evaluation events.

The system collects a wide range of log events. Each event is time-stamped and associated with both a learner and a related knowledge unit. The logs are systematically collected and stored within the G4L system's relational database. The logging architecture is centered on three interconnected tables: `LEARNER_LOG`, `LEARNER_LOG_DATA`, and `CONFIG_LOG`.

4.4 Thesis 3.

I developed the Graph4Learn system, grounded in the Evolving Knowledge Space Graph model, to integrate graph-based knowledge representation with a relational database, thus enabling real-time tracking of learner activity and adaptive learning path discovery. The system advances the state of the art by introducing the following key innovations. First, it implements an abstract time dependency to capture the dynamics of evolving curricula. Second, it adapts the Intuitionistic Fuzzy Logic model to represent learner knowledge states and forgetting. Third, it implements multiple knowledge state induction algorithms, including the proposed Weighted Distance Dependent Induction method to predict the knowledge state. Fourth, it applies an Intuitionistic Fuzzy Logic based algorithm for the recommendation of the adaptive learning path. Finally, it integrates a Generative AI powered assistant capable of generating curriculum content such as knowledge units, prerequisite relations, and assessment items.

4.5 Author's publications related to the thesis

Q4: [13]
[5], [14], [6]

Chapter 5
User Study

5.1 Research questions

To investigate the effectiveness and practical applicability of the G4L intelligent tutoring system, a mixed methods [30] user study was conducted involving 45 university students. Based on the G4L framework, I formulate the following research questions:

- **RQ1**: How effective is the EKSG model in structuring and representing domain knowledge and supporting learner navigation in a fast-evolving domain?
- **RQ2**: How do different adaptive learning algorithms compare in terms of learner performance and progression in an EKSG model based intelligent tutoring system?
- **RQ3**: How does the implementation of the EKSG model support real-time tracking of learner activity and knowledge state progression within the system?

5.2 Rubric for system evaluation

To evaluate the G4L system, I developed a rubric based on the insights of the course teachers, my implementation experience, the system logs and the learner database [21].

5.3 Effectiveness of the EKSG model in structuring domain knowledge and supporting learner navigation

In relation to RQ1, I developed a set of questionnaire items to discover learners' experiences in relation to knowledge representation and learning activities. The questionnaire was administered using Google Forms. The learners responded to the items on a 5-point Likert scale, where 1 indicated "strongly disagree" and 5 indicated "strongly agree." In addition, an open-ended item was included to allow learners to provide general suggestions and express their overall opinions on the system. The Google Form was made available to students at the end of the semester and remained open for responses until the end of the examination period.

The rubric items "Knowledge Decomposition" and "Graph-based Navigation Usability" received the highest average scores (4.41), with standard deviations of 0.71 and 0.78, respectively. These correspond to level 3 on the 3-point rubric scale. The item "Support for Learner Decision-Making" received a slightly lower average score of 4.21 (SD = 1.02), corresponding to level 2. The lowest-rated item was "Prerequisite Logic Clarity," with an average score of 4.16 (SD = 0.91), corresponding to level 2.

The items of highest rating, 'Knowledge Decomposition' and 'Graph-based navigation usability' suggest that the structural and visual design features of the system were well received by the participants. These components likely offered intuitive guidance, even for users with limited prior exposure to intelligent tutoring systems. In the longer term, these results suggest the model's adaptability and potential for rapid deployment. Given that the system provides a highly visual and graph-based structure for navigating knowledge, the strong ratings align well with its intended design. In addition, dedicated practice time and instructor guidance may have contributed to the learners' positive perceptions.

The average score for "Support for Learner Decision-Making" reflects more varied experiences. Although many learners valued the autonomy provided by the system as [35] also suggests, the larger spread of responses indicates that some may have required additional guidance or scaffolding. This variability probably results from differences in self-regulation skills, also emphasized by Zhang et al. in [41], learning preferences, or prior domain knowledge [26].

Similarly, the relatively lower score for "Prerequisite Logic Clarity" may indicate challenges experienced by learners with less background in interpreting conceptual hierarchies or graph structures as states [36].

5.4 Learner performance and progression using different adaptive learning algorithms

To address RQ2, a multifaceted evaluation approach is employed.

First, I compared changes in individual knowledge unit mastery between initial and final test sessions between different groups. The mastery level for a knowledge unit was calculated as the ratio of correct answers to all attempts, yielding a value between 0 and 1.

Then, I evaluated the general knowledge state of the curriculum by adding the mastery levels of the 15 knowledge units. This aggregate measure was tracked from the initial to the final state. Additionally, during the study, I used offline quiz sheets to assess the average knowledge retention within each group, complementing the system's internal data.

Comparison of initial and final test data indicates notable improvements in all groups. The measured knowledge state increased in each group, with the BN group improving from 0.72 to 0.89, and the KST group from 0.92 to 0.97. The predicted knowledge state, derived from the learner model, showed a more pronounced change, especially for the BN and WDDI groups, suggesting enhanced inferred mastery levels over time. It is worth noting that the predicted knowledge state for the KST group remained at 1.000 throughout. This behavior reflects a key characteristic of the KST model: upon successful completion of an item associated with a knowledge unit, the model infers full mastery (1.000) not only for that unit, but also for all its prerequisite units in the predicted mastery values. Consequently, these values should be interpreted with caution, since these values do not reflect knowledge gain as observed in other models.

The three adaptive learning algorithms effectively supported learner knowledge state improvement. Munir et al. [25] also underlined that AI algorithms are used effectively in digital education. My results show that the BN group exhibited the most substantial gain, with the measured knowledge state level increasing from 0.717 to 0.887, an improvement 24%. The other two groups also showed positive, albeit more moderate, gains.

These performance differences may be explained by the variation in learner behavior between groups. For example, we can observe significant differences in the time spent on the test sheets [22] and the total duration of engagement [20]. Furthermore, some learners practiced systematically with each knowledge unit, while others concentrated on a smaller subset, relying on repeated tests as shown in Figure 5.1. These distinct behavioral patterns probably contributed to the variation in group-level learning outcomes.

5.5 Real-time tracking of learner activity and knowledge state progression

To address RQ3, the system's ability to record and maintain real-time data related to learners' actions and transitions of knowledge states was analyzed.

Figure 5.1 depicts the learning trajectories of two selected learners.

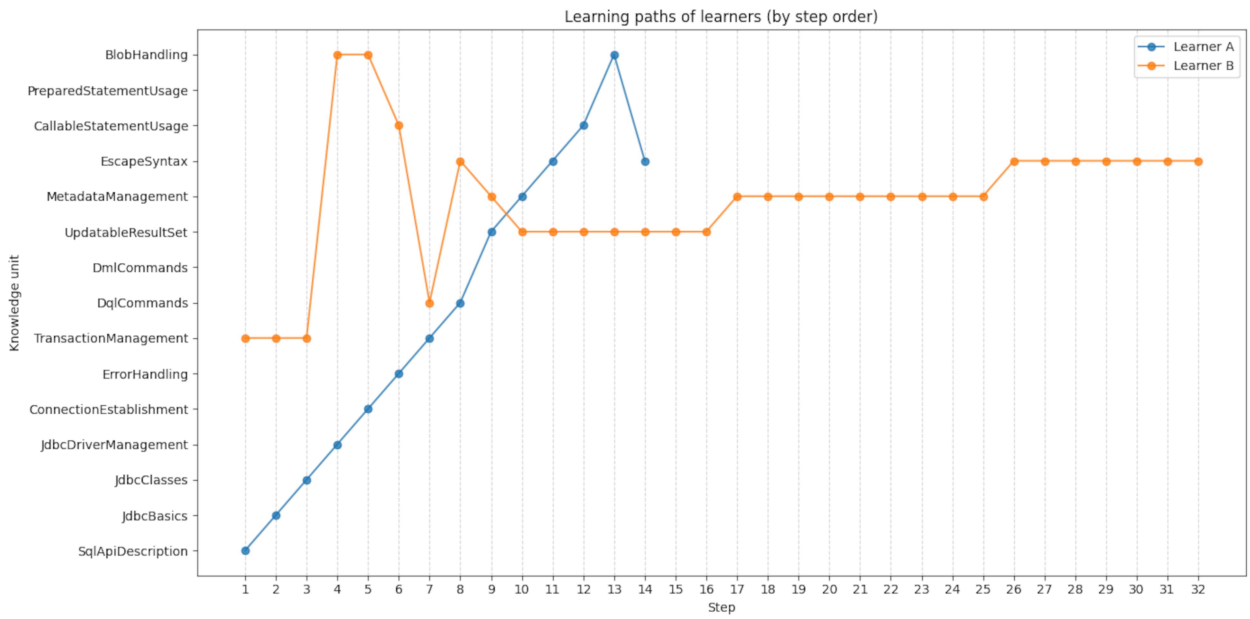


Figure 5.1: Learning path of two randomly selected learners

The G4L system supports 11 tracked capabilities, resulting in a fulfillment ratio of 85%. Based on the rubric tiered scoring logic (score = 3 if $> 66\%$), the system receives a learner activity tracking score of Good (3).

5.6 Thesis 4.

An empirical investigation involving Bachelor of Science students demonstrated that an intelligent tutoring system based on the Evolving Knowledge Space Graph model and implemented through the Graph4Learn framework effectively supports adaptive and self-regulated learning in rapidly evolving domains.

Regarding RQ1, the results confirm that the EKSG model provides a robust structure to represent domain knowledge and support the navigation of the learner.

In response to RQ2, the comparative evaluation revealed that the Bayesian Network approach achieved the highest learning gains among the adaptive algorithms considered.

Finally, addressing RQ3, the study validated that the system enables real-time tracking of learner activity and knowledge state progression, improving adaptability and personalization.

5.7 Author's publications related to the thesis

Q1, preprint, under review: [10]
[11], [1]

Chapter 6
Summary

This dissertation introduces the Knowledge-Sharing-Bridge framework, which embeds an implicit tutoring mechanism directly into Artificial Intelligence systems. The framework consists of four interrelated modules: *Explain*, *Report*, *Control*, and *Teach*, that collectively enable AI to function not only as a decision-support tool but also as an active pedagogical agent. Powered by an Explainable AI engine, the *Explain* and *Teach* components demonstrate how explainability can be effectively combined with instructional guidance. The KSB framework integrates structured knowledge representations, such as word clouds, to enhance the transparency, accessibility, and pedagogical value of complex decision logic.

A prototype implementation validates the hypothesis that embedding knowledge-sharing mechanisms within AI systems bridges the gap between passive technology use and active human learning. The findings indicate that when explainability is coupled with guided instruction, AI systems not only improve task performance but also foster user comprehension, engagement, and long-term knowledge retention.

In a broader sense, this work reconnects with the ancient roots of learning, where knowledge was continuously shared between the wise and the curious. With the advent of Artificial Intelligence, such continuous, dialogic learning becomes possible again, this time through intelligent systems capable of explaining, guiding, and teaching.

In addition to the KSB framework, another major contribution of this research is the development of an Intelligent Tutoring System capable of adapting to rapidly evolving curricula, such as those in computer science, while also supporting individual learner progression and self-regulated learning. The implemented Graph4Learn system was designed to meet the diverse needs of university students and adult learners.

The implementation is based on the Extended Knowledge Space Graph model, a graph-based knowledge representation framework also developed as part of this research. A relational database was integrated to enable real-time learning tracking and support adaptive algorithm decision making. The system introduced several innovations: (1) abstract temporal dependency to model evolving curricula, (2) adapted IFL to represent learner knowledge states and forgetting, (3) multiple adaptive learning algorithms, including our proposed WDDI method, and (4) the integration of a GenAI-based assistant to generate curriculum content, comprising knowledge units, prerequisite relationships, and quiz items.

The findings of the study indicate that the EKSG model effectively structured domain knowledge and supported learner navigation. Real-time tracking of both learner activity and knowledge progression was achieved successfully. Furthermore, our evaluation of adaptive algorithms in a coarse-grained curriculum setting revealed that the BN algorithm yielded the highest overall learning gains, outperforming both the KST and WDDI models.

Together, these findings highlight both the practical viability and theoretical relevance of the G4L system and the underlying EKSG model. By combining structured domain modeling, adaptive learning algorithms, and fine-grained learning activity tracking, the system offers a flexible and scalable solution to support personalized learning. These insights underscore the significance of graph-based representations and log-based analytics in the development of future intelligent tutoring systems.

6.1 Future research directions

Future work will focus on extending the application of the Graph4Learn system to multiple courses, one of them is currently under development and implementation.

Based on the experience gained so far, further refinements of the learner tracking database are also planned. In particular, modifications will be introduced to improve the representation and traceability of individual learning sessions.

Although the current framework already allows for the quantitative evaluation of learning gains through changes in learners' knowledge states, future extensions will aim to formalize additional metrics related to learning engagement and learning efficiency. In particular, navigation patterns within the knowledge graph, deviations from recommended learning paths, and temporal characteristics of learning sessions provide a strong foundation for defining explicit engagement and efficiency indicators.

Finally, a key direction for future development is the integration of a tutoring dialog assistant. This assistant will leverage the underlying graph structure and assessment questions to provide context-aware hints and explanations, thereby enhancing learner support and interaction within the system.

6.2 Concluding remarks

This dissertation aimed to address the overarching research question of how an intelligent tutoring framework can support adaptive, personalized, and sustainable learning in fast-evolving knowledge domains while preserving the central role of educators.

The proposed Evolving Knowledge Space Graph model and the Graph4Learn framework demonstrate that dynamic curriculum representation, actionable learner modeling, and adaptive learning strategies can be effectively combined within a single system. Through empirical evaluation, the work shows that such a framework can support learner progression, enable educator insight through transparent learner tracking, and remain robust amid continuous domain evolution.

Together, these contributions provide a coherent answer to the ORQ and establish a foundation for future research on intelligent tutoring systems.

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