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IDENTIFICATION OF LEARNER'S DIGITAL PROFILE AND LEARNING STYLE BASED ON AI CONVERSATIONAL AGENT

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Abstract- Online learning, based on the integration of emerging technologies in education, has experienced remarkable growth in recent years, completely transforming traditional classroom teaching environments. To enhance the online learning experience, it is essential to provide relevant learning materials tailored to students' needs and preferences. Identifying learners' learning styles and preferences is a challenge for educational institutions, educators, and researchers. This challenge has led to the incorporation of artificial intelligence technology into virtual classrooms. In this study, we use a chatbot agent - one of the most popular AI tools - to identify the digital profiles and learning style preferences of students. The Felder-Silverman Learning Style Model (FSLSM), a widely recognized model, serves as the foundation for the identification process. During interactions with the chatbot agent, integrated into an online learning platform, learners are classified based on the model's parameters.

Keywords: Artificial Intelligence, Chatbot, Education, Student's Digital Profile, Styles of Learning, Filder-Silverman Learning Style Model.

1. INTRODUCTION

Information and communication technology (ICT) are used extensively in today's educational institutions because it provides a new avenue for knowledge acquisition through a variety of sophisticated functions like accessibility, communication, flexibility, and engagement [1]. The Learning Management Systems (LMS) are online learning platforms that continuously digitize materials for students with different backgrounds and learning objectives to enhance the learning process and students' performance. Nevertheless, students may select materials from the vast amount of information that is available to them during their learning process that are not appropriate for their educational needs.

In this context, accurately recognizing the traits of the learners is crucial to the task of enhancing both the process of learning and the performance of the learners. Accordingly, LMS must consider the user's characteristics when delivering learning content [2]. Thus, it makes it possible to establish a system of adaptive learning based on the students' learning profiles.

It aims to attribute to learners a specific learning content, then ensure for each learner a learning in accordance with his aptitude, personal characteristics, or learning style. These adaptive learning systems are developed based on artificial intelligence (AI) technologies, learning analytics, and educational data mining [3]. They support learners in planning and monitoring their learning processes through automatic interactions with the system that provide independent progression from the typical course instruction. Besides, these characteristics represent the " student learning profile " they may be generated by a system (Computer learning Environments including a student model unit) , which is used to indicate the representation of a set of information about the learners, describing their knowledge, skills and/or conceptions, preferences, educational expectations, information about possible disabilities, information about motivation, emotions and learning styles., identified at the end of a pedagogical activity.

The present research focusses on the dimension of learning styles while employing artificial intelligence (AI) for identifying students' digital profiles and learning preferences using an educational chatbot. The process of Information and knowledge acquisition refer to term "learning style." which represent the most effective mode of instruction or study for them [4], [5]. With the aim to provide a higher educational resource and increase effectiveness of the learning process. Various scientific models are employed to identify learning styles; these models divide learners into groups based on their personality traits and environmental circumstances. However, for this project, the FSLSM is chosen for been the most frequently applied model considering its ability to categories students according to their preferences across four distinct groups. during a digital learning process. The Index of Learning Styles (ILS) is an assessment deployed in this model to evaluate learners' preferences among four categories.

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In this paper, we aim to experience the design of a chatbot as an artificial intelligence (AI) tool integrated among the different functionalities available in the learning environment, in the intent of detecting learning styles according to the FSLSM model. The chatbot will rely on the ILS instrument using all 44 questionnaires to specify the four distinct dimensions of each user's learning style, and it can propose recommendations of learning materials and content in real time. The chatbot's design is based on an earlier project that used a model for educational chatbots adapted to the educational field and served to all the personnel engaged in the process. The experiment described in this study was carried out on master's degree candidates in several disciplines engaged on the use of the educational chatbot.

Section 2 provides a theoretical foundation for the topic's subject. The experiment methodology is outlined in the 3rd section; while the findings are examined in section 4, and the paper concludes in the final section.

2. THEORETICAL FOUNDATION

2.1. Learning Styles Concept

While in didactic, learning is considered as the process that describe the conceptual changes of learner's perceptions about a special learning continent, the study of the conditions and the ways of this change is crucial to enhance the learning performance [6]. Learning outcomes are influenced by various contextual and individual factors, as many research studies have confirmed, especially with the growth of online learning. Learning style differences have been considered in the last several years as a major factor that influences the educational performance of learners, which drives teachers to take into consideration this diversity among learners in the course design [7].

Theoretically, learning styles reflect the individual preferences for learning; They constitute a part of the general concept of personality. The education experts define learning styles as the way individuals differ in their study mode or instruction, which is most effective. Other studies confirm that the recognition of learning style of learners is crucial to providing the best potential strategy for promoting learning and deeper understanding of the learning objects [8]. According to Felder and Silverman the founders of the previous model, learners may experience challenges during the learning process if the way of teaching is not compatible with their style of learning [9]. In this instance, adaptive learning systems integrate learning styles as a factor in personalized learning [10]. In [11], depending on a variety of models indicated in the literature, in order to classify learners into distinct groups.

2.2. Felder Silverman Learning Style Model

The literature provides a range of models for learning preferences, such as the David Kolb's, Honey and Mumford's model, the VARK model by Fleming & Mills, and finally Felder-Silverman's model. These models focus either on external conditions or personality; they analyse different characteristics and their impact on the learning styles of learners. FSLSM was selected as a reference for our investigation since it is regarded as the most frequently deployed as a reference of learning style model in technology-enhanced learning especially in adaptive learning systems [12]. In [13], the ability to classify learners into four dimensions; for FSLSM, the learning styles are tendencies rather than obligatory categories [14], unlike other models, and have been easy to implement [15]. While the Index of Learning Styles (ILS) is an investigation of 44 questions, originally developed by the two scientists Felder and Solman as an assessment for ranking learners' Classification processes. Each dimension of this model is defined on a ranging scale between +11 and -11.

The previous model used four distinct dimensions to define the style of learning among the categories: active-reflective, sensing-intuiting, visual-verbal, and sequential-global. While processing dimension including the active and the reflective sides of the FSLSM relate to how information is processed, students who scored higher on the active scale are more likely to learn through active experimentation, conversation, or teaching others. On the other hand, students who belong to the reflective scale are more likely to observe critically. The visual and verbal dimension is about how the information is perceived by the students. The ones on the sensing scale prefer to use their senses to take in information, while students on the intuitive scale rely more on their memories and insights. The third-dimension focusses on how information is received. Verbal learners prefer written words as their primary mode of learning, while learners with visual preferences prefer that information be presented through pictures, flow charts, diagrams, or videos. The final dimension is related to how the students understand information. Sequential learners tend to learn in logically linear phases, building one concept upon another. On the other hand, global learners need to develop a comprehensive understanding of a subject before delving into its specific details.

2.3. Chatbot as an Artificial Intelligence Educational Tool

Conversational AI opens up exciting new avenues for innovative tools in the field of information and communication across technologies, like AI chatbots. The rapid advancement of ICT will undoubtedly influence all sectors, including education, in significant ways [16]. A chatbot is considered as an advanced application that integrates first Artificial Intelligence (AI) technology with the Natural Language Processing technology, among other different technologies, to interact in meaningful conversations with humans via text form or voice [17].

In contemporary times, chatbots, also recognized first as conversational agents, then simply bots and virtual tutors, they are increasingly integrated across diverse fields within the sciences. Currently, in education, chatbots are being introduced and employed to improve current services or develop new ones, thanks to the digital transformation process [18].

Many educational chatbots are primarily focused on delivering support services, a field in which chatbots have previously demonstrated promising results in a variety of other industries. such as medicine, banking, or customer services. Conversely, there has been a significant rise in the number of chatbots designed for teaching. These chatbots aim to impart knowledge to specific students, typically focusing on particular topics. They are employed in all the forms of education settings, serving the purpose of generating knowledge similarly to a human tutor. Students appreciate the positive impact of educational chatbots, such as enhancing self-motivation, improving organization, and fostering autonomous learning, all of which are generally effective.

3. METHODOLOGY

For the purpose of realizing the initial goal of this study, identifying the learning style of learners, in order to collect data, a quantitative approach was adopted through a questionnaire. The conceptual framework of the study was build based on the FSLSM through the index of the model (ILS) Which is founded free online, valid, reliable, and appropriate for determining learning preferences. The research instrument's validity and reliability were confirmed through pilot studies based on previous expert opinions and judgements conducted by researchers.

3.1. Study Simple

The first section of the survey included demographic questions about the replier's personal backgrounds, which included gender, year of study, and programs. The research sample consisted of a representative population of students currently enrolled in the Faculty of Sciences Ben Music, University of Hassan 2 Casablanca, in the academic year 2023-2024. There were 115 respondents from different master's degree programs. As mentioned in Table 1, 56% of the respondents were female, while 44% were male. In terms of study program, 60% were enrolled in the computer sciences program, followed by 21% of chemistry program students, and 19% of educational engineering program. The student sample was divided between 1st- and 2nd-year students.

Table 1. Demographic data

Factor		Modality	Number	Percentage
Gender		Male	50	44%
		Female	65	56%
Master degree	Computer sciences	Year 1	40	35%
		Year 2	29	25%
	Educational Engineering	Year 1	12	11%
		Year 2	9	8%
	Chemistry	Year 1	17	15%
		Year 2	8	6%

3.2. Research Tool

For this study, an integrated educational Chatbot was deployed as conversational agent into the learning management system for the purpose of collect data from the responses of users. The chatbot was developed using a free online tool based on a previous model designed to assist in the identification of student's learning styles [19].

The chatbot's interface is released in accordance with Natural human conversation structure which is generalized using the natural language processing system (PNL) [20]. The Chatbot' interface is straightforward, with only one choice for each questioning, as in Figures 1 and 2.

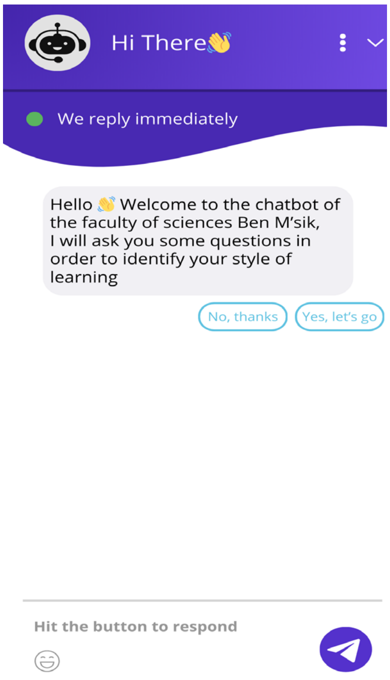

Figure 1. Interface of the 'Hello' message

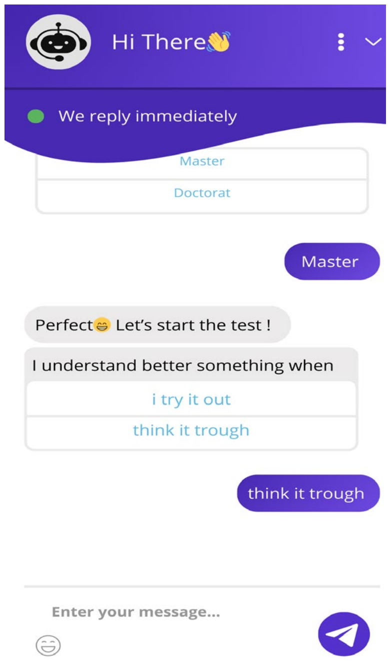

Figure 2. Question 1 of the first dimension

The repartition of questions in this study is divided into two sections. Section 2 consisted of 44 questions based on the ILS questionnaire, which was used in its original form to assess the preferred learning style among the Ben M'sik Faculty master degree' students in their educational process. Each question has two choices; both of them are correct, and students should choose the answer corresponding the most to their way of learning. Table 2 show the components of the Felder and Silverman Learning Style Index [21].

Table 2. Repartition of FSLSM Index Learning Style questions [21]

Dimension	Tendency	Questions items	total
Processing	Active reflective	1, 5, 9, 13, 17, 21, 25, 29, 33, 37, 41	11
Perception	Sensing intuitive	2, 6, 10, 14, 18, 23, 26, 30, 32, 34, 38	11
Input	verbal Visual	3, 7, 11, 15, 19, 24, 27, 31, 35, 39, 43	11
Understanding	Sequential Global	4, 8, 12, 16, 20, 25, 28, 32, 36, 40, 44	11
			44

Table 2 indicates that there are 11 question items in each dimension; as the total is 44 items, each question is calculated with a score ranging from 1 and 11 (representing the first option of the learning style category) to -11 and -1 (representing the second option of the learning style category). The data was recorded and analyzed using column charts, and the results were presented as figures in the following section.

4. RESULTS AND DISCUSSION

This research attempts to identify the tendency among the dominant learning styles and preferences of Master degree students. The interpretation of the score detecting each category of student learning style tendencies [21] is mentioned in Table 3.

Table 3. Learning Style Tendency [21]

Marge of the score	Category
9-11	Strong
5-7	Moderate
1-3	Balance

4.1. Preferences Toward Processing Information

Figure 3 indicates that 56.5% of respondents are classified as well-balanced between active and reflective learning styles, as their scores fall within the range of -3 to 3 on the scale.

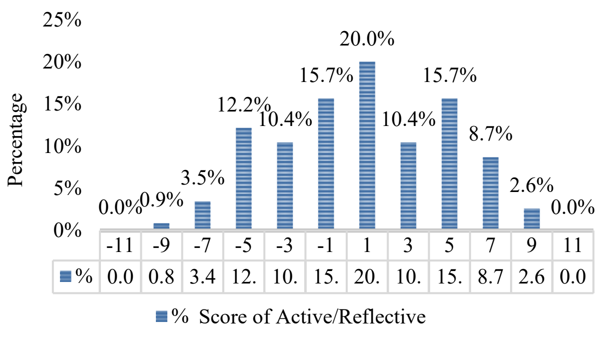

Figure 3. Chart of the Active/Reflective dimension

While 25.4% of repliers are moderate active learners, 15.7% are moderate reflective learners, and the remaining 2.6% are considered strong active learners, and 0.9% are strong reflective learners.

4.2. Preferences Toward Perceiving Information

For the sensing/intuitive dimension, Figure 4 shows that 47% of respondents are well-balanced on this scale, while 38.3% are moderately inclined toward sensing, and 11.1% exhibit a strong preference for the sensing style of learning. This suggests that most students prefer to process information through a blend of both sensing and intuitive approaches.

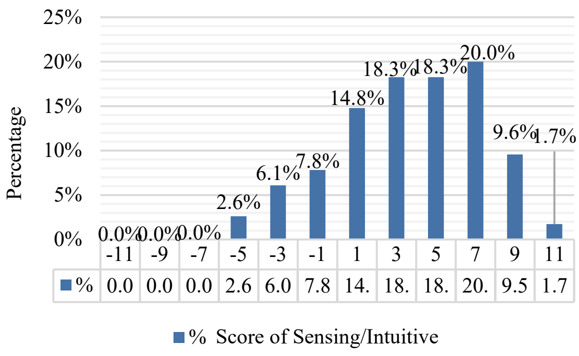

Figure 4. Chart of the Sensing/Intuitive dimension

4.3. Preferences of Sensory Channel to Perceive Information

The distribution of respondents in Figure 5 highlights preferences within the third dimension: visual or verbal learning styles. The figure clearly indicates that the majority of students are visual learners, with 20% exhibiting a strong preference and 34.8% showing a moderate preference for the visual sensory channel when processing external information. In contrast, only 1.7% of respondents demonstrate a moderate preference for verbal learning.

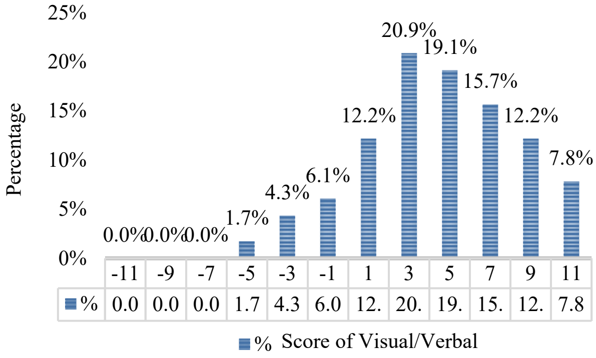

Figure 5. Chart of the Visual/Verbal dimension

4.4. Preferences Toward Understanding Information

The majority of participants (62.7%) demonstrated a well-balanced approach to sequential and global learning styles in the understanding component. Additionally, 3.5% showed a strong preference for one of these learning types, while 28.7% were moderately inclined toward sequential learning. These findings suggest that students in this study tend to equally favor both sequential and global approaches to understanding information.

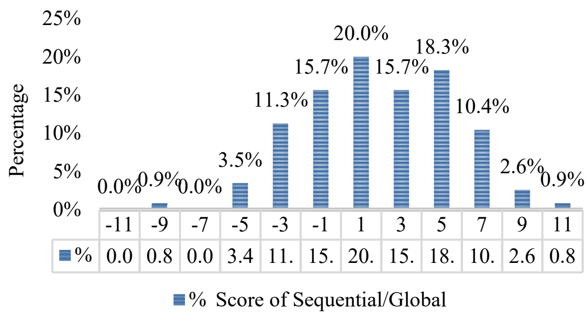

Figure 6. Chart of the Sequential/Global dimension

The study outcomes showed that over 50% of learners were identified as "well-balanced" on two out of four dimensions of learning styles, which are processing and understanding. The highly preferred tendency of learning was visual, followed by sensing, while the last chosen tendency of learning was intuitive, followed by verbal. These findings are in perfect correlation with a previous study [22] but different from others [23] and [24], which declare that all categories of learning styles are above 50%. For the processing dimension, the findings contradict a previous study released by Oxford [25] which pretends that learners are all the time reflective. Another study [26] reported that learners are not strictly classified into one of the active-reflective categories of the mean learning styles. Similarly, for the sequential/global dimension.

Regarding the sensory channel to perceive external-source information, the majority of respondents according to this study confirm that they prefer visual to verbal, which remains unchanged from an earlier study [27] and [28] that revealed most learners have a tendency towards receiving information in the shape of visual aids such as pictures, images, diagrams, and charts. Otherwise, the reason behind the last-opted tendency to be intuitive is that learners trust usually the senses rather than intuition.

5. CONCLUSION

Learning style is considered a major factor which impact the design and the advancement of personalized learning systems. While the online learning environments are in increasing use today, the learner's profile can be of great use for the advancement of the learning process. Identifying the learner's learning profile may help to better understand how the user interacts with the learning contents, which will play a vital role in designing adaptive and functional learning environments which are created in order to deliver the learning resources that are specific to the requirements and characteristics of each learner. The adaptive learning systems provide the possibility to create a cluster in order to group learners depending on their learning styles and preferences, which would help the instructor understand the variety of learner's groups and their behaviors towards different learning objects.

Through this work, we integrate AI technology for the sake of education. The created chatbot was designed to recognize the student's style and preferences of learning based on the FSLSM. The conversation with the chatbot applied the ILS instrument for the identification process.

The first step while detecting the user's learning style using the system was collecting general information about the user. This step was followed by the ILS questionnaire and the different questions of the four dimensions.

This survey provides the identification of users learning styles. Considering the processing and understanding dimensions, students were founded as "well-balanced" between the two tendencies of the dimensions, while for the perceiving and sensory channel of information dimensions, there was a relatively large preference for one tendency over the other. As an implication, this study has clarified the learning needs among the population of the survey and found out that there is large preference for one tendency over the other. Consequently, this study has clarified the learning needs among the population of the survey and found out that there is a preference for various forms of learning content, such as visual and sensing forms, which should be incorporated while developing the learning objects. As for the primary stakeholders of this study, we consider researchers, learners, educational staff, and decision-makers who can have an overview of student's perceptions online learning for further implementation of instructional strategies.

However, the findings of this study were the results of the first implementation of the chatbot into the learning system. The results should be considered with caution, as they are based on some specific levels and programs. A large-scale study that involves other students from different programs is a must before proceeding with the development of learning content adapted to the student preferences. As for a future work, it can be a study of students learning styles based on other models integrated into the same chatbot, which may provide fruitful findings from a diversity of perspectives on learning style. Lastly, an investigation study could be carried out as a comparison of student learning performance between a normal, unique learning process for all types of students and a learning process based on students' learning styles.

REFERENCES

[1] T. Karsenti, "How to Promote the Success of African Students in Open and Distance Learning: Pedagogical Principles", TICE et Development, Vol. 2, No. 9, pp. 9-23, 2006.
[2] J.T. Avella, M. Kebritchi, G.N. Sandra, T. Kanai "Learning Analytics Methods, Benefits, and Challenges in Higher Education: A Systematic Literature Review", Online Learning, Vol. 20, No. 2, pp. 13-29, June 2016.
[3] T. Kabudi, I. Pappas, D.H. Olsen, "AI-Enabled Adaptive Learning Systems: A Systematic Mapping of the Literature", Computers and Education: Artificial Intelligence, Vol. 2, No. 1, p. 100017, 2021.
[4] H. Pashler, M. McDaniel, D. Rohrer, R. Bjork, "Learning Styles: Concepts and Evidence", Psychological Science in the Public Interest, Vol. 9, No. 3, pp. 105-119, 2009.
[5] K. Hussain, S. Ullah, A. Salam, "Indexing of Learning Styles: A Case of the University Students Across

Faculties", International Review of Basic and Applied Sciences, Vol. 9, Issue 3, pp. 45-59, July 2021.
[6] I.F. Badaoui, M. Serghini, M. Chennaoui, Z. Habybellah, A. Khyati, "Design and Experimentation of a Didactic Device for Conceptual Change: The Case of Learning Electricity", International Journal on Technical and Physical Problems of Engineering (IJTPE), Issue 58, Vol. 16, No. 1, pp. 347-353, March 2024.
[7] S. Shrestha, M. Pokharel, "Determining Learning Style Preferences of Learners", Journal of Computer Science Research, Vol. 3, No. 1, pp. 33-43, 2021.
[8] M. Shuib, S.N. Azizan, "Learning Style Preferences Among Male and Female ESL Students in University Sains Malaysia", Journal of Educators Online, Vol. 12, No. 2, pp. 103-141, 2015.
[9] R.M. Felder, L.K. Silverman, "Learning and Teaching Styles in Engineering Education", Engineering Education, Vol. 78, No. 7, pp. 674-681, 1988.
[10] T.C. Yang, G.J. Hwang, S.J.H. Yang, "Development of An Adaptive Learning System with Multiple Perspectives Based on Student's Learning Styles and Cognitive Styles", Journal of Educational Technology and Society, Vol. 16, No. 4, pp. 185-200, 2013.
[11] G.J. Hwang, H.Y. Sung, C.M. Hung, I. Huang, "A Learning Style Perspective to Investigate the Necessity of Developing Adaptive Learning Systems", Journal of Educational Technology and Society, Vol. 16, No. 2, pp. 188-197, 2013.
[12] C.A. Carver, R.A. Howard, W.D. Lane, "Enhancing Student Learning Through Hyper-Media Courseware and Incorporation of Student Learning Styles", IEEE Transactions on Education, Vol. 42, pp. 33-38, 1999.
[13] P. Garcia, A. Amandi, S. Schiaffino, M.R. Campo, "Evaluating Bayesian Network's Precision for Detecting Student's Learning Styles", Computers and Education, Vol. 49, pp. 794-808, 2007.
[14] J. Lu, "A Personalized e-Learning Material Recommender System", in 2nd International Conference on Information Technology for Application (ICITA 2004), pp. 374-379, 2007.
[15] S. Graf, T.C. Liu, N.S. Chen, "Learning Styles and Cognitive Traits-Their Relationship and Its Benefits in Web-Based Educational Systems", Computers in Human Behavior, Vol. 25, No. 6, pp. 1280-1289, 2009.
[16] W. Kaiss, K. Mansouri, F. Poirier, "Pre-Evaluation with a Personalized Feedback Conversational Agent Integrated in Moodle", International Journal of Emerging Technologies in Learning, Vol. 18, No. 6, pp. 177-189, 2023.
[17] J.Q. Perez, T. Daradoumis, J.M. Puig, "Rediscovering the Use of Chatbots in Education: A Systematic Literature Review", Computer Applications in Engineering Education, Vol. 28, No. 6, pp. 1549-1565, 2020.
[18] C.G. Demartini, L. Benussi, V. Gatteschi, et al., "Education and Digital Transformation: The Riconnessioni Project", IEEE Access, Vol. 8, pp. 186233, 186256, 2020.
[19] R. Gandoul, N. Chafiq, M. Ghazouani, "Towards Adaptive Learning: AI Chatbot for Users Profiling and Learning Styles", International Journal on Technical and Physical Problems of Engineering, Issue 59, Vol. 16, No. 2, pp. 167-174, June 2024.
[20] W. Villegas Ch, A. Arias Navarrete, X. Palacios Pacheco, "Proposal of an Architecture for the Integration of a Chatbot with Artificial Intelligence in a Smart Campus for the Improvement of Learning", Sustainability, Vol. 12, No. 4, p. 1500, 2020.
[21] A. Hidayat, K. Adi, B. Surarso, "Detection of Student Learning Styles Using the Index of Learning Style", Advances in Social Science, Education and Humanities Research, The 1st International Conference of Education, Social and Humanities (INCESH 2021), Vol. 581, 2021.
[22] S. Graf, "Adaptivity in Learning Management Systems Focusing on Learning Styles", Ph.D. Diss., Technical University, Wien, Austria, 2007.
[23] M. Shuib, S.N. Azizan, "Learning Style Preferences Among Male and Female ESL Students in University Sains Malaysia", Journal of Educators Online, Vol. 12, No. 2, pp. 103-141, 2015.
[24] E. Ultanir, Y. Gurcan Ultanir, G. Temel, "The Examination of University Student's Learning Styles by Means of Felder-Silverman Index", Education and Science Education and Science, Vol. 37, No. 163, 2012.
[25] M. Nyikos, R. Oxford, "A Factor Analytic Study of Language-Learning Strategy Use: Interpretations from Information-Processing Theory and Social Psychology", The Modern Language Journal, Vol. 77, No. 1, pp. 11-22, 1993.
[26] Y. Wang, G. Ruhe, "The Cognitive Process of Decision Making", International Journal of Cognitive Informatics and Natural Intelligence (IJCINI), Vol. 1, No. 2, pp. 73-85, 2007.
[27] S. Rukh, "Student's Attitude Towards English Language Learning and Academic Achievement: A Case of Business Students in Punjab", European Academic Research, Vol. 2, No. 4, pp. 5596-5612, 2014.
[28] P.A. Noguera, "Urban Schools and the Black Male Challenge", Handbook of Urban Education, Routledge, pp. 152-166, 2013.

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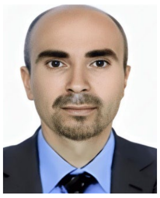

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