J. Internet Comput. Serv.
ISSN 1598-0170 (Print) / ISSN 2287-1136 (Online)
http://www.jics.or.kr

Next-Generation Chatbots for Adaptive Learning: A proposed Framework☆

정 하 림[1] 유 주 헌[2] 한 옥 영[3*]
Harim Jeong Joo Hun Yoo Oakyoung Han

ABSTRACT

Adaptive has gained significant attention in Education Technology (EdTech), with personalized learning experiences becoming increasingly important. Next-generation chatbots, including models like ChatGPT, are emerging in the field of education. These advanced tools show great potential for delivering personalized and adaptive learning experiences. This paper reviews previous research on adaptive learning and the role of chatbots in education. Based on this, the paper explores current and future chatbot technologies to propose a framework for using ChatGPT or similar chatbots in adaptive learning. The framework includes personalized design, targeted resources and feedback, multi-turn dialogue models, reinforcement learning, and fine-tuning. The proposed framework also considers learning attributes such as age, gender, cognitive ability, prior knowledge, pacing, level of questions, interaction strategies, and learner control. However, the proposed framework has yet to be evaluated for its usability or effectiveness in practice, and the applicability of the framework may vary depending on the specific field of study. Through proposing this framework, we hope to encourage learners to more actively leverage current technologies, and likewise, inspire educators to integrate these technologies more proactively into their curricula. Future research should evaluate the proposed framework through actual implementation and explore how it can be adapted to different domains of study to provide a more comprehensive understanding of its potential applications in adaptive learning.

☞ keyword : Adaptive Learning, Learning Attributes, ChatGPT, Educational Technology, Human-Computer Interaction Analysis

1. Introduction

Educational Technology (EdTech), which refers to learning through technology, continues to attract attention and interest due to its advantages of ubiquity and accessibility [1]. By offering an education tailored to the learner's characteristics, EdTech has been recognized for its potential to provide adaptive learning, which can maximize the effectiveness of learning [2]. Chatbots have garnered attention in the field of adaptive learning. Conversational agents using Natural Language Processing (NLP) technology can interact with learners and identify their needs, providing tailored education that suits their preferences and tendencies. This not only simplifies teachers' workload, reducing their burden but also allows students to enhance the effectiveness of their learning with such technology [3].

Various previous studies have been conducted on the adaptive learning capabilities that chatbots can offer. However, with the recent emergence of the powerful chatbot, ChatGPT, which far exceeds the abilities of conventional chatbots, there is a need to define the role that such advanced chatbots, including ChatGPT, can play in adaptive learning [4]. As services in EdTech must be continually used, usability is considered essential. Therefore, it is important to focus on chatbot design that considers Human-Computer Interaction, as the effectiveness of education can bes significantly affected by the usability of the service [5]. To achieve user-centered design, it is crucial to identify user attributes and provide an experience that is suitable for them [6]. Similarly, in adaptive learning, identifying the learner's attributes, such as gender, age, or learning tendencies, is essential for providing an appropriate learning path that maximizes the effectiveness of education tailored to the learner's characteristics [7].

1 Dept. of Interaction Science, Sungkyunkwan University, Seoul, 03063, Korea.
2 Dept. of Artificial Intelligence, Sungkyunkwan University, Suwon, 16419, Korea.
3 Universty College, Sungkyunkwan University, Seoul, 03063, Korea.
* Corresponding author (oakyoung@skku.edu)
[Received 10 April 2023, Reviewed 14 May 2023(R2 29 June 2023), Accepted 11 July 2023]
☆ A preliminary version of this paper was presented at ICONI 2022.

For these reasons, this paper aims to provide a guide for using advanced chatbots, such as ChatGPT, effectively in adaptive learning. To do so, we will first organize the learner's attributes and outline the role that chatbots should play to enhance the user-centered design and the effectiveness of education. Additionally, we will review relevant literature and analyze existing methodologies and techniques to identify learner attributes and implement adaptive learning. Through this study, we aim to provide guidance for educators who plan to use ChatGPT in learning, developers who seek to apply chatbots like ChatGPT to EdTech, and learners who wish to actively utilize ChatGPT in their learning within the context of adaptive learning scenarios. By doing so, we aim to provide direction for those who wish to utilize ChatGPT in adaptive learning. At the same time, we present the potential real-world applications and benefits of our research findings.

2. Literature Review

In the realm of EdTech, adaptive learning has been the subject of extensive research. By summarizing findings from previous studies, we aim to understand the current state of adaptive learning and organize learning attributes to determine which ones should be prioritized. Furthermore, we seek to explore the technologies behind chatbots, such as ChatGPT, that have been implemented in practice and discuss how these technologies can be effectively used in adaptive learning while considering learning attributes. In doing so, we first aim to summarize the roles that chatbots have played, or have been proposed to play, in adaptive learning. Then, we suggest a chatbot framework based on learning attributes identified through recent research and advancements in additional technologies. This will enable us to lay the groundwork for proposing a chatbot framework tailored to learning attributes in adaptive learning.

2.1 Adaptive Learning

Adaptive learning aims to provide a personalized learning experience for individuals, with the term meaning "different things to different people" [8]. In adaptive learning, personalization tailored to an individual's characteristics is crucial. Variables prioritized first include gender, age, and cognitive abilities, such as perceptual speed and processing speed [9]. This research further suggested that age should be considered as a primary variable in adaptive learning, given its importance in understanding the learner's prior knowledge. Moreover, it emphasized the need for gender-specific personalized education design, as motivation levels can vary between genders. The importance of cognitive ability as a factor in adaptive learning was also underscored. The authors explained that learner performance might vary depending on verbal ability and working memory capacity, hence the need for education tailored to each learner's level. In another systematic review related to adaptive learning, pacing was suggested as an important adaptive strategy in the pedagogical model [10].

Other research on adaptive learning has suggested that interaction strategies are necessary in addition to adjusting the pace based on the user's gender, age, and basic cognitive abilities [11]. In terms of interaction strategies, adaptive learning requires consideration of pre-instructional strategies. These include the format of tests (objective or subjective), the level of questions, and feedback strategies. Feedback strategies encompass factors such as the amount, timing, and type of feedback, all of which should be delivered in an appropriate form. Moreover, in the categories of adaptation in the learning environment, adaptive collaboration support is emphasized as important, involving the collaboration process and the significance of cooperative learning [12].

Based on the essential factors identified in prior research on adaptive learning, levels of learner control should be achieved. These levels include personal strategies, sequence tasks, control adaptivity tasks, and changes in the learning model [13]. An adaptive learning system should be designed with levels of learner control, including personal strategies, sequence tasks, control adaptivity tasks, and changes in the learning model. After using such a system, reflective and active components, such as sensing and concrete examples connected to real life, should be primarily adjusted for learners to review what they have learned [14]. If we summarize the learning attributes that should be considered in adaptive learning based on previous studies and the suggested contents that adaptive learning should have, they can be presented in the following table Table 1.

(Table 1) Learning attributes for adaptive learning

Learning Attributes	Adaptive Learning
Age, gender, cognitive ability [9]	Personalized design, targeted resources, and feedback [11]
Prior knowledge [9]	Customized learning paths [13]
Pacing, level of questions [10]	Adaptation strategies [14]
Interaction strategies [11]	Collaboration process [12]
Personal strategies, sequence task, control adaptivity task, changes in learning model [13]	Levels of learner control [13]
Reflective review, active sensing [14]	Adjustments based on user experience [11]

2.2 Chatbot Technologies in EdTech

Through the development of machine learning model architecture, learning on large amounts of data has recently been performed, and studies that overcome the limitations of existing AI learning models are emerging. Improvement of the transformer-based natural language processing model is being made, and the use of a language model with a dialog-type UI such as ChatGPT is attracting attention. The following section explains the four main technical characteristics of AI language models that can help adaptive learning through the key features of learning attributes and how they can be applied in the EdTech field.

2.2.1. Transformer-based models

The transformer-based language model replaces the existing recurrent neural network model using an attention mechanism [15]. Previously, recurrent models based on seq2seq had an issue of performance degradation due to bottlenecks occurring in context vectors extracted from large input values. However, the transformer model considers all the output values of the encoder and looks at the weight of each word and the correlation between words so that it has more important information about the input value. This can be adapted to provide accurate analysis results and feedback on learner responses.

Language models prior to transformers measured probabilities for labels trained to provide outputs when providing feedback on user responses. However, using a transformer model based on the attention mechanism can more accurately determine the correlation between words and context. In addition, multi-headed attention makes it possible to determine representative connections so that the same response can have different representations depending on the situation.

2.2.2. Multi-turn dialogue models

The language model has been implemented with the goal of providing a conversation suitable for a user's response or request. However, as the conversation continues, the importance of a multiturn architecture that provides responses based on previous conversations, rather than single-turn based only on the user's previous conversation, increases.

Multi-turn, which accumulates information on sequential weight in the recurrent structure and provides the probability of response at the current time by using this, can give users high reliability [16]. This multi-turn structure plays an important role in improving the learning efficiency of users in EdTech. While the user continuously learns through the chatbot, the language model can accumulate the user's previous responses to determine the learning speed and provide customized educational content accordingly.

2.2.3. Reinforcement Learning

Reinforcement learning and the fine-tuning method are adopted to continuously improve the performance of the learning model. A language model using a reward-based reinforcement learning structure can self-learn, tune, and improve model performance based on user responses [17]. In addition, when new training data is received, information on new data can be reflected through model updates. ChatGPT adopts a new reward model that reflects human preference by applying Reinforcement Learning from Human Feedback(RLHF) [18]. This reinforcement learning structure

will be applied as an important factor in chatbot-based EdTech.

When learners and tutors proceed with education using EdTech, model fine-tuning can be performed using the learner's learning preference for the response presented by the language model. Also, from the tutor's point of view, it will be possible to create a model with more accumulated knowledge by adding new information and training data to the language model. In other words, the more you use it, the more it can grow into an efficient AI education model for individual learners.

2.2.4. Encoder-Decoder Style Embedding

In the high-dimensional language model, the information of the input value is compressed through the encoder layer to remain the representative value. Then the decoder returns it as an appropriate output value. Recently, studies have been conducted to create chatbots that reflect persona by adding a style embedding layer to these model architectures [19]. Interaction with the user is an important factor in a chatbot that continues a conversation with the user, and this can be implemented by forming a persona through a style embedding vector that contains information about the speaker between the encoder layer and the decoder layer. In the EdTech chatbot, a persona suitable for the learner can be reflected through an encoder-decoder model architecture with a speaker-style embedding layer added, and high interaction can be formed between the learner and EdTech chatbot.

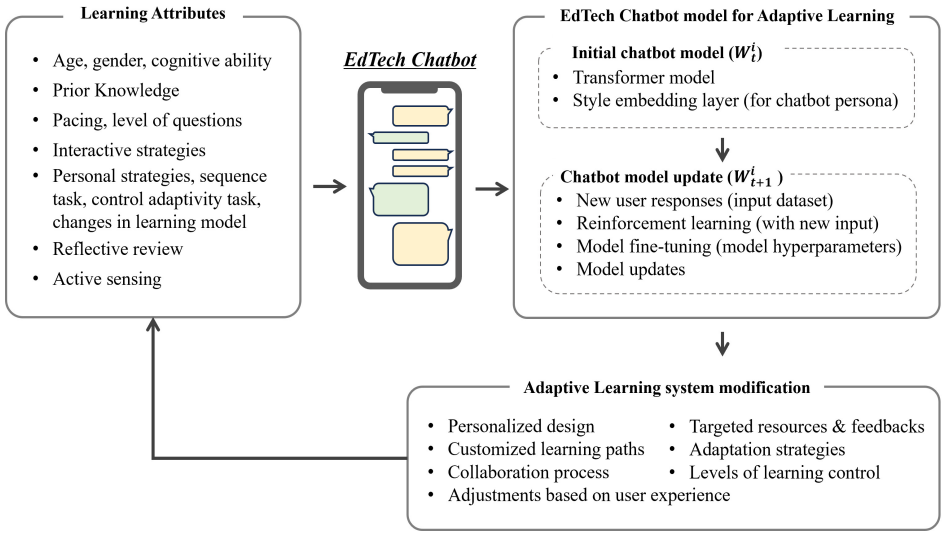
3. Proposed Framework

Based on a review of previous research on adaptive learning the role of chatbots in education, and the current and future technology of chatbots, we propose a framework for using ChatGPT or similar chatbots in adaptive learning as in Figure 1. Users can utilize the EdTech chatbot by first inputting their own learning attributes. The more initial information they provide, the better initial model they can obtain. The AI model denoted as Wt, is available to each individual user and can be further personalized as their education progresses. User responses collected during lectures are incorporated as new input data, and reinforcement techniques are applied to fine-tune and create the best EdTech chatbot model specifically tailored for each user.

The first element of the learning attributes identified in Table 1, which include age, gender, and cognitive ability, should be considered in the personalized design, targeted resources, and feedback for adaptive learning. Advanced chatbots can collect users' age and gender information and provide an appropriate encoder-decoder with an age-appropriate language style and gender-specific motivation, ensuring suitable personalized design and feedback.

Considering the elements of Human-Computer Interaction (HCI), research results suggest that children aged six to eight learn more effectively with peers, so chatbots with a persona that learns together could be effective [20]. Indeed, gender can influence learning preferences and interests, as often discussed in educational psychology [21]. For example, males tend to show more interest in mathematics and science, while females tend to be more interested in language and arts. Thus, it may be effective to provide examples, or problem sets with a mathematical or linguistic approach, depending on the learner's gender. However, it is crucial to note that this personalized learning path design is only a starting point and should be adjusted based on each individual's background, as differences between individuals can render the design ineffective. Therefore, the design should be modified into a customized one as more data is gathered on the user. Consequently, for future adaptations based on user characteristics, reinforcement architecture features of advanced chatbots like ChatGPT can be implemented, helping to adjust the learning path and provide targeted feedback that improves learner accuracy and satisfaction.

Chatbots can also play a crucial role in assessing cognitive ability and even evaluating prior knowledge. While traditional chatbots respond based on learned data, advanced chatbots utilize transformer technology to respond probabilistically without prior training. As a result, measuring via chatbot may offer a more detailed diagnosis of the learner's state rather than simply evaluating the learner's state as right or wrong. Advanced chatbots can thus play an important role in evaluating cognitive ability and



(Figure 1) EdTech Chatbot Framework for Adaptive Learning

prior knowledge. This more precise measurement and diagnosis of the learner's status can be used to identify specific knowledge gaps and provide appropriate learning paths.

For other learning attributes such as pacing and level of questions, transformer technology can be used to more accurately assess whether the learner is keeping up. With multi-turn capabilities, chatbots can accumulate and provide responses to the user's conversation, allowing adaptive learning to be provided at an appropriate pace and with suitable levels of questions. Through the investigation of learning attributes summarized through prior research, another important factor is interaction strategies. In the case of chatbots, transformer technology allows them to be free from formal constraints, enabling subjective or objective responses based on the user's preference and providing questions flexibly. This approach facilitates collaboration between the chatbot and the learner to progress their learning and deliver suitable adaptive learning.

The next important factor for providing adaptive learning, the level of learner control, can also be addressed by advanced chatbots through reinforcement and multi-turn technology. They can provide sequential tasks and adaptively adjust the tasks according to the results, continuously changing the learning model. Lastly, for the learning attributes of reflective review and active sensing, advanced chatbots can use multi-turn technology to track and provide adjustments to the encoding-decoding based on the user's experience, allowing for personalized adaptive learning through continuous tracking and adjustments.

To assess the feasibility and effectiveness of the framework proposed in this study for educational purposes, a simple evaluation was conducted using HTTP request with the ChatGPT model gpt-3.5-turbo-0613 developed by OpenAI, as illustrated in Figure 2.

As highlighted earlier, achieving effective adaptive learning begins with identifying and understanding the learner's attributes such as age, gender, and cognitive ability. Subsequently, based on these identified attributes, ChatGPT was able to provide tailored adaptive learning experiences for each user. Such outcomes were made possible due to the application of technologies in ChatGPT, as previously outlined, including the transformer-based model and encoder-decoder with style embedding. Upon initiating a dialogue that requested quizzes, as depicted in Figure 2, ChatGPT demonstrated its ability to offer varied pacing, levels of questions, and interaction strategies based on the previously provided learning attributes. The ability to achieve these outcomes can be attributed to the technological capabilities of ChatGPT, which includes multi-turn dialogue

Initial User information (Andrew): 27 years old, Male, College student		**Extracted Learning Attributes & Adaptive Learning features**	**Initial User information (Leslie):** 15 years old, Female, Middle school student	
Andrew:	Hi, my name is Andrew and I am a **27 years old** [1] **male** [2] **college student majoring in Computer Science** [3]. Can you tell me about "Federated learning"?	• Age [1] • Gender [2] • Cognitive ability [3]	Leslie:	Hi, my name is Leslie, and I am a **15 years old** [1] **girl** [2] **interested in Computer Science** [3]. Can you tell me about "Federated learning"?
EdTech:	Hello Andrew, **I'd be happy to explain federated learning to you** [6]. Federated Learning is .. This is a major paradigm shift, .. **centralized server where all the data is sent for training** [5]. **Here's a simple way to understand how federated learning works** [4]	• Personalized design [4] • Targeted resource [5] • Feedback [6]	EdTech:	Hello Leslie, **it's great to see you're interested in computer science** [6]! Federated learning is .. This is a new approach .. to training machine learning models that **respects user privacy** [5]. **Let's take an example of how it works. Imagine that you** [4] and several of your friends have a special app on your phones that recognizes …
Andrew:	I want to double-check that I understand well. Can you give me a quiz?	• Pacing [7] • Level of questions [8] • Interaction strategy [9]	Leslie:	I want to double-check that I understand well. Can you give me a quiz?
EdTech:	Of course, Andrew! It's great to confirm understanding through a quiz. Here are a few questions for you: 1. What is a key difference between federated learning and traditional machine learning in terms of where data is stored and processed? 2. **How does federated learning preserve user privacy** [7, 8]? ***(short answer questions)*** [9]		EdTech:	Sure, I'm glad to hear you're interested in testing your understanding! Here are a few questions for you: **What is the main purpose of federated learning** [7, 8]? a. To improve computational speed b. To centralize all data for machine learning c. To decentralize machine learning and improve privacy d. To improve the accuracy of machine learning models ***(multiple-choice questions)*** [9]

(Figure 2) An example of adaptive learning with chatbot

models, along with reinforcement learning and fine-tuning.

By delivering suitable learning attributes and employing new chatbot technologies in this manner, users can expect to receive personalized adaptive learning experiences. While ChatGPT, equipped with EdTech-friendly technologies, can offer a certain degree of adaptive learning, it is anticipated that users would see even more effective results tailored to their learning attributes if these machines were further modified to better suit the needs of EdTech.

4. Limitation

This study has several limitations that warrant mention. First, the proposed framework is premised upon an analysis of next-generation chatbot technology, using ChatGPT as an example. However, ChatGPT is not originally designed specifically for EdTech. As a result, the practical effectiveness of the proposed framework has not yet been fully established and requires further validation.

Second, although the learning attributes and necessary characteristics for learning systems were identified based on previous research, the general applicability of these findings across all areas of adaptive learning may be limited. The specific strategies could vary depending on the field of study, thereby potentially limiting the broad applicability of the proposed framework.

To mitigate these limitations, future research should focus on evaluating the effectiveness and usability of the proposed framework through the actual implementation in EdTech-specific systems. It is also essential to investigate how this framework can be adapted across different domains of study to provide a more comprehensive understanding of its potential applications in adaptive learning.

5. Conclusion

In conclusion, this study proposed a framework for using advanced chatbots, such as ChatGPT, in adaptive learning. Based on a review of previous research on adaptive learning, chatbot technology, and learning attributes, the proposed framework was designed to consider user-centered design and adaptability, personalization, interaction strategies, and

levels of learner control. The framework highlights the potential of next-generation chatbots in providing adaptive learning that is personalized, and interactive, with a more accurate measurement of the learner's state and the identification of specific knowledge gaps. However, the proposed framework has limitations in terms of actual usability and generalizability to different fields of study. Future research should focus on evaluating the effectiveness and applicability of the proposed framework in practice and exploring its potential applications in various domains of adaptive learning. By doing so, we hope to contribute to the advancement of EdTech and provide a guide for educators, developers, and learners seeking to utilize advanced chatbots in their adaptive learning scenarios.

References

[1] Donahoe, B., Rickard, D., Holden, H., Blackwell, K., & Caukin, N. "Using EdTech to enhance learning," International Journal of the Whole Child 4, No. 2, pp.57-63, 2019. https://libjournals.mtsu.edu/index.php/ijwc/article/view/1599/1124

[2] Bian, C. L., Wang, D. L., Liu, S. Y., Lu, W. G., & Dong, J. Y. "Adaptive learning path recommendation based on graph theory and an improved immune algorithm," KSII Transactions on Internet and Information Systems (TIIS), 13(5), pp.2277-2298, 2019. http://dx.doi.org/10.3837/tiis.2019.05.003

[3] Tarek, A. I. T., El Hajji, M., Youssef, E. S., & Fadili, H. "Towards highly adaptive edu-chatbot," Procedia Computer Science, 198, pp.397-403, 2022. https://doi.org/10.1016/j.procs.2021.12.260

[4] Baidoo-Anu, David, and Leticia Owusu Ansah. "Education in the era of generative artificial intelligence (AI): Understanding the potential benefits of ChatGPT in promoting teaching and learning," Available at SSRN 4337484, 2023. http://dx.doi.org/10.2139/ssrn.4337484

[5] Alebeisat, F., Altarawneh, H., Alhalhouli, Z. T., Qatawneh, A., & Almahasne, M. "The Impact of Human and Computer Interaction on eLearning Quality," International Journal of Interactive Mobile Technologies, 16(4), 2022. https://doi.org/10.3991/ijim.v16i04.27309

[6] Adikari, Sisira, and Craig McDonald. "User and usability modeling for HCI/HMI: a research design," 2006 International Conference on Information and Automation. IEEE, 2006. https://doi.org/10.1109/ICINFA.2006.374099

[7] Kim, Yanghee, and Quan Wei. "The impact of learner attributes and learner choice in an agent-based environment," Computers & Education 56.2 pp.505-514, 2011. https://doi.org/10.1016/j.compedu.2010.09.016

[8] Kerr, Philip. "Adaptive learning," Elt Journal 70.1 pp. 88-93, 2016 https://doi.org/10.1093/elt/ccv055

[9] Nakic, Jelena, Andrina Granic, and Vlado Glavinic. "Anatomy of student models in adaptive learning systems: A systematic literature review of individual differences from 2001 to 2013," *Journal of Educational Computing Research* 51.4 pp. 459-489, 2015. https://doi.org/10.2190/EC.51.4.e

[10] Martin, F., Chen, Y., Moore, R. L., & Westine, C. D. Systematic review of adaptive learning research designs, context, strategies, and technologies from 2009 to 2018. *Educational Technology Research and Development*, *68*, pp. 1903-1929, 2020. https://doi.org/10.1007/s11423-020-09793-2

[11] Park, O.-c., & Lee, J. Adaptive instructional systems. In D. H. Jonassen (Ed.), *Handbook of research on educational communications and technology*, pp. 651–684, 2004. https://doi.org/10.4324/9781410609519

[12] Paramythis, Alexandros, and Susanne Loidl- Reisinger. "Adaptive learning environments and e-learning standards," In *Second european conference on e-learning*, vol. 1, no. 2003, pp. 369-379. 2003. https://academic-publishing.org/index.php/ejel/article/download/1458/1421

[13] Magoulas, George D., Sherry Y. Chen, and Kyparissia A. Papanikolaou. "Integrating layered and heuristic evaluation for adaptive learning environments," In *Proceedings of the second workshop on empirical evaluation of adaptive systems, held at the 9th*

international conference on user modeling UM2003, Pittsburgh, pp. 5-14. 2003.
https://www.dcs.bbk.ac.uk/~gmagoulas/magoulasCP_UM03.pdf

[14] Yang, Tzu-Chi, Gwo-Jen Hwang, and Stephen Jen-Hwa Yang. "Development of an adaptive learning system with multiple perspectives based on students' learning styles and cognitive styles," *Journal of Educational Technology & Society* 16, no. 4 pp. 185-200, 2013.
https://www.jstor.org/stable/jeductechsoci.16.4.185

[15] Vaswani, Ashish, Noam Shazeer, Niki Parmar, Jakob Uszkoreit, Llion Jones, Aidan N. Gomez, Łukasz Kaiser, and Illia Polosukhin. "Attention is all you need," *Advances in neural information processing systems* 30, 2017.
https://proceedings.neurips.cc/paper/2017/file/3f5ee243547dee91fbd053c1c4a845aa-Paper.pdf

[16] Wu, Yu, Wei Wu, Chen Xing, Ming Zhou, and Zhoujun Li. "Sequential matching network: A new architecture for multi-turn response selection in retrieval-based chatbots," *arXiv preprint arXiv:1612.01627*, 2016.
https://doi.org/10.48550/arXiv.1612.01627

[17] Sharma, Akanksha Rai, and Pranav Kaushik. "Literature survey of statistical, deep and reinforcement learning in natural language processing," In *2017 International Conference on Computing, Communication and Automation (ICCCA)*, pp. 350-354, 2017.
https://doi.org/10.1109/CCAA.2017.8229841

[18] Christiano, Paul F., Jan Leike, Tom Brown, Miljan Martic, Shane Legg, and Dario Amodei. "Deep reinforcement learning from human preferences," *Advances in neural information processing systems* 30, 2017.
https://proceedings.neurips.cc/paper_files/paper/2017/file/d5e2c0adad503c91f91df240d0cd4e49-Paper.pdf

[19] Li, Jiwei, Michel Galley, Chris Brockett, Georgios P. Spithourakis, Jianfeng Gao, and Bill Dolan. "A persona-based neural conversation model," *arXiv preprint arXiv:1603.06155*, 2016.
https://doi.org/10.48550/arXiv.1603.06155

[20] Chandra, S., Alves-Oliveira, P., Lemaignan, S., Sequeira, P., Paiva, A., & Dillenbourg, P. Children's peer assessment and self-disclosure in the presence of an educational robot. In *2016 25th IEEE international symposium on robot and human interactive communication (RO-MAN)*, pp. 539-544, 2016.
https://doi.org/10.1109/ROMAN.2016.7745170

[21] Butler, Ruth. "Motivation in educational contexts: Does gender matter?," *Advances in child development and behavior* 47 pp. 1-41, 2014.
https://doi.org/10.1016/bs.acdb.2014.05.001

◐ Authors ◑

정 하 림(Harim Jeong)
2017 Bachelor of Music, University of Cincinnati, Ohio, United States.
2019 Master of Music, New England Conservatory of Music, Massachusetts, United States.
2022 Master of Cultural Management, Sungkyunkwan University, Seoul, Korea.
2022~Present: Ph.D. student in Dept. of Interaction Science, Sungkyunkwan University, Seoul, Korea.
Research Interests: Human-Computer Interaction, User Experience, Computational Method, Machine Learning.
E-mail : harim4110@gmail.com

유 주 헌(Joo Hun Yoo)
2020 B.S. in Applied Statistics, Chung-Ang University, Seoul, Korea.
2022 M.S. in Artificial Intelligence, Sungkyunkwan University, Suwon, Korea.
2022~Present: Ph.D. student in Dept. of Artificial Intelligence, Sungkyunkwan University, Suwon, Korea.
Research Interests: Machine Learning, Deep Learning, Federated Learning, Medical AI, Big Data Analysis.
E-mail : andrewyoo@g.skku.edu

한 옥 영(Oakyoung Han)
1985 B.S. in Computer Science, The University of Kansas, Kansas, United States.
1989 M.S. in Computer Science, California State University, California, United States.
1999 Ph.D. ABD in Computer Science, Korea Advanced Institute of Science & Technology (KAIST), Korea.
2012 Ph.D. in Computer Education, Sungkyunkwan University, Seoul, Korea.
1989~1991 Application Development Team, Samsung Electronics Computer Division
1991~1999 Head of Computer Science Department, Research Professor, Duksung Women's University
2000~2019 Adjunct Professor, Department of Computer Education, Sungkyunkwan University
2020~Present Assistant Professor, University College, Sungkyunkwan University
Research Interests: SW·AI Education, Computational Thinking, Data Structures, Algorithms, Problem Solving, Data Analysis, Artificial Intelligence, EdTech
E-mail : oakyoung@skku.edu