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The Impact of Pedagogical Agents On Learners' Cognitive Load in Mooc: A Quasi-Experimental Study

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Abstract

This study investigates the impact of pedagogical agents on learners' perceived cognitive load in a Massive Open Online Course (MOOC) environment. Using a quasi-experimental design, the study compares the cognitive load levels of two groups: one receiving learning lessons with a pedagogical agent and the other without. The sample comprises 66 students enrolled in multimedia-based courses at a Malaysian university. Data were collected using a questionnaire adopted from Leppink, Paas, Van der Vleuten, Van Gog, and Van Merriënboer (2013) A 10-item questionnaire measuring Intrinsic load, Extraneous load and German load. Results indicate that intervention of pedagogical agents in the MOOC learning environment improves learners' cognitive load. Although the differences between experiment groups based on the germane load are insignificant, the overall cognitive load upon learning with a pedagogical agent is significantly lower than that of the group that learnt without a pedagogical agent. These findings suggest that pedagogical agents might positively impact learners when embedded in the MOOC learning platform. Future research should explore long-term effects, diverse learner populations, and more interactive agent designs to better understand the potential of pedagogical agents in MOOC learning platform.

Keywords: *Cognitive Load, MOOCs, Pedagogical agents, Online learning, Quasi-experimental*

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Kesan Agen Pedagogi Terhadap Beban Kognitif Pelajar dalam Mooc: Kajian Kuasi-Eksperimen

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Abstrak

Kajian ini menyiasat kesan agen pedagogi terhadap beban kognitif yang dirasai oleh pelajar dalam persekitaran Massive Open Online Course (MOOC). Menggunakan reka bentuk kuasi-eksperimen, kajian ini membandingkan tahap beban kognitif antara dua kumpulan: satu menerima pembelajaran dengan agen pedagogi dan satu lagi tanpa agen tersebut. Sampel terdiri daripada 66 pelajar yang mendaftar dalam kursus berasaskan multimedia di sebuah universiti di Malaysia. Data dikumpul menggunakan soal selidik yang diadaptasi daripada Leppink, Paas, Van der Vleuten, Van Gog, dan Van Merriënboer (2013) yang terdiri daripada 10 item soal selidik untuk mengukur beban intrinsik, beban ekstrinsik, dan beban germane. Hasil kajian menunjukkan bahawa intervensi agen pedagogi dalam persekitaran pembelajaran MOOC menambahbaik beban kognitif pelajar. Walaupun perbezaan antara kumpulan eksperimen berdasarkan beban germane adalah tidak signifikan, beban kognitif keseluruhan semasa pembelajaran dengan agen pedagogi adalah lebih rendah secara signifikan berbanding kumpulan yang belajar tanpa agen pedagogi. Penemuan ini mencadangkan bahawa agen pedagogi mungkin memberi kesan positif kepada pelajar apabila diterapkan dalam platform pembelajaran MOOC. Penyelidikan masa depan harus meneroka kesan jangka panjang, populasi pelajar yang lebih pelbagai, dan reka bentuk agen yang lebih interaktif untuk memahami dengan lebih baik potensi agen pedagogi dalam platform pembelajaran MOOC.

Kata Kunci: beban kognitif, MOOCs, Agen pedagogi, pembelajaran atas talian, kuasi-eksperimen

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1.0. Pengenalan

Many are already aware of the effectiveness of instructional learning in improving learning. Among the features of instructional learning that benefit the learning are pedagogical agents. Pedagogical agents are digital characters designed to guide and support learning (Lane & Schroeder, 2022).It can take up multiple roles and forms in the learning environment, such as a 3-dimensional character, a 2-dimensional character, or just a mere text. This agent is equipped with a pedagogical agenda to represent actual tutors in carrying out and delivering the learning process towards learners. Not limited to that, pedagogical agents can also engage in multimodal interactions with learners, including verbal, nonverbal, and affective cues (Apoki, Hussein, Al-Chalabi, Badica, & Mocanu, 2022). This follows how the agent was designed and its role in the learning environment. With the current advancement of technology in teaching and learning, the features of pedagogical agents were expanding even better. To simplify it, one can say that a pedagogical agent represents an actual tutor as a virtual character in the learning environment.

Implementing pedagogical agents is not limited to physical classrooms, as they are integrated into various technology-enhanced learning environments, including online learning environments. Formerly, the pedagogical agent was commonly utilised in educational courseware to assist in learning (Schroeder & Gotch, 2015). Due to improper infrastructure and lacking internet accessibility, the pedagogical agent was made to function in an offline learning platform executed locally on the learner's desktop. Parallel with the advancement of the internet, the involvement of pedagogical agents has also evolved and was made accessible in the online learning environment. Massive Open Online Course, which goes by the abbreviation MOOC, is one of the online learning platforms that utilise instructional learning and may benefit from incorporating pedagogical agents into the learning platform itself. MOOCs have become a popular medium in online education as they can deliver towards large numbers of students and are accessible worldwide. MOOCs offer unprecedented access to high-quality educational resources, allowing learners from diverse backgrounds to engage with content at their own pace and convenience. However, despite these advantages, MOOCs face significant challenges, particularly concerning learner engagement and cognitive load, which can impact the overall effectiveness of these courses (Badali et al., 2022).

Incorporating a Pedagogical agent allows for several benefits towards learning. Research shows that pedagogical agents may positively impact the learner's cognitive load, motivation and learning outcomes (Armando, Ochs, & Régner, 2022; Wang et al., 2022). Features included in pedagogical agents such as cues, voice and feedback, offer better engagement from students towards learning content. By mimicking the role of human tutors, pedagogical agents aim to create a more engaging and supportive learning environment, which could help reduce the cognitive load experienced by learners. Cognitive load, a critical concept in educational psychology, refers to the mental effort required to process information and complete tasks. In MOOCs, where learners often have to navigate vast amounts of information with minimal guidance, cognitive load can become overwhelming, leading to decreased motivation, engagement, and, ultimately, higher dropout rates.

1.1 Massive Open Online Learning (MOOCs).

Pedagogical Agent is commonly used in instructional learning as it served instructional purposes of the learning (Beege, Nebel, Rey, & Schneider, 2024). MOOCs on the other hand, is another online platform that benefits the instructional design method in its development. Around 2016, Massive Open Online Courses (MOOCs) gained popularity in Malaysia's educational scene, providing a new level of online learning that can accommodate enormous enrolments of students. Anyone with an internet connection may usually access MOOCs, which are online courses created for large participation (Tzeng, Lee, Huang, Huang, & Lai, 2022). They provide numerous advantages, including flexible scheduling, an extensive selection of course alternatives, and the opportunity for students to interact with the material at their own pace (De Jong et al., 2020). MOOCs include drawbacks in addition to their advantages. The low completion rates of MOOCs which many courses have dropout rates as high as 90%, remain one of their biggest problems(Azhar, Iqbal, Shah, & Ahmed, 2024). This issue is exacerbated by a number of reasons, such as the dearth of individualised instruction, the restricted opportunities for contact between students and teachers, and the deluge of knowledge that students must assimilate independently(Jarial & Aggarwal, 2020). Due to the increased cognitive load caused by these factors, it may be challenging for students to remain motivated and engaged throughout the course (Badali et al., 2022).

Incorporating instructional agents into MOOCs can significantly improve learners' cognitive load (Ahuja et al., 2021). While MOOCs offer abundant resources, they may lack the individualized coaching and feedback necessary to facilitate learning (Floratos, Guasch, & Espasa, 2017). Pedagogical agents can bridge this gap by providing customized support, setting realistic goals, and delivering timely feedback, thereby cultivating a more supportive and friendly learning environment.

1.2 Cognitive Load

Cognitive load refers to the processing capacity of the learners during the learning process. The most common theory used to comprehend the learner's cognitive load is the Cognitive Load Theory(CLT) by Sweller (1988). According to the cognitive load theory, in an educational setting, there are three types of loads involved when the learner is engaging in the learning content: intrinsic, extraneous and germane. When the learners undergo the learning process, they will process novel information in the working memory before transferring it into long-term memory. These three types of loads were involved in processing novel information in the learners' working memory. Intrinsic cognitive load is related to the complexity of the material being learned, extraneous cognitive load refers to the unnecessary mental effort imposed by poor instructional design, and germane cognitive load is the mental effort dedicated to processing and understanding the material. However, the human brain has a limited capacity for processing information, and when this capacity is exceeded, learning becomes less effective. The strategy for optimizing cognitive load during learning is to eradicate as much as possible extraneous factors that may contribute to the high value of extraneous cognitive load as possible. When the extraneous load is lower, the learner's working memory can optimise the intrinsic cognitive load that is dedicated to comprehending and understanding the complexity of the learning content.

In the context of MOOCs, cognitive load can be particularly problematic due to the vast amount of content learners must process independently. When the learners are exposed to the learning content, they have to explore the content and figure out the proper structure and information needed to make sense of the learning. This unnecessary effort may hinder the learning process as it will contribute to the high value of extraneous load. Although some of the MOOC courses were already developed according to the instructional learning best practices that ease the learners in undergoing the learning content, they still lack real-time guidance in assisting the learners' understanding of the learning content. The lack of structured guidance and real-time feedback can exacerbate extraneous cognitive load, leading to frustration and disengagement. This is where pedagogical agents can play a crucial role. By providing real-time support, personalised feedback, and motivational encouragement, pedagogical agents have the potential to reduce cognitive load and enhance the overall learning experience.

1.3 Theoretical Framework

MOOCs became a sensation in Malaysian education scenery around 2015, as it is coherent with one of the Malaysian higher learning objectives: globalising learning. MOOCs have become one alternative for online learning platforms due to their ability to reach and cater towards large numbers of students worldwide. Among other features of MOOC that made it one of the prominent online learning platforms is flexible learning time which allows students to access the learning at their own time and pace (De Jong et al., 2020). However, despite its effectiveness and all the benefits that it can contribute to, MOOCs also suffer from several drawbacks that hinder learning. Among them is Cognitive load. Poorly designed MOOCs may impose a higher cognitive load towards learners and disrupt the learning content (Zimudzi et al., 2020). The phenomenon might be caused by weak instructional learning design that burdens the learner to navigate the learning material and comprehend the learning content itself.

Upon learning with MOOCs, the learners will have to engage and understand the learning platform presented to them and the learning content. In accordance with Cognitive Load Theory, Intrinsic load is the mental effort associated with the inherent difficulty of the learning content. Thus, in this context, the intrinsic load is imposed on the learner during the process of understanding and digesting novel information from the learning content itself. On the contrary, extraneous load is imposed towards the learner upon engaging with the learning platform (MOOCs) and navigating and browsing from one content to another. These are extraneous factors that will hinder learning and take up an unnecessarily large amount towards learners' cognitive load during the learning process. Another load, the German load, is a type of load that may benefit learning. This is the mental effort to process, understand, and integrate new information with existing knowledge. Therefore, in the context of optimising the effectiveness of the MOOCs module, it is by reducing the amount of extraneous imposed towards the learners, thus enabling learners to allocate more cognitive resources towards the intrinsic load and germane load that will contribute to the learning outcomes.

Social Agency Theory is among the most common theories used in developing and designing effective pedagogical agents. This theory, which was introduced by Mayer, Sobko, and Mautone (2003), indicates that incorporating social cues in multimedia learning, which in this case refers to the pedagogical agents, can mediate social conversation schema towards learners. Pedagogical agents are often included with social cues that assist in narrating the learning content to learners in the MOOCs platform (Davis, Vincent, & Wan, 2021). Social schema will lead the learners to act as if they are having a human-to-human interaction and communication with the learning content, thus eradicating any discomfort experienced by the learners upon learning through the MOOCs platform (Floratos et al., 2017). As a result, any possibility contributing to the learner's extraneous load can be reduced and prevented. However, in context of pedagogical agent design, Social Agency Theory mainly focused on the social cues element of the agent. This might happen to avoid drawbacks in the pedagogical agent design if the design is too complex or distracting. Some potential drawbacks that might derive are cognitive overload and the uncanny valley effect, as the main focus of social agency theory is to build a good relationship between the agent and the students.

Cognitive Theory of Multimedia Learning, also known as CTML, is another theory that is derived from cognitive load theory, which explains the cognitive process of the learners upon learning through multimedia. This theory, introduced by Mayer (1997), was primed with several prior cognitive-related theories, such as dual coding theory by Paivio (1990) and Cognitive Load Theory. Based on CTML, words and pictures were processed in two different channels during the learning, involving two different human senses. Similarly, with cognitive load theory, novel information is processed in working memory, which has limited capacity. Therefore, presenting words and pictures together in the learning material does not increase the learner's cognitive load but increases the learning content's effectiveness. In addition to that, several cognitive principles have been ruled out and tested in optimising a learner's cognitive load during learning (Mayer, 2008). The design of pedagogical agents in the MOOC learning platform will be primed by these principles to enhance the effectiveness of the learner's cognitive processes. Among the principles involved in designing the pedagogical agent are the Split-attention, Modality, Segmentation, and signalling principles. Leveraging these principles in pedagogical agent design aims to optimise the role of the pedagogical agent in facilitating the learning process. Facilitating the learning towards the learners may avoid any unnecessary extraneous load that might be imposed due to the learners' confusion and discomfort in navigating through the learning content by themselves.

The theories mentioned above aimed to understand the learner's cognitive architecture and process, thus finding theoretical solutions in managing learners' cognition through the intervention of pedagogical agent design in MOOCs learning platform.

2.0 Problem Statement

The contribution of MOOCs and their effectiveness towards online education is beyond question. As mentioned earlier, MOOCs provide independent accessibility and flexibility empowered with internet accessibility towards learners (Vázquez Cano, López Meneses, Gómez Galán, & Parra González, 2021).In addition to that, the MOOC learning platform also offers a wide range of courses across different fields and disciplines worldwide, making it one of the best alternatives for online learning, catering to huge numbers of learners.

Poorly designed online learning courses often risk imposing a higher cognitive load towards learners that might hinder learning (Chen, Woolcott, & Sweller, 2017; Dönmez, 2022).As another online learning platform, MOOCs were not excluded from suffering the same issue. It was further proven with several research that has been conducted concerning the cognitive demand of the learners upon learning in online learning platforms (Cabero-Almenara, Barroso-Osuna, Gutiérrez-Castillo, & Rodríguez, 2023; Zhao, 2023).

The potential of pedagogical agents to reduce cognitive load in MOOCs lies in their ability to provide personalised interactions and real-time feedback, which are often lacking in traditional MOOC environments. Pedagogical agents can offer explanations, answer questions, and provide motivational support, all of which can help learners manage their cognitive load more effectively (Ahuja et al., 2021; Dever et al., 2023). Several studies have demonstrated the effectiveness of pedagogical agents in reducing cognitive load. For instance, research by Schneider, Krieglstein, Beege, and Rey (2022) showed that students who learned with a better appropriate design of pedagogical agents experienced lower levels of cognitive load. Similarly, a study by Li, Wang, and Mayer (2023) found that students who interacted with an animated pedagogical agent during a multimedia lesson demonstrated improved retention and knowledge transfer, suggesting that the agent helped to manage cognitive load more effectively.

However, empirical research on the effectiveness of pedagogical agents in MOOC learning platforms is still lacking in number. Thus, this research investigates the impact of learners' cognitive load upon learning with pedagogical agents in MOOC learning platforms. The aim is to offer insight that improves MOOC learning outcomes through the learner's cognitive load with the intervention of pedagogical agents.

3.0 Research Objective and Hypothesis

3.1 Research Objective

1. Investigate the impact of pedagogical agents on the MOOCs platform towards the learner's cognitive load.

3.2 Research Question

1. Does a pedagogical agent in the MOOC platform significantly improve a learner's cognitive load compared to non-agents in the MOOC platform?

3.3 Hypothesis

1. Pedagogical agents in the MOOC platform significantly improved learner's cognitive load compared to the non-agents in the MOOC platform.

4.0 Methodology

The process of comparing the learning with and without pedagogical agents will be assessed via quasi-experiment. A quasi-experiment will be conducted to assess students' cognitive load when learning with and without a pedagogical agent. The experimental design is illustrated in Figure 1 and will include two experiment groups, namely a treatment group (X1) and a control group (X2). Students in the control group will engage with the MOOC learning content and modules without the assistance of a pedagogical agent. Conversely, those in the treatment group will complete the same learning content and materials but with the support of a pedagogical agent. After the learning

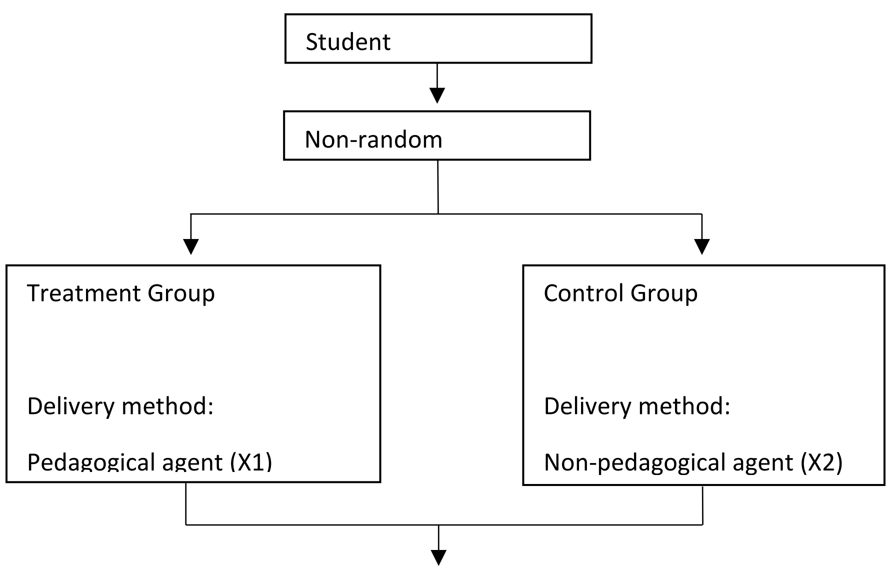

Figure 1. Experiment Design

process, participants in both groups will complete a questionnaire designed to measure the perceived cognitive load of learners across the different experimental conditions.

4.1 Sampling

The experiment involved sixty-six (n=66) students enrolled in multimedia-based courses called “Script and Storyboard” at a local university in Malaysia. The sample was chosen from a multimedia-based course to eliminate any extraneous factors that may arise due to low literacy in multimedia, such as difficulty navigating the learning platform (the MOOC), that could potentially interfere with the study. The mean age of the participants was 19 years. The students were evenly divided between the experimental groups.

4.2. Instrument

Questionnaires were used to measure learners' perceived cognitive load in both experiment groups. The set of questionnaires was originally adopted from a ten-item questionnaire for measuring intrinsic load, extraneous load and germane load developed by Leppink et al. (2013) . The instrument consisted of 10 items on a 5-point Likert scale divided into three different constructs: Intrinsic Load, Extraneous Load and Germane Load. Since the instrument was adopted, factor analysis and reliability tests were not conducted as the instrument has undergone the process during the development phase.

4.3 Analysis Method

As mentioned previously, the learner's Cognitive load was measured using the 5-point Likert scale. The mean value from the instrument was used as an indicator. An appropriate mean analysis test was used to compare means between the experiment groups. The parametric test, which is the Independent t-test, and the non-parametric test, which is the Mann-Whitney U test, will be used in accordance with the normality of the data.

5.0 Data Analysis

The normality of data was identified using the Shapiro-Wilk test to define the normality of the data according to the construct and the overall sum for each construct. The result is shown in Table 1 below. Then, the mean comparison test was chosen appropriately in accordance with the normality of the data.

Table 1: Data Normality Test.

Construct/variable	**Normality of data**	**Type of analysis**
Intrinsic load	Normally distributed	Independent T-test
Extraneous load	Not Normally distributed	Mann Whitney U test
Germane load	Not normally distributed	Mann Whitney U test
Cognitive load (overall)	Normally distributed	Independent T-test

Next, the mean value for each construct (intrinsic, extraneous, and germane load) and the variable (cognitive load overall) were computed. The mean value was compiled together in the Table 2 below. Based on the results, the mean values for the intrinsic load construct of the treatment and control groups are 3.1919 and 3.7778, respectively. It shows that the mean values for the treatment group construct are lower than those of the control group. Similarly with the intrinsic load construct, the result for the extraneous load construct indicates that the mean value for the treatment group is lower than the control group, with values of 1.8081 and 2.4747, respectively. As for the germane load construct, both experimental groups yield a mean value of 1.5152 for the treatment group and 1.4015 for the control group. The values for both groups do not differ that much. Next is the mean value for the overall cognitive load for both experiment groups. The mean value for the cognitive load value for the treatment group is lower than the control group, with a value of 3.2939 for the treatment group and 3.7152 for the control group. Based on the descriptive data given, it shows that the intervention used in the treatment group (pedagogical agent) succeeded in reducing the intrinsic and extraneous load of the learner, thus contributing to the lower overall cognitive load of the learners. The difference between mean value for each construct and variable (cognitive load) is best portrayed in the Figure 2 and Figure 3.

Table 1 : Mean value per construct and variable.

Constructs /Variable	**Mean value**			
	Treatment group		**Control Group**	
	Mean	**SD**	**Mean**	**SD**
Intrinsic load	3.1919	1.236	3.7778	1.033
Extraneous load	1.8081	1.080	2.4747	1.438
Germane load	1.5152	0.667	1.4015	0.483
Cognitive load (overall)	3.2939	0.5436	3.7152	0.7027

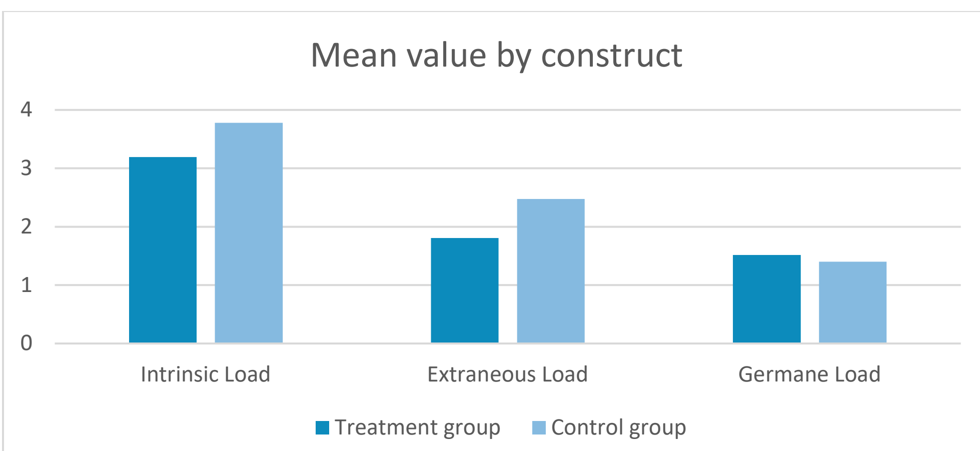

Figure 2 : Mean value by construct.

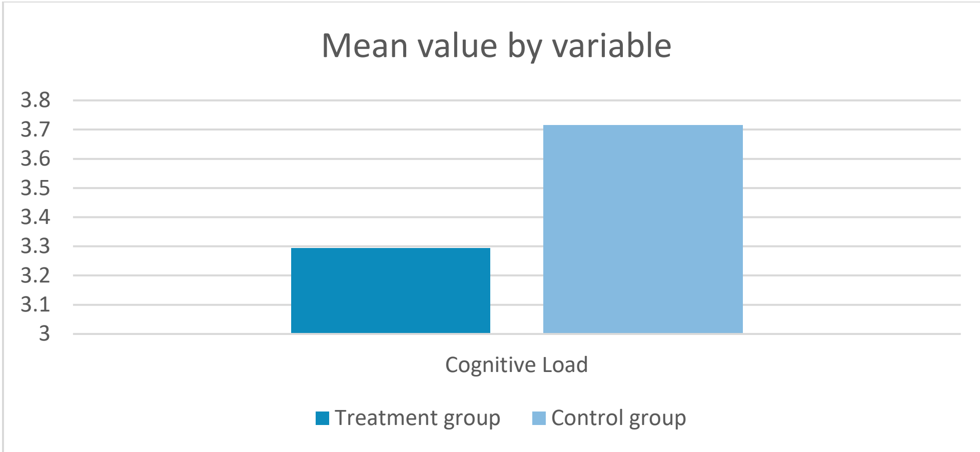

Figure 3 : Mean value by variable.

The difference in the mean value between the experiment groups must be statistically computed to ensure it is statistically significant. As mentioned above, an appropriate mean comparison test was used in accordance with the normality of data between each construct and variable to determine the significance value for the mean difference between experiment groups. The Independent t-test was used to measure the significance value for the intrinsic load construct and overall cognitive value, while a non-parametric (Mann Whitney U) test was used to measure the significance value for the extraneous load construct and germane load construct. The significant value was determined by a confidence interval percentage of 95%, where the difference is considered significant when the significance value does not exceed 0.05 ($p<0.05$). The result of the mean comparison test is as depicted in Table 3. The result shows that the mean difference between experiment groups for intrinsic load and extraneous load construct is significant, with significance values of 0.045 and 0.042, respectively. These values are below 0.05 ($p<0.05$) and indicate significant differences. Contrary to the other two constructs (intrinsic load and extraneous load), the significance value for the germane load construct is above 0.05 with a value of 0.628, indicating that the differences between the experiment groups are insignificant. Nevertheless, when the mean value between the experiment groups for overall cognitive load was compared, it showed that the differences were significant, with a significance value of 0.008. Thus, the hypothesis of this research is accepted.

Table 2 : Mean comparison test result.

Constructs /Variable	**Mean Comparison Test**				**Sig.**
	Treatment group		**Control Group**		
	Mean/Mean Rank	**SD/ Sum of Ranks**	**Mean/Mean Rank**	**SD/ Sum of Ranks**	
Intrinsic Load	3.1919	1.236	3.7778	1.033	0.041
Extraneous Load	28.80	950.50	38.20	1260.50	0.042
Germane Load	34.59	1141.5	32.41	1069.5	0.628
Cognitive Load	3.2939	0.5436	3.7152	0.7027	0.008

6.0 Findings

Previously, the result yield from the test analysis was presented in accordance with the construct and the variable itself. This subtopic will elaborated more on what the value indicates in coherence with the intervention used during the experiment and the cognitive load of the learners. As explained before, at the beginning of the experiment, the experiment group was divided into two different groups. The treatment group is the group where the learners undergo the learning process with the presence of a pedagogical agent in the MOOC learning platform, while the learners in another group (control group) undergo the learning process without a pedagogical agent in the MOOC learning platform. Thus, the analysis result presented in the previous sub-topic indicates the cognitive load value of the experiment group upon undergoing the learning process with and without a pedagogical agent in the MOOC learning platform.

The main aim of the pedagogical agent in the MOOC learning platform is to facilitate learning and assist the learners in undergoing all the learning content presented in the platform. Based on the result, it shows that upon the intervention of a pedagogical agent in the MOOC learning platform, the learners' intrinsic and extraneous loads are lower than those that learnt without a pedagogical agent. The difference is also statistically significant. It shows that the pedagogical agent not only contributes in reducing the extraneous load of the learners but also contributes towards the difficulty of the learning material itself (intrinsic load). Another construct of the cognitive load, which is germane load, upon learning with a pedagogical agent results in slightly higher than the group of learners that learnt without a pedagogical agent. However, the difference is not statistically significant and indicates that pedagogical agents have no significant impact on the germane load of the learners.

The result is also coherence with the overall value of the learner's perceived cognitive load. The results also suggested that the overall cognitive load of the learners who learnt with a pedagogical agent was lower than that of the learners who learnt without a pedagogical agent. This indicates that the intervention of pedagogical agents in the MOOC learning platform is able to improve learner's cognitive load. This is coherent with the hypothesis suggested at the earlier stages of the experiment.

7.0. Discussion and Conclusion

As explained previously, this experiment aimed to investigate the impact of pedagogical agents on MOOC learning platforms via quasi-experiment. The results indicate that the learners' cognitive load is significantly improved upon a pedagogical agent's intervention. Based on the previous literature, the impact of pedagogical agents on learners' cognitive load often produces mixed results. There are arguments that the risk of pedagogical agents might impose cognitive overload upon learners and hinder learning(Clark & Choi, 2007). However, more recent research indicates mixed results. Ahuja et al. (2021) in this study shows that the pedagogical agents do not increase the cognitive load of the learners but improve the germane load of the learners. This is also consistent with the findings from Dever et al. (2023) where it indicates that the findings show that a pedagogical agent's intervention improves the learner's cognitive load. In contrast, another study by Beege and Schneider (2023) indicates that pedagogical agents do increase the learner's cognitive load. However, most previous studies do not focus on the impact of the pedagogical agents on learners' cognitive load embedded in the MOOC learning platform. Thus, the result yielded from the experiment in this paper offers a new dimension and spectrum to the implantation of pedagogical agents on MOOC learning platforms and how they impact the learner's cognitive load. Implementing a pedagogical agent in MOOC assists learners in navigating through the learning content. This assists in resulting in lower extraneous load and better allocation of intrinsic load, which will be beneficial towards comprehending the learning content. In addition, the design of the pedagogical agent, which was primed by social agency theory and cognitive principles, has further improved the learner's cognitive load during learning.

The experiment involved in this research focused on the implementation of pedagogical agents on the MOOC platform in general. Thus, the presence of pedagogical agents in the MOOC learning platform served as an independent variable in this research. Although several other possibilities or features of the pedagogical agent might influence the learner's cognitive load during the learning process, these features were not discussed further and remained a limitation of this research. Examples of those features are the pedagogical agent design elements such as the visual appearance of the agents, types of voices, types of cues and form. These features might have different impacts towards the learner's cognitive load.

Therefore, those features might lead to several possibilities for future studies in the related field. Future research could explore the impact of different agent designs and personalities on learner cognitive load. Specifically, examining whether certain characteristics, such as the agent's appearance, voice, and demeanour, affect learners' cognitive load and learning outcomes. Additionally, future studies might investigate the effects of more interactive and adaptive pedagogical agents capable of responding to learners' emotional states and providing personalised feedback. Enhancing the interactivity of these agents could potentially lead to more significant improvements in cognitive load.

In conclusion, this study found that including a pedagogical agent in a MOOC platform significantly improves learners' cognitive load compared to a non-pedagogical agent MOOC environment. These findings suggest that the implementation of a pedagogical agent on the MOOC learning platform offers another benefit towards learning where it contributes to improving the learner's cognitive load during the learning process. Further research is needed to explore additional factors that could influence cognitive load in online learning environments and investigate pedagogical agents' effects on other learning attributes, such as motivation and learning outcomes.

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