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Long Paper

A Robotic Gamification Model for Climate Change Literacy for Green Innovation and Entrepreneurship in Sub-Saharan Africa

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Abstract

Purpose – The study aims to introduce the Gamified Climate Change Literacy for Green Innovation and Entrepreneurship Training Model, integrating the Social Robot Nao to enhance climate change education in Sub-Saharan Africa. The objective is to empower learners with knowledge about carbon emissions and to foster engagement in green innovations.

Method – The model integrates principles from Self-determination theory, Behavioral reinforcement theory, and the Mechanics, Dynamics, and Aesthetics gamification framework. Development and validation were conducted using Design Science Methodology and probability theory. The implementation involves desktop training via Moodle and interactive sessions with the Nao robot. The evaluation is based on the Technology Acceptance Model.

Results – The proposed model incorporates random badge awards to enhance engagement and sustain motivation, addressing the shortcomings of traditional reward systems that rely on extrinsic motivation. The integration of the Nao robot adds an interactive element, further increasing learner engagement and interest.

Conclusion – The study successfully develops a theoretical framework, mathematical modeling, and architectural design to sustain learner interest in climate change education. By combining gamification with interactive technology, the model redefines educational strategies in this domain.

Recommendations – Future implementations should consider scalability and the integration of additional interactive technologies to further enhance engagement. Continuous feedback from learners should be incorporated to refine and improve the model.

Research Implications – The study provides a robust framework for utilizing gamification and robotics in educational settings, particularly in regions with limited resources. It opens avenues for further research into the long-term impacts of such models on learner engagement and knowledge retention in climate change education.

Keywords – gamification, Nao robot, climate change literacy, green innovation entrepreneurship

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INTRODUCTION

Climate change represents a global phenomenon with profound consequences, impacting ecosystems, weather patterns, and human societies (Vílchez, 2021; Mahat 2020). Sub-Saharan Africa (SSA) confronts an array of climate-related challenges, including food security, water scarcity, and extreme weather events (Hubert et al., 2022). To effectively address these challenges, it is imperative to promote climate change literacy among SSA's population, spanning from policymakers to grassroots communities (Hubert et al., 2022). Climate change literacy encompasses the knowledge, awareness, and capability to comprehend and address climate change issues (Vílchez 2021; Mahat 2020; Hubert et al., 2022; Riedmann et al., 2022). It involves a grasp of scientific insights into climate systems, the ability to interpret climate data, and the motivation to take sustainable actions (Hubert et al., 2022). Nevertheless, fostering climate change literacy within SSA is a multifaceted endeavor, further complicated by the region's diverse linguistic, cultural, and socioeconomic contexts (Hubert et al., 2022, Balogun et al., 2022, Stevenson & Bondell, 2018). One of the primary hurdles in climate change education, not only within SSA but globally, revolves around maintaining learners' engagement and motivation over extended periods (Hilario et al., 2022, Chen et al., 2023). Traditional educational methods like classroom lectures, while valuable, often struggle to sustain students' interest in intricate and ever-evolving subjects like climate change (Chen et al., 2023, Donnermann, 2021; Yang et al., 2023). Learners may initially exhibit enthusiasm but frequently lose interest as the novelty of the subject wanes (Yang et al., 2023).

Gamification, which involves the infusion of game elements into non-gaming contexts has gained recognition as an educational strategy capable of addressing the challenge of engagement and motivation (Hamari, 2020; Hamari & Koivisto 2015; Wesseloh, 2020). By incorporating game-like elements such as points, rewards, challenges, and competition, gamification seeks to render learning enjoyable and intrinsically motivating. While gamification has exhibited promise in enhancing short-term engagement and motivation (Hamari, 2020; Wesseloh, 2020; Porto, 2021; Oguta et al., 2023), it often encounters difficulties in sustaining these positive effects over prolonged periods, especially within the intricate and dynamic realm of climate change education. Learners may initially respond positively to gamified elements but tend to lose interest as the novelty factor diminishes (Hamari, 2020; Wesseloh, 2020; Porto, 2021; Oguta et al., 2023). Gamified systems design has assessments and leaderboards that introduce competition in learning and this psychologically affects students. Learners also sometimes focus on winning badges till they forget the primary objective which is learning (Oguta et al., 2023).

This research underscores the necessity for an innovative approach that not only harnesses gamification's motivational prowess but also extends its impact to maintain long-term learner engagement (Yang et al., 2023; Ryan & Rigby, 2020). In recent years, robotics has emerged as a potential solution to the enduring challenge of sustaining engagement and motivation in education (Donnermann, 2021; Yang et al., 2023; Xefteris & Palaigeorgiou, 2019). Robots, with their interactive and dynamic nature, possess the capability to captivate learners' attention and sustain their interest (Xefteris & Palaigeorgiou, 2019; Kurtz & Kohen-Vacs, 2022; Madariaga et al., 2022). Furthermore, robots can adapt to learners' individual needs and provide personalized feedback, nurturing a sense of autonomy and competence, which are pivotal components of intrinsic motivation (Yang et al., 2003; Chew et al., 2021). The Social Robot Nao is a semi-humanoid device equipped with electro-mechanical components that can interact with humans through speech, facial expressions, and body movements (Riedmann, 2022; Donnerman, 2021; Peura et al., 2023). This programmable robot can be loaded with scripts to perform desired functions, such as speech and movement (Yang et al., 2023). Consequently, the robot can be set up as a tutor or teaching assistant in climate change literary classes (Peura et al., 2023).

The gamification components to be employed consist of points, leaderboards, and badges, specifically crafted to inspire and incentivize participants (Hamari, 2020; Ryan & Deci, 2000). These elements are mathematically modeled using probability theory in this model. Additionally, a reward system linked to the promotion of Green Innovation and Entrepreneurship (GIE) opportunities will be incorporated into the model. The integration of the Nao Robot represents a dynamic element in gamification, as it adds an emotional appeal, making the experience more enjoyable for participants (Vílchez 2021 and Yang, Lian, and Zhao 2023). In the design of the framework, we will consider the principles of Mechanics, Dynamics, and Aesthetics (MDA), Self-Determination Theory (SDT) regarding motivation, and Skinner's Behavioral Reinforcement Theory of random rewards (Yang et al., 2023; Liu et al., 2017). This research endeavors to address the critical challenge of maintaining sustained learner engagement and motivation in gamified training systems within the realm of climate change education. It aims to bridge the existing gap in gamification systems by incorporating robotics into the equation. The principal objectives of this study are outlined as follows:

i. To develop a comprehensive theoretical and mathematical model that integrates gamification, robotics, and motivation theories to sustain long-term learner engagement.
ii. To develop a methodological framework that integrates gamification, robotics, and motivation theories to sustain long-term learner engagement.

LITERATURE REVIEW

Climate Change Education

Climate change is a pressing global concern that requires continuous attention (Sono et al., 2021; Ostrom, 2010). Experts caution that climate change leads to global warming, resulting in various consequences, including increased heavy precipitation, rising temperatures, and droughts (Mahat, 2020; Galeote 2021; Rajanen, 2019). Recognizing the gravity of the issue, organizations such as the UN have advocated for the integration of environmental education into school curricula as a measure to combat climate change (Galeote, 2021; Douglas & Brauer, 2021). Climate change education in Sub-Saharan Africa is receiving more attention because of the region's susceptibility to climate-related challenges (Sono et al., 2010). Although climate change affects SSA as a whole, there is substantial variation in the level of education about this issue among different countries and communities (Vílchez, 2021; Hubert et al., 2022). Given that a significant portion of the SSA population depends on subsistence agriculture and natural resources, they are particularly vulnerable to the negative consequences of climate change (Riedmann et al., 2022; Shackleton et al., 2015). In this context, it is crucial to prioritize climate change education to empower individuals and communities to adapt to and reduce the impacts of climate change.

Climate literacy plays a pivotal role in driving change, influencing both governmental policy decisions and individual mindset adjustments (Rajanen, 2019; Douglas & Brauer, 2021). Traditional educational methods such as classroom learning often struggle to engage students effectively and lack lasting impact due to a deficiency in motivation (Donnermann, 2021; Yang et al., 2023). Technology has also been used to teach climate change. An intriguing example of successful carbon literacy training (CLT) harkens back to 1960 when it was incorporated into the television show "Coronation Street" (Chapple et al., 2020). The inclusion of carbon-related content in this soap opera led to a creation of awareness of carbon emissions. Furthermore, Malaysia has delved into Education for Sustainable Development (ESD) by introducing a low-carbon initiative as part of the Carbon Schools community program (Mahat, 2020; Wilhite, 2016). Students, ranging from 14 to 16 years old, underwent evaluation for carbon literacy, received training, and were subsequently assessed through a post-test to gauge their progress. Notably, this training was delivered through traditional classroom settings (Mahat, 2020). In 2021, a survey conducted across 31 countries in Africa, Asia, and Europe revealed that 124 out of 154 respondents include carbon literacy content when teaching accounting and finance at universities (Howell, 2018). However, the predominant mode of teaching remained the conventional classroom setting which lacks motivation and sustained learner engagement (Yang et al., 2023). Gamification stands out as a potential method to motivate learners and engage individuals and other stakeholders in climate change discussions and actions (Hamari & Koivisto, 2015; Galeote, 2021; Rapp, 2019; Hamari, 2014).

Gamification in Climate Change

Gamification has found application in the realm of climate change through diverse approaches, encompassing educational games, virtual simulations, and interactive platforms (Hamari, 2020; Rajanen, 2019; Rapp, 2019; Morschheuser et al., 2018). For instance, educational games have been developed to impart knowledge about climate science and mitigation strategies to individuals and communities in a captivating and immersive manner. Virtual simulations provide users with the opportunity to directly experience the ramifications of climate change, thereby nurturing empathy and comprehension. Furthermore, interactive platforms, often integrating elements of social networking, foster a sense of community and competition centered on eco-friendly behaviors (Rajanen 2019, Douglas and Brauer 2021). Apps and online mediums have been used to motivate positive behavior towards the environment (Douglas & Brauer, 2021).

Within the context of climate change, one of gamification's primary aims is to enhance awareness. By crafting interactive and captivating experiences, gamification effectively communicates intricate scientific concepts and underscores the pressing need for climate action to a wide-ranging audience (Mahat, 2020; Wesseloh, 2020). However, the effectiveness of gamified interventions in terms of heightening awareness exhibits variability. Empirical research indicates that while certain games and platforms have excelled at capturing and retaining users' attention, others grapple with the challenge of maintaining prolonged engagement and motivation (Wesseloh, 2020). Robotics has emerged as a promising remedy for addressing the issue of sustained engagement and motivation within educational contexts (Shackleton et al., 2015). Robots inherently possess qualities that render them highly appealing to learners. The MDA gamification framework points to the aspect of aesthetics as an integral part of attracting users to maintain enthusiasm for a system (Yang et al., 2023; Robinson, 2019; Turan et al., 2016; Riedman, 2022). The inclusion of robots in learning environments helps appeal to the learners' emotions and hence creates sustained engagement. Their tangible presence and interactive functionalities establish a dynamic and enthralling learning atmosphere (Robinson, 2019; Xefteris & Palaigeorgiou 2019; Yapa, 2019; Schez-Sobrino et al., 2020). Very few studies have been done on the use of gamified robots for training climate change. The closest research that came to climate change was a study by Lee and his colleagues on Robot Musical Theater for Climate Change Education (Lee et al., 2022). A musical theater model was used in a scenario where the robot text-to-speech mode was used to deliver content on climate change.

Related Works

Research on the use of technology in education attracted the attention of scholars especially after the Covid-19 incident which required that physical meetings be restricted (Oguta et al., 2023, 2023). Robots and gamification have been used together and separately in various technology-assisted frameworks and systems. Amram and his colleagues developed a conceptual framework to help in analyzing the effects of robots among poor and average geography students (Manining et al., 2022). Later, Lucas Moura introduced a framework called sBotics, which stands as a Gamified Framework for Educational Robotics. The main novelty of this platform is its ease of use coupled with the capacity to create a multitude of scenarios with boundless learning potential (Nascimento et al. 2021; Asadullah et al., 2023). No alternatives featuring these attributes were identified for the 12-K educational range that the research is targeting.

Earlier, Alexandre Coninx conducted research on long-term social child-robot interaction, employing multi-activity switching to engage young users (Coninx et al., 2015). Coninx observed that ongoing Chile robot interaction (cHRI) experiments often focused on singular interaction activities, such as games, leading to challenges arising from the repetitive nature of these interactions. To address this issue, he proposed the development of an adaptive robot capable of seamlessly transitioning between multiple activities within a single interaction (Coninx et al., 2015). Recently, Madariaga, Allendes, Nussbaum, Barrios, and Acevedo conducted research on the offline and online use of educational robots (Madariaga et al 2022). They found that physically setting up offline robots in the classroom increased learner motivation and engagement. However, they recommended random participant selection to avoid peer pressure from friendship. In the same year, Chen, Lin, and Hung explored gamified educational robots' impact on motivation and creativity in STEM education, indicating that these robots could enhance learning motivation and positively influence learners' creativity (Chen et al., 2023). Their research suggested the necessity of experiments in various settings beyond Taiwan. This recommendation opens the possibility of conducting research in the context of Sub-Saharan Africa to validate the claims made by Chen, Lin, and Hung (2023).

Yang, Li-Wen Lian, and Jia-Hua Zhao (2023) developed a gamified artificial intelligence educational robot with the goal of enhancing learning outcomes and behavior in laboratory safety courses for undergraduate students. Their research revealed that implementing the gamified AIER (Artificial intelligence educational robots) system is guided by the GAFCC model (Yang et al., 2023; Xefteris & Palaigeorgiou, 2019). They proposed further investigations to explore the potential of an iterative GAFCC model coupled with diverse types of robots. In a related context, Maartje de Graaf proposed utilizing humanoid robots in a study addressing the reasons behind people's reluctance to engage with robots over extended periods. This study arrived at the need for the inclusion of humanoid robots like Nao and Pepper among others because they have human-like physical features (Yang et al., 2023; de Graaf & Van Dijk, 2017).

Some studies on the use of robots and gamification in education have however revealed that the inclusion of these technologies does not have sufficient motivation among learners. Research conducted by Riedmann, Schaper, and Lugrin (2022) revealed that robotic gamification does not significantly improve learner engagement and motivation (Riedmann et al., 2022; de Graaf and Van Dijk 2017). Their research focused on the integration of a social robot and gamification in adult learning, examining the effects on motivation, engagement, and performance across four scenarios. These scenarios included normal learning without any technology, gamification alone, robots alone, and a combination of robots and gamification in a single session (Riedmann et al., 2022). A preceding study conducted by Donnermann and his colleagues explored the combination of social robots and gamification for technology-supported learning. Notably, this study aimed to integrate gamification and robots in one setting, as no prior research had explored both elements together. Surprisingly, their empirical study on engagement and motivation found no significant increase when adding gamification elements or the social robot individually.

Contrary to expectations, an interaction effect was observed when combining both elements, resulting in lower engagement. This unexpected outcome indicated that students felt distracted when using gamified robots for education. The study suggested the necessity for further research on combining robots and gamification, varying factors such as the number of sessions, participants, and delivery subjects (Donnermann, 2021; Riedmann et al., 2022).

In a different vein, Melissa and her colleagues investigated adaptive robot tutoring in long-term interactions in higher education. Their study revealed that students performed well with the adaptive robot (adaptive R), leading to improved exam results (Donnermann, 2021). These contrasting findings highlight the complexity of integrating robotics and gamification in educational settings, emphasizing the importance of continued research to better understand the nuances and optimize the educational impact of these technologies. However, there was no significant difference in motivation or overall learning experience across the conditions tested. This means that the inclusion of the gamified robot did not have a significant effect on motivation and learner engagement. This research however recommended that more time be allocated for the experiments to confirm the findings.

In summary, the studies cited in this section of related work indicate that gamified robots enhance motivation and improve learner outcomes (Riedmann et al., 2022; Donnerman, 2021; Yang et al., 2023). The existing studies on gamified robots in educational settings show that the majority of research was conducted in Europe, led by Spain at 23.8%, likely due to their strong government emphasis on technology-assisted learning (Hilario et al., 2022). Notably, African countries were absent from this list, highlighting the limited research on robotic learning in African contexts. Further research is needed to assess technology-assisted learning implementation in African nations. The Robotic Gamification Climate Change Literacy for Green Innovation and Entrepreneurship (CCL4GIE) training model is formulated for the SSA context. Further, mathematics and science dominated robotic gamification applications, accounting for Riedmann 2022% of publications. Geography and languages each comprised 14.2%, with information technology at 19% (Woo et al., 2021). There is a notable gap in climate change-related research, emphasizing the need for more studies in robotic gamification focused on climate change literacy (Lee et al., 2022). It is apparent that there has been limited research on the application of gamified robots in promoting climate change literacy. The most relevant study conducted to date is by Lee and his colleagues, centering on Robot Musical Theater for Climate Change Education. In this study, a musical theater model was employed, utilizing the robot's text-to-speech mode to convey information about climate change.

The system comprised modules for gamification, robotics, and a climate change content database (Lee et al., 2022). The robots contributed to heightened enthusiasm, motivation, and engagement among learners. Further, research reveals that Nao and Pepper are the most prevalent robots in learning environments, featured in Douglas and Brauer 2021.5% and 19% of studies, respectively (Woo et al 2021). The prevalence of Nao could be attributed to Pepper's discontinuation, highlighting the dynamic nature of robotic technologies in education (Papadopoulos et al., 2020).

Several previous studies have either combined simplified versions of self-determination theory with other models to create untested "homegrown" motivation models (Deterding et al., 2015) or proposed gamification design frameworks without a solid theoretical foundation. For example, Simões and colleagues devised a social gamification framework tailored for K6 students, but their study lacks empirical data, leaving uncertainties about the framework's effectiveness in guiding gamification design (Simões et al., 2013). While researchers like Rodrigues, Costa, Oliveira, Werbach, and Hunter have introduced gamification design frameworks primarily focused on business promotion or e-banking, they may not be directly applicable to educational contexts (Werbach et al., 2012). Moreover, alternative design models such as those by Hunicke, LeBlanc, and Zubek (2004) and Rodrigues seem geared more toward IT technicians rather than providing support for teachers implementing gamification strategies (Werbach et al., 2012; Rodrigues et al., 2016). Klevers and colleagues presented the GameLog Model, centering on gamifying crowdsourcing processes like order picking (Klevers et al., 2016).

Despite these efforts, there is a notable gap in the literature regarding comprehensive gamification frameworks tailored explicitly for educational purposes. Additional research and empirical evidence are warranted to ascertain the efficacy of gamification in educational settings. However, this model appears better suited for business applications than aiding instructors in incorporating gamification into their teaching and learning practices. The GAFCC model on the other hand was tailored to out-of-class tasks. The gamified CCL4GIE training model is designed to address the need for a model that is relevant for training climate change in a sustainable manner. The model would be set up with an NAO robot because it is available, dynamic, and presently supported by Softbank robotics.

PROPOSED Gamified CCL4GIE Training Model

Theoretical underpinnings

Self-Determination Theory (SDT)

SDT is a prominent framework in psychology that explores human motivation and personality (Ostrom, 2010; Yang et al., 2023). Propounded by Deci and Ryan, Self-Determination Theory asserts that individuals possess inherent psychological needs for autonomy, competence, and relatedness, influencing both their behavior and overall well-being. Autonomy, a cornerstone of SDT, represents the essential requirement for self-direction and the capacity to make decisions in accordance with personal values (Lu et al., 2023; Ryan & Deci, 2000). Autonomy as a motivation factor informs the design of the gamified CCL4GIE model through the incorporation of badges which is a gamification element. The model will have assessments followed by the award of points and then badges aimed at increasing motivation (Ryan & Deci, 2000). A person's engagement also increases in proportion to their level of feeling of autonomy (Lu et al., 2023). Meanwhile, competence embodies the aspiration to feel proficient and impactful in one's endeavors, and relatedness underscores the yearning for social bonds and a sense of belonging.

The competence aspect of SDT informs the gamified CCL4GIE model design of assessments. People feel competent when they prove it through assessments (Chen et al., 2018). The relatedness aspect also informs the model inclusion of leaderboards. These are gamification elements that rank students in line with the points they get after an evaluation. Students will feel connected to each other as they view the leaderboard and see how they are fair in relation to others. The model also has a group work component which also builds the relatedness aspect of human need. Student's engagement increases as they stay connected one to another, hence increasing intrinsic motivation. SDT has widespread applications in various domains, including education, work, sports, and healthcare. It has contributed to our understanding of how to foster motivation, enhance learning, and promote psychological well-being (Lu et al. 2023; Ryan & Deci, 2000). By recognizing the importance of autonomy, competence, and relatedness, SDT offers valuable insights into human behavior and the factors that drive individuals to achieve their goals and flourish

(Huang & Hew 2018; Ryan & Deci 2000). Self-determination theory will be applied to the Gamified CCL4GIE) training Model with Social Robot Nao because it focuses on the factors that influence individuals' intrinsic and extrinsic motivation, and how these motivations, in turn, impact behavior and well-being.

Behavioral Reinforcement Theory

During the 1950s, behaviorist B.F. Skinner introduced the concept of positively rewarding individuals for new behaviors, aiding the development of habits. Skinner suggested starting with continuous reinforcement for consistent rewards initially, transitioning to intermittent reinforcement once proficiency is reached to maintain curiosity. The gamified CCL4GIE model incorporates a random rewards scheme, where virtual badges recognize users' achievements, providing positive reinforcement. Motivation is sustained through the random awarding of badges, keeping learners engaged in anticipation of the next one. (Rowe et al., 2017). These badges play a role in encouraging and reinforcing the target behaviors, fostering engagement and motivation.

MDA Framework

MDA stands for Mechanics, Dynamics, and Aesthetic, and is referred to as MDE where E stands for emotions (18) (23). This framework is useful in explaining game elements. The Aesthetics bit of this framework has sometimes been interchanged with Emotions. Mechanics describes game procedures and rules, Dynamics describes game interactions and Aesthetics stands for the emotional appeal and experience in general including sound and appearance. Past studies reveal that that Octalysis (16%), MDA (Asadullah et al., 2023), Bartley player (8%), 6D (16%) and Werbach and Hunter (8%) design frameworks have been used frequently in designing gamified education systems (Hamari, 2020).

Summarily, the gamified CCL4GIE model leverages a theoretical framework weaving together Self-Determination Theory (SDT), Behavioral Reinforcement Theory, and the MDA Framework to optimize learner motivation and engagement as illustrated in Figure 1. SDT prioritizes intrinsic drives like autonomy, competence, and relatedness, which are nurtured through points, badges, and leaderboards. Points and badges empower learners with self-directed learning and a sense of accomplishment while leaderboards and group work foster social connections. Behavioral Reinforcement Theory advocates for random rewards like badges to reinforce desired behaviors and maintain curiosity, driving sustained engagement. Finally, the MDA Framework's emphasis on aesthetics, embodied by the Nao robot, injects novelty and excitement into the learning environment, further enhancing motivation and prolonging engagement. This multi-faceted approach prioritizes internal motivators while strategically employing external rewards, fostering positive social connections, and injecting novelty, paving the way for a deeply engaging and intrinsically motivating learning experience within the CCL4GIE model.

Mathematical Modelling

The proposed gamified CCL4GIE Training model is developed by intertwining together Self-Determination Theory (SDT), Behavioral Reinforcement Theory, and the MDA Framework as shown in Figure 1 to optimize learner motivation, engagement, and outcomes. The gamification elements of the design can be modeled mathematically to explain how the components work towards attaining sustained user motivation, engagement, and outcome.

Modeling Random badges

In line with Skinner's theory, this model makes use of random award of badges which is explained mathematically using probability theory that brings about variable award schedules in line with the unpredictable mode of operant conditioning theory(Aguiar et al 2022). To define badges and probabilities, let $B = \{b_1, b_2 \ldots b_{|B|}\}$ be the set of badges and $P = b_i$ stand for the likelihood of presenting each badge b_i. The badges in the model include bronze badges, silver or gold badges depending on the settings and status in which they are won. In this model, badges will be won for logging in for the class, completing the lesson, and for completing the assignments. The probability distribution of the badges takes the formula:

$$\sum_{i=1}^{|B|} P(b_i) = 1 \qquad (1)$$

Where Σ represents the summation of all badges to be equal to 1 in line with probability theory because the sum of all probabilities must equal to 1. Further, $i = 1$ stands for the lower or the beginning point of the badges $|B|$ which also means the cardinality stands for the total number of badges to be awarded. Equation 1 is the probability of a specific badge b_i from the set (list of badges) B being given. A pseudo-random number r in the interval $(0,1)$ is generated using a random number generator. This random variable captures the unpredictability characteristic in operant conditioning.

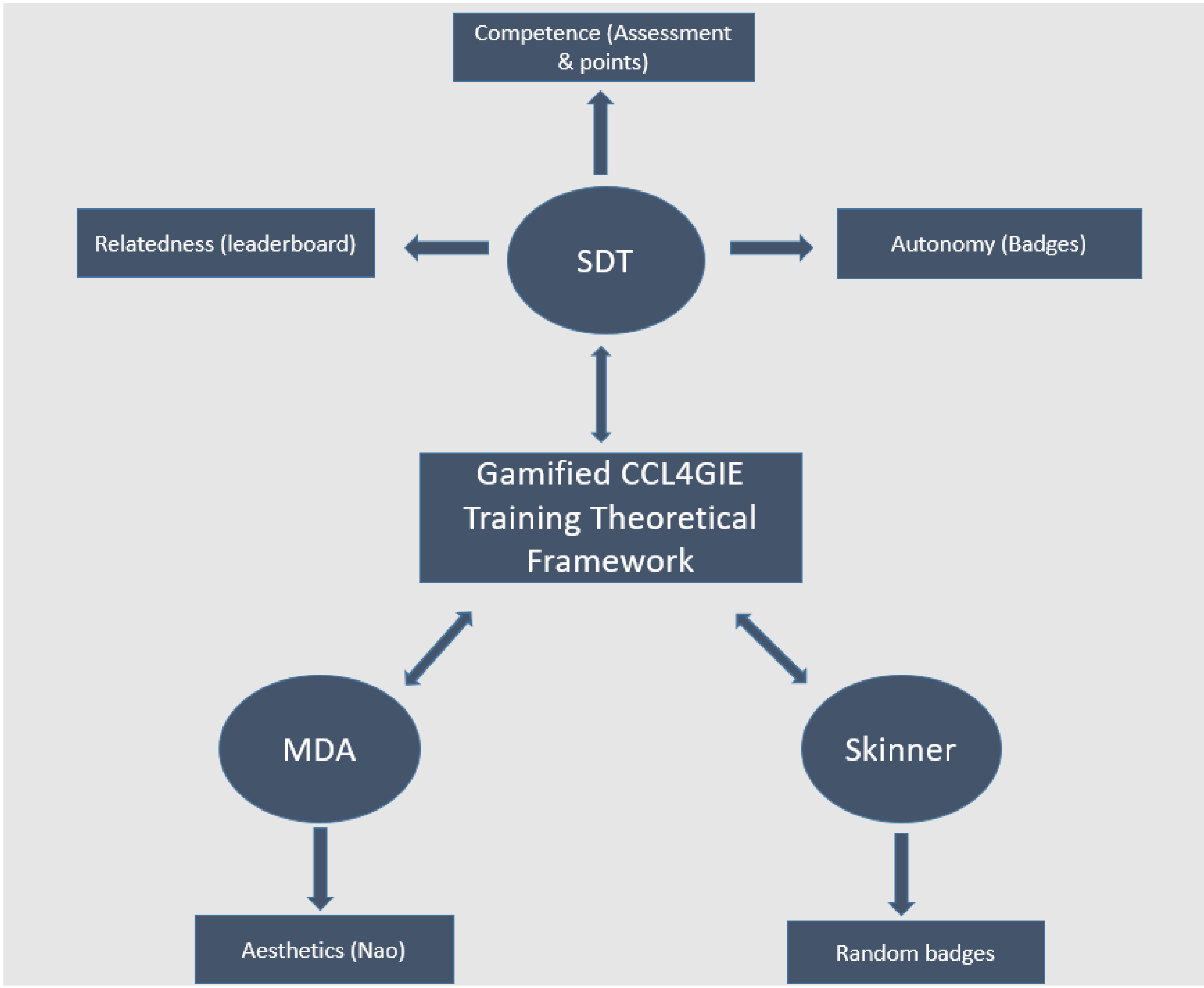

Figure 1. Theoretical Framework

Linear Congruential Generator (LCG) is a random number generator and is used in this model because it is a simple yet widely used pseudo-random number generator (PRNG) algorithm and it produces a sequence of numbers based on a recursive formula (Equation 2):

$$d + 1 = (a * d + c) \ mod \ m \qquad \textit{Equation 2}$$

Where:

- d Is the current random number.
- $d + 1$ is the next random number in the sequence.
- a is the multiplier
- c is the increment
- m is the modulus

The Gamified CCL4GIE training model uses a cumulative distribution function to make decisions on badge awards (Equation 3).

$$F(i) = \sum_{j=1}^{i} P(b_j) \qquad \textit{Equation 3}$$

The badge award decision is made by identifying the smallest i such that $F(i) \geq r$, where b_j is the badge awarded (Equation 4).

$$\begin{aligned} &r \leq F(1) \longrightarrow Award\ b_1 \\ &F(1) < r \leq F(2) \longrightarrow Award\ b_2 \\ &\ldots \\ &F(|B|-1) < r \leq F(|B|) \longrightarrow Award\ b_{|B|} \end{aligned} \qquad \textit{Equation 4}$$

Probabilities $P(b_1)$ are parameters that represent the likelihood of each badge being awarded in line with Skinnerian's theory. The normalization ensures that $P(b_1)$ forms a proper distribution, summing to 1, consistent with probability theory. This model contributes to the understanding and application of behavioral reinforcement in educational contexts.

Modelling Competence

In the context of Self-Determination Theory (SDT), competence refers to the feeling of effectiveness and mastery in performing a task. In the proposed gamification model, competence is awarded through points. Let C be the set of competence points awarded to users based on their performance. Each user is assigned a certain number of competence points denoted by c_i ∈ C whiich represents the user (Equation 5).

$$C = \{c_1, c_2 \ldots c_{|B|}\} \qquad \textit{Equation 5}$$

The awarding of competence points is determined by the user's performance in a task or assessment. Let P_i represent the performance of the user i, and $f(Pi)$ be a function that maps performance to competence points.

Therefore $Ci = f(Pi)$ *Equation 6*

The function f is customized based on the specific assessment criteria as shall be set in Moodle. Competence points are aggregated over time to reflect the user's cumulative competence. Let $Ci(t)$ represent the competence points of the user i at the time t. This can be expressed as the sum of competence points awarded up to that time:

$$Ci(t) = \sum_{j=1}^{t} C^j \qquad \textit{Equation 7}$$

Where C^j are the competence points awarded to a user i at a time j. Competence points are visually represented on a user profile to provide feedback on the user's mastery and progress.

Modeling Badges Based on Assessments

Mathematical modeling of badges is based on assessment grades. The model makes use of a system that maps specific grade ranges to corresponding badges. Let G be the grade obtained by a `student in the assessment and B be the badge awarded. The setting of grades is represented in percentage format such that grade ranges are A, B, C ... and then each range with a specific badge would be set as follows.

$$\text{A: } 70\% \leq \text{G} \leq 100\% \rightarrow \text{B} = \text{“Gold Badge”}$$
$$\text{B: } 60\% \leq \text{G} < 70\% \rightarrow \text{B} = \text{"Silver Badge"}$$
$$\text{C: } 50\% \leq \text{G} < 60\% \rightarrow \text{B} = \text{"Bronze Badge"}$$
$$\text{D: } 40\% \leq \text{G} < 50\% \rightarrow \text{B} = \text{"Green Badge"}$$
$$\text{F: G} < 40\% \rightarrow \text{B} = \text{"Red Badge"}$$

This mathematical representation captures the badge assignment process based on grade ranges.

Modelling Leaderboard

The mathematical model of a leaderboard in an educational context makes use of a scoring system where each student earns points based on their performance in assessments.

Let

- S be the student.
- P_s be the total points earned by a student S.
- l be the leaderboard.

The scoring system is defined as each correct answer in an assessment earns a certain number of points.

Correct Answer: $+X$ points
Incorrect Answer: 0 points

The value X is adjusted based on point distribution. The total points P for each student are calculated based on their performance in assessments.

$$Ps = \sum_{i=1}^{N} Xi \qquad \textit{Equation 8}$$

In the above equation (Equation 8), N represents the number of correct answers in the assessments and X_i is the points earned for each correct answer. Further, the students are ranked based on their total points P_s. In such a case, the highest-ranking student on the leaderboard is the one with the most points.

$$Rank\ (S)\ =\ Rank\ of\ Ps\ in\ L \qquad \textit{Equation 9}$$

The leaderboard can rank students in ascending or descending order. This representation can list students with their corresponding ranks and total points.

$$L\ =\ \{(S_1, Rank_1, P_1, (S_2, Rank_2, P_2), \ldots, S_n, Rank_n, P_n) \qquad \textit{Equation 10}$$

In Equation 10, S_i is the ith student, $Rank_i$ is their rank, and P_i is their total points. This mathematical model captures the essence of a leaderboard where students are ranked based on their total points earned from assessments.

Mathematical Model for Aesthetics

Aesthetics encompasses various sensory and emotional aspects, often subjective in nature. Introducing variables for emotional impact (EI), visual appeal (VA), and auditory pleasure (AP) enables quantification. EI ranges from 0 to 1, with 0 denoting low and 1 high emotional impact. Similarly, VA and AP range from 0 to 1, representing low to high visual appeal and auditory pleasure, respectively. Combining these factors yields the overall Aesthetic Experience (Aesthetics), synthesizing the individual components for a comprehensive assessment (Equation 11).

$$Aesthetics = W_{EI}.\mathrm{EI}\ +\ W_{VA}.\mathrm{VA}\ +\ W_{AP}.\mathrm{AP} \qquad \textit{Equation 11}$$

Where W_{EI}, W_{VA}, W_{AP} are weights reflecting the importance of each factor. This model attempts to quantify and combine various factors influencing aesthetics. The algorithms' complexity and scalability may pose challenges in larger implementations. Linear relationships assumed in models could limit accuracy. Subjectivity in weighting factors and potential biases may affect the gamification system's fairness and generalizability.

The Gamified CCL4GIE Model

The gamified CCL4GIE training model with the Nao robot was created about SDT, skinner's behavioral reinforcement theory, and SDT as discussed above (Lu et al 2023, Chen et al 2018, Rowe et al 2017, Ryan and Deci 2000). The model consists of two databases and two modules as shown in Figure 2. The other components of the model include learners, tutors, arrows, and evaluation sections.

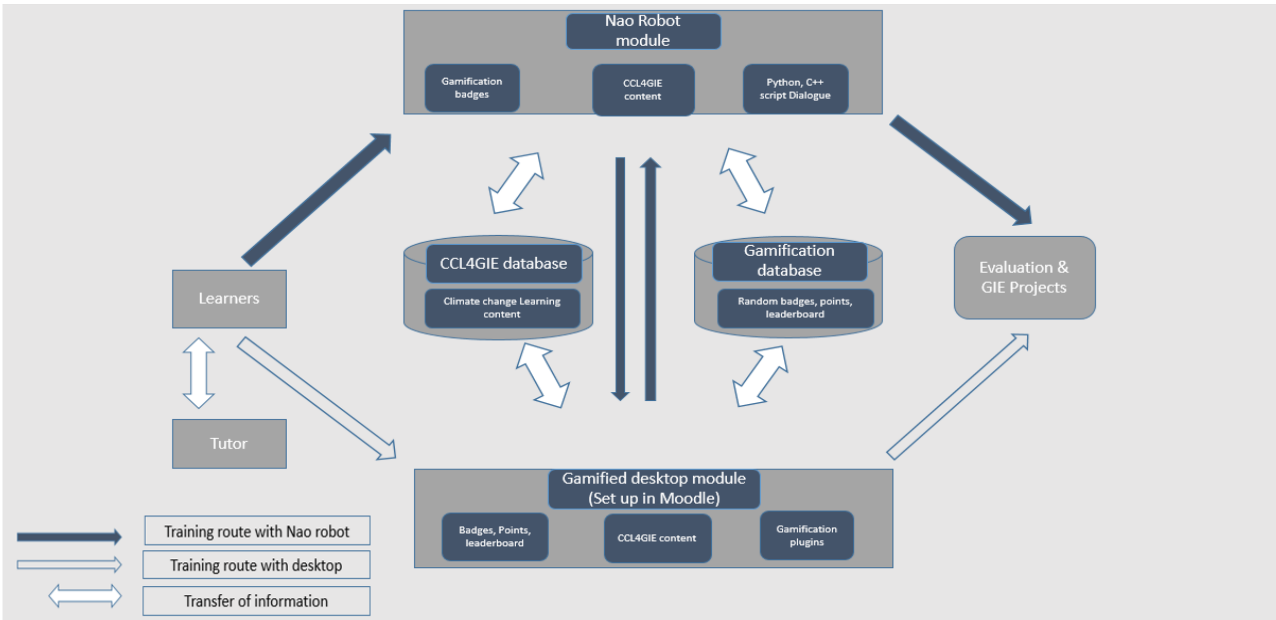

Figure 2. Gamified CCL4GIE training model

Learner and Tutor

The model section for learners refers to the participants of the climate change training. These are students who shall be requested to volunteer. A tutor section comes soon after the student section. The tutor shall instruct the students about the system setup and direct them either to the desktop section or the robot section.

Arrows

The arrows show the progression of the learners once they enter the training room. The white arrows show communication between the components of the model. The tutor and the learner coordinate and communicate with one another at the beginning of the experiment. The robot and the databases also link up when the robot fetches training information from the database and also receives gamification instructions. The robot will deliver training on climate change and so has to be scripted with such content. Further, the desktop module also links with the learning content and the gamification databases to deliver the training. The grey arrow shows the progression of learners who use the gamified desktop module while the green arrows show the progression of learners who interact with the Nao robot module.

Gamified Desktop Module

The gamified training module offers training to students using gamification principles. In this model, the desktop module will be implemented in the Moodle E-learning system where the

Carbon literacy course will be set up. The plugins that support gamification will be installed and designed to increase learner motivation, engagement, and outcome. The learners will sign up for this module and go through training on climate change literacy. This desktop module is gamified by including intrinsic motivation elements that add competence, relatedness, and autonomy to SDT theory (Chen et al., 2018; Ryan & Deci, 2000). Upon signing up, the students will win a badge for participation. This is a universal badge for any user of the system. The learner then takes the training on climate change content followed by an assessment. A random badge for consistency will be set in line with Skinner's theory when the student progresses from learning content to assessments. The assessment will be gamified by setting the questions in cross crossword puzzle game format. The model is set to award a badge to the student for completing the training before taking the assessments. Upon completion of the assessment, the learner will receive a badge for the marks attained. The leaderboard is set to show the ranking of students upon completion of the assessments (Rutledge 2018). The final stage of the desktop module is a team project where the student will be asked to partner with two other classmates to brainstorm on GIE projects and report to the tutor after 48 hours. The desktop training module will be used as a control setup for analysis purposes.

Nao Robot Module

The model includes a Nao robot to boost user engagement and motivation. Figures 3 and 4 are selected in this model because its production is continuing, and the robot is readily available. The robot has two body cameras and several sensors as illustrated in figures 3 and 4. Nao can be programmed to engage in a discussion, move limps, and rotate its head while delivering climate change education. Besides delivering the climate change content, Nao will also award badges to learners for participation and completion of the assessments. Other robots can be used in settings where they are available and supported.

CCL4GIE Learning Content Database

The CCL4GIE Learning content database will carry climate change content to be delivered to the students. This database will feed the desktop and robot modules. The content will cover basic definitions of climate change, carbon footprints, and greenhouse gases among others. The causes and remedies of climate change shall also be included in the training content. The assessments and their responses will also be included in this database.

Gamification Database

The main agenda of this model is to create a climate change literacy system that would keep learners sustainably engaged and motivated. The gamification database is therefore a vital component. The model shall avail badges, points, and leaderboards besides the GIE projects to motivate learners. SDT states that intrinsic motivation increases when users' inert needs of competence, relatedness, and autonomy are met (Riedmann et al., 2022; Donnermann, 2021). The badges will appeal to the competence needs of the users. The relatedness will be achieved through the leaderboard and the GIE project that shall be delivered through teamwork (Robinson, 2019; Rajanen, 2019, Hamari 2014; Yaşar, 2020). Further, autonomy will be achieved through points that shall be attained by learners upon completion of the assessment. The robot will add aesthetics to the model to keep learners' emotions high hence increasing engagement in the training as stipulated by the MDA framework (Sono et al., 2021; Hamari, 2014). Lastly, skinner's theory of behavior reinforcement refers to creating a reward system that is random and not systematic (10). Learners will receive badges randomly after completing the training to keep them going and so increase engagement, motivation, and learner outcome. The setting of these gamification badges, points, and leaderboards is in line with the described mathematical models.

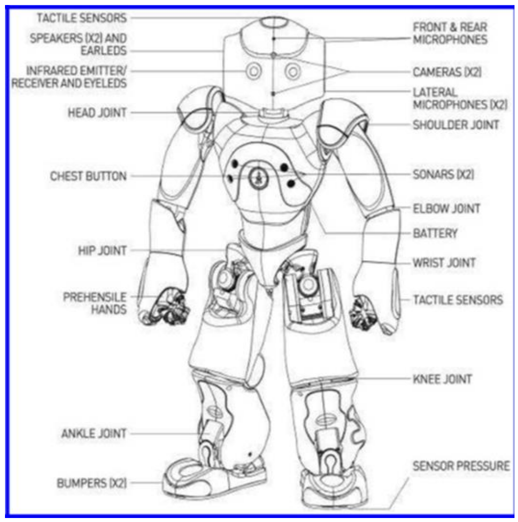

Figure 3: Nao Robot (Klevers, Sailer and Günthner 2016)

Figure 4. Nao Robot

Evaluation and GIE projects

The last phase of this model is the evaluation section where the students will take a survey based on the TAM model and so give feedback for analysis. The last stage would be used to gather information from the learners after the training followed by communication of results. An expert survey will also be done. Within the realm of computing, the Technology Acceptance Model (TAM) serves as a pivotal tool for assessing computer systems. Derived from the Theory of Reasoned Action (TRA), TAM is a framework employed to gauge user acceptance of information systems (Veiga & de Andrade 2021; Davis 1989). This model integrates external variables, including Perceived Usefulness (PU), Perceived Ease of Use (PEOU), attitude (A), as well as skills engagement (SE) and interaction engagement (IE) (Veiga and de Andrade 2021). TAM, rooted in TRA principles, provides a comprehensive lens through which the user's acceptance of information systems can be effectively examined and understood (Durodolu, 2016). The user gives feedback on these five areas to help evaluate the system. This research will apply the TAM to evaluate the designed model. Besides TAM, this research will utilize SDT, flow theory, Cognitive Load Theory, and Human-Computer Interaction (HCI) frameworks to empirically and comparatively evaluate the designed model (Davis, 1989). Learners would then be required to do a group work project session with two other students and report their findings to the tutor in Papadopoulos et al 2020 hours. This gamified CCL4GIE training model incorporating social robot Nao is developed to create sustained learner engagement, motivation, and outcomes because the conventional class environment is boring and devoid of long-term learner motivation.

METHODOLOGY FRAMEWORK

The Design Science Methodology (DSM) is used to implement the gamified CCL4GIE model (Sitorus, 2017; Darmawansah et al., 2023). The DSM is best for this research because a prototype would be developed and validated. DSM entails the identification of a problem, defining objectives, design, and development followed by demonstration and evaluation as shown in Figure 5.

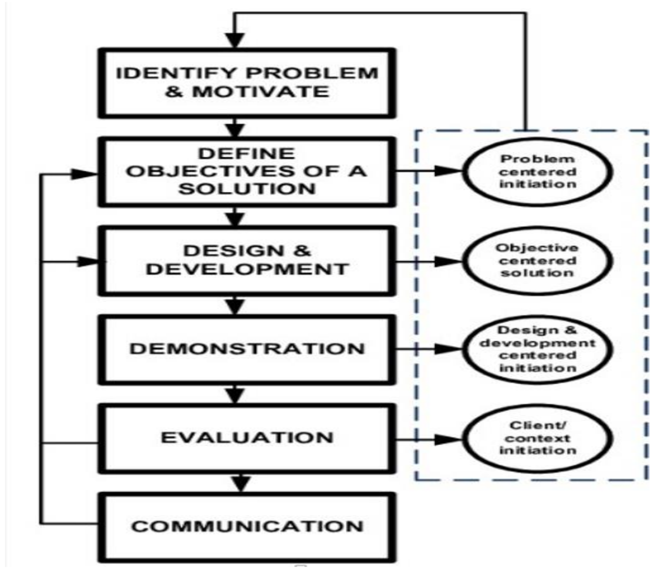

Figure 5. Design Science Summary (DSM)

In line with the DSM, the identified problem for this study is the need to design a gamified CCL4GIE training model as shown in Table 1. The motivation for this model is the need to have climate change literacy training that is sustainable, has a long-term impact, and motivates learners to participate. The design and development stage in this research would incorporate coming up with the prototype of the gamified model (Morschheuser et al., 2018). This includes setting up a gamified model in a computer section without Social Robot Nao, and then setting up another unit with the robot included. The gamified setting would be done by writing codes and scripts in Python and C#. These programming languages have libraries that can deliver the gamified system. The game and block game plugins will be downloaded from Moodle to set up gamification elements that support badges, leaderboards, and game settings in line with SDT. The next stage of the DSM is the demonstration phase. Here, the developed model would be tested and then used to train learners on climate change literacy (Stevenson & Bondell 2018). The learners would experience the route without the robot followed by a route with the robot. The last stage is the evaluation phase where a survey based on the Technology Acceptance Model would be used to gather information from the learners after the training followed by communication of results.

Participation in the training will be voluntary and will incorporate at least 20 participants randomly selected. They will be trained in at least two sessions the first session will be the training and the second session will be a feedback moment to collect the GIEs. The participants will be students from any faculty because the issue of climate change affects everyone hence the need for climate information for each person. At least twenty students will be selected for the validation process of the gamified training model. Most studies on robotic gamification use an average of 20 students to carry out validation (Vílchez, 2021; Mahat, 2020). The number can be more or less because the focus of this research is not on which student, or numbers are selected but on providing feedback on the designed model. The request for participation will be done through email with permission from the department of IT as the gatekeepers. The collected data will be confidential. A modified TAM tool would be used to gather data in five areas which include perceived usefulness (PU), perceived ease of use (PEOU), measure of attitude (A), skills engagement (SE), and interaction engagement (IE). Data will be collected both for the route with a robot and the one with desktop gamification. The data collection would be followed by a statistical analysis to compare the experience of learners in the two-route training followed by analysis and publication of the results.

Table 1. DSM Phases

Phases DSM, Objectives, Methods, and deliverables.			
DSM Phase	**Objective**	**Method**	**Deliverables**
1. Problem identification	Identify the need for a robotic gamification CCL4GIE training model in the SSA context	Systematic literature review with research synthesis and meta-analysis	State-of-the-art Robotic Gamification with Gap in the literature to address Research problem Statement with thesis statement Survey Paper on the state-of-the-art gamification…..
2. Defining the objectives to address the gap	Establish the specific objectives for the Robotic Gamification CCL4GIE training model	Research Synthesis Systematic literature review	Research questions and objectives
3. Model Design	To critically assess the gamification elements required for an SSA contextualized Robotic Gamification CCL4GIE training model	A systematic literature review of the gamification elements required an SSA contextualized Robotic Gamification CCL4GIE training model	Robotic Gamification SLR article. Building block elements of robotic gamification training model
	To develop a desktop Gamification CCL4GIE training model incorporating these gamification elements.	Design synthesis of the desktop Gamification CCL4GIE training model	The architecture of the gamified desktop CCL4GIE training model and description of components
	To semi-humanoid robot-enhance the model for improved learner motivation, engagement, and learning outcomes	Design synthesis of the semi-humanoid robot-enhanced model	The architecture of the semi-humanoid robot-enhanced model and description of its components

Table 1. DSM Phases (cont.)

Phases DSM, Objectives, Methods, and deliverables.			
DSM Phase	**Objective**	**Method**	**Deliverables**
4. Prototyping	To prototype the designed models (Desktop gamification training model and Robotic gamification training model)	Develop the CCL4GIE Gamified training system for desktop and robot modules	Gamified CCL4GIE robot and desktop training system
5. Evaluation	To comparatively empirically validate the models	Recruit participants for the Gamified CCL4GIE training	A list of student participants recruited for training
		Deploy the gamified CCL4GIE Training model and semi-humanoid robot in a pilot study with target audience members.	A pilot study report detailing the implementation process, user experiences, and preliminary learning outcomes.
		User and expert survey based on TAM and SDT frameworks to collect data on user experiences and learning outcomes of learners and technical experts.	Survey responses from experts and users of the gamified CCL4GIE training model and semi-humanoid robot and the analyzed statistical report
6. Communication	Share the findings of the comparative empirical validation with relevant stakeholders.	Publish evaluation results in peer-reviewed academic journals; present findings at national and international conferences, workshops, seminars, etc.	Academic publications in peer-reviewed journals, conference presentations

IMPLICATION OF THE STUDY

The study contributes a theoretical framework, mathematical modeling, architectural design, and methodology to sustain learner interest. It seeks to redefine climate change education in Sub-Saharan Africa by integrating gamification and the Social Robot Nao to inspire long-term engagement, motivation and sustained learning outcomes.

SUMMARY, CONCLUSION, AND RECOMMENDATIONS

The Gamified Climate Change Literacy for Green Innovation and Entrepreneurship (CCL4GIE) training model, enriched by the integration of the Social Robot Nao, emerges as a promising solution to the critical challenge of climate change education in Sub-Saharan Africa. The design of the CCL4GIE model is grounded in motivation theories such as SDT, Behavioral reinforcement theory, and the MDA gamification framework. Through the application of the DSM, the model has been crafted to cater to desktop platforms and seamlessly integrate the Social Robot Nao, ensuring a multifaceted and immersive learning experience. The significance of this model lies in its potential to redefine climate change education by not only imparting knowledge but also fostering sustained learner interest and motivation. By incorporating the Social Robot Nao, the model introduces an element of fun and engagement that is often lacking in traditional educational approaches. This infusion of gamification and robotics aims to create an environment where learners actively participate in green innovation and entrepreneurship. The planned implementation of the gamified CCL4GIE model at the Durban University of Technology in South Africa, involving the participation of 20 volunteers in at least two sessions, signifies a practical approach to validating its effectiveness. The use of the Technology Acceptance Model (TAM) in the evaluation process ensures a thorough understanding of user experiences and acceptance. The recommendation is that prototyping and validation of the model should be done to assess its effectiveness. The Gamified Climate Change Literacy for Green Innovation and Entrepreneurship training model with the integration of the Social Robot Nao represents a pioneering step towards reimagining climate change education in Sub-Saharan Africa, fostering sustained motivation, engagement, and actionable solutions among learners.

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DECLARATIONS

Conflict of Interest

The researcher declares no conflict of interest in this study.

Informed Consent

Not applicable. No humans are used in research.

Ethics Approval

Not applicable. No humans are used in research.

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