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DEVELOPMENT AND EVALUATION OF A CONCEPTUAL FRAMEWORK FOR AN INTELIGENT PROJECT TOPIC RECOMMENDATION AND TIOMELINE SYSTEM IN UNDERGRADUATE PROJECT COUTSES TO ENHANCE ALIGNMENT WITH COURSE ENHANCE ALIGNMENT WITH COURSE LEARNING OUTCOMES

ANGSANA PHONSUK[1], SUWUT TUMTHONG[2*]
[1,2]Rajamangala University of Technology Suvarnabhumi, Bangkok, Thailand
E-mail: [1]166491432006-st@rmutsb.ac.th, [2*]Suwut.t@rmutsb.ac.th

ABSTRACT

Undergraduate capstone project development faces critical challenges, including students' difficulty in selecting topics aligned with course learning outcomes, inefficient time management, and prolonged topic approval processes that delay graduation timelines. This research develops and evaluates a conceptual framework for an intelligent project topic recommendation and timeline management system integrating Constructive Alignment theory, artificial intelligence, and project management principles. The framework comprised five core components data management and integration,intelligent recommendation system (Hybrid techniques), natural language processing for topic-CLO analysis, automated timeline planning and continuous evaluation Expert evaluation by nine specialists across five dimensions showed highly favorable results (mean = 4.50, SD = 0.56), with System Quality (M = 4.56), Intelligence Quality (M = 4.44), Decision Quality (M = 4.52), Learning Quality (M = 4.44), and User & Environment Quality (M = 4.56) all achieving "High" to "Highest" appropriateness levels. The developed framework has significant potential to address capstone project challenges and is feasible for practical implementation in educational institutions.

Keywords: *Project Topic, Recommendation, Timeline System, Chatbot, Tracking, Course Learning Outcomes*

1. INTRODUCTION

Proposing an undergraduate capstone project topic is a critical step and crucial for graduation success, as it demonstrates students' ability to integrate knowledge and skills acquired throughout their studies. However, a significant problem frequently encountered in many educational institutions is that students' proposed project topics often do not adequately align with the defined Learning Outcomes (LOs) of the course, which include cognitive abilities, practical skills, and expected professional development. This misalignment results in significant delays in the topic approval process and the commencement of actual research, requiring students to spend extended time refining and revising their topics multiple times. This can even impact students' normal academic schedules. Constructive Alignment between curriculum objectives, learning activities, and assessment methods is critically important for the quality of teaching and learning, student skill development, and educational process effectiveness [1]. When project topics lack alignment with the curriculum, assessment loses its logical connection to curriculum objectives, which may negatively affect student skill development and academic progress, resulting in prolonged topic proposal periods and students experiencing difficulty and confusion when modifying topics.

Artificial Intelligence (AI) technology, particularly Intelligent Recommender Systems and Conversational AI combined with Intelligent Educational Systems, has high potential in addressing these challenges. Intelligent recommender systems can analyze massive data sets by integrating various data sources such as curriculum learning outcomes, student academic records, learning characteristics, and personal interests to provide project topic recommendations that align with curriculum objectives. According to research by Mahfouz et al. [2], educational recommender systems can analyze students' academic records to develop customized study plans suited to individual needs and strengths. Furthermore, AI-powered intelligent educational systems using Natural Language Processing can

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provide personalized learning by adjusting content and task difficulty to match student abilities and needs, coupled with personalized feedback that increases student motivation and understanding [3]. Advanced AI-based Chatbots can provide 24-hour advising services, answering questions and providing real-time recommendations about the alignment of proposed topics with the curriculum. According to Roca et al. [4], AI-powered Chatbot systems can assist in monitoring and analyzing student interactions, recording and classifying frequently asked questions to help identify weaknesses in the topic recommendation process.

To address these challenges, the researchers developed an intelligent undergraduate project topic recommendation and timeline management system that integrates AI technology with data analysis methods. The system comprises three main interconnected components: 1) an Intelligent Recommendation System using AI and Machine Learning techniques [5] to analyze curriculum learning outcomes and student academic data to provide project topic recommendations appropriately aligned with the curriculum; 2) a Monitoring and Tracking System [6] that records topic approval status in real-time, provides appropriate alerts when delays occur, and tracks individual student progress to help reduce the time required for topic proposal; and 3) an Intelligent Chatbot system that provides 24-hour student support services, answering questions and providing guidance on refining and aligning topics with the curriculum, along with integrated guidance and serving as an educational information resource for students. Advanced AI-based Chatbots offer additional advantages for addressing topic approval delays, providing 24-hour advising services and answering questions about the alignment of proposed topics with curriculum requirements, significantly reducing response delays and students' wait times for advisor feedback. According to Roca et al. (2024), AI-powered Chatbot systems can assist in monitoring and analyzing student interactions, recording and classifying frequently asked questions to help identify weaknesses in the topic recommendation process, enabling continuous improvement of advisory support. Furthermore, these technologies can provide immediate preliminary feedback on topic-CLO alignment before formal advisor review, enabling students to self-correct and streamline the approval process. Integrating these AI technologies into a comprehensive system addressing both topic recommendation and timeline management offers a promising and evidence-based pathway to address the documented challenges of topic-CLO alignment and inefficient timeline management identified above.

2. RESEARCH OBJECTIVES

2.1 To develop the conceptual framework and components of an intelligent project topic recommendation and timeline management system for undergraduate capstone courses.

2.2 To develop an intelligent project topic recommendation and timeline management system for undergraduate capstone courses.

2.3 To evaluate the appropriateness of the conceptual framework for an intelligent project topic recommendation and timeline management system for undergraduate capstone courses.

3. RESEARCH HYPOTHESIS

3.1 The structure of the five system components will demonstrate consistency and systematic interconnectedness

3.2 The system structure will be stable and sufficiently reliable for prototype development.

4. RESEARCH SCOPE

4.1 Constructive Alignment

Constructive Alignment is a learning design approach of paramount importance in promoting meaningful learning that emerges from learner engagement [7]. It emphasizes that precise alignment between intended learning outcomes, learning activities, and assessment methods is the key to creating effective curricula. Teachers employing constructive alignment can verify that students engage in appropriate learning activities to achieve defined outcomes, enabling students to develop deep understanding and apply knowledge effectively [8]. Measurement tools have been developed to assess alignment levels from the student perspective, helping teachers refine curriculum design for greater effectiveness.

Project-based learning has been proven to be an effective teaching methodology for developing essential student skills. From a study of Joo and colleagues [9], the capstone project represents the pinnacle of the curriculum, synthesizing and integrating all knowledge students have acquired. Project-based learning promotes student development of problem-solving skills, teamwork collaboration, communication skills, and the ability to apply knowledge to solve real-world problems. Furthermore, systematic analysis [10] reveals that effective capstone projects typically span approximately one semester, involve students working in small groups, and maintain high

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relevance to real-world contexts. Meta-analytic studies [11] confirm that project-based learning significantly enhances academic achievement, critical thinking skills, and positive attitudes toward learning.

Learning environments play a crucial role in promoting student learning and skill development. According to theory of Jonassen [12], well-designed learning environments create contexts that facilitate learner understanding through engagement and exposure to authentic problems. Student-centered learning environments help develop critical thinking skills and enable effective application of knowledge in diverse situations [13]. However, effective learning environments must align with context, cognitive development, and individual differences. Research [13] demonstrates that applying scientific design with constructivist theory can increase motivation and improve student learning strategies. Furthermore, effective learning environments must align with context, cognitive development, and individual differences [14].

The Understanding by Design (UbD) framework developed by Wiggins and McTighe [15] emphasizes the importance of backward curriculum design, beginning with defining enduring understanding—core concepts students should retain long after course completion. Assessment methods are then designed to measure this understanding, and appropriate learning activities are finally designed. This approach gives curricula clear purpose and systematic development [16]. Application of UbD in capstone curriculum design has resulted in improved student learning efficiency [16]. The framework describes the six facets of understanding, helping teachers design diverse and varied assessments [17].

Regulated learning processes are closely related to student success, particularly in capstone projects. Research indicates that students who can self-regulate their learning processes demonstrate higher likelihood of achieving educational goals [18] . Developing time management skills, goal-setting, feedback provision, and reflection enhances students' capacity for self-regulated learning [19]. Summary of multiple studies reveals that self-regulated learning strategies such as time management, effort control, and help-seeking are important for success in online learning environments [19]. Further studiesdemonstrate that metacognitive support provision enhances the effectiveness of self-regulated learning and improves student learning experiences [20][21]

Table 1: Synthesis Of Teaching And Learning Processes

Component	Content	Ref.
Constructive Alignment	Constructive Alignment is an important learning design system that links intended learning outcomes, teaching activities, and assessment methods in alignment. Research shows that creating clear alignment helps students engage in appropriate learning activities, resulting in deep understanding and effective knowledge application.	[7],[8]
Project-Based Learning	Projects represent the pinnacle of the curriculum, synthesizing and integrating knowledge students have learned. Studies show that projects spanning approximately one semester with students working in groups of 4-5 are highly effective. Project-based learning develops problem-solving skills, teamwork collaboration, and communication skills significantly.	[9],[10],[11]
Learning Environments	Well-designed learning environments create contexts that promote learner understanding through practice. Student-centered learning environments develop critical thinking skills and effective knowledge application. However, effective environments must align with context, cognitive development, and individual differences.	[12],[13],[14]
Understanding by Design	The UbD framework emphasizes backward curriculum design, beginning with defining enduring understanding, then designing assessment and appropriate learning activities. This approach gives curricula clear purpose and higher efficiency.	[15],[16],[17]
Regulated Learning Processes	Systematic self-regulated learning is important for student success. Developing time management, goal-setting,	[18],[19],[20],[21]

Component	Content	Ref.
	feedback provision, and metacognitive support helps students better control their learning processes, increasing independence and responsibility for learning.	

4.2 Recommender systems

Recommender systems are important tools for managing vast amounts of data and play a key role in improving user experience. These systems filter data and recommend products, content, or services by considering past behavior, preferences, and interaction patterns [22][23]. In educational contexts, recommender systems help reduce the time and effort learners expend searching for appropriate content while improving learning experience quality through provision of individually relevant content. Fundamental recommender system techniques include multiple approaches: Collaborative Filtering (CF), which identifies users with similar preferences from rating history; Content-Based Filtering (CBF), which recommends items based on characteristics of previously preferred items; and Matrix Factorization, which reduces data dimensionality to identify latent features [24]. These approaches provide important foundations for developing more adequate recommender systems.

4.2.1 Hybrid AI Recommendation Systems

Although each individual technique has merits, each also has limitations. For example, Collaborative Filtering suffers from cold-start problems (when new users or items are introduced), while Content-Based Filtering often causes users to see only categories they already prefer. Hybrid recommender systems have emerged to combine the strengths of various approaches [25][26]. These systems employ advanced Deep Learning techniques such as Neural Collaborative Filtering (NCF) to capture non-linear relationships between users and items. The system can learn from more complex data and provide more accurate recommendations. Additionally, hybrid systems effectively reduce the cold-start problem by combining data from multiple sources [27], making them appropriate for educational programs with continuously new students and curricula.

4.2.2 Personalized Learning Resources

Adjusting content to individual needs is a key principle in modern education. Personalized Learning Resources involve creating student profiles encompassing diverse data such as learning levels, learning styles, interests, and educational goals [28]. Based on this information, systems can analyze learning behaviors, identify knowledge gaps, and select and prioritize content to align with learning goals and student capabilities [29][30]. This approach not only promotes more efficient learning but also reduces frustration and increases learning motivation.

4.2.3 LSTM-Based Educational Recommender Systems

Long Short-Term Memory (LSTM) is a neural network type designed to handle sequential data and efficiently remember long-term relationships. Unlike traditional RNNs suffering from vanishing gradient problems, LSTM features a Memory Cell structure controlled by gates (Input Gate, Forget Gate, Output Gate) to manage data flow [31]. In educational contexts, LSTM-based recommender systems can model the evolution of learner interests by distinguishing long-term and short-term interests [32]. These systems incorporate Attention Mechanisms to assign different weights to different interactions. Recent studies demonstrate that such systems improve recommendation accuracy and provide more appropriate, timely recommendations [33]

4.2.4 AI Agent Theory

In recent years, AI Agent technology in education has received increasing attention. Intelligent Agents are computer programs capable of perceiving their environment, making decisions, and acting independently to achieve defined goals [34]. AI Agents possess memory management capabilities, enabling storage and processing of complex, long-duration data. In education, AI Agents can serve various roles including teaching assistants, learning assessors, or even peer learners [35]. These agents can continuously interact with students, analyze their understanding, and provide individualized support to significantly enhance educational quality.

4.2.5 Multi-Agent Systems

Multi-Agent Systems (MAS) extend single AI Agent concepts to comprise multiple intelligent agents working collaboratively, with each agent having specific roles and capabilities. They can communicate and coordinate through established mechanisms to solve complex problems [36]. In education, Multi-Agent Systems have interesting applications including simulating virtual classrooms with agents assigned roles such as Teacher Agent, Student Agents, and Tutor Agents to create virtual interactions and learning [37]. Additionally, Multi-

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Agent Systems assist in instructional design by having multiple agents collaborate to create high-quality, diverse activities and provide efficient feedback through multi-perspective data analysis [38].

4.2.6 Deep Learning

Deep Learning uses multi-layer neural networks to learn complex, abstract data representations. Deep Learning's effectiveness derives from its ability to automatically "mine" important features from raw data. Various Deep Learning architectures address different data types: Convolutional Neural Networks (CNN) handle image data using convolution operations to detect image patterns [39]; Recurrent Neural Networks (RNN) and LSTM handle sequential time-series data by maintaining historical information. Additionally, Autoencoders reduce data dimensionality [40], and Attention Mechanisms emphasize important data [40][41]. In educational recommender systems, these Deep Learning techniques improve recommendation accuracy, reduce data sparsity and cold-start problems, and enable systems to learn from multi-format data including text, images, and video.

Table 2 Recommended System synthesis

Component	Content	Ref.
Recommender Systems	Recommender systems are tools for filtering data and recommending products/content to users based on user behavior and preferences. These systems reduce search time for appropriate information and improve user experience using techniques such as Collaborative Filtering (CF), Content-Based Filtering (CBF), and Matrix Factorization. (CF), Content-Based Filtering (CBF) และ Matrix Factorization	[22],[23],[24]
Hybrid AI Recommendation	Hybrid recommender systems combine strengths of various methods such as Collaborative Filtering and Content-Based Filtering to solve problems of individual methods. These systems use Deep Learning techniques such as Neural Collaborative Filtering (NCF) to capture non-linear relationships between users and items, and effectively reduce the Cold-Start Problem.	[25],[26],[27]
Personalized Learning Resources	Learning resources adjusted to individual needs and learning patterns, involving student profiling, learning behavior analysis, content selection and prioritization to align with learning goals and learner capabilities, promoting efficient and personalized learning.	[28],[29],[30]
LSTM-based Educational Recommender	Educational recommender systems using Long Short-Term Memory (LSTM), a neural network capable of remembering long-term relationships in sequential data. These systems model long-term and short-term learner interests separately and use Attention Mechanisms to assign different weights to different interactions, enabling appropriate and timely educational resource recommendations.	[31],[32],[33]
AI Agent Theory	AI Agent theory studies intelligent agents capable of perceiving environments, making decisions, and acting independently to achieve defined goals. AI Agents in education can serve as teaching assistants, student assessors, or educational tools, and can manage memory while processing complex and long-duration data.	[34],[35]
Multi-Agent Systems	Systems comprising multiple AI Agents working collaboratively, with each agent having specific roles	[36],[37],[38]

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Component	Content	Ref.
	and capabilities, able to communicate and coordinate to solve complex problems. In education, Multi-Agent Systems enable simulating classrooms, designing learning activities, and providing efficient feedback through strategies such as Task Decomposition and Collaborative Decision-Making.	
Deep Learning	Deep learning using multi-layer neural networks to learn complex data representations. Deep Learning employs techniques such as Convolutional Neural Networks (CNN) for image data, Recurrent Neural Networks (RNN) and LSTM for sequential time-series data, Autoencoders for dimensionality reduction, and Attention Mechanisms to emphasize important data, improving recommendation accuracy and classification.	[39],[40],[41]

4.3 Natural Language Processing

Natural Language Processing (NLP) is a fundamental technology for educational systems, playing a role in converting text into vector representations called Embedding Vectors [42] to analyze similarity and relationships between content. Word2Vec [42] creates a new approach for representing words in continuous vector space, enabling semantically similar words to have similar vector representations. Sentence-BERT [43] extends this capability to sentence and full document representations, proving highly useful for assessing semantic similarity between large text passages. Recent research [44] demonstrates the importance of NLP models in handling scientific symbols and equations encountered in educational problems. With ability to understand text meaning, AI educational systems can provide personalized suggestions, analyze student work, and formulate intelligent queries.

Data Integration is the critical process of combining data from various sources to create comprehensive data views for education. Modern educational systems store data in diverse repositories including Student Information Systems (SIS), Learning Management Systems (LMS), assessment systems, and even social media [45]. Research on data integration for learning analytics [46] reveals that many universities face challenges integrating data from multiple heterogeneous sources. Effective data integration requires comprehensive strategies for data standardization, quality verification, and field mapping between systems. Technology standards such as xAPI (Experience API) [47] have increased compatible methods for recording and sharing learning data across contexts. Using these interoperability frameworks, educational institutions can smoothly create integrated data systems essential for diverse educational analytics and data-driven decision-making.

Education Data Warehouses (EDWs) are centralized data repositories specifically designed to store and analyze vast amounts of data from educational institutions [48]. Unlike operational databases focused on real-time transactions, data warehouses support OLAP (Online Analytical Processing) for complex data mining. Efficient warehouse design must consider multiple factors including data normalization, schema design (such as star schema or snowflake schema), and performance optimization [49]. Additionally, educational institutions must establish effective data governance policies to protect student privacy while promoting legitimate data use for improvement. Case studies [50] demonstrate that functional education data warehouses enable institutions to track thousands of students over decades and conduct rigorous analyses of relationships between exam performance and subsequent advanced education success.

Educational Data Mining (EDM) employs machine learning and statistical analysis techniques to discover hidden patterns and knowledge in educational data [51][52]. EDM has diverse applications improving student learning outcomes, from predicting student performance to detecting behaviors indicating failure risk. Current research proves that various machine learning algorithms including Random Forest, Support Vector Machine, and deep neural networks can classify student performance into categories with approximately 70-75% accuracy [51] using parameters such as exam scores, department enrollment data, and performance history. Beyond classification, EDM enables educational institutions to analyze student learning behaviors, identify learners at risk of attrition, and develop evidence-based teaching strategies [52]. Furthermore, EDM assists in creating personalized recommendation systems and adaptive learning design.

Intelligent data management for education refers to frameworks and technologies designed to

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manage educational data effectively in the digital age [53][54][55]. These systems must prioritize learning by functioning as core components alongside Learning Management Systems (LMS), Student Information Systems (SIS), and other education management information systems (EMIS). Intelligent Data Management Cloud (IDMC) services for higher education [53] have proposed comprehensive approaches for managing student data, creating 360-degree views of each student's journey including academic records, extracurricular activities, financial assistance, and post-study outcomes. With this integrated perspective, educational institutions can provide targeted support and engagement according to individual needs. Recent research on intelligent education management system design emphasizes the importance of integrating big data and artificial intelligence technologies in data management, highlighting the importance of enabling institutions to leverage massive data and advanced analytics for decision-making and improvement [54][55].

Information Retrieval (IR) is an engineering discipline for extracting information from large document collections according to user search queries [56][57][58]. In educational contexts, IR plays an important role in helping learners search for educational resources, Open Educational Resources (OER), and reference materials. Traditional IR systems use approaches such as Boolean retrieval or Vector Space Models employing TF-IDF to measure search-document relevance [57]. However, over the past decade, "Learning to Rank" methods employing machine learning techniques have become standard approaches [56]. These advanced tools can integrate multiple features such as topic similarity, document diversity, information source quality, and other factors to rank search results more effectively. Recent research [58] confirms that document retrieval for educational purposes (Knowledge Acquisition Passage Retrieval) requires additional consideration beyond topic relevance, including "informativeness"—how well a document supports user learning. By considering these factors, IR systems for education can deliver truly useful resources for learning.

Table 3: Natural Language synthesis

Component	Content	Ref.
Natural Language Processing	Principles and techniques for natural language processing, including converting text into Embedding Vectors to analyze similarity and relationships between content.	[42],[43],[44]
Data Integration	Principles of integrating data from various sources to create comprehensive data views that can be analyzed efficiently.	[45],[46],[47]
Data Warehouse Design	Guidelines for designing efficient data warehouses for storing and analyzing educational data, supporting large-scale data retrieval and analysis.	[48],[49],[50]
Data Mining Techniques	Data mining techniques for discovering hidden knowledge and patterns in data, applicable to developing recommender systems and analyzing learner behavior.	[51],[52]
Intelligent Data Management	Conceptual framework for intelligent educational data management systems supporting learning in the digital age, emphasizing efficient data management and deep analysis.	[53],[54],[55]
Information Retrieval	Principles and techniques for efficient information retrieval, including measuring relevance and ranking results.	[56],[57],[58]

4.4 Project management systems

Project management systems comprise a comprehensive framework covering project planning, scheduling, and control to achieve objectives [59][60]. These systems prioritize integration of various project processes, enabling students to see the complete project picture and control operations systematically. Systematic project management structure reduces risk and increases success likelihood. Detailed planning, reasonable timeline setting, and continuous monitoring are inseparable components.

The Project Management Body of Knowledge (PMBOK) represents internationally recognized standard guidelines for project management [61]. The 8th Edition of the PMBOK Guide from the Project Management Institute comprises 10 project management knowledge areas: integration management, scope management, schedule management, cost management, quality management, resource management, communications management, risk management, procurement management, and stakeholder management [62]. Understanding and applying these approaches helps students approach their capstone projects systematically and standardly, making time and risk management more effective.

In the era of Machine Learning and AI technology, these techniques are being applied to project management, particularly timeline and budget aspects. AI can analyze historical project data to estimate new task timeframes more accurately [63]. Additionally, AI can detect complex patterns and relationships that might not be apparent from human analysis, thereby improving planning accuracy and reducing delay risk. Google Developers research indicates that Machine Learning project planning must include understanding uncertainty from project experimentation [64]. Although AI has significant potential, sole reliance without human decision-making may produce erroneous results.

A key aspect of good project management is identifying and managing factors potentially leading to project failure. Research by Belassi and Tukel [65] developed a framework for determining critical success and failure factors in projects. Results show that factors leading to project failure include poor planning, insufficient resource allocation, ineffective communication, and weak risk management [66]. Fortune and Peters add that project size, complexity, and duration also affect failure rates. Students who can identify these factors can prevent and manage risk in advance.

When projects have multiple options and decision criteria, the Analytic Hierarchy Process (AHP) is a valuable tool. AHP, developed by Saaty, is a methodology helping decision-makers prioritize various criteria and evaluate alternatives systematically [67]. The AHP process involves creating a problem hierarchy, making pairwise comparisons, and synthesizing results to obtain option priorities. For students, AHP is useful in prioritizing capstone topics, selecting work methods, and allocating resources effectively. Tools such as BPMSG AHP Online System [68] make AHP application easier and practically feasible.

Table 4: Synthesis of Timeline Planning

Component	Content	Ref.
1. Project Management Systems	Conceptual framework for systematic project management covering planning, scheduling, and control to achieve objectives.	[59],[60]
2. PMBOK Guidelines	Project management guidelines following PMI standards, covering all 10 project management knowledge areas, including time management and risk management.	[61],[62]
3. AI-based Timeline Planning	Application of project management techniques for estimating timelines and budgets, finding that AI use improves planning accuracy and reduces delay risks.	[63],[64]
4. Critical Failure Factors Analysis	Study of critical failure factors in projects for preventing and managing risks in student capstone projects.	[65],[66]
5. Analytic Hierarchy Process	AHP technique for multi-criteria decision-making, applicable to prioritizing capstone topics and allocating resources.	[67],[68]

4.5 Chatbots

Chatbots are defined as tools employing Artificial Intelligence technology with ability to conduct conversational interactions with users. In recent years, chatbots have developed rapidly from simple rule-based systems to complex Large Language Models (LLMs). This development has opened new opportunities across various fields including education, mental health, healthcare, and information search.

Chatbots can be built using different architectures including rule-based systems, machine learning models, and LLMs [69], [70], [76]. Rule-based systems dominated research until 2023, while LLM-based chatbots increased to 45% of new studies in 2024. Architecture selection significantly impacts system functionality, scalability, and interaction types the system can handle. This shift reflects researchers' efforts to develop chatbots with better understanding and responsiveness.

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Thailand is seeking new methods to improve its education system. AI-based chatbots benefit students through homework assistance, personalized learning tailored to individuals, and various skill development [69], [77]. Teachers benefit through time-saving assistance and improved teaching methods. However, significant challenges remain including reliability, accuracy, and ethical considerations in integrating chatbots into education. Recent studies show that establishing clear learning frameworks and verifying effectiveness are equally important to technology development.

Social chatbots have emerged as tools for reducing anxiety and supporting well-being [72], [73], [75], [76]. Randomized controlled trials demonstrate effectiveness of generative AI chatbots (such as Therabot) in treating major depression, general anxiety, and eating disorders. Factors related to user engagement include emotional connection, reliability, and expressiveness. These findings are significant because they show chatbots may be effective supplementary tools for mental healthcare, especially in areas with psychological resource shortages. However, additional research is needed to understand mechanisms and long-term impacts.

Chatbot technology has potential to increase access to quality healthcare [71], [76]. Research reveals increasing trends in bibliometric analysis of chatbot publications across diverse healthcare applications. Important considerations include verifying clinical effectiveness, developing usage protocols for health systems, and integrating chatbots into hospital workflows. The bibliometric analysis shows chatbot healthcare research has increased significantly recently, reflecting research community interest in exploring this technology's potential.

Conversational chatbots have become influential tools for online information search [74]. Users compare chatbots with traditional internet search. Research examines four important dimensions: information timeliness, information customization, reliability, and media richness. However, chatbots face various challenges including hallucination problems where systems present incorrect information confidently, and bias risks from training data. Understanding these problems is important for developing next-generation chatbots with greater accuracy and reliability.

Interaction between humans and chatbots occurs through written text (ChatGPT, Claude, Gemini) or voice commands (Siri, Alexa) [70], [72]. Social cognition research shows different AI forms including robots, avatars, and chatbots have different user engagement levels. Key factors affecting chatbot acceptance include affect, habit, and system reliability trust. Chatbot design emphasizing these factors improves acceptance and use levels.

Chatbots tend to exhibit hallucination problems presenting incorrect information with confidence [74], [76]. They also replicate biases in training data and may amplify existing stereotypes. Although LLM systems represent technological advancement, they currently show limited clinical effectiveness testing, with only 16% of LLM studies passing clinical effectiveness tests, with most still in early validation phases. Overcoming these challenges requires collaboration among developers, researchers, and various field experts.

Recent research shows AI chatbots can change opinions more effectively than traditional political advertisements [78]. Chatbots supporting different candidates changed voter opinions 2.3 to 3.9 points on a 100-point scale, greater than previous political advertising effectiveness. However, most persuasive models spread more false and inaccurate information, highlighting the dual nature of chatbot influence. This raises ethical concerns and responsibility in using chatbots for political communication.

Research models exploring user engagement with AI chatbots explain 62.8% of variance in engagement intention and 74% of variance in engagement behavior [72], [74]. Design factors including human-centered design, ethical considerations, and character development for credibility are critically important for acceptance. Prior user experience with chatbots affects user perception of technology. More experienced users typically have more realistic views and can use chatbots more effectively.

Increasing recognition exists regarding gaps in chatbot research [69], [76], [77], particularly regarding clinical verification, comparative studies of different AI models, and long-term effectiveness evaluation. Researchers must also explore methods for reducing bias, improving reliability, and fact-checking. The convergence of internet and chatbot technology offers opportunities for studying real-time chatbot answer updates and evolution of consumer information-search behavior. Additional study is needed regarding chatbot integration into education, health, and other services in well-integrated forms.

Table 5: Synthesis of Timeline Planning

Component	Content	Ref.
Architecture & Design	Chatbots can be built using different architectures including rule-based systems, machine learning models, and Large Language Models (LLMs). Rule-based systems dominated until 2023, while LLM-based chatbots increased to 45% of new studies in 2024. Architecture selection significantly impacts system functionality, scalability, and interaction types.	[69], [70], [76]
Applications in Education	AI-based chatbots benefit students through homework assistance, personalized learning tailored to individuals, and various skill development. Teachers benefit through time-saving assistance and improved teaching methods. However, significant challenges remain including reliability, accuracy, and ethical considerations.	[69], [77]
Mental Health & Well-being	Social chatbots emerged as tools for reducing anxiety and supporting well-being. Randomized controlled trials demonstrate effectiveness of generative AI chatbots in treating major depression, general anxiety, and eating disorders. Factors include emotional connection, reliability, and expressiveness.	[72], [73], [75], [76]
Healthcare Implementation	Chatbot technology has potential to increase access to quality healthcare. Research reveals increasing trends in bibliometric analysis of chatbot publications across diverse healthcare applications. Important considerations include clinical effectiveness verification and usage protocols for health systems.	[71], [76]
Information Search Behavior	Conversational chatbots have become influential tools for online information search. Research examines information timeliness, customization, reliability, and media richness. However, chatbots face challenges including hallucination problems and bias risks.	[74]
Human-AI Interaction	Interaction between humans and chatbots occurs through written text or voice commands. Social cognition research shows different AI forms have different user engagement levels. Key factors affecting acceptance include affect, habit, and system reliability trust.	[70], [72]
Limitations & Challenges	Chatbots exhibit hallucination problems and replicate training data biases. Although LLM systems are technological advancement, they show limited clinical effectiveness testing (only 16% of LLM studies passed). Overcoming challenges requires collaboration among developers, researchers, and experts.	[74], [76]
Persuasion & Social Influence	Recent research shows AI chatbots can change opinions more effectively than traditional political advertisements. Chatbots changed voter opinions 2.3 to 3.9 points on a 100-point scale. However, most persuasive models spread more false information, highlighting the dual nature of chatbot influence.	[78]
9. User Engagement & Adoption	Research models explain 62.8% of variance in engagement intention and 74% of variance in engagement behavior. Design factors including human-centered design, ethical considerations, and	[72], [74]

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Component	Content	Ref.
	character development are critically important for acceptance. Prior user experience affects perception.	
10. Future Research Directions	Increasing recognition exists regarding gaps in chatbot research, particularly in clinical verification, comparative studies of different AI models, and long-term effectiveness evaluation. Convergence of internet and chatbot technology offers opportunities for studying real-time answer updates and evolution of information-search behavior.	[69], [76], [77]

4.6 Framework appropriateness evaluation

Evaluating conceptual framework appropriateness requires assessment tools with validity and reliability. Lynn's work [34] and Lawshe's Index of Item-Objective Congruence (IOC) [78] are primary references for content validity measurement, with standard criterion requiring values ≥ 0.67 for appropriateness. Reliability analysis uses Cronbach's Alpha approach [79] for measurement internal consistency, with acceptable values exceeding 0.70 to confirm measurement consistency. Nunnally and Bernstein [80] further developed this through comprehensive psychological measurement theory.

The comprehensive evaluation framework covering five dimensions used in this research—System Quality, Intelligence Quality, Decision Quality, Learning Quality, and User & Environment Quality—was designed based on AI system and information system quality assessment principles [81], emphasizing complete structural and functional evaluation. Nielsen [82] proposed usability engineering principles and techniques emphasizing user convenience, comprehensibility, and satisfaction, which were applied to system user interface (UI) design for appropriateness and ease of use, particularly Dashboard and various display systems. Data analysis used statistical methods by Montgomery and Runger [83] including means, standard deviations, and hypothesis testing, as well as methods by Larsen and Marx [84], which are standard for analyzing expert evaluation data and enabling reliable conclusions about framework appropriateness.

Table 6: IOC Design Synthesis

Component	Content	Ref.
Content Validity (IOC)	Guidelines for measuring content validity using IOC index, with standard criterion requiring values ≥ 0.67 for appropriateness and alignment with objectives.	[78],[79]
Reliability Analysis	Tool reliability analysis using Cronbach's Alpha, with acceptable values exceeding 0.70 to confirm measurement consistency.	[80],[81]
Evaluation Framework	Comprehensive evaluation framework covering five dimensions: System Quality, Intelligence Quality, Decision Quality, Learning Quality, and User & Environment Quality.	[82]
Usability Engineering	Principles and techniques for system design emphasizing user convenience, comprehensibility, and satisfaction.	[83]
Kirkpatrick's Evaluation Model	Four-level evaluation model: Reaction, Learning, Behavior, and Results, which is standard for assessing training and learning program effectiveness.	[84]
Statistical Analysis Methods	Statistical methods for data analysis, including means, standard deviations, and hypothesis testing.	[85],[86]

4.7 IPOF Model (Input-Process-Output-Feedback)

The IPOF Model is a powerful and versatile tool for analyzing and optimizing various processes. This model has been widely recognized in multiple fields including business organizations, education, public health, and research [87], [88].

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The IPOF Model was developed based on general systems theory, which specifies that overall system structure is important for determining how it works efficiently, as are individual components [87]. This model comprises four essential components, each playing crucial roles in system success.

Data input refers to factors and conditions existing before group or system activities [87], [88]. Input comprises three main types: individual-level factors, group-level factors, and environmental factors. Individual-level factors are what group members bring to the group, including motivation, personality, abilities, experience, and demographics [87]. This affects how members participate in group activities and respond to processes. Group-level factors include work structure, team norms, and group size [87], determining group organization and structure. Environmental factors encompass broader context in which groups operate, including reward structure, stress level, task characteristics, and organizational context [87], creating the work framework group members must navigate.

Process or operations refer to interactions among group members [87], [88]. These include activities such as communication, decision-making, conflict resolution, and collaborative work strategies. Process quality and effectiveness are crucial for converting input into quality output [87], [89]. Teams with good input may lose success if work processes are inefficient. Conversely, teams with limited input may achieve good results with good processes. Project manager Ivan Steiner proposed an interesting formula explaining this phenomenon: Actual Output = Potential Output – Process Loss [87]. This formula shows that although group potential may be high, process losses such as group conflict, communication disruptions, coordination difficulties, and member social loafing may result in actual output below potential.

Output refers to group activity results valuable to teams or organizations [87], [88]. Output may include decision quality, member satisfaction, goal achievement rates, productivity increases, and member well-being in various contexts. Output meanings differ—in public system construction policy, output may mean designed legislation, completed projects, or resource allocation [90]. In education, output may mean learning outcomes, skill development, and positive attitudes [90].

Feedback is an important but often overlooked component [88], [90]. Feedback functions as the system's control mechanism. When output fails to match set goals, feedback provides information for improving input and process [4]. Feedback takes multiple forms including evaluation, data collection, stakeholder feedback, and strategy adjustment [88], [90]. Through this feedback mechanism, systems can learn and develop themselves, enabling continuous improvement.

The IPOF Model is often presented in simple linear form (Input → Process → Output), but relationships are actually more complex [87], [88]. These relationships are non-linear with dynamic feedback loops, where one stage's output becomes another stage's input. For example, if group output receives organizational recognition and reward, group members may receive increased motivation (increased input), affecting subsequent process quality [87], [88]. Similarly, detected output defects may lead to input improvements (such as additional training) or process changes (such as improved communication.

Table 7: IPOF Design Synthesis

Component	Content	Ref.
INPUT	Factors and conditions existing before group activities, including individual characteristics (motivation, personality, abilities), group-level factors (team norms, group size), and environmental factors (reward structure, task characteristics).	[87,[88]
PROCESS	Interactions among group members, including communication, decision-making, conflict resolution, and work strategies.	[87],[88],[89]
OUTPUT	Results of group activities valued by team or organization, such as decision quality, member satisfaction, and goal achievement.	[87],[88],[89]
FEEDBACK	Control mechanism used to improve input or process when output fails to meet goals (through evaluation, data collection, and adjustments).	[88],[90]

5. METHODOLOGY

5.1 Framework design

This research's framework design references the IPOF Model (Input–Process–Output–Feedback) [91], a systemic model aimed at explaining the relationships of components within a system [92]. It emphasizes a holistic view of operations and learning from feedback loops for continuous system improvement [93]. The IPOF model comprises four critical components:

1. Input: Information inputs such as historical project data and student academic performance data
2. Process: Data processing, analysis, and synthesis using artificial intelligence technology [94]
3. Output: Decision results such as reports and predictive analysis [95]
4. Feedback: Evaluation and learning mechanisms that affect process improvement in subsequent cycles [96]

To strengthen the system's learning and decision-making capabilities, this research integrates the AI Agent Core model [97], which operates under four main cycles: Perceive–Decide–Act–Learn [98]. This concept references Agent Theory [99] and Learning Theory [100] to enable the system to perceive its environment, analyze situations, make technical decisions, and continuously learn from results. This creates automatic adaptation capability (Adaptive Intelligence) [101]. Combining both models creates a framework with structural completeness and cognitive intelligence [102], where the IPOF model functions as the system structure, while the AI Agent Core serves as the artificial intelligence mechanism that strengthens the system's decision-making and learning capabilities [103]

5.2 Conceptual framework

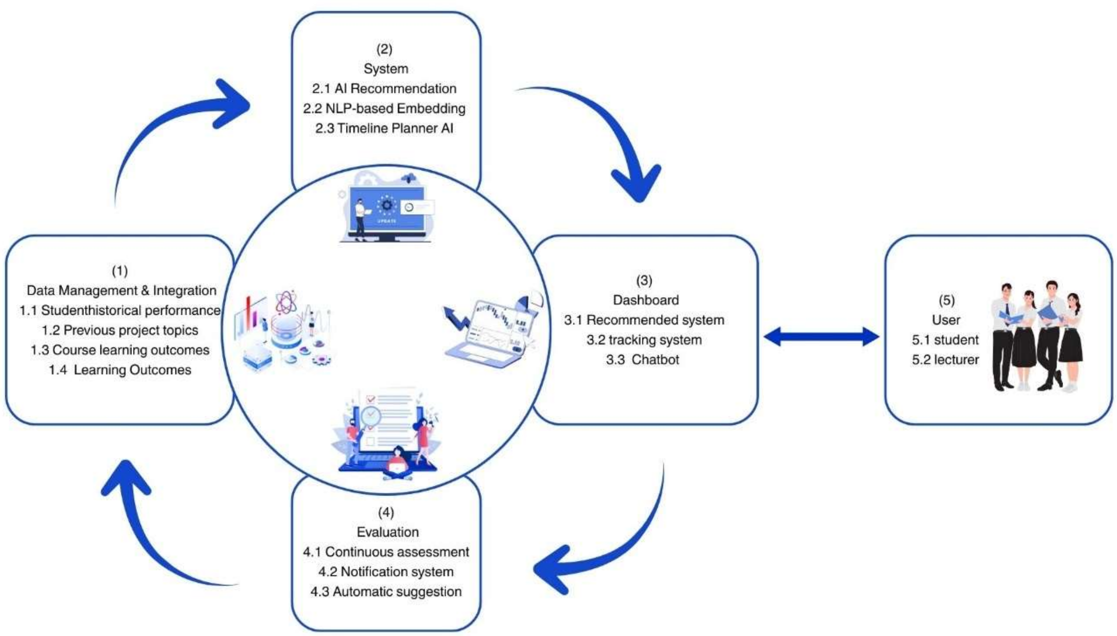

Figure 1: The Conceptual Framework For The Intelligent Project Topic Recommendation And Timeline Management System

As illustrated in Figure 1, the development of a conceptual framework for an intelligent project topic recommendation and timeline supervision system in undergraduate project courses aims to enhance alignment with course learning outcomes. The conceptual framework presented in this illustration represents an integrated research and development model with the principal objective of addressing commonly encountered problems in undergraduate project courses. The primary challenges identified include: students frequently experiencing difficulties in selecting project topics appropriate to their capabilities and interests, inefficient time management in project execution, and most critically, the potential misalignment between selected project topics and the Course Learning Outcomes (CLOs) established by the educational institution. The structure of this conceptual framework is designed as a cyclical model comprising four interconnected core components that continuously influence one another, similar to the PDCA (Plan-Do-Check-Act) cycle in quality management. While each component serves distinct roles and holds varying degrees of importance, all components collectively converge toward a unified goal: enhancing the effectiveness of project-based teaching and learning and achieving the predetermined learning outcomes.

1. Data Management & Integration System (Component 1)

An intelligent project topic recommendation and timeline management system for undergraduate capstone courses to enhance alignment with course learning outcomes comprises five core components that function systematically together to support undergraduate students' project development in alignment with Course Learning Outcomes (CLOs), utilizing Artificial Intelligence (AI) as the primary mechanism for processing and providing appropriate recommendations.

1.1 Student Historical Performance Data includes cumulative GPA, previously taken courses, and acquired skills. This data is important for analyzing student readiness and capability for different project types. Using historical learning data to analyze and predict learning outcomes was confirmed as effective by Ahmadian Yazdi et al. (2024), who developed an educational recommender system using LSTM neural networks and found that historical academic records significantly improve recommendation accuracy [104].

1.2 Previous Project Topics Data serves as the system's knowledge base by collecting completed projects, development approaches, encountered problems, and solutions. This knowledge management approach aligns with Zhao et al. (2022) who proposed designing intelligent educational data management systems to support learning in the digital age [105].

1.3 Course Learning Outcomes (CLOs) determine which project topics align with the course's learning goals. Systematically linking project topics with CLOs is an important concept Pereira et al. (2024) presented in developing project management curricula using large language models to create constructive alignment [106].

2. Intelligent Processing System (Component 2)

The system works together to analyze data and provide appropriate recommendations, comprising four main modules

2.1 Intelligent Recommendation System using Hybrid Recommendation techniques combining multiple methods: Content-based Filtering, Collaborative Filtering, and Knowledge-based Filtering to increase accuracy in project topic recommendations. Zhang et al. (2021) showed that using Hybrid AI in recommender systems can overcome limitations of single techniques and provide more diverse and needs-specific results [107]. Wei et al. (2021) studied personalized online learning resource recommender systems and found that combining AI with educational psychology increases efficiency in recommending resources appropriate for individual students [108].

2.2 Natural Language Processing-based Embedding converts descriptive text of project topics and CLOs into numerical vectors (Embedding Vectors) to accurately analyze similarity and relationships between project topics and learning outcomes.

2.3 Intelligent Timeline Planner automatically creates and adjusts project implementation plans considering factors such as project complexity, student skills, and available time. The system can modify plans according to actual progress and alert when delays occur. Khan et al. (2023) studied applying project management techniques for timeline and budget estimation, finding that AI improves planning accuracy and reduces delay risk [68].

3. Output System - Dashboard (Component 3) The system generates results addressing user needs:

3.1 Recommended System displays recommended project topics with rationale, appropriateness scores, and CLO relationships. Recommendations are personalized according to each student's abilities and interests.

3.2 Tracking System displays project progress compared to established plans, including milestones to be achieved and remaining work. Continuous tracking helps reduce late submission problems, a significant issue in capstone projects, tracking across a 15-week project schedule.

3.3 Chatbot functions as a conversational program designed to interact with users through text or voice, serving as an advisor for students consulting on capstone projects 24/7 to accelerate project execution and enable students to graduate on schedule [109].

4. Evaluation System (Component 4) Evaluation is a critical process improving both student projects and system performance:

4.1 Continuous Assessment evaluates progress and work quality continuously using established criteria and compares against best practices from previous projects. Continuous evaluation enables timely problem correction.

4.2 Notification System sends alerts when tasks are due, deadlines approach, or deviations from plans occur. Intelligent alert systems select appropriate channels and timing based on user behavior.

4.3 Automatic Suggestion generates specific feedback based on identified problems. For example, if topics don't align with certain CLOs, the system recommends concrete improvement methods. Timely and specific feedback improves learning efficiency, as Vieriu & Petrea (2025) found that AI can significantly positively impact student academic development [110].

5. Users (Component 5)

The final component is the operational environment comprising two groups:

5.1 Students are the primary system users, using it to search for project topics, plan work, track progress, and receive consultation. Adequate student support reduces problems such as inappropriate topic selection, poor time management, and lack of guidance in project development.

5.2 Lecturers use the system to monitor students, provide consultation, and evaluate results. The system reduces lecturer workload by performing initial tasks such as screening inappropriate topics, alerting problematic students, and gathering decision-making data, helping solve the problem of lecturers needing 15-20 hours per student for topic selection guidance.

5.3 Evaluation Framework

The framework evaluation was designed under the concept of Evaluation Dimensions for the Conceptual Framework of AI Agent-Based Intelligent System Development [111], encompassing five major dimensions: (1) System Quality [112], (2) Intelligence Quality [113], (3) Decision Quality [74], (4) Learning Quality [115], and (5) User & Environment Quality [116]. Each dimension reflects important characteristics of comprehensive, transparent, and sustainable artificial intelligence systems [117]

1. System Quality evaluates completeness, interconnection, and practical applicability of the framework integrating IPOF and AI Agent Core models [118]. Systems with clear structure and consistent components reflect system strength and capability for developing stable and reliable prototypes[119].

2. Intelligence Quality reflects AI Agent intelligence in operations, considering AI's main cycle: Perceive–Decide–Act–Learn [120]. Good systems must appropriately perceive, analyze, decide, and act in response to actual data and context [121], continuously adapting to new data—the essence of adaptive intelligence [122].

3. Decision Quality requires AI Agent-driven systems to provide correct, logical, and traceable decisions [123], particularly important in procurement and policy planning contexts. System explanation capability is critical for trust [124]. Incorporating Explainable AI (XAI) concepts [125] increases transparency and user understanding, an important evaluation criterion for this dimension [126].

4. Learning Quality reflects system potential in learning and improving from feedback, both explicit and implicit [127], to continuously develop models. Reinforcement Learning concepts [88] and Experiential Learning [128] form the basis for creating systems adaptable to changing contexts—the essence of sustainable intelligent systems[129].

5. User & Environment Quality assesses appropriateness, ease of understanding, operational convenience, and actual user impact [130], including system alignment with local community context [131]. Developing systems addressing user needs and differences efficiently increases system acceptance, consistent with Technology Acceptance Model (TAM/UTAUT) concepts [132]

5.4 Expert Validation

To ensure the developed framework's correctness and appropriateness in structure and content, expert evaluation [134] was conducted with nine experts divided into three main groups:

1. System & Technical Experts [135]
2. AI & Decision-Making Experts [136]
3. User & Quality Assurance Experts [137]

Additionally, three additional experts evaluated Index of Item-Objective Congruence (IOC) [138] to verify the appropriateness of questionnaire items and indicators [139].

Evaluation occurred in two stages:

Stage 1: Content Validation [102] using IOC index, with standard criteria requiring values ≥ 0.67[140] for appropriateness.

Stage 2: Framework appropriateness evaluation using a 5-level Likert Scale questionnaire [141] covering five evaluation dimensions: System Quality, Intelligence Quality, Decision Quality,

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Learning Quality, and Environment Quality [142]. Data from the evaluation was analyzed using basic statistics [143] including mean (Mean), standard deviation (S.D.), and IOC value to measure expert consensus levels on each dimension [144], confirming the framework's structural consistency before developing it into a prototype system [145]. This expert validation design approach confirms that the developed framework is academically correct, theoretically and practically comprehensive [146]

6. RESULTS AND DISCUSSION

Based on synthesis of all relevant research, the appropriateness of the conceptual framework was evaluated by nine experts. The evaluation data is presented in Table 8

Table 8: Evaluation results of the conceptual framework's appropriateness by experts

Components	$\bar{x}$	S.D	Level
1. System	4.56	0.52	Highest
1.1 Data Management and Integration System	4.56	0.53	Highest
1.2 Appropriateness of Five Major Components Structure	4.44	0.53	High
1.3 Consistency and Linkage Among System Components	4.67	0.50	Highest
2. Intelligence Quality	4.44	0.59	High
2.1 Completeness of Hybrid Recommendation System	4.33	0.71	High
2.2 Timeline Planner AI Capability for Planning and Automatic Adjustment	4.56	0.53	Highest
2.3 Appropriateness of Learning Outcomes Analysis	4.44	0.53	High
3. Decision Quality	4.52	0.58	Highest
3.1 Correctness and Rationality in Project Topic Recommendation	4.67	0.50	Highest
3.2 Dashboard Appropriateness for Displaying Decisions and Recommendations	4.33	0.71	High
3.3 System Reliability in Supporting Decision-Making	4.56	0.53	Highest
4. Learning Quality	4.44	0.59	High
4.1 Alert System Effectiveness in Preventing Delays	4.44	0.53	High
4.2 Appropriateness of Continuous Assessment	4.56	0.53	Highest
4.3 Quality of automatic feedback	4.33	0.71	High
5. User & Environment Quality	4.56	0.52	Highest
5.1 Understanding and utilization for students	4.67	0.50	Highest
5.2 Suitability for instructors in monitoring and providing consultation	4.56	0.53	Highest
5.3 Feasibility for practical implementation	4.44	0.53	High
Average results	4.50	0.56	High

Based on Table 8, the evaluation of the appropriateness of the intelligent project topic recommendation and timeline management system for undergraduate project courses by nine experts using a 5-level Likert Scale questionnaire, encompassing evaluation across five major dimensions:

1. System Quality received the highest level evaluation with a mean score of 4.56 and standard deviation of 0.52. Detail examination reveals that consistency and linkage among system components received the highest score of 4.67, showing expert complete agreement that the system structure is systematically interconnected. This is followed by data management and integration systems scoring 4.56 and the appropriateness of five major component structures scoring 4.44. Low standard deviations (0.50-0.53) reflect high expert consensus,

confirming the strength of the developed system structure.

2. Intelligence Qualit received evaluation at a high level with a mean score of 4.44 and standard deviation of 0.59. Timeline Planner AI's capability for planning and automatic adjustment received the highest score in this dimension at 4.56, showing expert confidence in the system's intelligent timeline planning potential. This is followed by learning outcomes analysis appropriateness scoring 4.44 and completeness of the hybrid recommendation system scoring 4.33. Integration of diverse AI techniques reflects appropriate complexity of the artificial intelligence system.

3. Decision Quality received the highest-level evaluation with a mean score of 4.52 and standard deviation of 0.58. Correctness and rationality in project topic recommendation received the highest score of 4.67, showing high expert confidence in the system's recommendation quality. System reliability in supporting decision-making scored 4.56, and dashboard appropriateness for displaying decisions and recommendations scored 4.33. High evaluation of this dimension reflects the importance of quality decision-making in learning support systems.

4. Learning Quality achieved evaluation at a high level with a mean score of 4.44 and standard deviation of 0.59. Appropriateness of continuous assessment received the highest score of 4.56, aligning with continuous assessment concepts as the heart of effective learning. This is followed by alert system effectiveness in preventing delays scoring 4.44, and quality of automatic suggestions scoring 4.33. High evaluation of this dimension shows the system's potential in promoting continuous learning and development.

5. User & Environment Quality received the highest-level evaluation with a mean score of 4.56 and standard deviation of 0.52. Understanding and ease of use for students received the highest score of 4.67, a critical factor for system acceptance and use. Appropriateness for lecturers in monitoring and providing consultation scored 4.56, and feasibility for practical application scored 4.44. Evaluation results in this dimension reflect high feasibility for real system implementation in educational institutions.

7. CONCLUSION

This research successfully achieved integration of diverse theories and technologies including Constructive Alignment and Understanding by Design learning design theories, Hybrid Recommendation Systems, and the IPOF Model combined with AI Agent Core. This integration enables the system to possess both clear structure and continuous learning and adaptation capabilities—important characteristics of efficient and sustainable intelligent systems. The framework design encompassing both project topic recommendation and timeline management in a single system represents a significant advancement.

This research successfully developed a comprehensive and appropriate conceptual framework for an intelligent project topic recommendation and timeline management system for undergraduate project courses by effectively integrating learning design theory, artificial intelligence technology, and project management principles. Expert evaluation results across five evaluation dimensions—System Quality, Intelligence Quality, Decision Quality, Learning Quality, and User & Environment Quality—confirmed the framework's high appropriateness with a mean score of 4.50 and standard deviation of 0.56, reflecting high expert consensus.

The developed framework has high potential in addressing significant current project development problems, particularly assisting students in selecting appropriate topics aligned with learning outcomes, managing time efficiently, and providing personalized and timely support. Implementing and operating this system in educational institutions is expected to improve project quality, reduce topic change and delay rates, and promote student success in graduating on schedule, aligning with goals for improving educational quality and learning in the 21st century.

The evaluation results of the conceptual framework's appropriateness, with an overall mean score of 4.50 (S.D. = 0.56), align with numerous research studies that have developed educational recommendation systems using artificial intelligence technologies. The research by Ahmadian Yazdi et al. [104], which developed a dynamic educational recommendation system using LSTM neural networks, found that utilizing students' academic history data significantly improved recommendation accuracy. This finding is consistent with component 1.1 of the system developed in this research, which emphasizes the management and integration of students' historical academic performance data.

There are no questions; the problems have been answered in this research. The only suggestion for future research is the development of a real-world system prototype.

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