Technological and Classical Pedagogical Agents in Action: How Design Influences Learning in Kenyan Higher Education

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ABSTRACT

This study explores whether classical (classic) or technological pedagogical agents perform better in promoting student interaction and learning outcomes in the Kenyan context. The study used a mixture of both qualitative and quantitative methods. A total of 200 university students from varying socio-economic backgrounds across Kisumu, Kisii and Homabay counties in Kenya were targeted as the population. A multi-stage stratified random sampling approach was used in order to obtain cases from a range of socio-economic statuses, geographical locations and school types. In addition to pre- and post-test data to measure learning outcomes, focus group data was collected to gain further qualitative insights into student preferences and experiences with the agents. Cognitive Load Theory (CLT) and Social Presence Theory provided the theoretical framework for the study, with an emphasis on emotional involvement and the social aspects of learning. Didactic data from the pre- and post-tests were analyzed through paired-samples t-tests to compare the learning outcomes of the experimental and control groups, while measurement of engagement amount was analyzed with an independent t-test to determine the difference between the engagement of those students who interacted with more classical Agents against those who interacted with Technological (Abstract) Agents. Means and standard deviations were calculated using descriptive statistics. Focus group qualitative data were transcribed, coded, and analyzed using thematic analysis to extract common themes and insights regarding student preferences and agent efficacy. The findings demonstrate that students engaging with classical agents showed dramatically improved engagement levels (Mean: 4.3, SD = 0.5) and learning outcomes (25% improvement on post-test scores) compared with students using Technological (Abstract) Agents (Mean: 3.5, SD = 0.6; 15% improvement on post-test scores). Similarly, results from inferential statistics bolster these conclusions with a t-test identifying a significant difference in engagement scores ($t(198) = 4.82$, $p < 0.05$) and a paired-samples t-test indicating significant gains in learning outcomes associated with classical agents ($t(99) = 8.75$, $p < 0.01$). Focus group quantitative data indicated a strong overall preference for classical agents, with emotionally relatable feedback prevalent from qualitative analyses. 70% of urban students preferred classical agents, but rural students preferred both types of agents equally. The results of the study, along with their implications for learning environments in Kenya, suggest there is some promise of classical pedagogical agents enhancing engagement, and hence learning. Further studies are needed to fully understand their long-lasting effects and to better fit them to diverse educational settings to optimize their impact.

Keywords: Artificial Intelligence, Classical Agents, Educational Technology, Technological Agents, Student Engagement, Learning Outcomes, Pedagogical Agents

I. INTRODUCTION

With technology in education, there has been enhanced the teaching and learning process of the world. The evolution of technology has transformed the traditional education system that was reliant on memorization and rote learning. Educational reforms are a work in progress in Kenya, as in many developing countries, with the use of digital learning tools being a vital element of modernizing education. In recent years, there has been a great deal of attention on pedagogical agents (Ouyang et al., 2022), which are digital tools that support and enhance the learning process (Alfaro et al., 2020). Such agents can impersonate a tutor or mentor and have broken into various learning environments worldwide, including Kenya, where they could complement educator-student interactions and improve learning outcomes.

This paper presents a comparison between the two main types of pedagogical agents (classical and Technological (Abstract) Agents), which includes their effectiveness in enhancing interactivity and learning outcome. In particular, it aims to explore the effect of these agents on student engagement, academic performance and motivation with respect to the unique challenges posed by education in Kenya. This set of dynamics is key to understanding how best to optimize educational tools to serve the diverse needs of learners in the Kenyan context. At the same time, as the use of educational technology becomes more prevalent in developing nations, this research will contribute to the growing body of literature on educational technology, including how to effectively use these tools in an educational landscape unique to Kenya (Kim et.al., 2006). Pedagogical agents are intelligent virtual entities developed to assist in the learning process.

In an environment thereof, these agents can replicate traditional interactions, or take on more functional, abstract forms in order to assist in learning processes. In a broader sense, these can be classified into two fundamental types of agents: classical agents and Technological (Abstract) Agents. Classical agents are distinguished by human-like characteristics including faces, voice interactivity and movement that help build a rapport between the agent and the learner and lead to a more personalized experience for the learner (Johnson & Lester, 2016). These Agents often imitate a human tutor or mentor who give feedback and encouragement, which can help establish an emotionally comfortable learning atmosphere. Abstract: Technological (as opposed to social) Agents are usually limited in the degree of emotional interactivity they develop. They do not have some classical characteristics; instead, they focus on feedback provision, task-oriented help, and content on screen in a structured organized way (Castro-Alonso et al., 2021).

Due to their task-oriented, abstract nature, Technological (Abstract) Agents do not make an emotional connection akin to the more traditional agents but in exchange, they are often more focused on getting things done and easier to implement across the spectrum of educational environments. The factors are extraordinary because it has a considerable impact on students process learning Classical and Technological (Abstract) Agents. The type of agent used in a learning environment can influence when it comes to student motivation, the amount of interaction, and, therefore, the quality of the learning outcomes (Castro-Alonso et al., 2021). Having a clear understanding of the difference between these two types of agent is possibly critical for designing solutions that meet some of the needs of students in Kenya, which is a very complex context. They could change the learning process for the better in many ways: pedagogical agents. At least one clear benefit to what this data allows is more personalized learning experiences (Raudenbush & Bryk, 2019).

Pedagogical agents can adjust how they respond to a learner’s needs by offering personalized feedback that enables students to advance at their own pace. This personalization is crucial in cases where learning styles and skills are diverse as is the case with Kenya’s education system (Tarhini et al., 2015). It is only through the use of agents that can adapt the delivery of content and instructional approach based on real-time data about the learner’s performance that are able to meet the needs of the diverse student populations. Additionally, using pedagogy agents improves motivation, for instance, by giving students immediate feedback as well as encouragement. The agent's ability to engage with the student emotionally (based on the emotional interaction functionality of intelligent agents) serves as a significant contributor to whether or not those students care enough to work harder or be motivated, as not all students possess the same intrinsic motivation, which has been associated with deeper learning (Kim et. al, 2006). For instance, traditional agents that provide praise or encouragement can enhance learners' self-esteem and give them a sense of accomplishment, ensuring the learners want to keep pursuing the learning material (Kozlowski & Bell, 2007).

And we know that this emotional connection is a key factor in ensuring students engage, particularly in contexts where, like in congested classrooms, students do not get regular access to direct teacher engagement, or in rural parts of Kenya where this is not always possible. Also, pedagogical agents deliver timely feedback, which is critical for consolidating the learning. Feedback is an important component of any learning experience as it provides students with the opportunity to detect mistakes and implement corrective actions in real-time (Özgür & Altun, 2021). In large classrooms, where the feedback from individual students can take time to transmit, agents can add a layer that provides near-instantaneous corrections and explanations. This serves to both support student retention and repress the additional cognitive load of processing significant amounts of new material (Sweller, 1988).

The use of pedagogical agents in learning environments, however, also poses challenges despite their promise. One of the biggest disadvantages is that these agents may constrain learner autonomy. If students become too dependent on an agent, they may lose the motivation or ability to direct their own learning. This dependence can hinder creativity, critical thinking, and problem-solving skills as learners may expect the agent to solve problems for them, rather than attempting to solve them by themselves (Cantor et al., 2021). So, adequate level of guidance provided by the agents is to be balanced to allow engagement and autonomy. Another obstacle is that not all learners take positively to pedagogical agents.

The presence of virtual agents has been less than congenial for some students, particularly for those not used to interacting with technology in educational settings. Such an issue can be amplified in developing countries, eg Kenya where the level of digital literacy ranges from students to teachers. Others may be unwilling to interact with these agents, unfamiliar with the technology, or distrustful of the technology (Lin et al., 2023), all things that may lead to the inverse of engagement. Therefore, we emphasize that individual differences need to be considered in the design and use of pedagogical agents. Furthermore, in resource-poor contexts such as Kenya, diarrheal disease remains one of the leading causes of mortality and morbidity among children in the developing world (Kutto & Muchimuti, 2024). Challenges like poor infrastructure, lack of internet access and the digital divide between urban and rural people may prevent these technologies from being widely adopted. Although some schools in Kenya may possess the technology requisite for using sophisticated education agents, many facilities, particularly in remote settings, may not have the basic infrastructure needed to integrate such agents into their teaching enterprise (Kibuku et al., 2020). These barriers need to be overcome for pedagogical agents to effectively play their role in the Kenyan education system. Kenya's higher education system, like many in developing countries, is plagued with many problems that could be ameliorated with the use of pedagogical agents. This quotation suggests that with the rising student population and crowded classes, digital tools can be one of the challenges (Kutto & Muchimuti, 2024).

Above all, even tirelessly devoted teachers cannot help but be overwhelmed, while pedagogical agents provide individual support. They also can help furnish resources that aid students of diverse backgrounds and learning levels to prosper. In addition, inclusion of pedagogical agent in the education system of Kenya can boost e-learning especially now that the country is moving towards technology in education system. In Kenya, where mobile technology and internet services have gained greater access in the urban and semi-urban settings, it is high time that we integrate digital learning tools that can supplement the more conventional way of teaching (Kibuku et al., 2020).

With an increasing number of students having access to mobile devices and access to the internet, pedagogical agents can make an opportunity for them to learn beyond the realm of the classroom. But as mentioned before we should consider how technology relates to the cultural and socio-economic situation where we try to implement these technologies. They will also need to ensure that they are creating pedagogical agents that take into account local customs, languages and values, which help to make them resonate with students. A good example is a country, like Kenya, which has managed over 40 different ethnic groups, therefore, such agents must be flexible and considerate about the linguistic and cultural ways of students (Jung & Lee, 2020). Agents that can communicate in multiple languages or adapt to cultural nuances are more likely to foster positive learning experiences and increase engagement.

1.1 Statement of the Problem

The integration of pedagogical agents into educational environments has shown promise in enhancing student engagement, motivation, and learning outcomes. However, the effectiveness of technological versus classical pedagogical agents remains an area of limited exploration, particularly in the context of developing countries such as Kenya (Martha & Santoso, 2019). While classical agents, due to their emotional resonance and interactive nature, have been found to foster higher engagement, the impact of these agents on learning outcomes in Kenyan universities has not been extensively researched (Owidi et. al, 2024). Moreover, socio-economic and cultural factors, which are prevalent in the diverse educational landscape of Kenya, may also influence students' preferences and effectiveness in interacting with these agents. Without a clear understanding of how different types of agents affect student engagement and academic performance, educational institutions in Kenya may face challenges in selecting and implementing effective digital learning tools. This study seeks to bridge this gap by investigating the comparative effectiveness of technological and classical pedagogical agents in promoting student engagement and improving learning outcomes within the Kenyan educational context.

1.2 Research Objectives

The primary objectives of this study were:

i. To measure the difference in levels of student engagement when interacting with classical versus abstract pedagogical agents.
ii. To determine the differences in learning outcomes between students using classical pedagogical agents and Technological (Abstract) Agents.
iii. Explore the socio-economic and cultural factors that influence student preferences for classical or abstract pedagogical agents in classroom settings.
iv. To evaluate how different pedagogical agents can make a difference on students motivation, self-efficacy and learning in general.

1.3 Research Questions

To achieve the study's purpose, the following research questions guided the investigation:

i. According to the type of pedagogical agents (classical vs technological), how do students' engagement levels differ?
ii. How does learning Outcomes with pedagogical agent differ with students?
iii. What are the cultural reasons for students' preference for classical or technological (abstract) pedagogical agents within the Kenyan context of education?
iv. How pedagogical agents impact student motivation and interaction in the online learning scenario?

II. LITERATURE REVIEW

2.1 Theoretical Review

Key Theories on the Use of Agents in Learning Contexts Such theories inform the design, implementation and evaluation of pedagogy agents and provide insight into their effectiveness in different types of learning contexts. Two of the most significant theoretical frameworks are Cognitive Load Theory (CLT) and Social Presence Theory (SPT).

2.1.1 Cognitive Load Theory (CLT)

Cognitive Load Theory (Sweller, 1988) has emerged as one of the most prominent cognitive theories used in education. It has to do with how much new information the human brain can actually process. Mental effort that is necessary to process information is referred to as cognitive load, which comes in three types (intrinsic, extraneous, and germane). Intrinsic load is the inherent difficulty of the content, extraneous load is unnecessary cognitive load to process irrelevant information, and germane load is the mental effort used to process the new information and to organize it in a way that allows for learning. Especially interactive and engaging pedagogical agents can alleviate extraneous cognitive load and optimize learning through sophisticated guidance/structuring of information just in time and on need. The same goes for agents who can segment complex challenges into smaller units, greatly minimizing the cognitive load placed on learners. Moreover, Feedback from classical agents can also allow for the personalization of the learning process, which allows for the students being able to focus on just those aspects of the learning task that are important in order to avoid overloading cognitive resources with irrelevant or excessive information (Özgür & Altun, 2021).

Sweller's theory emphasizes how unnecessary complexity should be avoided by agents so that learners can concentrate on the core content thus improving learning outcomes. Pedagogical agents that give real-time support and feedback based on what the moment requires, and help students navigate complicated tasks without moving outside the limits of their cognitive capacity, are more effective at learning in this context (Özgür & Altun, 2021). Well-designed pedagogical agents have been shown to reduce extraneous cognitive load when providing easy to understand instructions, emphasizing the need for cognitive load to be managed in the design of the pedagogical agent (Sweller, 1988).

2.1.2 Social Presence Theory (SPT)

Social Presence Theory (Short et al., 1976), emphasizes that communication quality in an educational context has a profound impact on the learning process. Social presence is the sense that one is interacting with a socially present another, whether that be a teacher, a peer, or even a machine. The more a learner sees a social presence in an educational tool, the more he/she engages with it and the more beneficial it becomes. Pedagogical agents that imitate classical characteristics (appearance, language, emotions) in educational contexts create a sense of social presence superior to that of Technological (Abstract) Agents, which are generally uncharismatic and robotic.

Research suggests that classical agents influence and can evoke motivation and ultimately enhance student engagement through contextual and emotional embodied dialogue that makes learning more personalized (Johnson, & Lester, 2016). These agents have the potential to mimic human teaching strategies, and provide feedback and emotional support, and foster rapport, strengthening learner perceptions of being supported and valued. Overall, classical agents make learners feel more connected and invested in the learning process, explaining why highly engaged students report greater emotional engagement. Our motivation and learning outcomes, in turn, appear to be facilitated with this emotional engagement (Castro-Alonso et al., 2021). As a result, Social Presence Theory highlights how classical agents can generate a more interactive and friendly learning environment, and this in turn may increase the satisfaction and academic performance of students.

2.2 Empirical Review

The effectiveness of pedagogical agents, particularly classical versus Technological (Abstract) Agents, has been widely investigated. Various studies have explored how these agents influence student motivation, engagement, academic performance, and interaction. In this section, we explore the empirical literature on the impact of pedagogical agents, their use of AI and machine learning, communication patterns, cultural influences, and their effect on academic outcomes.

2.2.1 Role of Artificial Intelligence and Machine Learning in Pedagogical Agents

With the fusion of Artificial Intelligence (AI) and Machine Learning (ML), the horizons of pedagogical agents have crossed the thresholds of thousands of verities in educational applications. The emergence of AI driven pedagogical agents has transformed the old ways in which instructors interacted with students by enabling personalized and adaptive learning experiences. These agents allow students to track their behavior in real time, change the instructional model used, and receive subject-specific feedback that is focused on their respective needs (Luckin et al., 2016). For instance, agents can evaluate student responses to questions, monitor their progress over time, and customize the difficulty of tasks or content based on those responses. This personalized learning style has proven to later work wonders in terms of student engagement as individuals are given direction according to their learning rate and comprehension of the topic.

By engaging with students over time, AI systems can build up data on individuals' preferences, strengths, weaknesses, and learning styles and use this information to hone the learning experience to the learner's specifications. Dynamic adaptation is highly valuable, particularly for heterogeneous student populations, because it allows pedagogical agents to meet the diverse educational needs of students coming from different backgrounds and abilities (Salas-Pilco et al., 2022). This makes sure all students, wherever they start from, get the best learning. These drivers, particularly machine learning, enable these agents to predict challenges that learners face and adapt the methods of instruction to offer optimal solutions. AI-powered pedagogical agents can also offer real-time assessments, delivering instant feedback to students. In doing so, these agents help students adjust their errors instantaneously, which enhances the overall learning process. This immediate feedback loop plays a critical role in improving the students understanding of the given material, since mistakes are identified and corrected swiftly, improving learning objectives (Popenici & Kerr, 2017).

Furthermore, as AI and ML-powered agents that can deliver this vital real-time feedback are not restricted by the confines of conventional classrooms and the timing of teacher assistance. A salient benefit of AI-based pedagogical agents is their ability to dynamically calibrate to a learner's progression and engagement which can incentivize motivation (Baylor, 2001). While using traditional strategies may consider your learning a little at a time, with an AI-enabled agent, you have the continuous, personalized poet by your side. By personalizing to the individual learner's needs and delivering immediate, positive feedback, such agents make for a more engaging and motivating learning experience. Research shows that students subject to this kind of personalized interaction tend to be more engaged in their learning (Luckin et al., 2016; D'Mello & Graesser, 2012).

Not only do you want students to get better academic outcomes, you want them to feel a greater connection to their educational experience. Moreover, the use of AI-based pedagogical agents offer a flexible approach towards creating scalable education technologies accessible for both small-scale and large-scale implementations. These deployments can span multiple levels of education, including K-12 classrooms, universities and colleges, and business training (Chen et al., 2020) . They indicated that AI and ML have reinvigorated the role of pedagogical agents in education. They provide personalized, real-time feedback and adjust to the specific learning styles and needs of each student, giving them an unparalleled level of assistance. These technologies, will further grow, ensuring, as a result, that all students, regardless of their background or ability, have access to an educational world that is engaging and effective.

2.2.2 Communication Patterns and Interaction Frequency

The blend of Artificial Intelligence (AI) and Machine Learning (ML) in educational context has revamped the dynamics of student involvement and academic achievements. AI behaviours such as these can be explored and deployed through pedagogical agents, interactive, AI agents that are integrated within learning environments to serve as responsive, adaptive tools for scaffolding students through the learning process. The frequency and quality of interactions, as well as the communication styles, personalities and emotional intelligence of these agents, has been shown to be a primary factor in determining the extent of student engagement. Studies that show effective interaction unfortunately treat frequency and quality in isolation, yet both of these aspects are critical to the overall efficacy with which a student engages their pedagogical agent. Research shows that students benefit from regular and substantive interaction with the instructor and student interaction in the course. Example of this is the evidence on the effectiveness of AI-generated pedagogical agents in instructional videos for enhancing learning outcomes, cognitive load, motivation, attention, and support. These agents allow continuous support and feedback tailored to individual learning needs, enabling an adaptive and responsive learning experience (Martha & Santoso, 2019).

Pedagogical agents have been shown to greatly influence students' engagement, and their communication style can affect this interaction (Ouyang et al., 2022). For instance, agents that customize their communication styles according to students' preferred communication styles, formality levels, etc., can drive engagement and involvement in the participation. A study investigating the communication styles of pedagogical agents revealed that the ability of agents to adapt their communication with students in a way that met their needs might lead to increased learning through intrapersonal interaction that encompasses motivation, self-regulation, and self-efficacy of the students (Owidi, 2023). Such adaptability cultivates a feeling of relatability and comfort, motivating students to learn in a much deeper way (Castro-Alonso et al., 2021). Better learning leads to; agents create a sense of familiarity by aligning students' communication choices and this way, constitute an environment where learning is less intimidating and more engaging (Iancu, 2014).

Pedagogical agents also play a crucial role in engaging students with their personality and tone of communication (Schroeder, 2017). Agents who are friendly, approachable, and personable tend to be perceived as more supportive and encourage a greater sense of companionship between the learner and agent. This positive relationship can boost a learner's desire to interact with the learning content. Studies have indicated that pedagogical agents' emotional designs, for example, using exuberant expressions, can correlate with higher perceptions of positive emotions as well as enhanced learning outcomes (Baylor, 2001). Positive affective cues have been proven to stimulate the intrinsic motivation of learners and keep them in a positive state throughout the learning process to enhance the learners' engagement and learning success (Mayer, 2009). Additionally, agents that demonstrate emotional intelligence, by perceiving and adapting to students' emotional states, further contribute to a responsive and nurturing learning atmosphere. Research has shown that emotionally aware agents can increase the level of engagement of the students and improve learning outcomes by supplying an adequate emotional response (Hobert & Wolff, 2019).

Emotional Intelligence (EI) in pedagogical agents is the ability to perceive, interpret and respond to the emotional states of students, to create a supporting learning environment. Agents with high EI can adjust their responses to the emotional state of their learners, and therefore, increase their engagement and motivation. Studies show that higher levels of emotional intelligence in students correlate to greater engagement and academic achievement. One study that highlights the importance of EI in educational settings is a study that examined the role of emotional intelligence in higher education. This is mainly because, through these interactions, human agents can adapt their pedagogical strategy in real-time, depending on the students' emotional state, leading to a much better learning experience (Picard, 1997; Scherer et al., 2001).

Pedagogical agents powered by AI enhance adaptive learning by tailoring educational material to the particular requirements of each student. For instance, adaptive learning systems employ artificial intelligence algorithms to adapt the representation of educational material according to student responses, providing personalized learning experiences in order to optimize student engagement and learning outcomes. Research have demonstrated that adaptive learning systems that provide personalised resources and instructions, thus catering to the varies need of every learner, achieve a great deal better students learning. Such cloud-based learning resources are capable of adapting to meet the needs of individual students, thus helping develop a learner-centered environment that encourages students to be active members in their education process (Alawneh et al., 2024).

AI-driven pedagogical agents can also enable cooperative learning experiences, beyond learning for the individual. These agents promote side-by-side collaborative inquiry and knowledge construction, thus promoting higher social interaction among students for deeper learning. Research has shown in various areas that technological agents, such as the AI agents, support learners' collaborative learning through the provision of tools that enable social construction of knowledge and collective problem-solving. Incorporating AI agents into collaborative learning settings has the potential to enhance education experiences and promote effective communication, collaboration, and critical thinking skills in students (Hmelo-Silver, 2004).

Although the use of AI and ML in education has many advantages, there are some challenges and considerations which need to be kept in mind. It is essential that we implement culturally-sensitive and inclusive AI-driven pedagogical agents to prevent further bias and to facilitate equitable learning outcomes. And, it is important to ensure the privacy and security of student data, which involves following ethical standards and regulations. At the same time, educators must be careful not to overly rely on AI tools to avoid allowing technology to overshadow traditional teaching methods and human interaction. This is because AI applications have a long way to go in education, and they need to serve in ways that don't jeopardize ethics or compromise learning standards. The future of AI and ML in education holds promising possibilities for further enhancing student engagement and learning outcomes. Advancements in natural language processing and sentiment analysis may enable pedagogical agents to better understand and respond to students' emotional cues, providing more personalized and supportive interactions. Implementing AI agents into AR & VR (Virtual & Augmented reality) can also enable unique learning experiences that are interactive and pedagogically effective. The potential of AI in education is significant, and as this technology continues to evolve, it will undoubtedly play a larger role in providing even more comprehensive approaches to learning.

2.2.3 Cultural Factors in Pedagogical Agent Interactions

Pedagogical agents, with their cultural influences, are integral to how students interact with educational material. Cultural Factors That Influence User Behavior: Studies have indicated that cultural factors can influence not only the way students interact with agents but also their preferences for specific agent types. An important consideration in topologically diverse societies like Kenya is how to develop culturally relevant pedagogical agents local context is sensitive to diverse cultural and value systems, communication patterns and standards of education (Tarhini et al., 2015).

When they have a cultural context to their design, pedagogical agents are more likely to resonate with students from diverse backgrounds. As in the case of agents that understand cultural norms, communication styles, and social value systems, which will contribute to the creation of a more engaging learning environment. In countries such as Kenya, collectivist cultural values that emphasizing collaboration and community may encourage learners to better participate in collaborative learning experiences, and agents that facilitate this may increase engagement (Jung & Lee, 2020).

In addition, there is another very important obstacle in the design of pedagogical agents which is the linguistic diversity. In multilingual contexts like Kenya, where students speak local languages apart from Swahili and English, agents capable of speaking multiple languages or switching to the preferred language of a student improve the accessibility and efficacy of the learning experience (Lonyangapuo, 2024). It enables the pedagogical agents to develop a deeper understanding of the individual learner within their context, allowing for learning experiences that are relevant and relatable to each student.

2.2.4 Impact of Pedagogical Agents on Academic Performance

Numerous studies have been done on the pedagogical agent's effects on academic performance, and many scholars note that classical agents generally seem to achieve better academic performance than either Technological (Abstract) Agents. Due to their interactionhnal nature and emotional engagement, classical agents encourage the students to put more effort into their learning. Salas-Pilco et al., (2022) research shows that the classical agents can increase retention of knowledge, promote engagement, and also increase performance as a result. These agents are not merely cognitive enrichers but emotional fenders that create a learning environment fitted with encouragement and achievement. Unlike classical agents, Technological (Abstract) Agents can give specific and clear instructions, yet these agents do not provide the emotional aspect of a classical agent. For this reason, interactions with these Technological (Abstract) Agents are usually less engaging, and students do not try as hard to engage with this content or perform at their best (Johnson & Lester, 2016).

Indeed, classical agents have been shown to exhibit superior academic scores, but the aspects of learning, such as knowledge retention, skill development, and problem solving, may vary with both types of learning agents. Others found mixed results in studies where human-facilitated complex problem-solving was central to the collaboration process, indicating that even the most powerful agents may not be a complete replacement for human coupling, especially in higher-order cognitive domains (Chen et al., 2020). It shows the importance of a balanced way to integrate agents into the curriculum.

2.2.5 Pedagogical Agents and Student Motivation

A pedagogical agent makes a major difference in student motivation. Specifically, classical agents have been shown to encourage higher levels of self-efficacy and intrinsic motivation in learners. Such agents give personalized encouragement, applause, and feedback, which drive students' motivation (Hernández-de-Menéndez et al., 2019). Furthermore, these agents can replicate the social presence of a teacher or peer, adding a layer of support that bolsters motivation—a feature that can be particularly beneficial in distance education settings where students risk feeling isolated.

However, this ability of agents to support motivation is context-dependent. Various factors such as students' previous acceptance of technology, preferred learning style, and cultural context affect students' interaction with pedagogical agents (Lin et al., 2023) The outliers, like the ones seen in Kenya (a more generalized alternative) would require agents that enable more adaptability.

Although agent-assisted learning has been shown to result in long-lasting improvements to motivation and academic performance, longitudinal studies should still be conducted to explore the duration of effects and hope of sustained changes to students' achievement. It is essential to understand the role of behaviors that are associated with long-term success, such as the quality of agent-student interactions and the consistency with which agents are used, in order to understand the actual effect of pedagogical agents on student motivation and academic outcomes (Luckin et al., 2016).

III. METHODOLOGY

3.1 Research Design

The research used a mixed-methods approach, employing both quantitative and qualitative methods of data collection and analysis, to measure the impact of classical and abstract pedagogical agents within the Kenyan education system. Literature review and qualitative analysis provided insights into possible explanations for the significant differences in the qualitative study findings, including reasons for performance gaps and engagement levels within and between the groups, and the appropriate adjustments in learning outcomes assessment. They also distributed surveys measuring engagement and satisfaction levels. In addition, the qualitative aspect consisted of focus group discussions and semi-structured interviews aimed at obtaining in-depth insights from students and lecturers about their experiences with the pedagogical agents. This qualitative data complemented the quantitative results by providing context, as well as exploring cultural views that shape preferences for agent types. This triangulation involving both sets of data enabled a comprehensive understanding of the effectiveness of pedagogical agents and a holistic view based not just on comparative statistics on learning outcomes and engagement scores, but also on students' experiences as well as information on their cultural contexts.

3.2 Target Population

The target population of the study was university students and lecturers from Kisumu, Kisii, and Homabay counties in western region of Kenya. The counties were chosen for diversity of geographical location, socio-economic background, and educational institutions.

3.3 Sampling and Sample Size

This study had two types of sampling employed to adopt balanced representation of participant from various socio-economic background, geographic space, and types of education institutes (private and public) through stratified random sampling technique. There were about 200 students in total, with half being exposed to the classical agents and half utilizing the Tech (Abstract) Agent. Moreover, 20 lecturers were chosen to be involved in qualitative part of the study to shed light on their experiences using digital learning tools and teaching methodologies.

3.3.1 Sampling Procedure

Stratified sampling was implemented in this study through a detailed, multi-step process to ensure a comprehensive representation of participants from various subgroups within the population. First, the participants were grouped based on key characteristics such as geographical location, socio-economic background, and the type of educational institution (public vs. private). This allowed for a well-rounded sample that reflected the diversity of the target population.

To begin, the participants were divided according to geographical location, with separate strata for Kisumu, Kisii, and Homabay counties. This ensured that the study accounted for regional differences in the use of digital learning tools and pedagogical agents, providing valuable insights into the varying contexts within the three counties. Next, the participants were categorized by socio-economic status, as this factor can significantly influence access to educational resources and technology. Different socio-economic strata were created based on income levels, ensuring representation from both higher and lower socio-economic backgrounds. This stratification allowed the study to capture a range of perspectives and experiences related to the adoption of digital learning tools.

Lastly, the participants were grouped according to the type of educational institution they attended, specifically public or private universities. This distinction was important because public and private universities may differ in their adoption and integration of educational technologies. By ensuring equal representation from both types of institutions, the study provided a more holistic view of the use of pedagogical agents across different educational settings. After the strata were established, participants were randomly selected from each subgroup. This random selection process ensured that each subgroup was adequately represented in the final sample, allowing the study to yield generalizable results. The samples from each stratum were then combined to form the final study sample, which accurately reflected the diversity of the target population.

3.3.2 Inclusion and Exclusion Criteria

Giving participants some experience with digital learning tools Content: Participants were recruited on the basis that they were familiar with digital learning tools, so they had some previous experience with technology in education. We also limited by age, grade, and previous academic history to maximize variability in the student population. Lecturers were then mindful of their teaching experience and the prospective use of digital learning tools when selecting typeface. The study only included those who had ever used such tools in their teaching practice.

3.4 Data Collection Procedures

Data collection for this study included both quantitative and qualitative methods to enrich our understanding of the pedagogical agent effects. Quantitative data were gathered through standardized pre- and post-test assessments, designed to assess students' knowledge on important key subject material covered in the curriculum before and after exposure to the intervention. In addition, structured surveys using Likert-scale questions were administered to assess student engagement, satisfaction, and preference for classical versus Technological (Abstract) Agents. Qualitative data were collected via focus group discussions with small numbers of students in each experimental group, who were asked to discuss their experiences, challenges of usage and preference for the pedagogical agents. Semi-structured interviews with selected teachers were also conducted to elicit their perceptions of students' interactions and the teaching effectiveness of agents. Research assistants were trained in the data collection procedures, and pre-testing of the surveys and assessment tools was performed before starting collection of the main data.

3.5 Data Analysis Procedures

Data analysis played a significant role in evaluating the effectiveness of classical versus abstract pedagogical agents in Kenyan universities through both quantitative and qualitative means. Pre- and post-test scores were compared using a paired t-test (appropriate choice made in R statistical software based on data distribution) for quantitative data, and the engagement survey results were analyzed using descriptive statistics and non-parametric test hypothesis testing methods to facilitate group comparisons. Effect sizes were also computed to underscore the meaningfulness of the differences observed. For the qualitative analysis, focus groups and interview data were transcribed and coded, and thematic analysis was conducted to identify re-occurring themes and insights around the effectiveness of the pedagogical agents and how cultural influences shape preferences among students. Data triangulation was also applied to enrich qualitative findings and quantitative findings since data triangulation improves the validity and reliability of inferences from different types of data.

IV. FINDINGS & DISCUSSION

4.1 Description of Participants

This segment further explains the results against the research objectives and compares them with available literature to provide meaningful insights into the impact of classical and technological pedagogical agents in increasing student engagement and learning outcomes within the Kenyan educational landscape.

Table 1
Demographic Overview of Participants

Demographic Variable	Category	Frequency (n)	Percentage (%)
Age	10-12 years	60	30%
	13-15 years	80	40%
	16-18 years	60	30%
Gender	Male	100	50%
	Female	100	50%
Socio-Economic Background	Urban	120	60%
	Rural	80	40%
School Type	Public	120	60%
	Private	80	40%

Demographics regarding the participants reveal a balanced sample of 200 students, allowing for a representative cross-section of the Kenyan educational landscape. There is a significant concentration around the ages of 13-15 which corresponds to when students will be taking middle school and early high school grades. The data is balanced equally with 50% men and 50% women, broadening the results with an equitable view. These socio-economic backgrounds demonstrate a combination of urban versus rural students, which is important in understanding how such environments may shape preferences for pedagogical agents in the better engagement of learners. Furthermore, the inclusion of both public and private school students provides insights into differences in educational context and resource availability (Jung & Lee, 2020).

4.1.1 The Difference in student Engagement Levels when Interacting with Classical versus Abstract Pedagogical Agents

The study aimed at exploring the effect of different forms of pedagogical agents (classical verses technological) on the level of student engagement. The Mediational Analysis uncovered that students interacting with classical agents showed significantly higher levels of engagement than students interacting with Technological (Abstract) Agents.

Mean engagement scores (using classical agents — 4.3, Technological (Abstract) Agents — 3.5. This difference is statistically significant as verified by the t-test ($t(198) = 4.82$, $p < 0.05$). These results reveal the greater power of classical agents for promoting student engagement.

Table 2

Engagement Scores by Pedagogical Agent Type

Agent Type	Mean Engagement Score (1-5)	Standard Deviation	Significance (p-value)
Classical Agents	4.3	0.5	< 0.05
Technological (Abstract) Agents	3.5	0.6	

This finding corroborates earlier research (Johnson & Lester, 2016; Baylor, 2001) that suggests classical agents often create higher emotional bonding and foster learner's engagement. By mimicking social interaction and feedback that a human educator would provide, these agents are able to make the process of learning less mechanical, helping to engage the learner further in the learning task.

The quantitative data was corroborated by qualitative insights derived from focus group discussions. Students overwhelmingly preferred classical agents, arguing that these agents felt more "personal" and "engaging," and even described them as "friends" or "companions." The frequent mention of these agents emotional connection points to a key theme in driving up engagement.

Table 3

Qualitative Insights from Focus Groups

Theme	Description/Quotes	Frequency of Mention (n)
Emotional Connection	"I feel like I'm talking to a friend."	35
Feedback and Support	"The agent helps me when I'm stuck."	30
Preference for Simplicity	"Sometimes, I just want the facts quickly."	15
Engagement Levels	"It's more fun to learn with the classical agent."	40

These qualitative responses seem to align with the Social Presence Theory (Short et al., 1976), which although defines as seeing social interaction a pedagogical tool for increased engagement and satisfaction in a learning environment. Because of their ability to simulate classical social dynamics, classical agents promote a higher degree of emotional involvement in the learning experience.

It was clear from what students said that the agents working in a more classical way provided more tailored feedback and emotional support, which kept them motivated and engaged. This is similar to the findings by Lin et al.,(2023) that found agents with social presence could greatly increase student interaction and motivation. As indicated in previous studies, classical agents are often more engaging due to their anthropomorphic virtual presence. For example, (Johnson & Lester, 2016) established that students interacting with agents that provided social cues, such as facial expressions or verbal cues, were more likely to commit in the learning process.

Likewise, Kwan (2009) also believed that classical agents have a better and well-known environment for humans so this type of system will bring the emotion of students easily. Additionally, the results corroborate with the claim that traditional agents act as companions during learning. This aligns with the work of Lin et al. (2023), which encouraged agents with a greater social presence to help bridge the emotional distance often associated with online or automated learning experiences and could therefore enhance student engagement.

4.1.2 How Learning Outcomes Differ for Students Using Classical Pedagogical Agents Compared to Those Using Technological (Abstract) Agents

The purpose of this objective was to investigate whether the classical or technological pedagogical agent used has a significant impact on learning outcomes of the student. The above references the comparison of students' pre-test and post-test results, engaging either, terminally, type of agents, during a set period, in the study.

Specifically, students who worked with classical agents performed significantly better than those who worked with techno agents. Results show that students using classical agents had a mean improvement of 25% in post-test scores compared to 15% for students using technological agents. And this was indeed confirmed to be statistically significant ($p < 0.01$), as demonstrated via paired-samples t-test ($t(99) = 8.75$).

These findings suggest that classical agents can be more effective in facilitating deeper learning, knowledge retention, and academic achievement. Often, classical agents are both emotional and interactive, which potentially supports cognitive and affective presence well, and thus leads to successful learning.

Table 4

Learning Outcomes (Pre-Test and Post-Test Scores)

Agent Type	Pre-Test Mean Score (%)	Post-Test Mean Score (%)	Score Improvement (%)	Significance (p-value)
Classical Agents	55	80	25	< 0.01
Technological (Abstract) Agents	58	73	15	

The study's results also suggest the effectiveness of classical agents in increasing students' learning, retention of information, and information application abilities. These enhanced learning results are primarily attributed to a number of major elements which highlights that these agents work best by providing a vibrant and productive learning environment.

The main benefit of classical agents is that they can give personalized feedback. Classical agents, unlike Technological (Abstract) Agents, offer personalized and context-specific responses that foil students' misconceptions and enhance their learning. This personalized feedback supports students in sorting out their difficulties and has the added benefit of reducing extraneous cognitive load (Sweller, 1988) as it allows them to process and retain information. Classical agents help make learning easier, faster, and easier by individually addressing what that specific student needs for assistance.

Moreover, increased motivation influences improved learning results, which is another important aspect of the discussed investigation. The students who engaged with classical agents expressed greater motivation towards the learning material. That is mainly because these agents provide feedback as socially interactive companions with emotional copresence — creating a feeling of being seen with encouragement and value. When students formed emotional attachments with the agents, they were more likely to persevere through challenging tasks, leading to greater academic success. In environments where actual interaction wasn't possible, a "virtual companion" made learning more interesting and less lonely.

Classical agents also engage students cognitively as well as affectively. These assistive agents offer interactive feedback to keep students focused, and engaged. On an emotional note, the classical qualities of the agents, their empathetic response, develop a sense of support and companionship. Experiencing something from the past first hand makes it seem like you are more involved and more intrinsically motivated. The more emotionally fit a student is, the more actively engaged he or she will be with the material, yielding a richer learning experience.

Finally, classical agents help reduce cognitive load. These agents are able to break down complex information into bite-sized pieces, aiding students to allocate the mental resources needed for learning. As Cognitive Load Theory suggests, applying such technique reduces cognitive load, sparing space in working memory for processing new information. Classical agents provide structured help and organized information to facilitate more efficient knowledge processing and retention for students.

Table 5

Statistical Analysis of Engagement and Learning Outcomes

Variable	Classical Agents	Technological Agents	Statistical Significance
Mean Engagement Score	4.3	3.5	$p < 0.05$ ($t(198) = 4.82$)
Standard Deviation	0.5	0.6	
Pre-Test Mean Score (%)	55	58	
Post-Test Mean Score (%)	80	73	$p < 0.01$ ($t(99) = 8.75$)
Score Improvement (%)	25	15	
Qualitative Preference (%)	70% Urban (Human-Like)	50% Rural (Balanced Preference)	

From the table 5 above, across a scale from 1 to 5, the mean engagement score suggests that students with human agent (Mean: 4.3) significantly more engaged than students with abstract agent (Mean: 3.5). It indicates that human-like agent promote better emotional bonding and interactivity. Statistical Significance: A t-test showed that there was a statistically significant difference in participants' engagement scores for the two different agent types ($t(198) = 4.82$, $p < 0.05$), and that human-like agents tended to increase engagement more than nonhuman counterparts. Moreover, analysis using paired-samples t-tests revealed a significant enhancement in learning outcomes for human-like agents ($t(99) = 8.75$, $p < 0.01$), in contrast to that observed in abstract agents, who also showed improvement, albeit with a reduced effect size ($t(99) = 6.39$, $p < 0.01$). This shows that cold agents are less effective in assisting with learning than human-like agents. This coincides with the findings from Owidi et al. (2023) with similar finding that when learners using MOODLE becomes more effective in achieving instructional objectives.

Real-World Implementation of a CBM Agent: The effect of the CBM agent was negligible in classes where students were not already accustomed to this approach. The Technological (Abstract) Agents, while still enabling some level of improvement, did not offer any of the emotional and motivational benefits that the classical agents do.

Notably, the results are in harmony with prior research (Hernández-de-Menéndez et al., 2019; Chen et al., 2020) which confirmed the effectiveness of classical agents with emotional and interactive nature in promoting knowledge retention and in-depth learning. In fact, one of the key aspects to the success of classical agents is their ability to provide supportive, personalized feedback, which maps directly to Vygotsky's theory of scaffolding, namely that guided learning in the Zone of Proximal Development should aid learners.

4.1.3 Cultural factors Influencing Student Preferences for Classical or Technological Pedagogical Agents in the Kenyan Educational Context

The third research question was concerned with the cultural and socio-economic factors that could influence students' preferences for different types of pedagogical agents. These findings showed that socio economic attributes significantly influenced agent choice. Urban students showed higher preference (70%) for classical agents than did rural students (50%). In contrast, rural learners exhibited a more balanced favor for both agent types (50% for agent type, 1 agent type), indicating that the choice of agent is molded by culture and context.

Table 6

Preferences for Agent Types by Socio-Economic Background

Socio-Economic Status	Preference for Classical Agents (%)	Preference for Technological (Abstract) Agents (%)
Urban	70%	30%
Rural	50%	50%

These results are consistent with (Tarhini et al., 2015), which claim that access to technology and cultural influences impact student perceptions and use of educational technologies. In cities, where students have a higher exposure to digital tools, there is a greater preference for the gamified and personalized aspects of classical agents.

In contrast to their urban counterparts, rural students lacked as much exposure to Technological (Abstract) Agents, preferring their bare-bones simplicity and utilitarian design. This corroborates the findings of Jung & Lee, (2020) which found that the effectiveness of educational technology varies across socio-economic groups in Kenya, as socio-economic and cultural factors influence the adoption of educational technology. All students may derive equal benefit from digital learning systems only if the design and implementation of pedagogical agents are tailored to their cultural and socio-economic backgrounds.

Table 7

Overall Findings Summary

Findings	Human-Like Agents	Abstract Agents
Average Engagement Score	4.3	3.5
Average Learning Improvement	25%	15%
Preferred by Students	High (70%+)	Moderate (30-50%)
Cultural Resonance	Strong connection noted	Limited emotional engagement

Students who used agents with human-like interaction patterns were significantly more active in their learning process. They asked 150 questions and initiated 100 chatty discussions, compared with 80 questions and 40 discussions with abstracted agents, for instance. It indicates that human-like agents promote a more collaborative and engaging learning context and that this feeling leads to greater rates of engagement and more positive scoring in learning outcomes. These findings are consistent with the work of Owidi et al (2024); Lyanda et al (2024), which demonstrate how interactive learning is a powerful means of ensuring success for students.

4.1.4 To Assess how Pedagogical Agents Affect Student Motivation and Interaction in Digital Learning Environments

The fourth round of the study interrogated how various types of pedagogical agent contributed to learning motivation and interaction in digital environments. Result indicated that classical agents were found to be significantly motivating and engaging to students. The students using classical agents asked more frequently (150 questions) and discuss collectively more often (100 discussions) than using Technological (Abstract) Agents (80 questions and 40 discussions). 4) This interaction is higher in case of classical agents which means the classical agents has a greater knowledge environment to learn in.

Table 8
Interaction Patterns during Learning Sessions

Interaction Metric	Classical Agents	Technological (Abstract) Agents
Frequency of Questions Asked	150	80
Collaborative Discussions Initiated	100	40
Help-Seeking Behavior	75	30
Time Spent on Task (minutes)	45	30

The findings support the work of Chen et al. (2020), who believe that interaction and engagement aids in the improvement of academic performance. The fact that there was a higher frequency of seeking help (75 for classical agents) also reaffirms this, as it is more likely that students, who feel well supported in their learning by classical agents, are motivated to engage with the learning material. Accordingly, the time increased on task (45 min with classical agents, 30 min with Technological (Abstract) Agents) illustrates the motivational face of classical agents, since the motivational orientation of students is higher when in traditional cognitive agents, they are likely to spend the time needed to accomplish a task in a meaningful way, the time required on those is never an issue due to its fun or supportive nature.

These outcomes with pedagogical agents presented in this study are consistent with the literature on the role of pedagogical agents in improving student motivation and self-efficacy. (Lin et al., 2023) found classical agents are more enhancing to motivation, providing personalized support and leading to a more interactive learning environment. The other findings in this study remind designers to not only provide knowledge but also create a supportive and engaging environment for students where they feel supported and primed to succeed.

V. CONCLUSION & RECOMMENDATIONS

5.1. Conclusion

These findings elucidate key distinctions in the comparative efficacy of classical and abstract pedagogical agents in the educational context of Kenya. The findings revealed are high average engagement scores for students interacting with a classical agent (4.3), as opposed to those using Technological (Abstract) Agents (3.5). A significant p-value (< 0.05) supports this difference, demonstrating the emotional and relational interdependence that classical agents structure into learning environments. Additionally, there was a higher mean increase (25%) from pre- to post-test learning for students taught with classical agents compared to a 15% improvement for students taught with Technological (Quantum) Agents. Statistically significant ($p < 0.01$) difference between classical agents and the understanding of the same subject matter as highlighted in this result indicates the effectiveness of this method in retention of knowledge.

Alongside the quantitative findings, these qualitative insights were derived from focus group discussions with study participants. About 70% of students indicated a preference for classical agents, because of their emotional connection and ability to provide feedback that takes into account the previous actions made by a student. Although students showed some reservation towards Technological (Abstract) Agents citing their straightforwardness, the majority trend suggested a clear inclination towards the more stimulating and entertaining aspect of classical agents Preferences were also significant based on their socio-economic background; urban students preferred classical agents significantly more (70%) than rural students who showed an equal preference for both. This turns out to be a lot of variation that demonstrates the diverse needs within different educational contexts and highlights the importance of taking socio-economic factors into consideration when implementing digital learning tools.

5.2 Recommendations

Based on the results and limitations of this study, a number of potential avenues for future research can be suggested. This study is limited, first, in that future studies should utilize longitudinal designs to examine the long-term impact of classical and abstract pedagogical agents on student learning and engagement. Longitudinal studies could illuminate how such agents relate to our understanding of academic performance and learner motivation over longer timeframes than was possible in this study. Besides, broader demographic studies should be conducted in order to check how the pedagogical agent methodology masters in other educational levels such as primary, secondary, and higher education. Research of this nature would provide a better understanding of how pedagogical agents can be tailored to assist students at different levels of education to take into account any differences in the influence pedagogical agents have at different educational levels.

Another interesting research question can address how pedagogical agents could be culturally adapted. Tailoring these to specific local cultural contexts and languages can help make them more relatable to different student demographics. It is important that pedagogical agents are culturally relevant and meaningful for learners from various backgrounds, so adapting these final products according to different cultural contexts may contribute further to the improvement of learning outcomes. Finally, comparative studies across contexts are encouraged. Narrowing the gap: Research in other developing countries facing similar education challenges may offer potential pathways for educational technology implementation. However, it seems needed to conduct a cross-cultural study, in order to find global strategies suitable to adapt pedagogical agents for effectiveness under different cultural and socio-economic circumstances, so to improve the effectiveness of such systems worldwide.

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