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The Impact of Pedagogical Agents on Intrinsic Motivation in MOOCs: A Quasi-Experimental Study

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Abstract

This study examines the impact of pedagogical agents on learners' perceived intrinsic motivation in a Massive Open Online Course (MOOC) environment. Using a quasi-experimental design, the study compares the intrinsic motivation levels of two groups: one receiving learning lesson with a pedagogical agent and the other without. The sample consists of 66 students enrolled in multimedia-based courses at a Malaysian university. Data were collected using a questionnaire adapted from the Intrinsic Motivation Inventory (IMI) and the Motivated Strategies for Learning Questionnaire (MSLQ). Results indicate that there are no statistically significant differences in intrinsic motivation between the groups. While both groups reported high levels of interest, enjoyment, competence, effort, and pressure, the presence of a pedagogical agent did not significantly enhance intrinsic motivation. These findings suggest that while pedagogical agents may offer benefits, their impact on intrinsic motivation in MOOCs is limited. Future research should explore long-term effects, diverse learner populations, and more interactive agent designs to better understand the potential of pedagogical agents in online learning environments.

Keywords: *Pedagogical agents, Intrinsic motivation, MOOCs, Online learning, Quasi-experimental*

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Kesan Agen Pedagogi Terhadap Motivasi Intrinsik Dalam MOOC: Kajian Kuasi-Eksperimen

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Abstrak

Kajian ini mengkaji kesan agen pedagogi terhadap motivasi intrinsik yang dirasai oleh pelajar dalam persekitaran *Massive Open Online Course* (MOOC). Menggunakan reka bentuk kuasi-eksperimen, kajian ini membandingkan tahap motivasi intrinsik antara dua kumpulan: satu menjalani pembelajaran dengan agen pedagogi dan satu lagi tanpa agen tersebut. Sampel terdiri daripada 66 pelajar yang mengikuti kursus berasaskan multimedia di sebuah universiti di Malaysia. Data dikumpul menggunakan soal selidik yang diadaptasi daripada *Intrinsic Motivation Inventory* (IMI) dan *Motivated Strategies for Learning Questionnaire* (MSLQ). Hasil kajian menunjukkan tiada perbezaan yang signifikan secara statistik dalam motivasi intrinsik antara kumpulan tersebut. Walaupun kedua-dua kumpulan melaporkan tahap minat, keseronokan, kompetensi, usaha, dan tekanan yang tinggi, kehadiran agen pedagogi tidak meningkatkan motivasi intrinsik secara signifikan. Penemuan ini mencadangkan bahawa walaupun agen pedagogi mungkin menawarkan faedah, kesan mereka terhadap motivasi intrinsik dalam MOOC adalah terhad. Penyelidikan masa depan harus meneroka kesan jangka panjang, populasi pelajar yang pelbagai, dan reka bentuk agen yang lebih interaktif untuk memahami dengan lebih baik potensi agen pedagogi dalam persekitaran pembelajaran dalam talian.

Kata Kunci: Agen pedagogi, motivasi instrik, MOOCs, pembelajaran atas talian, kuasi-eksperimen

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1.0 Introduction

One of the tools that is commonly used in e-learning platforms and environments is the Pedagogical Agent. Pedagogical agents are virtual characters designed to facilitate learning by interacting with learners in an educational environment (Apoki, Hussein, Al-Chalabi, Badica, & Mocanu, 2022).These agents can take on various roles, such as tutors, mentors, or peers, and are often integrated into instructional learning systems to provide personalized feedback, guidance, and support. They are equipped with intelligence capabilities that allow them to adapt to the learner's needs and preferences, creating a more dynamic and engaging learning experience. By simulating human-like interactions, pedagogical agents can offer explanations, answer questions, and even provide motivational support, thereby enhancing the overall effectiveness of instructional learning (Petersen, Mottelson, & Makransky, 2021).Simply put, the pedagogical agent represents a human tutor in the learning platform to deliver a pedagogical agenda and learning content.

The usage of pedagogical agents is not limited to online learning. Initially, before the age of the internet, pedagogical agents were used in traditional e-learning platforms to serve as tutors or learning companions. One notable example is the use of robotic pedagogical agents in classrooms by Leyzberg, Spaulding, Toneva, and Scassellati (2012).These physical robots can interact with students in real time, providing personalized instruction and feedback. Another example is blended learning environments, which combine online and face-to-face instruction and have also benefited from the use of pedagogical agents. Agents can bridge the gap between online and offline learning in such settings by providing continuous support. For instance, a study by Moreno, Mayer, Spires, and Lester (2001), explored the use of an animated pedagogical agent in a multimedia science lesson. The study found that students who interacted with the agent in a classroom setting showed improved retention and knowledge transfer compared to those who received traditional instruction alone. The current age of the internet has shifted the education landscape towards more globalized online learning. As a result, instructional learning has been extensively utilized to create engaging, interactive, and effective educational experiences. Instructional learning has benefited pedagogical agents in improving instructional learning. The usage of pedagogical agents in instructional learning has been widely researched, with studies highlighting their potential to improve educational outcomes. For example, Baylor and Kim (2004) demonstrated that pedagogical agents could simulate various instructional roles, such as a coach or a peer, which helps deliver content that is more relatable and understandable. This flexibility allows instructional designers to create more effective and engaging learning environments that cater to diverse learning styles and preferences. The interactive nature of pedagogical agents makes the learning process more engaging, as learners can receive immediate feedback and support, which is crucial for maintaining motivation and interest in the subject matter.

Evidence from past literature suggests that pedagogical agents can significantly improve intrinsic motivation among learners. Intrinsic motivation refers to the internal drive to engage in an activity for its own sake, rather than for external rewards. Kim and Baylor (2006) found that the presence of a pedagogical agent in a learning environment increased students' intrinsic motivation by providing emotional support and reducing anxiety. This is particularly important in online learning environments, where the lack of human interaction can lead to feelings of isolation and disengagement. Similarly, a review by Sikström, Valentini, Sivunen, and Kärkkäinen (2022) reported that students who interacted with a pedagogical agent showed higher levels of intrinsic motivation and better learning outcomes compared to those who did not. These findings underscore the potential of pedagogical agents to enhance the educational experience by fostering intrinsic motivation and engagement, ultimately leading to improved learning outcomes.

1.1 Massive Open Online Learning (MOOCs).

Massive Open Online Courses (MOOCs) became a buzzword in Malaysian education landscape around 2016 as it became another spectrum for online learning that can cater to large numbers of students. MOOCs are online classes intended for many students and are frequently accessible to anybody with an internet connection (Tzeng, Lee, Huang, Huang, & Lai, 2022). MOOCs provide many benefits, including flexible scheduling, a wide range of course options, and the chance for students to interact with the content at their own pace (De Jong et al., 2020). Despite all of their advantages, low completion rates are a recurring problem for MOOCs (Azhar, Iqbal, Shah, & Ahmed, 2024). Students may find it difficult to stay motivated throughout a course because they are frequently struggling with the lack of in-person engagement and individualized instruction (Jarial & Aggarwal, 2020).

Researchers and educators have looked into creative ways to solve this motivating gap; one potential approach is incorporating educational agents into the MOOC setting (Alfaro et al., 2020). Personalized interactions, feedback, and assistance are offered via virtual characters or intelligent helpers known as pedagogical agents. These agents became representatives of actual tutor in delivering pedagogical agenda (Apoki et al., 2022).

According to Apoki et al. (2022) pedagogical agents can provide customized support, accommodate different learning styles, and foster a more dynamic and captivating learning environment. Pedagogical agents can fill the gap by giving real-time support, responding to questions, and delivering encouragement—a feature that traditional online courses frequently lack. Learner engagement and understanding have been demonstrated to be positively impacted by this personalised interaction (Buddemeyer et al., 2021).

Incorporating instructional agents into MOOCs can potentially significantly boost learners' intrinsic motivation (Adams & Davis, 2016). According to Ryan and Deci (2000)Intrinsic motivation is the internal drive and desire that propel people to participate in a task for their own reason and derive pleasure and satisfaction from the process. Although MOOCs offer many materials, they may fall short of the individualised coaching and feedback necessary to promote intrinsic motivation (Floratos, Guasch, & Espasa, 2017). By providing tailored assistance, establishing realistic objectives, and providing prompt feedback, educational facilitators can bridge this gap and foster a more encouraging and encouraging learning environment.

Incorporating pedagogical agents into MOOC systems is a game-changer that can make online learning more dynamic, participatory, and engaging. Higher completion rates may result from learners' improved willingness to persevere through course content under the guidance of virtual mentors who are aware of their particular needs (Lane & Schroeder, 2022). Tutors can open up new avenues for improving online education's overall efficacy and success by fusing the benefits of MOOCs with the capacities of pedagogical agents (Caballé, Conesa, & Gañán, 2021).

2.0 Problem Statement

Massive Open Online Courses (MOOCs) provide several benefits, including accessibility, flexibility, and a wide range of course alternatives (Vázquez Cano, López Meneses, Gómez Galán, & Parra González, 2021). However, completion rates are frequently poor on these platforms (Santosa, 2022). Learner motivation is a potential contributing factor to this obstacle (Badali et al., 2022).Even though MOOCs offer never-before-seen access to educational resources, they can find it difficult to keep students interested during the course.

One important factor affecting MOOC completion rates has been shown to be learner motivation (Badali et al., 2022). Although MOOCs have many advantages, learners may become less motivated if they do not receive the kind of individualised attention and interactive components they would in a typical classroom. This could negatively affect learners' ability to continue with the course until the end

Scholarly investigations have examined inventive methods to tackle this deficiency in motivation, emphasising the incorporation of instructional facilitators in the MOOC setting (Caballé et al., 2021).By offering individualised feedback, direction, and assistance, pedagogical agents—virtual characters or intelligent assistants—have shown promise in raising student motivation. Research conducted outside of MOOCs has demonstrated the beneficial effects of pedagogical agents on student motivation and engagement (Apoki et al., 2022).

Nevertheless, despite the encouraging results seen in other learning environments, there is a significant lack of empirical data about the efficacy of pedagogical agents in improving intrinsic motivation in the context of MOOCs. Despite the fact that a number of research points to the potential advantages of pedagogical agents in raising student motivation, a thorough knowledge of their effects in the context of MOOCs is currently lacking.

In order to close this gap, a quasi-experimental study on the impact of educational agents on participants in MOOCs' intrinsic motivation will be conducted. Our goal in filling this research gap is to offer insights that enhance MOOC learning outcomes by improving learners’ intrinsic motivation.

3.0 Research Objective and Hypothesis

3.1 Research Question

1. Does a pedagogical agent in the MOOC platform significantly improve student’s intrinsic motivation compared to non-agents in the MOOC platform?

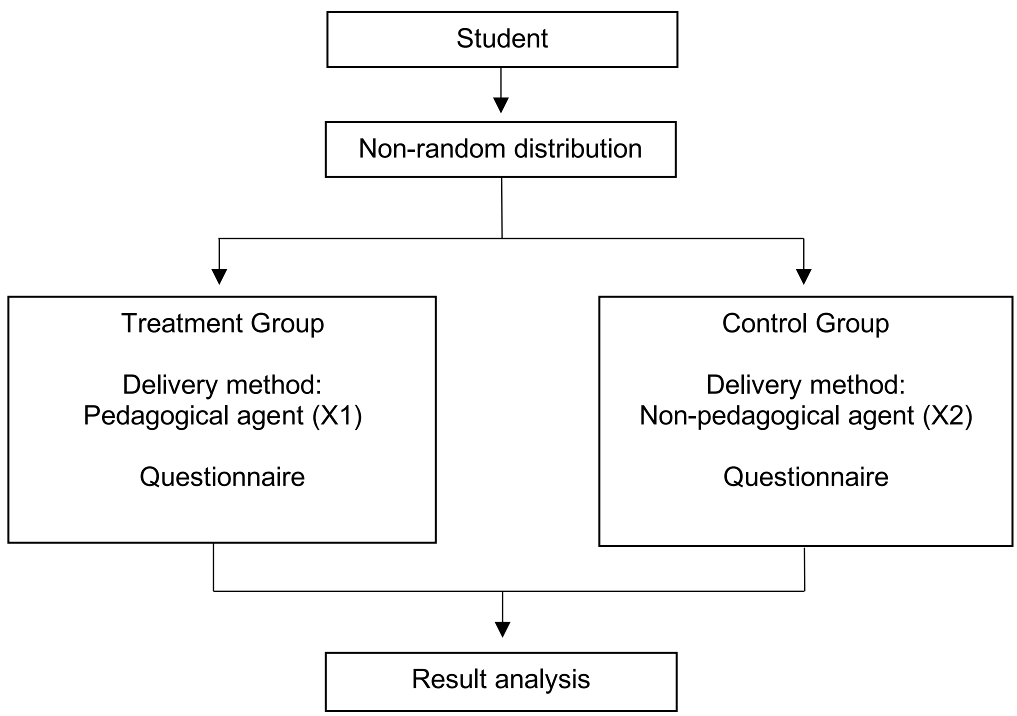
3.2 Hypothesis

1. Pedagogical agents in the MOOC platform significantly improved students' intrinsic motivation compared to the non-agents in the MOOC platform.

4.0 Methodology

A quasi-experiment will be used to measure the students' perceived intrinsic motivation upon learning with a pedagogical agent. The quasi-experiment method was chosen as it seems to be the best option in comparing the impact of the pedagogical agents in the MOOC learning platform. The experimental method was also applied in previous pedagogical agent studies in investigating the impact of pedagogical agent(Ahuja et al., 2021; Brachten, Brünker, Frick, Ross, & Stieglitz, 2020). The significance of quasi-experimental research is highlighted since it provides a methodological framework that can be used in actual classroom settings and enables the establishment of causality in educational phenomena (Jelena & Jelena, 2022) . The experiment will be conducted following the design as depicted in

Figure 1 . The experiment will involve the treatment group(X1) and the control group(X2). Students in the control group will undergo the learning content and module in MOOC without a pedagogical agent (non-pedagogical agent). On the other hand, students in the treatment group will undergo the learning content and material in the presence of the pedagogical agent. After the learning process, both groups were asked to answer the questionnaire to measure the perceived intrinsic motivation between the learners in



different experiment groups.

Figure 1 : Experiment Design

4.1 Sampling

The experiment was conducted towards total sample size of sixty-six (n=66) students undertaking multimedia-based courses, namely script and storyboard, at a local university in Malaysia. The sampling was determined using the convenience sampling method, also known as haphazard sampling. This method was chosen as it is hard to determine the sample's total population as the sampling criterion, which is students undertaking multimedia-based courses in higher learning, was not recorded or regulated by any authority. The sample was taken from the multimedia-based course to eradicate any extraneous factor that might disrupt the learning, such as low literacy in assessing the learning platform (the MOOC). The criteria and the sample size were also determined based on previous research on pedagogical. agents and cognitive load as depicted in **Table 1** below. The mean age of the sample is 19 years old. The participants were divided equally between the experiment groups.

Table 1: Sample size of previous research.

Research	Sample Size	Age mean
Schroeder (2017)	75	21
Lang, Xie, Gong, Wang, and Cao (2022)	117	19.79
Moon and Ryu (2020)	64	22.55
Lin, Ginns, Wang, and Zhang (2020)	96	21.14

4.2 Instrument

A set of questionnaires was used as an instrument to measure the perceived intrinsic motivation of students in the experiment group. The set of questionnaires was originally adapted from the Intrinsic Motivation Inventory (IMI) that was proposed by (Ryan, 1982) and Motivated Strategies for Learning Questionnaire(MSLQ) by Duncan and McKeachie (2005) then were further improvised. The instrument consisted of 21 items on a 5-point Likert scale divided into four different constructs: Interest enjoyment, competence, effort, and pressure.

4.3 Data Collection

Data collection was conducted in accordance with the experiment design as explained previously (see

Figure 1). Students were divided into two groups equally at the beginning of the lesson. Students were briefed before starting the lesson on the process of the experiment. Students in the treatment group will undergo the learning content in the MOOC platform, which has been embedded with pedagogical agents. Another group, namely the control group, will undergo the learning lesson in MOOC but without the presence of the pedagogical agent. The MOOC platform used for this study is called Openlearning. Once the lesson is finished, students in each group will be given a set of questionnaire items and asked to answer the questions.The questionnaire was given online, Google Forms, and Students had to answer all questions. The answers gathered from the questionnaire items were gathered for the data analysis process. The flow of data collection is as portrayed in Figure 2 below.

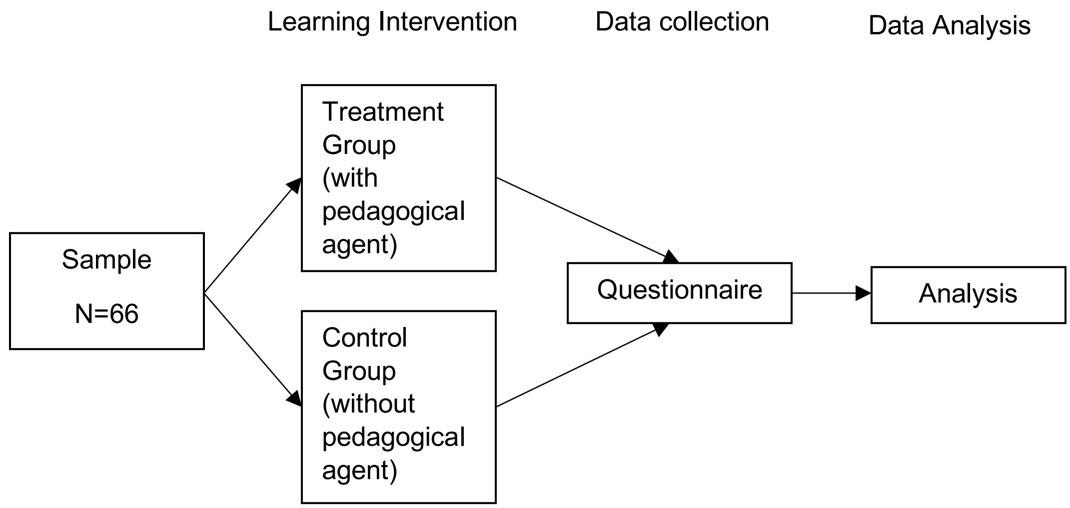


Figure 2: Data collection process

4.4 Analysis Method

Intrinsic motivation was measured using the 5-point Likert scale, as mentioned previously. The mean 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 Findings

The data was checked to ensure there were no defects in the questionnaire answers. Since the sample size for the experiment is small, defects during data collection can be avoided by manually checking during the data collection process. Then the data were sent to a software called SPSS for further analysis. A normality test was conducted towards the data to determine the appropriate mean analysis test that will be used for the 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 2 below. Then, the mean comparison test was chosen appropriately in accordance with the normality of the data.

Table 2 : Data Normality Test.

Construct/variable	Normality of data	Type of analysis
Interest-enjoyment	Not normally distributed	Mann Whitney U test
Competence	Normally distributed	Independent T-test
Effort	Not normally distributed	Mann Whitney U test
Pressure	Not normally distributed	Mann Whitney U test
Intrinsic Motivation (Variable)	Not Normally distributed	Mann Whitney U test

Next, the mean value for both experiment groups per construct and variable was computed. The mean value for each construct (interest-enjoyment, competence, effort and pressure) and variable (intrinsic motivation) were computed to measure the perceived intrinsic motivation descriptively. The mean value for each construct and variable for both experiment groups is depicted in **Table 3**. The interest-enjoyment construct shows that the control group yielded a slightly higher mean value, which is 4.3788, compared to the treatment group, with a mean value of 4.1818. This indicates that for the interest-enjoyment construct, both experiment groups agree that they have a high value (Likert scale-4). Similarly, in The effort construct, the treatment and control groups yield mean values of 4.2061 and 4.3212, respectively. This also indicates that the value for the effort construct is high (above 4). As for the competence construct, the mean values for the treatment and control groups are 3.7727 and 3.8838, respectively. Followed by the pressure construct with the treatment and control group yielded a mean value of 3.8890 and 3.7828, respectively. This indicates that the perceived value for both constructs is above the neutral value (3) and leaning towards a high value (4). When the mean value for the whole variable was computed, both the treatment and control groups yielded a value of 3.9899 and 4.0534, respectively. This shows that the mean value for the control group (non-pedagogical agent) yields a slightly higher perceived intrinsic motivation than the treatment group. The same thing applies to constructs, whereas only the pressure construct of the treatment group yields a higher value than that of the control group. The mean distribution data by construct is best described in **Figure 3** and by variable in **Figure 4**.

Table 3 : Mean value per construct and variable.

Constructs /Variable	Mean value			
	Treatment group		Control Group	
	Mean	SD	Mean	SD
Interest-enjoyment	4.1818	0.671	4.3788	0.549
Competence	3.7727	0.639	3.8838	0.534
Effort	4.2061	0.530	4.3212	0.415

Pressure	3.8990	0.839	3.7828	1.084
Intrinsic Motivation (Variable)	3.9899	0.472	4.0534	0.441

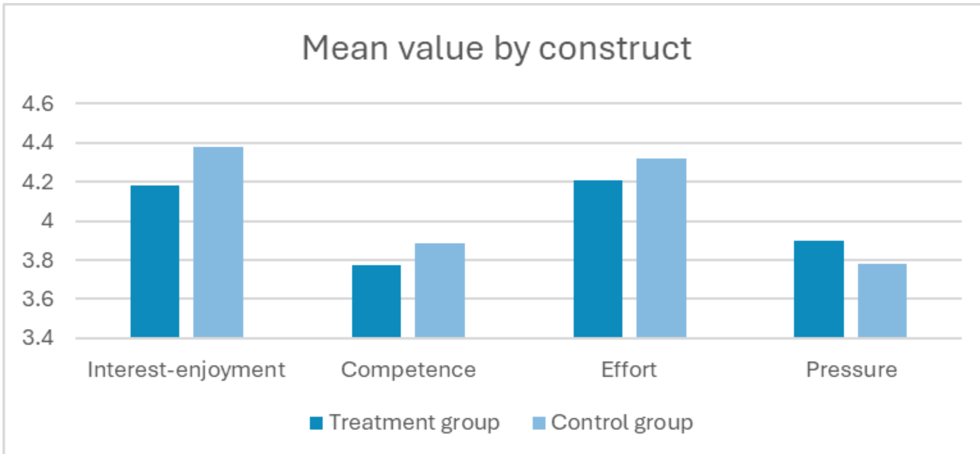


Figure 3 : Mean value by construct.

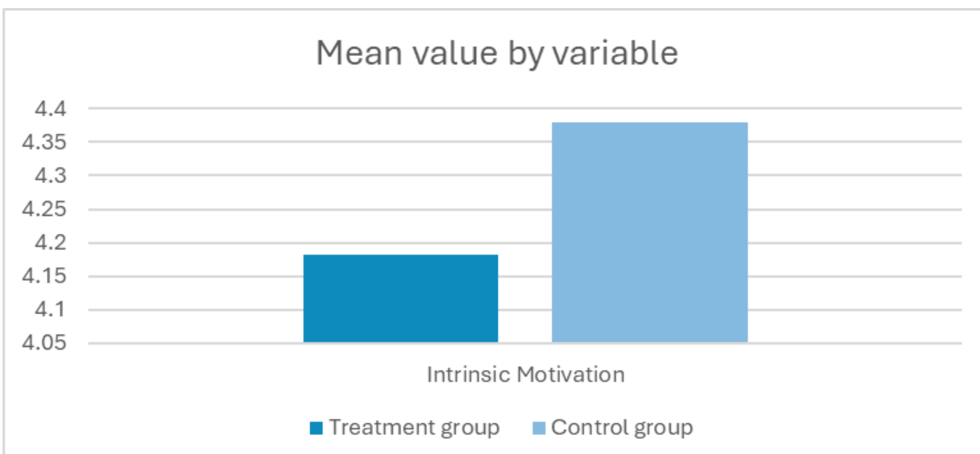


Figure 4 : Mean value by variable.

However, a mean comparison test should be conducted to determine whether the difference between the control and treatment groups is statistically significant. The Mean comparison test (independent t-test/Mann Whitney U test) was conducted to define significant values for the differences between the values from the experiment group. The result is depicted in **Table 4** below. The result shows that none of the differences between experiment groups, by construct or variable, are statistically significant. The significant values for the construct interest-enjoyment, competence, effort and pressure are 0.281,0.447,0.598 and 0.903, respectively. This value is above the significant value, which is 0.05, which indicates the differences are not significant. The same applies to the variable's value of 0.492 and above the significant value (0.05). Based on the result of the experiment, it can be concluded that the intervention of pedagogical agents in MOOC does not influence the learner's intrinsic motivation.

Table 4 : 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**	
Interest-enjoyment	30.98	1022.5	36.02	1188.5	0.281
Competence	3.7727	0.639	3.8838	0.534	0.447
Effort	32.27	1065.00	34.73	1146.00	0.598
Pressure	33.21	1096.00	33.79	1115.00	0.903
Intrinsic Motivation (Variable)	31.88	1052.0	35.12	1159.00	0.492

6.0 Discussion and Conclusion

The results of this study indicate that the presence of a pedagogical agent in a MOOC platform does not significantly influence learners' intrinsic motivation. The mean values for intrinsic motivation and its constructs (interest-enjoyment, competence, effort, and pressure) were slightly higher in the control group, which did not have a pedagogical agent, compared to the treatment group, which did. However, these differences were not statistically significant, as indicated by the p-values being above the significance threshold of 0.05 for all constructs and the overall intrinsic motivation variable. Previous studies on pedagogical agents' impact on learner's intrinsic motivation show mixed results. The result of this research is coherent with studies conducted by Zeitlhofer, Zumbach, and Aigner (2023) .Their studies indicate that pedagogical agent intervention does not significantly impact the learners' motivation. In contrast, Dinçer and Doğanay (2017) in their studies found out that pedagogical agents had a positive impact towards learners' motivation. Several factors might influence the outcome of the result. For example, the design of the pedagogical agent. Pedagogical agents are made of several elements such as visual, social cues, audio and form. Further study on every element that may improve learners' perceived intrinsic motivation shall be conducted to attend to this matter. Another possible factor might be the learning content of the MOOC itself. Although pedagogical agents can potentially improve the learner's intrinsic motivation, well-designed MOOC courses with an instructional learning design might also improve the learner's intrinsic motivation. Thus, the outcome of this experiment shows that both experiment groups have a good value of perceived intrinsic motivation.

This study's experiment concentrated on pedagogical agents' broad application on the MOOC platform. Thus, the independent variable in this study was the presence of pedagogical agents within the MOOC learning platform. Despite the fact that a number of other pedagogical agent features or qualities might affect the learner's intrinsic motivation during the learning process, these aspects were not further explored and remained a limitation for this study. Pedagogical agent design components, such as the agents' visual appearance, voice types, cue types, and form, are examples of those features. These characteristics may affect the learner's intrinsic motivation in different ways. Apart from that, while sufficient for preliminary analysis, this study's sample size of 66 students may not be large enough to generalise the findings to a broader population. The limited sample size may affect the statistical analyses' robustness and the results' generalizability to other contexts or institutions.

This experiment, however, opens up many possibilities for future studies. Based on the findings of this study, several recommendations can be made for future research and practice in the use of pedagogical agents in MOOCs. In future, Investigating the impact of different agent designs and personalities on learner motivation could be beneficial. Research could focus on whether certain characteristics, such as the agent's appearance, voice, and demeanor, influence learners' engagement and motivation. Apart from that, Future studies could investigate the effects of more interactive and adaptive pedagogical agents that can respond to learners' emotional states and provide personalized feedback. Enhancing the interactivity of these agents may lead to more significant improvements in intrinsic motivation.

In conclusion, this study found that including a pedagogical agent in a MOOC platform did not significantly enhance learners' intrinsic motivation compared to a non-pedagogical agent MOOC environment. The slight differences in mean values for intrinsic motivation and its constructs were not statistically significant. These findings suggest that while pedagogical agents may have potential benefits, their impact on intrinsic motivation in the context of MOOCs may be limited. Further research is needed to explore other factors that may influence intrinsic motivation in online learning environments and to investigate the long-term effects of pedagogical agents on learner engagement and motivation

References

Ahuja, N. J., Thapliyal, M., Bisht, A., Stephan, T., Kannan, R., Al-Rakhami, M. S., & Mahmud, M. (2021). An investigative study on the effects of pedagogical agents on intrinsic, extraneous and germane cognitive load: experimental findings with dyscalculia and non-dyscalculia learners. *IEEE Access, 10*, 3904-3922.

Alfaro, L., Rivera, C., Luna-Urquizo, J., Castañeda, E., Zuñiga-Cueva, J., & Rivera-Chavez, M. (2020). *New trends in pedagogical agents in education.* Paper presented at the 2020 International Conference on Computational Science and Computational Intelligence (CSCI).

Apoki, U. C., Hussein, A. M. A., Al-Chalabi, H. K. M., Badica, C., & Mocanu, M. L. (2022). The role of pedagogical agents in personalised adaptive learning: A review. *Sustainability, 14*(11), 6442.

Azhar, K. A., Iqbal, N., Shah, Z., & Ahmed, H. (2024). Understanding high dropout rates in MOOCs–a qualitative case study from Pakistan. *Innovations in Education and Teaching International, 61*(4), 764-778.

Badali, M., Hatami, J., Banihashem, S. K., Rahimi, E., Noroozi, O., & Eslami, Z. (2022). The role of motivation in MOOCs' retention rates: a systematic literature review. *Research and Practice in Technology Enhanced Learning, 17*(1), 5.

Baylor, A. L., & Kim, Y. (2004). *Pedagogical agent design: The impact of agent realism, gender, ethnicity, and instructional role.* Paper presented at the International conference on intelligent tutoring systems.

Brachten, F., Brünker, F., Frick, N. R., Ross, B., & Stieglitz, S. (2020). On the ability of virtual agents to decrease cognitive load: an experimental study. *Information Systems and e-Business Management, 18*(2), 187-207.

Buddemeyer, A., Hatley, L., Stewart, A., Solyst, J., Ogan, A., & Walker, E. (2021). *Agentic Engagement with a Programmable Dialog System.* Paper presented at the Proceedings of the 17th ACM Conference on International Computing Education Research.

Caballé, S., Conesa, J., & Gañán, D. (2021). *Evaluation on using conversational pedagogical agents to support collaborative learning in MOOCs.* Paper presented at the Advances on P2P, Parallel, Grid, Cloud and Internet Computing: Proceedings of the 15th International Conference on P2P, Parallel, Grid, Cloud and Internet Computing (3PGCIC-2020) 15.

De Jong, P. G., Pickering, J. D., Hendriks, R. A., Swinnerton, B. J., Goshtasbpour, F., & Reinders, M. E. (2020). Twelve tips for integrating massive open online course content into classroom teaching. *Medical teacher, 42*(4), 393-397.

Dinçer, S., & Doğanay, A. (2017). The effects of multiple-pedagogical agents on learners' academic success, motivation, and cognitive load. *Computers & Education, 111*, 74-100.

Duncan, T. G., & McKeachie, W. J. (2005). The making of the motivated strategies for learning questionnaire. *Educational psychologist, 40*(2), 117-128.

Floratos, N., Guasch, T., & Espasa, A. (2017). *Student engagement in MOOCS with appropriate formative assessment and feedback practices.* Paper presented at the EDULEARN17 Proceedings.

Jarial, P., & Aggarwal, H. (2020). *To Study various Issues and Challenges faced in MOOCs.* Paper presented at the 2020 IEEE International Conference on Machine Learning and Applied Network Technologies (ICMLANT).

Jelena, O. Z., & Jelena, M. (2022). Quasi-Experimental Research as An Epistemological-Methodological Approach in Education Research. *International Journal of Cognitive Research in Science, Engineering and Education, 10*(3), 177-183.

Kim, Y., & Baylor, A. L. (2006). A social-cognitive framework for pedagogical agents as learning companions. *Educational technology research and development, 54*(6), 569-596.

Lane, H. C., & Schroeder, N. L. (2022). Pedagogical Agents. In *The Handbook on Socially Interactive Agents: 20 years of Research on Embodied Conversational Agents, Intelligent Virtual Agents, and Social Robotics Volume 2: Interactivity, Platforms, Application* (Vol. 48, pp. 307–330): Association for Computing Machinery.

Lang, Y., Xie, K., Gong, S., Wang, Y., & Cao, Y. (2022). The Impact of Emotional Feedback and Elaborated Feedback of a Pedagogical Agent on Multimedia Learning. *Frontiers in psychology, 13*, 810194.

Leyzberg, D., Spaulding, S., Toneva, M., & Scassellati, B. (2012). *The physical presence of a robot tutor increases cognitive learning gains.* Paper presented at the Proceedings of the annual meeting of the cognitive science society.

Lin, L., Ginns, P., Wang, T., & Zhang, P. (2020). Using a pedagogical agent to deliver conversational style instruction: What benefits can you obtain? *Computers & Education, 143*, 103658.

Moon, J., & Ryu, J. (2020). The effects of social and cognitive cues on learning comprehension, eye-gaze pattern, and cognitive load in video instruction. *Journal of Computing in Higher Education*, 1-25.

Moreno, R., Mayer, R. E., Spires, H. A., & Lester, J. C. (2001). The case for social agency in computer-based teaching: Do students learn more deeply when they interact with animated pedagogical agents? *Cognition and instruction, 19*(2), 177-213.

Petersen, G. B., Mottelson, A., & Makransky, G. (2021). *Pedagogical agents in educational vr: An in the wild study.* Paper presented at the Proceedings of the 2021 CHI Conference on Human Factors in Computing Systems.

Ryan, R. M. (1982). Control and information in the intrapersonal sphere: An extension of cognitive evaluation theory. *Journal of personality and social psychology, 43*(3), 450.

Ryan, R. M., & Deci, E. L. (2000). Intrinsic and extrinsic motivations: Classic definitions and new directions. *Contemporary Educational Psychology, 25*(1), 54-67.

Santosa, P. I. (2022). *Analysis of MOOCs Design based on Herzberg's Theory: A Literature Review.* Paper presented at the 2022 10th International Conference on Information and Education Technology (ICIET).

Schroeder, N. L. (2017). The influence of a pedagogical agent on learners' cognitive load. *Journal of Educational Technology & Society, 20*(4), 138-147.

Sikström, P., Valentini, C., Sivunen, A., & Kärkkäinen, T. (2022). How pedagogical agents communicate with students: A two-phase systematic review. *Computers & Education, 188*, 104564.

Tzeng, J.-W., Lee, C.-A., Huang, N.-F., Huang, H.-H., & Lai, C.-F. (2022). MOOC evaluation system based on deep learning. *International Review of Research in Open and Distributed Learning, 23*(1), 21-40.

Vázquez Cano, E., López Meneses, E., Gómez Galán, J., & Parra González, M. E. (2021). Innovative university practices on the educational advantages and disadvantages of MOOC Environments.

Zeitlhofer, I., Zumbach, J., & Aigner, V. (2023). Effects of Pedagogical Agents on Learners' Knowledge Acquisition and Motivation in Digital Learning Environments. *Knowledge, 3*(1), 53-67.