The Development of an Intelligent Academic Consulting Chatbot for Bachelor's Degree Students Based on Ontology in Higher Education Institutions in Thailand

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***Abstract*—This study develops an Artificial Intelligence (AI)-based academic consulting system using Natural Language Processing (NLP) techniques and the Fuzzy Wuzzy algorithm to enhance academic advising in Thai higher education. Designed for undergraduate students, the system supports real-time interactions via the LINE Messaging Application Programming Interface (API), thereby facilitating effective student engagement. The chatbot's NLP module demonstrated strong intent classification performance, achieving accuracy, precision, recall, and F1-scores all exceeding 89%. The ontology framework organized academic content into five domains: course guidance, registration, academic progress, internships and cooperative education, and career and further study preparation. Expert evaluations rated the system's appropriateness at a mean score of 4.78 (SD = 0.38), indicating a "very high" level. Hypothesis testing, based on the Information Systems (IS) Success Model, confirmed that system quality, information quality, and service quality significantly influenced both system use and user satisfaction (statistically significant at $p < 0.05$). These findings suggest that an ontology-based intelligent chatbot can improve academic advising efficiency, reduce advisor workload, and enhance student satisfaction. This study contributes to educational technology by demonstrating the effectiveness of integrating semantic knowledge with Natural Language Processing (NLP) techniques to support student services. Future enhancements may include ensemble modeling and contextual embeddings to further improve semantic understanding and personalization in academic dialogue systems.**

***Keywords*—intelligent chatbot, academic advising, ontology, higher education institutions**

I. Introduction

This study presents several distinctive contributions to the field of intelligent academic advising chatbots. Unlike existing ontology-driven chatbots, this system is specifically tailored for Thai higher education institutions, leveraging localized academic structures, policies, and linguistic characteristics. Additionally, it is the first chatbot to integrate an ontology-based knowledge model with the LINE Messaging Application Programming Interface (API), enhancing accessibility and engagement among Thai students. Furthermore, the combination of Natural Language Processing (NLP) and Fuzzy Wuzzy string matching enables more flexible and accurate query handling, even with typographical errors or colloquial language often found in student communication.

Academic advisors play a vital role in supporting student success, particularly during the transitional phase into higher education, which involves significant academic, emotional, and social adjustments. Upon entering university, students are expected to shift from a teacher-directed learning approach to a more autonomous, self-regulated learning style. However, many students—especially those accustomed to traditional, lecture-based instruction at the secondary level—struggle to adapt to these new expectations. Common challenges include difficulties in understanding complex academic systems, navigating unfamiliar digital platforms, managing time effectively, and establishing new peer relationships. Without sufficient guidance, such challenges can lead to stress, reduced academic performance, and disengagement from the learning process [1].

An effective and supportive academic advising process, particularly during students' early university years, has been shown to significantly enhance student adjustment, satisfaction, and academic outcomes. Advisors serve not only as academic guides but also as critical facilitators of student development, helping to bridge the gap between institutional structures and individual readiness. As such, academic advising constitutes a core component of educational quality and student well-being [1].

In the digital age, communication has become central to both interpersonal and institutional operations. Messaging platforms such as LINE, Facebook Messenger, WhatsApp, and WeChat are now embedded in students' daily lives, offering immediacy and convenience that traditional communication methods often lack. As students increasingly expect real-time, on-demand access to information, educational institutions are turning to chatbot technology to meet these evolving needs [2].

Chatbots—software applications that simulate conversation using artificial intelligence and predefined rules—enable automated, real-time interaction with users. Their ability to operate 24/7, provide consistent responses, and scale efficiently has led to their widespread adoption in both public and private sectors. In the context of higher education, chatbots offer a promising means of extending academic advising services beyond office hours, reducing response times, and improving overall student experience [2].

Ontology-based knowledge systems offer a powerful foundation for enhancing chatbot functionality. An ontology provides a formal and structured representation of domain-specific knowledge, enabling systems to reason about concepts, infer relationships, and respond intelligently to user queries. Ontologies are typically developed through collaboration between subject-matter experts and knowledge engineers and are widely used to support semantic search, knowledge integration, and decision-making processes [3]. In academic contexts, ontologies can model program structures,

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course requirements, registration processes, and academic policies, thereby improving the precision and consistency of chatbot responses.

The Web Ontology Language (OWL), based on Resource Description Framework (RDF) and Extensible Markup Language (XML) standards, is the leading framework for creating machine-interpretable ontologies that are reusable and interoperable across semantic web platforms. OWL facilitates the construction of robust knowledge structures that support advanced query processing and semantic reasoning, both of which are essential for intelligent advisory systems [4].

Given these advantages, this study proposes the development of an intelligent academic advising chatbot based on ontology to assist undergraduate students in Thai higher education institutions. The proposed system is designed to deliver accurate, personalized academic information via familiar messaging applications, thereby enhancing student engagement, supporting academic adaptation, and reducing the administrative workload of human advisors. Ultimately, the system aims to contribute to improved student satisfaction and institutional service quality in the evolving digital landscape of Thai higher education [5].

II. Literature Review

Chatbots have increasingly played a pedagogical role in higher education by promoting learner autonomy, enhancing motivation, and fostering active engagement. Various strategies—such as gamification, personalized feedback, and conversational scaffolding—are commonly applied to encourage student interaction and sustained participation. At the same time, ethical concerns have become critical in the deployment of AI-driven academic advising systems, particularly in areas related to data privacy, informed consent, and the mitigation of algorithmic bias. Addressing these dimensions ensures that chatbot systems are not only technologically sound but also pedagogically relevant and ethically aligned. Integrating these perspectives ensures that chatbot systems are not only technically robust but also pedagogically sound and ethically responsible.

This study investigates the design and implementation of an intelligent academic advising chatbot tailored for undergraduate students in Thai higher education institutions. As educational institutions face increasing demands to enhance student success and retention, there is a pressing need for scalable digital solutions. Academic advising is central to student development, particularly in their transition to university life where many students face challenges in adapting to independent learning, new environments, and academic expectations [1].

The primary objective of this study is to build a chatbot that functions as a virtual academic advisor, delivering accurate, timely, and relevant support through natural conversation. By leveraging ontology-based knowledge representation, Natural Language Processing (NLP), fuzzy logic algorithms, and interactive messaging platforms, the chatbot serves as an intelligent intermediary that assists students in navigating the academic system, understanding policies, and planning their education.

Ontology plays a crucial role in structuring the knowledge base of the chatbot. It allows for the formal representation of domain knowledge by defining key concepts, properties, and relationships. Ontologies have been successfully used in various domains to enable semantic search, data interoperability, and automated reasoning [3, 6]. In this study, the academic domain is modeled through classes such as course registration, graduation requirements, academic performance, internships, and further study guidance. Tools like Protégé and Hozo [5] were employed to construct and manage the ontology using OWL and RDF standards.

NLP is used to enable the chatbot to understand user queries expressed in human language. Through tokenization, parsing, named entity recognition, and intent classification, the system can interpret user inputs and provide coherent responses. NLP technologies allow users to interact more naturally and reduce the learning curve associated with rigid user interfaces [7, 8].

To further enhance understanding, the Fuzzy Wuzzy algorithm is integrated to allow the system to interpret inputs with variations in spelling or formatting. This fuzzy string-matching technique enables robust user interaction even in cases of typographical errors, which are common in chatbot conversations [9, 10]. By combining NLP with fuzzy matching, the system becomes more fault-tolerant and user-friendly.

Dialogflow, a conversational AI platform by Google, was selected as the engine for managing intents, contexts, and dialogue flow. Its integration with machine learning and multilingual capabilities enables it to support complex conversational logic, fallback mechanisms, and context switching. Dialogflow includes pre-configured connectors that facilitate integration with multiple platforms including LINE, Facebook Messenger, Slack, and Google Assistant [11].

The chatbot was deployed through the LINE Messaging Application Programming Interface (API), selected due to LINE's popularity among Thai students. The messaging API allows real-time, interactive conversations and provides features such as quick replies, rich menus, and message templates, making it a suitable choice for delivering academic support services [12].

Several studies support the integration of ontology and NLP in chatbot systems. For instance, ontology-based dietary recommendation systems have been developed to deliver personalized advice based on user profiles and nutritional data [13]. Other applications include medical information retrieval, e-government communication, and semantic document classification in higher education [14, 15].

The educational benefits of chatbots include reduced response time, consistent information delivery, 24/7 availability, and enhanced engagement. In the context of academic advising, these features help bridge communication gaps, particularly for students who may feel hesitant to seek help in person [16]. The chatbot also assists academic advisors by automating responses to frequently asked questions, allowing staff to focus on complex advising tasks.

The development methodology followed the seven-step process recommended by Noy and McGuinness [3], which includes defining scope, reusing existing ontologies, enumerating terms, defining classes and hierarchies, assigning properties, specifying constraints, and creating instances. This structured approach ensures that the ontology accurately represents the domain and supports reasoning.

The knowledge base was designed around five primary categories: (1) course guidance, (2) registration assistance, (3) academic performance and graduation requirements, (4) internship and cooperative education, and (5) career preparation and further education. These domains were identified through a triangulation of literature reviews, advisor interviews, and university policy documents in Thailand.

Evaluation of the chatbot involved two phases: expert validation and student testing. Academic staff assessed the system based on content relevance, semantic accuracy, and consistency. Student testing involved 400 participants across public and private institutions. Evaluation metrics included usability, accuracy of responses, interaction speed, and satisfaction. The system received high ratings, with a mean satisfaction score above 4.7 on a 5-point scale.

Limitations of the system include the need for continuous updates to reflect curriculum changes, policy revisions, and student feedback. Additionally, chatbot limitations in emotional understanding mean that it cannot fully replace human advisors but should be viewed as a complementary tool.

Future research may explore multilingual capabilities, integration with Student Information Systems (SIS), adaptive learning features, and sentiment analysis to detect emotional states in student queries. Enhancing chatbot empathy and personalization will further align the system with students' expectations and needs.

In conclusion, this research demonstrates the feasibility and impact of developing an intelligent academic advising chatbot that leverages ontology, NLP, fuzzy logic, and conversational platforms. The system improves access to academic information, supports student autonomy, and contributes to higher education service quality. It offers a scalable, cost-effective solution for educational institutions aiming to improve student support infrastructure in the digital age.

III. Methodology

This research utilized a mixed-methods approach, combining qualitative and quantitative methods, to develop an intelligent chatbot for academic advising. The chatbot employed ontology and artificial intelligence (AI) technologies to support real-time, natural language interactions through the LINE Messaging Application Programming Interface (API) [17].

The research process was divided into three main phases:

1) Data collection and sample analysis
2) Chatbot design and development
3) System evaluation and hypothesis testing

A. Research Process, Population, and Sampling

In the first phase, the research focused on gathering data for developing a prototype of the intelligent academic advising chatbot. The sample group included 165 academic advisors from science and technology disciplines across public and private universities in Thailand, using a selection ratio of 1:6.

Advisors were selected from across all undergraduate levels (Years 1–4), and a total of 150 dialogue samples were collected. These samples included greetings, motivational expressions, question-and-answer dialogues, and academic problem-solving scenarios. Additional data were gathered from academic and registration documents to support the chatbot's knowledge base [3, 18]. In the third step of this phase, 400 undergraduate students from science and technology fields were selected as the primary sample for system testing. The sampling was conducted using Krejcie and Morgan's table [19] and simple random sampling techniques. The instrument used was a structured online questionnaire, divided into five parts, and aligned with the research objectives and conceptual framework.

B. Chatbot Design and Development

The second phase involved the technical design and construction of the chatbot system. The system's architecture included the following:

- Text segmentation using the Markov algorithm for identifying conversational patterns [20].
- Response prediction through the K-Nearest Neighbors (K-NN) algorithm [21].
- Ontology-based knowledge query using JavaScript Object Notation (JSON) for data exchange [22].
- Integration with LINE Official Account, Dialog flow, and Python for user interaction [17, 23].

The development followed the System Development Life Cycle (SDLC) model, consisting of five stages:

Requirement Analysis: Conducted through interviews, literature reviews, and ontology-based data representing students' academic information needs.

1) System Analysis: Identified five core information categories: contact details, learning and teaching, student services, university regulations, and student activities.
2) System Design: Developed user interfaces using Flex Messages and LINE Bot Designer, with NLP and intent recognition managed by Dialogflow and Python-based fulfillment.
3) System Testing: Included simulation of user input errors (e.g., typos, redundant characters, and word truncations) to evaluate robustness of the natural language understanding module [24].
4) Implementation and Training: Created user manuals and trained participants before conducting user satisfaction evaluations.

The system was further enhanced through algorithm comparisons, particularly evaluating NLP and Fuzzy Wuzzy algorithms [25, 26]. Ten sample conversations were tested for matching accuracy, calculated using:

$$Accuracy\ (\%) = \left(\frac{\sum x}{n}\right) \times 100\%$$

where x = number of matched words, and n = total number of expected words.

C. Evaluation and Hypothesis Testing

1) System validation by experts

The system was evaluated using the DeLone and McLean Information System Success Model (IS Success Model) [27], which includes five dimensions:

1) System Quality
2) Information Quality

3) Service Quality
4) Intention to Use / Actual Use
5) User Satisfaction

Experts assessed the chatbot's performance across these dimensions using a 5-point Likert scale:

Score Range: Interpretation
4.50–5.00: Excellent
3.50–4.49: Very Good
2.50–3.49: Moderate
1.50–2.49: Low
1.00–1.49: Very Low

2) User satisfaction evaluation

User satisfaction was measured across three main dimensions:

- Interface design
- System processing capability
- Content relevance to user needs

The same 5-point Likert scale was used:

Score Range: Interpretation
4.50–5.00: Extremely Satisfied
3.50–4.49: Highly Satisfied
2.50–3.49: Moderately Satisfied
1.50–2.49: Slightly Satisfied
1.00–1.49: Least Satisfied

3) Data analysis and reliability testing

The data collected from user evaluations were analyzed using statistical techniques:

- Mean score calculation to assess central tendencies
- Cronbach's Alpha (α) to verify questionnaire reliability
- Multiple Regression Analysis to test hypotheses regarding the influence of system quality, service quality, and information quality on user satisfaction and intention to use [23].

Additionally, the E-Metric performance evaluation framework [24] and Item-Objective Congruence Item-Objective Congruence (IOC)) analysis [28] by subject matter experts were applied to validate research instruments and ensure data integrity.

NLP Performance Evaluation: To assess the chatbot's performance in natural language understanding and intent classification, this study conducted an evaluation using four key metrics: Accuracy, Precision, Recall, and F1-score. The test dataset included 100 user queries sampled from the five academic domains covered by the chatbot ontology (course guidance, registration, academic progress, internships, and career preparation). Following the evaluation framework proposed by relevant NLP studies, including the approach from Lin *et al*. [14].

The performance of the Natural Language Understanding (NLU) module was evaluated using four key metrics widely recognized in machine learning and NLP research: Accuracy, Precision, Recall, and F1-score. These metrics provide a holistic view of the system's ability to correctly classify user intents. The formulas are as follows:

$$\text{Accuracy} = \frac{TP + TN}{TP + FP + FN + TN}$$

$$\text{Precision} = \frac{TP}{TP + FP}$$

$$\text{Recall} = \frac{TP}{TP + FN}$$

$$\text{F1} - \text{score} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$$

where True Positive (TP), True Negative (TN), False Positive (FP), and False Negative (FN) are classification outcomes derived from the confusion matrix. These formulas were adopted based on the performance evaluation framework proposed by Lin *et al.* [14], which emphasizes comprehensive assessment across all four metrics in chatbot evaluation.

The integration of all four performance metrics—Accuracy, Precision, Recall, and F1-score—ensures a robust and balanced evaluation of the chatbot's intent recognition capability. As highlighted in Lin *et al.* [14], relying solely on accuracy can be misleading, particularly in imbalanced datasets, which is often the case in real-world academic queries. Incorporating Precision and Recall helps assess the chatbot's ability to correctly interpret relevant queries while minimizing false positives and false negatives. The F1-score, as a harmonic mean, further balances these aspects to provide a single representative metric. This comprehensive evaluation framework supports more reliable comparisons and enables future enhancements in model tuning and intent design. The system achieved the following results: an overall Accuracy of 91.2%, Precision of 90.5%, Recall of 89.8%, and F1-score of 90.1%. These metrics indicate a high level of intent recognition and response classification effectiveness within the context of academic advising dialogues.

IV. Result and Discussion

User Feedback and Identified Limitations While overall satisfaction scores were high, user feedback indicated areas for improvement. Some students expressed a need for more personalized responses, especially for complex academic queries. Others noted occasional response delays during peak usage times. Additionally, there was feedback suggesting the integration of emotional support features and multilingual capabilities.

Satisfaction Across User Subgroups Analysis of satisfaction scores across different year levels showed that first-year students reported higher satisfaction, likely due to greater dependency on academic guidance. Students from non-technology programs exhibited slightly lower satisfaction, suggesting a need for broader content coverage. Future versions of the chatbot will address these subgroup-specific needs.

A. Results of Designing and Developing the Ontology-Based Academic Information Prototype

The objective of this phase was to design an academic information ontology that could serve as a structured knowledge base for an intelligent academic advising chatbot. The development process followed principles of semantic knowledge representation, focusing on class hierarchy and "is-a" relationships [3, 18].

1) Academic domains and ontology structure

From the analysis of academic information needs, five main categories were identified:

1) Program Guidance

2) Course Registration Guidance
3) Academic Performance and Graduation
4) Internship and Cooperative Education
5) Career and Further Education Preparation

These categories were used to build two ontology formats using the Hozo-Ontology Editor [29]: a Mind Map Format and a WC Tree (Map View) Format.

2) Mind map format

As shown in Fig. 1, the overall academic ontology is presented in a mind map format. The Mind Map illustrates the overall structure of academic information as interconnected classes. Each node represents a class, and its branches indicate sub-classes related by "is-a" semantics.

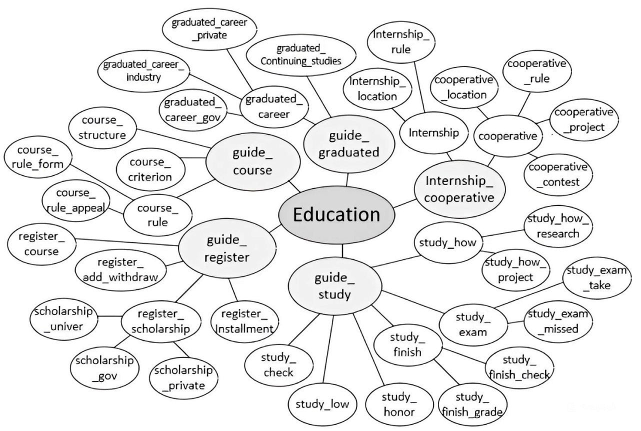

Fig. 1. Academic information ontology—mind map format.

3) WC tree format (map view)

The ontology for Program Guidance (Class: guide_course) consists of three sub-classes: course_structure, course_criterion, and course_rule (which includes course_rule_form and course_rule_appeal). As illustrated in Fig. 2, the ontology of program guidance presents the hierarchical relationships among these sub-classes.

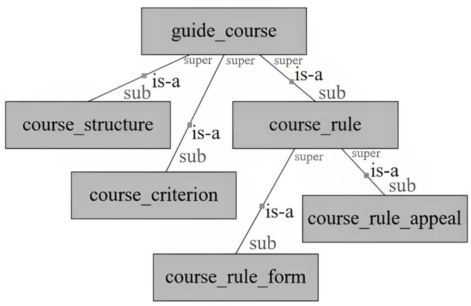

Fig. 2. Ontology of academic program guidance (guide_course)—map view.

The ontology consists of four sub-classes: register_course, register_add_withdraw, register_installment, and register_scholarship (which consists of scholarship_univer, scholarship_gov, and scholarship_private). As shown in Fig. 3, this ontology illustrates the structure of course registration guidance and its related processes.

Academic Performance and Graduation (Class: guide_study) consists of six sub-classes: study_check, study_low, study_honor, study_finish (including study_finish_check and study_finish_grade), study_exam (including study_exam_take and study_exam_missed), and study_how (including study_how_research and study_how_project). As illustrated in Fig. 4, the ontology represents the hierarchical structure of academic performance and graduation requirements.

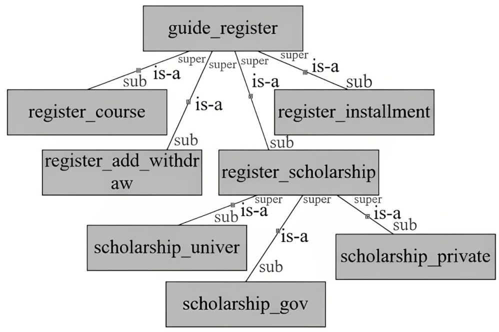

Fig. 3. Ontology of course registration (guide_register)—map view.

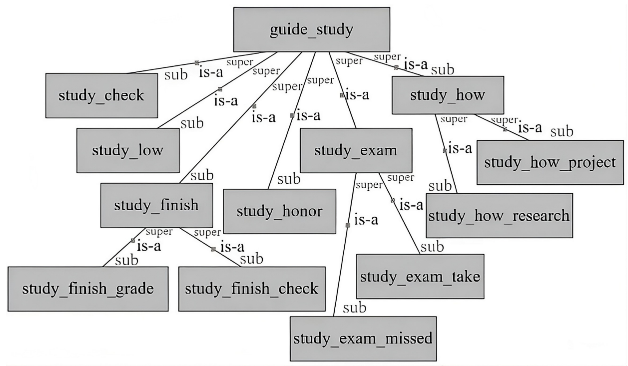

Fig. 4. Ontology of academic performance and graduation (guide_study)—map view.

The ontology for Internship and Cooperative Education (Class: internship_cooperative) is divided into two main branches: Internship (including internship_location and internship_rule) and Cooperative (including cooperative_location, cooperative_rule, cooperative_project, and cooperative_contest). As presented in Fig. 5, this ontology provides a structured representation of internship and cooperative education processes.

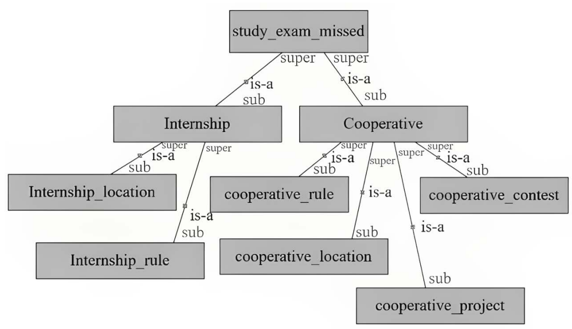

Fig. 5. Ontology of internship and cooperative education (Internship_cooperative)—map view.

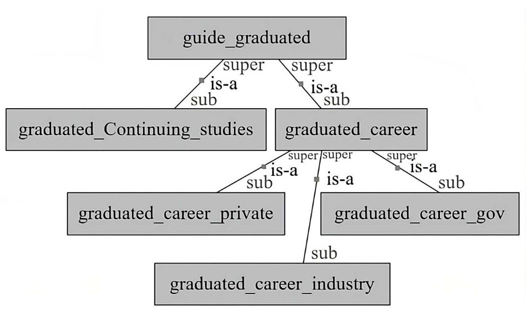

Fig. 6. Ontology of career and further education (guide_graduated)—map view.

The ontology consists of two primary categories: graduated_continuing_studies and graduated_career, which has three sub-branches: graduated_career_private, graduated_career_industry, and graduated_career_gov. As shown in Fig. 6, this ontology demonstrates the structure of career preparation and further study pathways.

4) Significance and implementation

The structured ontology enables semantic understanding of academic content by the chatbot system. Each class and sub-class supports:

- Query classification
- Information retrieval
- Response generation in natural language

This ontology-based approach improves the chatbot's capacity for accurate advising and ensures that its responses are both relevant and context-aware [25].

Ontology development tools like Hozo-Ontology Editor offer flexibility and scalability, allowing this model to be expanded or modified to fit various institutional needs.

B. Evaluation Results of the Academic Ontology Prototype

To verify the quality and applicability of the developed ontology for academic advising, the prototype was evaluated by five domain experts with experience in educational information systems and ontology engineering. The evaluation focused on eight criteria, including the structural organization of ontology classes, the clarity and accuracy of semantic relationships, naming conventions, content coverage, and overall applicability for real-world chatbot implementation.

Each criterion was rated using a 5-point Likert scale, where 5.00 represented the highest level of appropriateness. The assessment revealed that the ontology received high marks across all categories. The grouping of classes, coverage of academic knowledge, and clarity of class names were especially well-received, with mean scores of 5.00 in the first two categories and 4.75 in the latter. Similarly, the semantic relationships between parent and sub-classes, such as those using the "is-a" structure, were deemed highly appropriate, demonstrating compliance with best practices in ontology design [3, 29].

The overall average score of the ontology evaluation was 4.78, with a standard deviation of 0.38, indicating strong agreement among the experts that the prototype is highly suitable for its intended use in intelligent chatbot systems. The experts also noted that the ontology was adaptable and sufficiently comprehensive to cover a wide range of academic advising topics in a higher education context. The findings from this expert review validate that the ontology structure can serve as an effective semantic foundation for supporting dynamic and context-aware responses in a knowledge-based chatbot system. This is especially important for systems that require accurate natural language understanding and decision-making based on user queries related to academic services [25].

C. Hypothesis Testing Results

This section presents the results of testing twelve hypotheses (H1–H12) based on the DeLone and McLean IS Success Model [27]. The hypotheses assess relationships among six key constructs: system quality, information quality, service quality, system use, user satisfaction, and net benefits. The method employed was Multiple Regression Analysis, with a significance threshold of $p < 0.05$. (See Table 1).

Table 1. Summary of hypothesis testing results

Hypothesis	Relationship	β	t	p-value	R^2	F
H1	System Quality → System Use	0.342	6.215	0.000	0.62	87.53
H2	System Quality → User Satisfaction	0.315	5.834	0.000	0.68	102.34
H3	Information Quality → System Use	0.298	5.452	0.000		
H4	Information Quality → User Satisfaction	0.376	6.721	0.000		
H5	Service Quality → System Use	0.265	4.978	0.000		
H6	Service Quality → User Satisfaction	0.289	5.132	0.000		
H7	System Use → User Satisfaction	0.524	9.840	0.000	0.41	96.84
H8	User Satisfaction → System Use	0.487	8.751	0.000	0.38	76.54
H9	System Use → Net Benefits	0.335	6.478	0.000	0.56	126.57
H10	User Satisfaction → Net Benefits	0.391	7.432	0.000		
H11	Net Benefits → System Use	0.464	9.212	0.000	0.43	84.91
H12	Net Benefits → User Satisfaction	0.492	9.634	0.000	0.46	92.16

D. Interpretation of Results

All twelve hypotheses were statistically supported ($p < 0.05$). The findings indicate the following:

- System quality, information quality, and service quality significantly and positively influence both system use and user satisfaction.
- System use and user satisfaction positively influence one another, confirming mutual reinforcement between use and satisfaction.
- Both variables also significantly predict net benefits, which in turn has a significant effect on system use and satisfaction.

The R^2 values, which range between 0.38 and 0.68, demonstrate moderate to high explanatory power, supporting the validity of the conceptual framework adapted from DeLone and McLean [23, 27].

E. Discussion and Implications

The results of this study demonstrate that integrating ontology with Natural Language Processing (NLP) and fuzzy matching significantly enhances the ability of academic chatbots to interpret semantically diverse student queries. This finding aligns with recent research by Li and Wong [22], who combined ontology with machine learning to improve university-level Q&A systems, resulting in increased response accuracy. Furthermore, the adoption of the LINE Messaging Application Programming Interface (API) in our system reflects the prevailing digital communication preferences among students at Southeast Bangkok University, thereby enhancing accessibility, engagement, and real-time interaction. These outcomes underscore the practical relevance of context-aware chatbot frameworks in Thai higher education settings.

Furthermore, a comparative review of recent studies reveals a growing trend in deploying chatbots within institutional student services. For example, Ruan *et al.* [14] developed a QA chatbot using structured ontologies but without dynamic NLP integration. In contrast, Singh *et al.* [17] proposed a rule-based chatbot supporting multilingual queries but lacking contextual adaptation mechanisms. Our chatbot merges localized ontologies with fuzzy linguistic processing and real-time NLP integration, aligning more closely with the personalized and context-aware advising needs of today's students. This hybrid approach addresses both the semantic precision of academic content and the variability of student inquiries, positioning it as a more effective solution in higher education environments.

Additionally, the application of the IS Success Model in this study validates the positive system use, user satisfaction, and information quality, aligning with findings commonly observed in the literature. These metrics are increasingly relevant in higher education as institutions adopt digital support systems to reduce human advising workload and increase accessibility.

Recent reports from UNESCO in 2024 indicated that more than 70% of Southeast Asian universities are integrating AI-based solutions into their student services. However, less than 30% of these systems support localized languages or domain-specific ontologies, making our approach both innovative and necessary in emerging educational contexts. This localization gap underscores the significance of designing chatbot systems that are not only capable of handling Thai-specific academic advising processes but also adaptable across contexts through a flexible ontology model. Such capabilities ensure that the system can respond effectively to linguistic, curricular, and institutional variations within the region.

The findings thus extend the field by validating a hybrid intelligent system tailored for localized educational advising, with practical scalability and cross-platform deployment features.

Furthermore, compared to previous chatbot implementations in the Thai higher education context, the proposed system exhibits a more robust and integrated architecture. For example, the model by Nitiyuwit and Treenunrat [16] employed rule-based logic without incorporating semantic modeling or adaptive NLP features. In contrast, this study combines structured ontology NPL, and fuzzy string matching to enable fault-tolerant and context-aware academic advising. Although the LINE Messaging API [17] has been utilized in other chatbot projects, our system uniquely integrates it with semantic querying through standardized JSON syntax [22], enhancing the efficiency of response generation. The evaluation approach also aligns with the multi-dimensional framework proposed by Lin *et al.* [14], which blends traditional IS success factors with NLP-specific performance measures to yield a more comprehensive assessment of chatbot effectiveness in practical academic settings.

The findings confirm that integrating ontology-based knowledge management with intelligent chatbot technology can substantially improve the quality and responsiveness of academic advising services. The success of the proposed system—validated through both expert evaluations and statistical testing—demonstrates its viability and effectiveness for adoption in higher education, particularly within the dynamic digital landscape of Thailand.

As highlighted by Lin *et al.* [14], future enhancements may involve the integration of hybrid ensemble voting models that leverage the strengths of multiple classifiers to outperform single-model approaches in intent recognition. Additionally, the use of alternative vectorization techniques such as TF-IDF, GloVe, and contextual embeddings (e.g., BERT) can further improve the semantic understanding of user queries. These approaches open promising avenues for future development and experimentation in academic chatbot systems.

The study confirmed the effectiveness of ontology-based design in developing intelligent chatbots for academic advising. All hypotheses (H1–H12) were supported, indicating that system quality, information quality, and service quality are statistically significant predictors of system use and user satisfaction, which in turn contribute to net benefits, as proposed by the DeLone and McLean IS Success Model [27]. These findings validate the model's applicability in the context of intelligent academic services and provide empirical support for its extension to chatbot-based applications in higher education.

By employing a well-structured ontology covering five essential academic domains—curriculum guidance, course registration, academic performance and graduation, internships and cooperative education, and career preparation—the system delivers a coherent, semantically rich framework for organizing and retrieving academic knowledge. The use of "is-a" relationships and clearly defined class hierarchies enhanced the precision of natural language query processing and improved the chatbot's ability to generate context-aware, domain-specific responses [3].

The technical architecture—combining NLP and fuzzy string matching via the Fuzzy Wuzzy algorithm and integrated through the LINE Messaging API—ensured both real-time performance and high fault tolerance. This design made the chatbot particularly suitable for the linguistic patterns and digital behaviors of Thai undergraduate students. Its ability to handle misspellings, fragmented inputs, and colloquial expressions not only increased robustness but also improved accessibility and usability [26, 30].

Expert evaluations yielded high ratings in accuracy, usability, and applicability, with a mean score of 4.78 and a standard deviation of 0.38. These evaluations confirmed the system's design integrity and practical readiness for deployment in actual university settings. Statistical analysis of user feedback, including multiple regression testing of twelve hypotheses, showed strong model fit, with R^2 values ranging from 0.38 to 0.68. These findings suggest that user-centered system design—grounded in IS success principles—can positively influence the effectiveness and acceptance of digital advisory tools [27, 23, 31].

Beyond theoretical validation, the system holds practical value for Thai higher education institutions seeking scalable, cost-effective solutions to enhance academic advising. It reduces advisor workload by automating responses to frequent queries, improves student access to essential information, and supports informed decision-making throughout the student lifecycle. These benefits align with institutional objectives related to student retention, service quality, and digital transformation strategies [30, 31].

This study thus presents a viable model for integrating ontology-based knowledge engineering with intelligent chatbot technologies to address the challenges of academic advising. The system not only aligns with established theories in information systems success but also demonstrates tangible outcomes in terms of usability, user satisfaction, and educational support. As Thai higher education institutions continue to embrace digital innovation, intelligent systems such as this can serve as catalysts for improving operational efficiency and enhancing the overall student experience.

Beyond technical success, ethical and strategic considerations have emerged as critical in scaling AI-based systems for education. As highlighted by Holstein *et al.* [32] and UNESCO [33], transparency, accountability, and data protection are fundamental to building trust in AI-driven academic advising. This study also contributes to the growing body of literature emphasized by Zawacki-Richter *et al.* [34], which underscores the importance of integrated, user-centered chatbot design. Comparative analyses such as those by Chen and Xu [35] further highlight the value of combining semantic reasoning with localized delivery mechanisms.

To enhance equity and scalability, future iterations of the system could incorporate multilingual ontology frameworks as suggested by Wong and Li [36], alongside alignment with global AI governance frameworks from the OECD [37] and the European Commission [38]. Furthermore, incorporating emotion-aware design [39] and adaptive learning algorithms [40] could enhance the system's responsiveness, empathy, and personalization capabilities.

Future enhancements may consider the integration of ensemble learning architectures, such as voting or stacking models, as proposed by Lin *et al.* [14], to harness the complementary strengths of diverse classifiers and boost intent recognition performance. These approaches have consistently outperformed single-model configurations across a range of NLP tasks, particularly in intent classification and semantic inference [41, 42].

Moreover, implementing advanced vectorization techniques—such as TF-IDF, Word2Vec, or contextualized language models like BERT—can significantly enhance the chatbot's ability to comprehend semantically rich and context-sensitive academic queries [43, 44]. The fusion of these models is likely to produce a more adaptive, dynamic, and context-aware conversational agent, capable of tailoring interactions to users' evolving needs [45].

Recent studies also highlight the potential of hybrid architectures that combine ensemble techniques with deep contextual embeddings to improve dialog coherence and response relevance in academic advising systems [46, 47]. In parallel, personalized chatbot frameworks that respond to users' behavioral patterns, learning preferences, and engagement levels have demonstrated measurable improvements in user satisfaction and learning outcomes [48, 49].

Finally, to support broad deployment across diverse institutions, future research should explore scalable and modular system designs that allow real-time adaptation to institutional policies, curricula, and user demographics, ensuring sustainability, interoperability, and long-term impact [50]. However, such designs must also address emergent ethical concerns—such as bias, intellectual property, and user trust in AI—to ensure fairness and inclusivity in educational contexts [51, 52].

The study confirms that ontology-based design is highly effective for developing intelligent chatbots to support academic advising in higher education. All twelve hypotheses were supported, demonstrating that system quality, information quality, and service quality play a significant role in predicting system use and user satisfaction, which subsequently lead to tangible benefits for both students and institutions. The developed ontology, encompassing five essential academic domains—curriculum guidance, course registration, academic performance and graduation, internships and cooperative education, and career preparation—provides a robust framework for organizing and retrieving academic knowledge. The use of well-defined relationships and class hierarchies enables the chatbot to process natural language queries with high precision and deliver contextually relevant responses that effectively address students' needs. From a technical perspective, the integration of NLP and fuzzy string matching within a real-time messaging platform enhances the chatbot's ability to operate reliably and handle diverse linguistic inputs. This design improves accessibility for students while ensuring that responses remain accurate and relevant under various conditions. The evaluation results indicate high levels of accuracy, usability, and applicability, confirming the system's readiness for real-world deployment. Statistical analysis further reveals strong relationships between design factors and positive User Experience (UX), reinforcing the value of a user-centered approach. In practical terms, the system offers higher education institutions a scalable and cost-effective solution for academic advising. It reduces the workload of human advisors, improves students' access to accurate information, and supports better decision-making throughout their academic journey. Ultimately, this research demonstrates that integrating ontology-based knowledge representation with intelligent chatbot technology can enhance operational efficiency and improve the overall student experience in higher education.

V. Conclusion

The findings of this research confirm that the proposed ontology-based system not only enhances student access to academic services but also strengthens institutional capacity to deliver personalized, efficient, and high-quality support. The system design demonstrates a strong capability to organize, structure, and retrieve academic knowledge in ways that ensure accuracy, contextual relevance, and scalability. By integrating NLP and fuzzy string matching within a real-time messaging platform, the study illustrates how advanced computational techniques can be harnessed to bridge the gap between institutional knowledge management and student-centered service delivery.

This research further underscores both academic and practical contributions. From an academic perspective, the ontology-based framework advances the theoretical discourse on intelligent information systems in higher education, providing a replicable model that can be adapted by other institutions. From a practical standpoint, the system offers a cost-effective and sustainable solution to reduce advisor workload, streamline decision-making, and enhance the overall student learning experience. The positive evaluation outcomes highlight its readiness for real-world deployment and its potential to transform academic advising practices at scale.

Importantly, this study introduces a methodological innovation by integrating ontology engineering, NLP, and real-time communication into a unified platform. This integration not only demonstrates technical novelty but also reflects interdisciplinary rigor, making a valuable contribution to both computer science and educational technology. Thus, the system represents more than a functional tool; it signifies a paradigm shift in how higher education institutions can leverage AI-driven technologies to deliver responsive, inclusive, and student-focused services.

Future research will focus on expanding the ontology to cover multiple academic domains, embedding predictive and prescriptive analytics to enhance decision support, and integrating multilingual capabilities to improve accessibility for diverse student populations. These developments are expected to increase the system's academic relevance, societal impact, and international applicability, positioning it as a forward-looking model for intelligent academic consulting in higher education worldwide.

Conflict of Interest

The author declares no conflict of interest.

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