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Effect of Chatbot-Assisted Learning on Students' Learning Motivation and Its Pedagogical Approaches

Nisa Dwi Septiyanti[1*], Muhammad Irfan Luthfi[2,3], Darmawansah Darmawansah[4]

[1] Department of Informatics, Universitas Muhammadiyah Karanganyar, Indonesia

[2] Department of Electronics and Informatics Engineering Education, Universitas Negeri Yogyakarta, Indonesia

[3] Graduate Institute of Network Learning Technology, National Central University, Taiwan

[4] Empower Vocational Education Research Center. National Taiwan University of Science and Technology, Taiwan

*nisadwiseptiyanti@umuka.ac.id

Abstract-The use of chatbots in the learning process has been increasingly investigated and applied. While many studies have discussed the chatbot's ability to motivate students' interest in learning, few have examined whether students' perception of learning affects the effectiveness of chatbots and the pedagogical approach taken by chatbots as conversational agents during the learning process. There is a need for new analysis to capture the effects of Chatbot-Assisted Learning (Chatbot-AL) and student-chatbot conversations. In an eight-week semester, 48 first-year undergraduate students participated in a chatbot-assisted learning environment integrated into an engineering course. Data were collected through questionnaires on students' learning motivation and discourse in chatbot conversations. Statistical non-parametric analysis and Epistemic Network Analysis (ENA) were used to explore the research questions. The results showed that students with high learning perception had better learning motivation using chatbot-AL than students with low learning perception. Additionally, most of the questions asked by students were aimed at receiving emotional support through casual conversation with the chatbot. Finally, the pedagogical implication of this study is the needs of utilizing AI tool in teaching and learning practice for better learning outcomes.

Keyword: Artificial intelligence, chatbot, chatbot in education, learning motivation, epistemic network analysis

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1. Introduction

A Chatbot is essentially a computer program designed to simulate human-like conversations using natural language processing [1], [2]. It acts as a digital assistant with the capability to provide accurate responses to a wide range of user inquiries. In recent years, there has been a significant surge in the adoption of Chatbots across various industries, including Marketing, Education, Healthcare, Support Systems, Cultural Heritage, Entertainment, and many others [2]. This widespread adoption of Chatbots can be attributed to factors such as their cost-effectiveness [3], the availability of diverse development options, as emphasized [4], [5] and their seamless integration into social networks, making their adaptation more accessible [6].

In recent times, there has been a notable upswing in the integration of Chatbots into e-learning platforms, aimed at bolstering and enriching the learning experience for students. Educational chatbots are adept at engaging with learners, offering them comprehensive instructional support [4]. Furthermore, these chatbots excel in tailoring personalized learning [7] [8]. Moreover, it provides instantaneous feedback [9]. Researchers have demonstrated their expertise by creating specialized chatbots for distinct academic subjects. For example, Freudbot system, designed specifically for psychology education [10], Cleverbot's application in English as a second language education [11] revealed its considerable utility, its capacity to alleviate the workload of educators.

The integration of Chatbots in education yields profound implications by fostering an interactive learning experience [12]. These bots play a pivotal role in evaluating students' behavior and monitoring their progress [13], thereby enhancing individual learning outcomes. There are several other cases of the use of Chatbots for e-learning. For instance, they enable the creation of personalized learning systems, accommodating the fact that each student acquires knowledge at their own pace. Chatbots can adeptly tailor the learning speed, ensuring that it aligns with individual needs without undue pressure [2]. Additionally, Chatbots serve as facilitators of social learning, allowing students from diverse backgrounds to share their perspectives and insights on specific subjects while adapting to each student's unique requirements. This technology fosters increased student engagement and encourages interaction within the classroom by assigning group tasks and projects [2]. Moreover, Chatbots prove invaluable to teachers by assisting with routine tasks such as responding to student queries, checking homework, and even serving as online assessment tools [13]. In larger classes, where individual attention becomes arduous for instructors, Chatbots excel by efficiently engaging with multiple students and groups simultaneously. Furthermore, they serve as valuable aids to teachers by identifying spelling and grammatical errors, assigning projects, and most importantly [14], tracking the progress and accomplishments of each student.

As few studies on chatbot-assisted learning had focused on teaching an information engineering course, and even fewer have investigated the effect of chatbot-assisted learning on the pedagogical approach on students-chatbot interaction, the current study explores students' learning motivation through chatbot-assisted learning employment and its pedagogical approaches as conversational agent. We investigate these issues in our study with the following research questions.

(a) Do high-perception students have better learning motivation than low-perception students in learning with chatbot-assisted learning (chatbot-AL)?
(b) What are the common pedagogical approaches of chatbot-AL's answers in the chatbot-AL learning environment?

2. Literature Review

a. Chatbot-assisted learning

Researchers have conducted extensive reviews within the domain of educational chatbots, with a primary objective of critically evaluating their overall efficacy and multifaceted functionalities. Zhang and Cheng [15] undertook a meticulous analysis encompassing 46 scholarly articles derived from SSCI journals, spanning the chronological spectrum. They conducted an examination of chatbot-assisted learning across 14 distinct academic disciplines, predominantly implemented within a single in-class session. The outcomes of these assessments were generally favorable, encompassing both academic and emotional dimensions. Building upon these findings, they introduced a model for effective chatbot-assisted learning, designated as the RAISE model, which encapsulates key factors: Repetition, Authenticity, Interactivity, Student-Centeredness, and Enjoyment.

Pérez et al. [16] conducted an exhaustive systematic review, encompassing a compendium of 80 pertinent studies on chatbot-assisted learning. Their scholarly inquiry discerned a spectrum of educational chatbot typologies currently in deployment across variegated academic domains. The empirical findings derived from this comprehensive review illuminated three important pedagogical affordances inherent to educational chatbots: the provision of untethered instructional support, the facilitation of iterative and repetitive learning tasks, and the bespoke tailoring of learning materials to individualized learner needs. Despite their instrumental role in augmenting educational services and optimizing the learning trajectory in a manner reminiscent of human tutors, it remains axiomatic, as contended by Pérez and associates, that chatbots cannot support the pivotal role of human educators within the educational landscape.

Huang et al. [17] conducted an analysis of 25 research studies focused on the utilization of chatbots in language learning, covering the period from 2010 to 2021. Their investigation unveiled three prominent characteristics associated with chatbot-assisted language learning: immediacy, user-friendliness, and personalization. Chatbots contributed to the improvement of language acquisition through five distinct approaches: (a) acting as learning companions, (b) creating authentic environments for speaking practice, (c) delivering educational materials, (d) facilitating the retrieval of information, and (e) providing learning recommendations. By virtue of these capabilities, chatbots held the potential to foster emotional, open, and cohesive interactions among students, thereby augmenting their social presence. Additionally, the researchers identified three primary challenges inherent in chatbot-assisted language learning: technological constraints, the impact of novelty, and cognitive workload.

b. Students' learning motivation

Many previous studies investigated the effect of chatbots on learning motivation. Motivation encompasses the potential to actively participate in learning activities and sustain one's commitment to learning [18]. In essence, engagement emphasizes the act of involvement, while motivation underscores the underlying intention [19]. Motivation can be divided into two primary categories: intrinsic and extrinsic motivations [20]. Intrinsic motivation centers on the inner sense of fulfillment that learners derive, while extrinsic motivation pertains to behaviors driven by external and separable rewards or outcomes [21]. It was observed that voice-based chatbots had a positive impact on the motivation of middle school students [22]. Additionally, the integration of chatbot-assisted instructional videos and micro-learning systems proved to be effective in fostering motivation [23], [24].

Yin et al. [23] conducted a study to assess the influence of a micro-learning system utilizing chatbots on students' motivation to learn and their academic performance. They scrutinized instances where chatbot-assisted learning was implemented across 14 different academic disciplines, predominantly in a classroom setting for a single session. The overall outcomes of these implementations were positive, impacting both the academic and emotional dimensions of learning. Based on their comprehensive review, they introduced the RAISE model, which encapsulates key factors for effective chatbot-assisted learning: Repetition, Authenticity, Interactivity, Student-Centeredness, and Enjoyment. Their research employed the Self-Determination Theory (SDT) approach to gauge student motivation within the context of chatbot-based learning. The findings from their investigation revealed that students in the chatbot learning group exhibited significantly higher levels of intrinsic motivation compared to the traditional learning group. This heightened intrinsic motivation was primarily driven by the perception of choice and perceived value, serving as central predictors of this motivation.

Besides, Guo et al. [25] designed a chatbot called Argumate, which was designed to assist students in formulating ideas to support their arguments and anticipate counterarguments. Their research aimed to assess how the use of chatbots impacted students' ability to construct arguments and their motivation for tasks. The research involved 44 Chinese undergraduate students from two distinct classes. To gauge the impact on argumentation skills, particularly concerning argument structure complexity and argument quality, they employed a pretest-posttest quasi-experimental design. The findings, as revealed by Quade's test, demonstrated that integrating argumentative chatbots into classroom debates had a beneficial effect, resulting in improved argumentation skills and heightened task motivation among undergraduate students.

c. ARCS Model

Since its inception by John M. Keller in the early 1980s, the ARCS Model, which stands for Attention, Relevance, Confidence, and Satisfaction, has served as a prominent framework in educational psychology. While its initial conceptualization laid the groundwork for understanding and enhancing learner motivation, the post-1990 era has witnessed the model's continuous evolution, refinement, and adaptation to meet the dynamic demands of modern education.

Keller [26] revisited the ARCS Model within the context of online learning, demonstrating how its components can effectively motivate learners in virtual environments. This expansion into the digital realm marked a significant shift in the application of the model, acknowledging the changing landscape of education. Additionally, Wlodkowski and Jaynes [27] extended the ARCS Model's scope by introducing the concept of volition, emphasizing its role in sustaining learner motivation over time.

Empirical applications of the ARCS Model have explored its practical implications. Chen [28] delved into the effectiveness of the model in computer-aided instruction, shedding light on how each component influences student motivation. Meanwhile, Jimenez [29] examined the integration of the ARCS Model in educational video games, offering insights into its potential to engage and motivate learners in innovative ways.

However, critical assessments have also emerged. Keller [30] reflected on the fundamental principles of the ARCS Model and discussed its limitations and areas for improvement, particularly in the context of e-learning. Additionally, while not directly focused on the ARCS Model, Vallerand and Bissonnette [31] provided a theoretical foundation for understanding the underlying factors influencing learner motivation, which can be related to the ARCS components.

These contributions collectively highlight the enduring relevance and adaptability of the ARCS Model in educational psychology, underscoring its capacity to address the evolving challenges and opportunities in contemporary learning environments. As researchers and educators continue to explore its applications and refine its theoretical underpinnings, the ARCS Model remains a valuable tool for enhancing learner motivation and engagement in education.

3. Methods

a. System Development

Chatbot-assisted (chatbot-AL) learning is designed to provide students with a powerful tool for personalized education by utilizing advanced technologies and AI models. This part outlines the key phases of development, including planning, system design, development, deployment, and delivery, shedding light on the meticulous steps taken to create a robust learning platform. The chatbot-AL system is depicted in Figure 1.

The initial phase of chatbot-AL development involves critical decision-making regarding technology selection, course selection, and learning material inclusion. The chosen technology stack, comprising Code Igniter 3, Apache 2.4, MySQL 10.6, PHP 7.4, Python 3.10, and Llama Index, forms the foundational infrastructure of the chatbot-AL. Careful consideration is given to the selection of an experimental course, based on relevance and potential for improvement through chatbot-AL intervention. Furthermore, specific learning materials are identified to ensure the chatbot-AL 's effectiveness in aiding student learning.

System design is a pivotal stage that encompasses User Interface and User Experience (UI/UX) design, technology integration, and AI model incorporation. Tools like the Pencil App are employed for UI/UX design, allowing for the creation of wireframes and mock-ups to visualize the system's layout and functionality. The selected technology stack provides a robust foundation for the chatbot-AL, with Python 3.10 and the Llama Index enhancing its capabilities. The chatbot-AL leverages embedded GPT-3 models such as ADA and Dalvik-003 to offer advanced features, including answering student queries and providing personalized learning experiences.

The development process begins with the conversion of learning materials into text format, enabling the chatbot-AL to access and analyze content efficiently. The vectorization of learning materials using the Llama Index optimizes processing speed and organization. These vectorized materials are then exported to JSON files, allowing for structured storage and retrieval. The chatbot-AL further integrates these JSON files with the GPT using the Ada Model, rendering the learning materials ready for question-and-answer (QnA) interactions, all powered by the GPT-3 Dalvik-003 model.

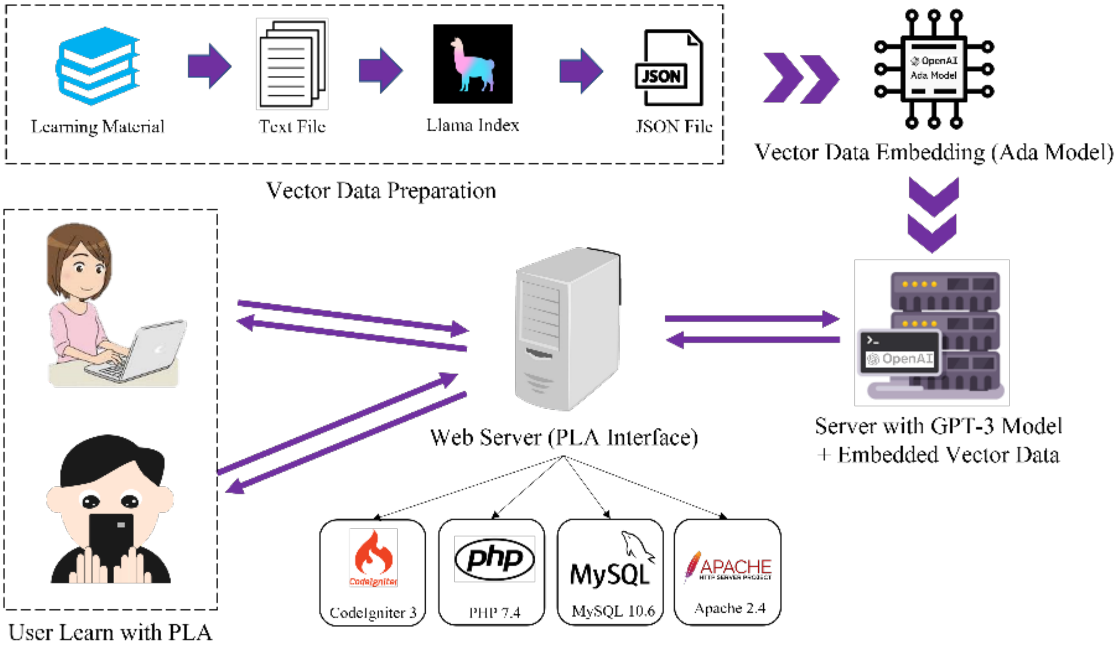

Figure. 1. Chatbot-AL System

The deployment phase focuses on transforming UI/UX designs into functional web applications, ensuring accessibility and user-friendliness. Web applications are seamlessly connected to a database, recording and managing user interactions for subsequent analysis and performance optimization. The QnA machine, incorporating AI models developed in earlier phases, is integrated into the web application using the GPT PHP Library. This integration enables students to engage in dynamic and interactive learning experiences by asking questions and receiving answers based on embedded learning materials.

In the final phase, the chatbot-AL is delivered to students, making it accessible through shared hosting. Aligning settings and parameters ensures the smooth operation of all functions, and necessary adjustments are made to optimize performance. Students can then access the chatbot-AL, interact with the AI-powered QnA machine, and benefit from personalized learning experiences. The chatbot-AL becomes an invaluable tool for students, providing instant answers to queries and facilitating a deeper understanding of course materials.

The development process of the chatbot-AL represents a significant advancement in personalized education. Through meticulous planning, thoughtful system design, meticulous development, smooth deployment, and successful delivery, the chatbot-AL empowers students to engage with course materials and learning resources in innovative ways. This research report highlights the comprehensive journey undertaken to create a robust and effective learning platform, demonstrating the potential for transformative impacts on education.

b. Research Procedures

This study involved 48 first-year undergraduate students consisting of 35 males and 13 females. All students access the chatbot-AL through their devices for four months in a course of information engineering. Regarding students' experiences with chatbots, 79.6% of students in this study reported that they had encountered chatbots in online activities outside of their studies.

Moreover, as illustrated in Figure 1, our framework comprises both a back-end and a front-end component. The back-end serves as a provider for learning objects. The front-end, on the other hand, handles user queries and initiates the inference process to deduce users' intentions. Figure 2 provides an illustrative example of this system in action.

An instance of the proposed solution in the realm of e-learning can be illustrated with the scenario of university students enrolled in Analysis Design System courses. When this student accesses our system and requests an in-depth study on a particular topic, such as "What are the phases of system analysis and design?", the chatbot receives and processes the request. It responds to the student by either providing relevant materials as attachments or offering textual insights on the subject. Figure 2 visually represents this described example.

Figure. 2 Screenshot of the chatbot-AL

Prior obtaining the data for the first research question, we conducted field research by selecting the ARCS model as the learning model to be applied to the class. To evaluate learning motivation, a survey of students' learning motivation was given as the post questionnaire. There were 25 items which consists of four dimensions; attention, relevance, confidence, and satisfaction. It was used a 5-point Likert scale, with 1 represents "strongly disagree" and 5 represents "strongly agree". The Cronbach's α value of the questionnaire was 0.97.

Furthermore, we asked students' perception toward the course offered. We took students' learning perception as an independent variable to investigate students' learning motivation (See figure 3).

For the second research question, the ENA (epistemic network analysis) was applied to examine whether and what difference pedagogical approaches that occurred in the chatbot-assisted learning between the students-chatbot conversation and students-students conversation. The ENA web tool (https://www.epistemicnetwork.org/) was used to analyze the encoded data. ENA utilizes a sliding window mechanism to construct an epistemic network model by calculating the co-occurrence of pedagogical dimension elements. The aim is to understand the interaction between these elements. ENA's core concepts are code, unit of analysis, and stanza. Code refers to a group of pedagogical approaches elements, and the interaction among these elements is the focus of ENA analysis. Unit of analysis refers to the objects of ENA, such as types of answers by either chatbot or other students and referenced users ID. Finally, the stanza refers to the scope of co-occurrence of cognitive elements. When the stanza is set to 14, ENA calculates the co-occurrence of cognitive elements every 14 utterances.

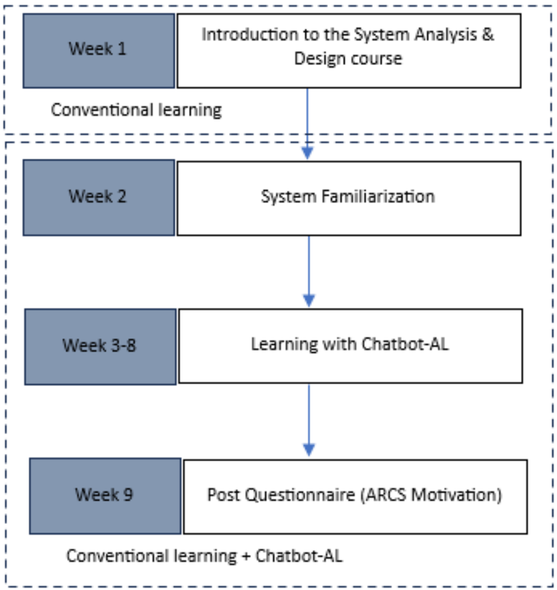

Figure. 3. Research procedures

ENA represents the co-occurrence data as an adjacency matrix and visualizes the relationship among cognitive elements in a two-dimensional space via normalization, dimension reduction, and singular value decomposition [32]. The nodes in the epistemic network generated by ENA represent pedagogical approach elements. The thickness of the links between nodes represents the frequency of co-occurrence of pedagogical approach elements, with thicker links indicating higher frequencies.

The discourse data of students on chatbot-assisted learning platform was collected and coded. A coding scheme was adapted from Zhang et al. [15]. The coding scheme contains four pedagogical dimensions which aims to investigating students-chatbot conversation. Table I shows the dimensions, code, and descriptions used in this study.

Table 1. The coding framework of pedagogical approaches

Pedagogical dimension	Code	Descriptions
Delivering knowledge	DK_AI	Questions forwarded to chatbot and answered by chatbot
	DK_LR	Questions answered by learning references
	DK_ID	Questions answered by reference ID

Pedagogical dimension	Code	Descriptions
Facilitating practices	FP_PE	Presenting exercises
	FP_EV	Evaluating students' performance in activities and provide immediate feedback
	FP_KP	Explaining knowledge points according to students' outputs
Supervising and guiding learning activities	SG_GR	Scoring/grading students' output
	SG_GU	Asking guiding questions to trigger students' knowledge retrieval and application
Providing emotional support	ES_ER	Encouraging/Rewarding students
	ES_CC	Making casual conversation and telling jokes

4. Results and Discussion

a. Students' learning motivation

We conducted the Mann-Whitney U test to analyze the learning motivation survey. We chose non-parametric statistical analysis due to our small sample size and non-normal distribution, as determined by the Shapiro-Wilk test [33].

Table II shows that students with high perception had higher attention scores than students with low perception, with U = 149.00, z = −2.84, p = 0.004, and r = 0.41. In terms of relevance, high perception student had higher relevance than low perception students, with U = 170.50, z = −2.39, p = 0.016, and r = 0.34. In terms of confidence, high perception student had higher confidence than low perception students, with U = 156.50, z = −2.69, p = 0.007, and r = 0.38.

Additionally, high perception students had higher satisfaction than low perception students with U = 169.00, z = −2.45, p = 0.014, and r = 0.35. These findings suggest that students who have high perception had better attention, relevance, confidence, and satisfaction in their learning motivation compared to those who had low perception toward the integration between chatbot-assisted learning on engineering course

Table 2. The Mann-Whitney U test result for the students' learning motivation

Variable	Students' Learning motivation	N	Mean Rank	Sum Of Ranks	U	Z	r
Attention	Low	26	19.23	500.00	149.00	−2.84	0.41
	High	22	30.73	676.00			
Relevance	Low	26	20.06	521.50	170.50	−2.39	0.34
	High	22	29.75	654.50			
Confidence	Low	26	19.52	507.50	156.50	−2.69	0.38
	High	22	30.39	668.50			
Satisfaction	Low	26	20.00	520.00	169.00	−2.45	0.35
	High	22	29.82	656.00			

b. Analysis of pedagogical approaches in chatbot-assisted learning

Figure. 3 shows the overall ENA networks of pedagogical approaches that occurred in chatbot-AL. Students' questions that were answered by chatbot-AL are represented by red lines in the ENA space, while the students' questions that were answered by referenced users ID are represented by blue lines. The red square represents the centroid of the students-chatbot conversation, and the blue represents the centroid of the students-referenced users ID conversation.

The distribution of projection points between both lines in the ENA space was compared by developing a Mann-Whitney U test. A statistically significant difference was shown at the alpha = 0.05 level on the horizontal axis (SVD2) of the ENA space (Mdn = -0.33, N = 48, U = 476.00, p = 0.00, r = 0.62).

Based on Figure. 3, it is found that most of the questions answered by chatbot-AL aimed to provide emotional support for students by engaging in casual conversation and telling jokes (ES_CC). Meanwhile, most of the questions answered by referenced users ID aimed to evaluate students' performance in activities and provide immediate feedback (FP_EV).

Moreover, Figure 4 presents the mean network for the online conversation. As can be seen from both figures in Figure 3, there was a strong connection among ES_CC (casual conversation or making jokes), FP_EV (providing immediate feedback), and FP_PE (presenting exercise). This result indicates that answers from both Chatbot and referenced users ID actively facilitated practices and provided emotional support by delivering knowledge to students in the chatbot-AL learning environment.

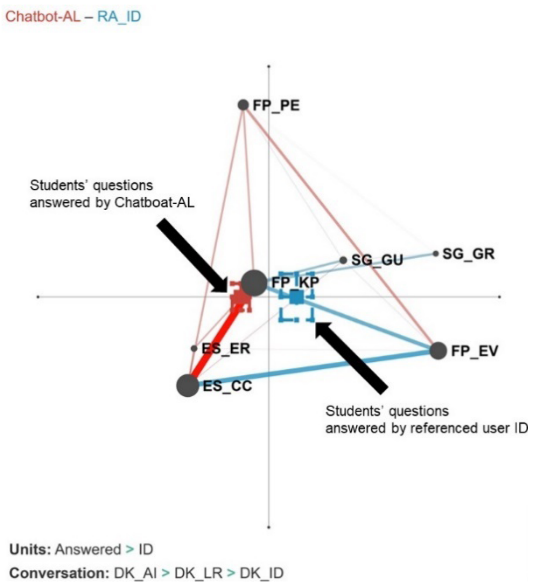

Figure. 3. ENA network of pedagogical approaches by chatbot-assisted learning.

As shown in figure 3 the red line represents the students' questions answered by chatbot-AL and the blue line represents students' questions answered by referenced user ID.

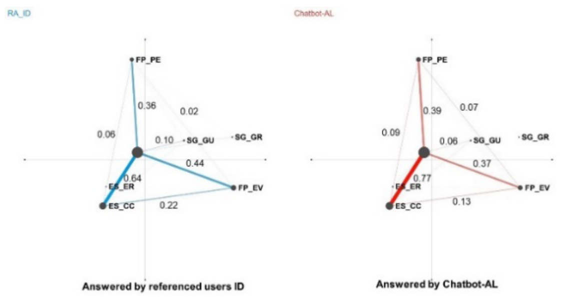

Figure. 4. Mean network for the online conversation

5. Conclusion

This study developed and implemented a personalized learning assistant called chatbot-AL in the context of an information engineering course. The study revealed the positive effects of chatbot-AL on students' motivation to learn. Specifically, it suggests that students with a higher perception had better learning motivation compared to those with a lower perception. Moreover, through epistemic network analysis, chatbot-AL mainly provided emotional support to students by engaging in casual conversations and sharing jokes. This is significantly different from human answers, which primarily focus on evaluation and feedback.

These findings highlight the significant advantages of using chatbot-AL to motivate and engage students during the learning process, enhancing enjoyment and promoting overall learning experiences through interactions with the chatbot. However, it is important to acknowledge certain limitations:

(a) The sample size was relatively small and consisted of only one group.
(b) The intervention duration was short
(c) Data were relied on self-report measures and chatbot-AL logs.

These limitation could be taking into consideration for future studies to include larger and more diverse sample, conduct long-term intervention, and incorporate objective measures (i.e., performance assessment, and rubrics). These limitations should be taken into consideration for future studies, which could include larger and more diverse samples, longer-term interventions, and the incorporation of objective measures such as performance assessments and rubrics.

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