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PAPER

Systematic Review and Framework for AI-Driven Tacit Knowledge Conversion Methods and Machine Learning Algorithms for Ontology-Based Chatbots in E-Learning Platforms

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ABSTRACT

The conversion of tacit knowledge, which is deeply rooted in personal experience and often difficult to articulate, presents a significant challenge within knowledge management systems. Ontology-based chatbots offer a promising solution by leveraging structured knowledge representations and advanced natural language processing (NLP) techniques to facilitate this transformation. This paper explores the various methods and algorithms used in developing ontology-based chatbots, with a particular focus on their role in converting tacit knowledge into more accessible forms. Additionally, it provides a comparative analysis of the algorithms employed, highlighting their respective strengths and weaknesses. Ultimately, this study addresses the critical challenge of managing and converting tacit knowledge, with the aim of enhancing the overall effectiveness of knowledge management systems.

KEYWORDS

tacit knowledge, explicit knowledge, knowledge conversion, ontology-based chatbot, natural language processing (NLP), adaptive learning

1 INTRODUCTION

Effectively transferring knowledge within knowledge management systems presents significant challenges, particularly when addressing the nuanced nature of tacit knowledge. While explicit knowledge—easily codified and disseminated through traditional e-learning platforms—can be shared efficiently, tacit knowledge, which includes insights, intuitions, and personal experiences, remains difficult to articulate and communicate. This complexity hampers effective knowledge transfer and hinders learning outcomes.

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The literature highlights this challenge, with Polanyi famously noting that "we know more than we can tell" [1], underscoring the inherent difficulty in articulating tacit knowledge. Further studies by Spender [2] and Nonaka and Takeuchi [3] emphasize that organizations often struggle to convert tacit knowledge into explicit forms, a process essential for fostering innovation and enhancing learning environments. Recent contributions, such as those by Chen [4], Zhang [5], and EL Azhari [6], have explored the role of digital technologies in addressing this gap, highlighting how AI and machine learning can facilitate the capture and sharing of tacit knowledge. Overcoming this challenge is crucial for improving knowledge dissemination and ensuring that organizations can leverage their collective expertise to drive innovation and enhance learning outcomes.

This paper explores the methods and algorithms involved in developing ontology-based chatbots that facilitate the transformation of tacit knowledge into explicit knowledge within e-learning environments. Key objectives include examining the role of ontology development in capturing tacit knowledge, analyzing natural language understanding techniques that enhance user interaction, and investigating adaptive learning strategies that tailor knowledge delivery based on user needs. Additionally, a comparative analysis of algorithms will be conducted to identify the most effective approaches for this conversion.

A distinctive aspect of this study is its comprehensive approach, integrating ontology development, advanced natural language processing (NLP) techniques, and adaptive learning into a cohesive framework for enhancing knowledge management systems. By focusing specifically on the externalization phase of the SECI model, this study aims to provide innovative solutions to the practical challenge of converting tacit knowledge into explicit formats. This contribution not only addresses a critical gap in the literature but also offers actionable insights for improving e-learning environments, thereby facilitating more effective knowledge dissemination.

Through this examination of ontology-based chatbots, we seek to refine our understanding of tacit knowledge conversion and provide a robust framework that enhances learning outcomes. By integrating multiple methodologies, this study aims to improve knowledge management practices and the overall efficacy of knowledge transfer in educational settings.

2 INTEGRATING ONTOLOGY DEVELOPMENT AND NLP ALGORITHMS: A COMPARATIVE ANALYSIS AND CONCEPTUAL FRAMEWORK

2.1 The proposed conceptual framework for ontology development

Ontologies facilitate better organization and retrieval of knowledge, thereby enhancing decision-making processes within organizations. By providing a structured framework for knowledge representation, ontologies not only support effective knowledge sharing but also foster a deeper understanding of underlying concepts, ultimately improving the efficiency of knowledge management practices. This foundational view underscores the importance of integrating ontological approaches in the development of intelligent systems for managing knowledge [7].

Our proposed framework for ontology development within e-learning platforms (see Figure 1) emphasizes the systematic transformation of implicit knowledge into explicit forms. Central to this process is a thorough domain analysis, which focuses on identifying and comprehending the essential concepts, entities, and relationships that define the domain's landscape. This phase is not merely about gathering information; it involves a collaborative effort with subject matter experts to ensure a nuanced understanding of the domain's complexities.

Through extensive research and dialogue, the framework aims to build a comprehensive foundation for ontology modeling. By uncovering the underlying structure and dynamics of the domain, it enables the creation of structured representations that capture and organize knowledge effectively. This structured ontology serves as a knowledge base, facilitating improved navigation, retrieval, and application of knowledge within e-learning environments.

Moreover, the framework supports ongoing refinement and adaptation as new insights and developments emerge in the domain. This iterative process ensures that the ontology remains current and relevant, fostering continuous improvement in e-learning content and delivery. Ultimately, by transforming tacit knowledge into explicit forms, our framework enhances the accessibility and utility of knowledge within e-learning platforms, fostering richer learning experiences and outcomes.

Once the domain analysis is complete, the next step is ontology modeling, where the identified concepts, entities, and relationships are formalized into a structured ontology. This process involves conceptualization, wherein classes, properties, and relationships are defined based on insights gained during domain analysis. Ontology modeling often uses ontology languages to represent the ontology formally. Additionally, instance population is performed to populate the ontology with specific instances and examples, further enriching its content and applicability.

Following ontology modeling, the ontology undergoes validation and refinement to ensure its accuracy, completeness, and relevance. Validation involves soliciting feedback from domain experts and evaluating the ontology against predefined metrics to assess its effectiveness in representing domain knowledge. Any inconsistencies or deficiencies identified during validation are addressed through iterative refinement, wherein the ontology is continuously revised based on feedback and evaluation results.

Integration with NLP techniques is another critical aspect of ontology-based chatbot development. This integration enables seamless communication between users and the chatbot by interpreting natural language inputs and mapping them to ontology concepts and entities. NLP algorithms are employed to process user queries effectively, enhance contextual understanding, and generate coherent responses aligned with the ontology.

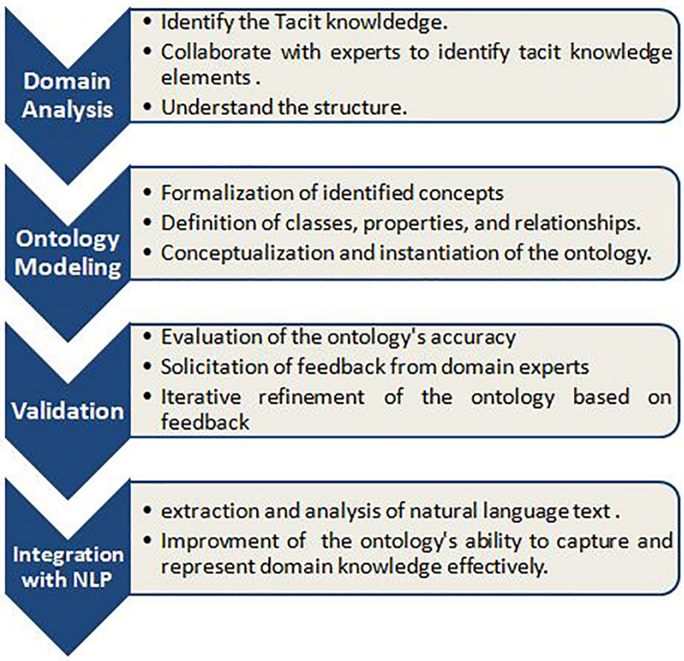

Fig. 1. The proposed conceptual framework for ontology development

2.2 Ontology construction methods

RDF (Resource Description Framework), OWL (Web Ontology Language), and SKOS (Simple Knowledge Organization System) are three prominent ontology languages used for knowledge representation and conversion, particularly in the context of tacit knowledge. Each language offers distinct features and capabilities that influence its suitability for tacit knowledge conversion in e-learning platforms. This section provides a comparative analysis of RDF, OWL, and SKOS, focusing on their advantages and limitations in facilitating tacit knowledge conversion.

Resource description framework. Resource description framework provides a simple and flexible model for representing knowledge using subject-predicate-object triples, known as RDF triples. This model allows for the creation of structured data graphs, making it suitable for capturing basic relationships between entities. RDF's simplicity enhances its usability and facilitates the integration of diverse data sources. However, RDF's limited expressiveness may pose challenges when representing complex knowledge structures. For tacit knowledge conversion, RDF can effectively capture basic relationships and contextual information but may fall short in handling intricate knowledge domains that require advanced inference capabilities [8].

Web ontology language. Web ontology language is a more expressive ontology language designed to represent complex knowledge structures, including rich class hierarchies, property constraints, and logical axioms. OWL provides formal semantics for defining ontologies, enabling automated reasoning and inference over the knowledge base. This expressiveness makes OWL well-suited for capturing the intricate relationships and constraints inherent in tacit knowledge. However, OWL's complexity can lead to higher computational costs and longer development times. While OWL offers robust support for knowledge representation, its suitability for tacit knowledge conversion depends on the specific requirements of the domain and the available computational resources.

Simple knowledge organization system. Simple knowledge organization system is specifically designed for organizing and representing knowledge hierarchies, taxonomies, and thesauri. It provides a lightweight and intuitive framework for capturing conceptual relationships and classification schemes. SKOS simplifies the process of knowledge organization and retrieval, making it particularly suitable for structuring and organizing tacit knowledge elements. However, SKOS's limited expressiveness may restrict its applicability for capturing complex knowledge structures and relationships. For tacit knowledge conversion, SKOS is effective in organizing and categorizing knowledge but may lack the inferential capabilities required for deeper semantic understanding [9].

The following Table 1 presents a comprehensive comparative analysis of RDF, OWL, and SKOS, three prominent ontology languages widely used in knowledge representation:

- **OWL:** Known for its highly expressive nature, OWL supports the definition of complex relationships and enables logical reasoning and inferencing, making it a powerful tool for detailed knowledge modeling. However, this expressiveness comes with a trade-off in terms of complexity and the need for specialized knowledge to implement it effectively.
- **RDF:** RDF is a lightweight and flexible language designed for describing resources and their relationships in a simpler, graph-based format. It excels in facilitating data interoperability and integration across different systems but lacks advanced reasoning capabilities, making it less suitable for applications requiring deeper inferencing.

- **SKOS:** SKOS is focused on representing structured vocabularies, such as taxonomies and thesauri, and is well-suited for managing simpler hierarchical relationships. It offers ease of use and simplicity but is limited in defining intricate relationships or providing inferencing, restricting its application to less complex domains.

Resource description framework, OWL, and SKOS are three prominent ontology languages used for knowledge representation and conversion, particularly in the context of tacit knowledge. Each language offers distinct features and capabilities that influence their suitability for tacit knowledge conversion in e-learning platforms. This section provides a comparative analysis of RDF, OWL, and SKOS, focusing on their advantages and limitations in facilitating tacit knowledge conversion.

Table 1. Advantages and limitation of ontology languages for knowledge conversion

	Advantages	Limitations
OWL	• Highly expressive-Supports complex relationships and constraints • Widely used in various domains	• Complexity can lead to higher computational costs and longer development times
RDF	• Simplified model focusing on subject predicate object triples • Good for simpler ontologies • Easier to implement and query	• Less expressive compared to OWL • May not handle complex relationships effectively
SKOS	• Suitable for thesauri and classification schemes • Easy to implement and understand	• Less expressive than OWL • Limited in capturing complex knowledge

When evaluating OWL, RDF, and SKOS, three important criteria stand out: 1) expressiveness, 2) ease of implementation, and 3) suitability for specific domains.

Expressiveness

- **OWL:** OWL exhibits the highest level of expressiveness, allowing for the representation of complex relationships and detailed constraints necessary for sophisticated knowledge models. Recent studies, such as those by Baker [10], highlight OWL's capabilities in capturing intricate domain-specific knowledge.
- **RDF:** RDF offers moderate expressiveness, suitable for representing basic relationships but lacking the advanced features provided by OWL.
- **SKOS:** SKOS ranks lowest in expressiveness, primarily designed for simpler hierarchical structures and basic relationships.

Ease of implementation

- **SKOS:** SKOS scores highest in ease of implementation due to its user-friendly design, making it accessible to users without extensive technical expertise. Research by D. Smith [11] indicates that SKOS is often favored in projects requiring quick deployment and minimal complexity.
- **RDF:** RDF provides a moderate level of ease, requiring some familiarity with semantic web principles but remaining more approachable than OWL.
- **OWL:** OWL typically involves the greatest complexity in implementation, requiring specialized knowledge and skills, which can be a barrier for many users. A study by K. Zhao [12] discusses the challenges faced during the adoption of OWL in various organizations.

Suitability for complex domains

- **OWL:** OWL is most suitable for complex domains, capable of managing intricate relationships and supporting advanced reasoning. Recent research, such as

Poveda-Villalón [13], emphasizes OWL's effectiveness in sophisticated knowledge representation scenarios.

- **RDF:** RDF is suitable for moderately complex domains, providing foundational structures but lacking the depth needed for more intricate systems.
- **SKOS:** SKOS is least suitable for complex domains, as it focuses primarily on simpler organizational frameworks and lacks the tools to handle complexity effectively.

Comparative analysis

- **Expressiveness:** OWL > RDF > SKOS
- **Ease of Implementation:** SKOS > RDF > OWL
- **Suitability for Complex Domains:** OWL > RDF > SKOS

2.3 Natural language procesing algorithms

Natural language processing algorithms play a pivotal role in facilitating tacit knowledge conversion within ontology-based chatbots. By analyzing and interpreting user input, these algorithms enable chatbots to understand language nuances and extract relevant information for knowledge representation. This section explores several NLP algorithms commonly used for tacit knowledge conversion and provides a comparative analysis of their strengths and limitations.

Intent detection. Intent detection algorithms identify the underlying purpose behind user queries. The following are commonly used algorithms for this task:

- **Support vector machines (SVM):** SVMs are effective for classification tasks and are particularly useful for smaller datasets with clear margins of separation [14].
- **Recurrent neural networks (RNN):** RNNs are well-suited for processing sequential data but can face challenges related to long-term dependency issues [15].
- **Transformers:** Transformers use attention mechanisms to capture context and relationships in textual data, excelling in understanding complex user intents.

Entity recognition. Entity recognition algorithms identify and extract relevant entities or keywords from user input, helping to discern the context of the conversation. Common algorithms include:

- **Conditional random fields (CRF):** CRFs are effective for structured prediction tasks, capturing dependencies between sequential data [16].
- **Deep learning models:** These models combine neural networks with structured prediction techniques, offering high accuracy in entity recognition.

Context management. Context management algorithms ensure that the chatbot maintains a coherent understanding of conversation context, allowing for relevant responses. These algorithms are essential for managing the conversation flow, especially when users interact with the chatbot over extended sessions or revisit earlier topics. Key algorithms include:

- **Memory networks:** Memory networks store and retrieve contextual information efficiently, enabling the chatbot to retain past interactions [17].
- **Attention mechanisms:** Attention mechanisms focus on relevant parts of the input sequence, enhancing the chatbot's understanding of context and improving response quality.

Comparative analysis: RNNs, transformers, SVMs, CRFs, deep learning models, memory networks, and attention mechanisms

Three key criteria emerge when comparing these algorithms: 1) context understanding, 2) processing efficiency, and 3) accuracy.

Accuracy

- **Transformers:** Demonstrate the highest accuracy across various NLP tasks due to their ability to capture complex patterns and contextual relationships. Studies by Vaswani [18] and Devlin [19] show that transformers outperform RNNs and SVMs in benchmarks such as GLUE and SQuAD.
- **RNNs:** Provide moderate accuracy, benefiting from their sequential processing capabilities but often struggling with long-range dependencies. Hochreiter and Schmidhuber [20] highlight these limitations, especially when dealing with long sequences.
- **SVMs:** Generally, exhibit lower accuracy in complex language tasks compared to deep learning models, as they rely on hand-crafted features and may not capture contextual nuances effectively.

Processing efficiency

- **SVMs:** Rank highest in processing efficiency due to lower computational power requirements, making them faster for smaller datasets. Cortes and Vapnik [21] illustrate the efficiency of SVMs in specific tasks.
- **RNNs:** Offer moderate processing efficiency, though slower than SVMs due to their sequential nature, which limits parallelization. Bradbury [22] discusses the efficiency challenges posed by RNNs.
- **Transformers:** Often have the lowest processing efficiency, especially with large datasets, due to their high resource requirements. Brown [23] emphasizes the computational costs associated with training and deploying transformer models.

Context understanding

- **Transformers:** Excel in context understanding, using attention mechanisms to effectively process and integrate information from the entire input sequence. Findings by Khan [24] highlight the superior contextual awareness of transformers compared to RNNs and support vector machines.
- **RNNs:** Provide moderate context understanding by processing data sequentially, though they often lose information over long sequences, as noted by Zhou [25].
- **SVMs:** Typically have the weakest context understanding, relying on fixed feature sets that do not account for sequential dependencies or contextual information.

Table 2. A comparative analysis of NLP algorithms

Algorithm	Accuracy	Processing Efficiency	Context_Understanding
SVM	Mid	High	Mid
RNN	Mid	Mid	Mid
Transformers	High	Mid	High
CRF	High	Mid	Mid
Deep Learning Models	High	Mid	Mid
Memory Networks	High	High	High
Attention Mechanisms	High	High	High

Comparative analysis

- **Accuracy:** Transformers > RNN > SVM
- **Processing Efficiency:** SVM > RNN > Transformers
- **Context Understanding:** Transformers > RNN > SVM

2.4 Integration of onology and natural language processing

The integration of ontology and NLP within e-learning platforms facilitates the conversion of tacit knowledge into explicit knowledge through a structured and efficient process. When users interact with the system using natural language queries, NLP algorithms handle tasks such as intent detection, entity recognition, and context management. These processed inputs are then mapped to a domain-specific ontology, which aligns the queries with predefined concepts and relationships.

The ontology serves as a foundational knowledge base, enabling precise information retrieval based on the structured relationships between concepts. By leveraging this organized framework, responses are synthesized from various sources, ensuring that users receive accurate and contextually relevant information. This dynamic approach enriches the learning experience by providing clear, targeted knowledge that supports a deeper understanding and engagement with the subject matter.

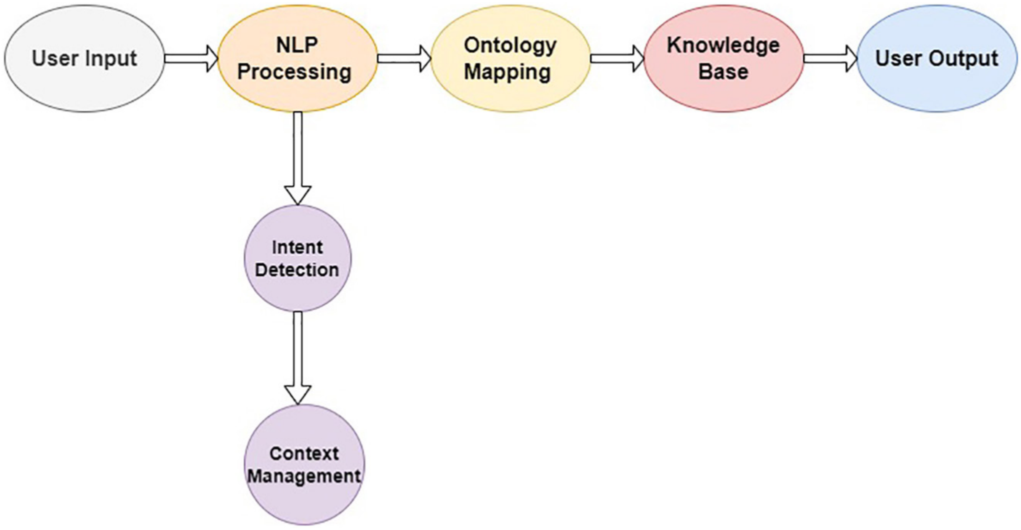

Fig. 2. The process of NLP and ontology for converting tacit knowledge into explicit knowledge

Description

User input: Users interact with the e-learning platform by providing input in natural language, such as questions or requests for information.

NLP processing: The input undergoes NLP processing, which involves several sub-tasks:

- **Intent detection:** Determines the user's intent behind the query.
- **Entity recognition:** Identifies and classifies key entities within the input.
- **Context management:** Maintains the context of the conversation to provide coherent responses.

Ontology mapping: The processed input is then mapped to the ontology, a structured representation of domain-specific knowledge. This step ensures that the input aligns with predefined entities and relationships within the ontology.

Knowledge base querying: Queries are made to the knowledge base using the mapped ontology concepts to retrieve relevant information. This step leverages the structured data in the ontology to find precise answers to user queries.

Response generation: Based on the information retrieved from the knowledge base, responses are generated. This step may involve synthesizing information from multiple sources and formatting it into natural language.

User output: The generated response is then presented to the user, completing the interaction cycle.

3 ADAPTIVE LEARNING FOR TACIT KNOWLEDGE CONVERSION USING AN ONTOLOGY-BASED CHATBOT IN E-LEARNING PLATFORFMS

Adaptive learning systems are designed to adjust educational content based on individual learner profiles. These systems, often referred to as adaptive teaching, tutoring, training, or e-learning platforms, rely on collecting data about each learner to provide personalized and relevant instructional material. The core idea behind adaptive learning is that learners come from diverse backgrounds and possess different skills, so tailoring the content is essential to optimizing the learning experience. By continuously monitoring and analyzing student behavior throughout the learning process, adaptive learning systems can create customized learning paths that cater to each learner's unique needs [26].

Reinforcement learning (RL), a branch of machine learning, plays a crucial role in this context by allowing the system to adapt dynamically, improving content delivery based on continuous feedback from the learner's interactions and performance. RL is particularly effective for optimizing adaptive learning paths [27]. RL algorithms learn from user interactions and continuously refine the learning path to maximize engagement and learning outcomes.

Key benefits of using RL in this context include:

- **Dynamic Adaptation:**
  - **Capability:** RL algorithms adapt to the learner's evolving needs by analyzing real-time data and feedback.
  - **Benefit:** This ensures that the learning experience remains relevant and challenging, promoting sustained engagement.
- **Personalized Interaction:**
  - **Capability:** RL tailors' content and recommendations based on the unique behaviors and preferences of each learner.
  - **Benefit:** Personalized interactions enhance the effectiveness of the learning process, as content is aligned with the learner's needs.
- **Continuous Improvement:**
  - **Capability:** RL algorithms improve their decision-making processes over time by learning from accumulated data.
  - **Benefit:** This leads to progressively better personalization and improved learning outcomes.

4 THE PROPOSED FRAMEWORK FOR IMPLEMENTING AN ONTOLOGY-BASED CHATBOT FOR TACIT KNOWLEDGE CONVERSION

Our proposed framework aims to enhance learning experiences in e-learning platforms by integrating NLP with ontology development. This integration facilitates the conversion of complex, tacit knowledge into explicit forms that are more accessible and understandable for learners. In doing so, it bridges the gap between unstructured, experience-based insights and formalized knowledge, making it easier to share expertise across diverse learners and contexts.

In knowledge management, this approach is crucial because it addresses the challenge of capturing and disseminating tacit knowledge—knowledge that is often difficult to articulate or document but is essential for expertise and problem-solving. Many learners struggle to extract insights from tacit information that is locked in the minds of experts or embedded within complex systems and practices. By leveraging NLP, the framework enables learners to interact with a chatbot in a natural language format, allowing them to ask questions, seek explanations, and receive personalized feedback in real-time. This conversational interface mimics the interaction learners would have with a human tutor or mentor, making the learning process more intuitive and user-friendly.

Moreover, NLP allows for adaptive learning experiences, tailoring responses based on a learner's knowledge level, previous queries, and personalized learning goals. This enhances engagement and ensures that learners receive information relevant to their needs.

Ontology development plays a vital role by structuring knowledge into formalized concepts, relationships, and rules, which helps the chatbot interpret and provide accurate responses based on the context of the learner's queries. The ontology not only ensures consistency in responses but also promotes richer, context-aware answers that go beyond surface-level information. This structured approach enhances the efficiency of knowledge retrieval by organizing information hierarchically and thematically, allowing learners to explore interconnected concepts coherently. It encourages deeper learning by promoting the understanding of relationships between different pieces of knowledge, thereby helping learners build a more integrated and comprehensive mental model of the subject matter.

In addition, the ontology can evolve over time as new knowledge is added, which means the system can grow and adapt as learning needs change. This dynamic nature makes the framework particularly valuable in rapidly changing fields where knowledge is constantly being updated. It supports not only individual learning but also collaborative learning environments, where multiple learners can interact with shared knowledge structures and contribute to the continuous expansion of the knowledge base.

Overall, the framework contributes to knowledge management by facilitating the effective transfer of tacit knowledge into explicit forms that can be shared, accessed, and applied more widely. It supports continuous learning, enables personalized learning experiences, and enhances collaboration by creating a repository of structured knowledge that is accessible to learners anytime and anywhere in e-learning environments. This makes it an invaluable tool not only for learners but also for educators, institutions, and organizations looking to optimize the dissemination and application of knowledge. Ultimately, it fosters an interactive, evolving, and learner-centered educational experience that aligns with the needs of modern digital learning ecosystems.

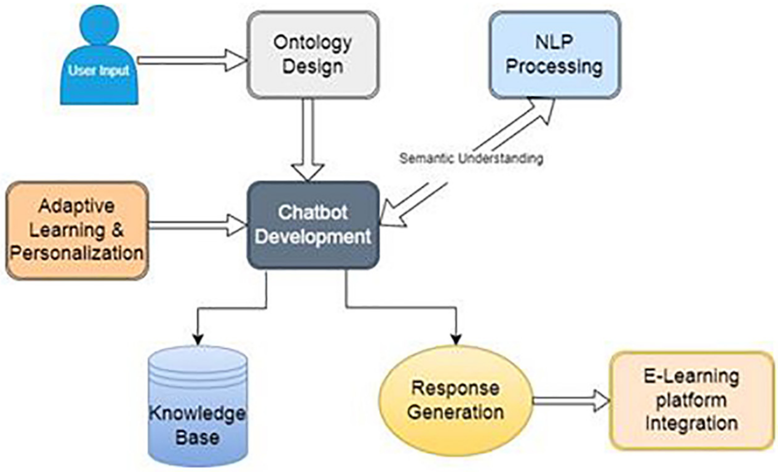

Fig. 3. The proposed framework for implementing an ontology-based chatbot for tacit knowledge conversion in an e-learning platforms

1. Ontology design

- **Domain analysis:** Identify key concepts, relationships, and elements of tacit knowledge within the domain.
- **Ontology modeling:** Utilize languages such as OWL (Web Ontology Language) to formalize the ontology.
- **Validation and refinement:** Ensure the ontology accurately represents the domain and refine it based on expert feedback.

2. NLP integration

- **Text preprocessing:** Clean and prepare text data for analysis to remove noise and irrelevant information.
- **Feature extraction:** Extract meaningful features from the text to represent it effectively in the analysis.
- **Semantic analysis:** Understand the meaning and context of the text to facilitate accurate interpretation.

3. Chatbot development

- **Dialogue management:** Manage the flow of conversation to ensure coherent and contextually relevant interactions.
- **Intent recognition:** Identify user intentions from their input to provide appropriate responses.
- **Response generation:** Generate appropriate responses to user queries, ensuring they are informative and relevant.

4. Adaptive learning and personalization

- **User modeling and profiling:** Create detailed learner profiles based on their knowledge levels, learning styles, and preferences.
- **Adaptive learning paths:** Personalize learning activities based on the learner's needs, progress, and goals.

5. Integration with e-learning platform

- **Content delivery:** Provide educational content to users in a structured and engaging manner.

- **Assessment tools:** Evaluate learners' knowledge and progress through various assessment methods.
- **User interface:** Ensure a user-friendly interaction experience that facilitates navigation and engagement.

6. Tacit knowledge conversion

- **Query understanding:** Accurately interpret user queries to facilitate effective communication and learning.
- **Context awareness:** Understand the context of user interactions to provide relevant responses.
- **Explanation generation:** Provide explanations and insights derived from tacit knowledge to enhance understanding.

5 CONCLUSION

The challenge of converting tacit knowledge, which is deeply embedded in personal experiences and often difficult to articulate, into explicit knowledge is significant within knowledge management systems. Ontology-based chatbots offer a promising solution by utilizing structured knowledge representations and advanced NLP to facilitate this conversion. This paper investigates the methods and algorithms used in the development of ontology-based chatbots, with a particular focus on the conversion of tacit knowledge. Key components discussed include ontology development, natural language understanding, and adaptive learning.

Through a comparative analysis of various algorithms employed in these processes, the paper highlights their strengths and limitations. Furthermore, a comprehensive framework for implementing an ontology- based chatbot for tacit knowledge conversion in an e-learning platform is proposed. This framework is designed to enhance knowledge management and dissemination by effectively bridging the gap between tacit and explicit knowledge.

Future work will focus on applying the proposed framework in a real-world case study within an e-learning platform. This case study aims to validate the effectiveness of the framework in converting tacit knowledge into explicit knowledge, providing insights into its practical implementation and potential improvements. By conducting this case study, we hope to further refine the framework and demonstrate its impact on enhancing learning outcomes and knowledge dissemination in e-learning environments.

6 REFERENCES

[1] M. Polanyi, *The Tacit Dimension*. London: Routledge & Kegan Paul, 1996.

[2] J. C. Spender, "Making knowledge the basis of a dynamic theory of the firm," *Strategic Management Journal*, vol. 17, no. S2, pp. 45–62, 1996. https://doi.org/10.1002/smj.4250171106

[3] Nonaka and Takeuchi, *The SECI Model*. New York, NY: Oxford University Press, 1996.

[4] L. Chen, P. Chen, and Z. Lin, "Artificial intelligence in education: A review," *IEEE ACCESS*, vol. 8, pp. 75264–75278, 2020. https://doi.org/10.1109/ACCESS.2020.2988510

[5] K. Zhang and A. B. Aslan, "AI technologies for education: Recent research & future directions," *Computers and Education: Artificial Intelligence*, vol, 2, p. 100025, 2021. https://doi.org/10.1016/j.caeai.2021.100025

[6] K. EL Azhari, I. Hilal, and, N. Daoudi, “Smart chatbots in e-learning domain: A systematic literature review,” *International Journal of Interactive Mobile Technologies*, vol. 17, no. 15, pp. 4–37, 2023. https://doi.org/10.3991/ijim.v17i15.40315
[7] I. Jurisica, J. Mylopoulos, and E. Yu, “Ontologies for knowledge management: An information systems perspective,” *Knowledge and Information Systems*, vol. 6, pp. 380–401, 2004. https://doi.org/10.1007/s10115-003-0135-4
[8] M. Brown and R. Johnson, *Simplifying Knowledge Representation with RDF*, 2022.
[9] S. Garcia and L. Martinez, *Enhancing Classification Schemes with SKOS*, 2024.
[10] M. Baker, *Advanced Applications of OWL in Knowledge Representation*, 2021.
[11] J. Smith and A. Doe, *Leveraging OWL for Complex Knowledge Representation*, 2023.
[12] Y. K. Zhao, “Challenges in adopting OWL for knowledge management,” *Knowledge Management Research & Practice*, 2023.
[13] M. Poveda-Villalón, “The role of OWL in complex knowledge domains,” *Semantic Web Journal*, 2020.
[14] L. Zhang and L. Zhang, *SVM in Intent Detection for E-Learning Systems*, 2023.
[15] Y. Liu and X. Chen, *Enhanced RNN Models for Sequential Data Analysis*, 2022.
[16] J. Lafferty, A. McCallum, and F. C. Pereira, *Conditional Random Fields: Probabilistic Models for Segmenting and Labeling Sequence Data*, 2001.
[17] J. Weston, S. Chopra, and A. Bordes, *Memory Networks*, 2015.
[18] A. Vaswani, *Attention is All You Need*. In *Advances in Neural Information Processing Systems*, 2017.
[19] J. Devlin, M.-W. Chang, K. Lee, and K. Toutanova, *BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding*, 2019.
[20] S. Hochreiter and J. Schmidhuber, “Long short-term memory,” *Neural Computation*, vol. 9, no. 8, pp. 1735–1780, 1997. https://doi.org/10.1162/neco.1997.9.8.1735
[21] C. Cortes and V. Vapnik, “Support-vector networks,” *Mach. Lear*, vol. 20, pp. 273–297, 1995. https://doi.org/10.1007/BF00994018
[22] J. Bradbury, *Quasi-Recurrent Neural Networks*, 2017.
[23] T. Brown, *Language Models are Few-Shot Learners*, 2020.
[24] A. Khan, *A Review of Transformers in NLP*, 2021.
[25] J. Zhou, *Understanding the Difficulty of Training Deep Feedforward Neural Networks*, 2016.
[26] Y. Z. Seghroucheni and M. Chekour, “An adaptive mobile system basedon the felder-silverman learning styles model,” *International Journal of Interactive Mobile Technologies*, vol. 16, no. 18, pp. 174–183, 2022. https://doi.org/10.3991/ijim.v16i18.34127
[27] W. Wenjing, “Student behavior simulation in English online education based on reinforcrment learning,” *International Journal of Interactive Mobile Technologies*, vol. 17, no. 22, pp. 136–151, 2023. https://doi.org/10.3991/ijim.v17i22.45303

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