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The impact of educational gamification on cognition, emotions, and motivation: a randomized controlled trial

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Abstract
This study examines the impact of gamification on education using a novel gamified digital learning platform and a randomized controlled trial (RCT) protocol. Following established research guidelines (CONSORT, Cochrane Collaboration, EVAT©), we assessed the individual and combined effects of points, badges, and challenges against a control group without gamification. The RCT evaluated participant characteristics (sociodemographics, game habits, player traits) and outcomes in cognition (learning, engagement, webcam-based eye-tracking for visual attention, cognitive load), emotions (affective states, webcam-based facial emotion recognition), and motivation (intrinsic motivation). Results showed significantly higher learning for participants using all game elements versus the control group, while badges alone increased cognitive load compared to the other gamification groups. These findings suggest that gamification is more effective when thoughtfully integrating game elements rather than applying elements in isolation, aligning goal-setting with feedback, and combining intrinsic and extrinsic motivational cues. The absence of significant results in other variables may reflect the novelty effect, emphasizing the importance of aligning gamification with pedagogical goals, considering individual and contextual factors, and designing systems that address usability and long-term impact. Educational implications and design recommendations are provided.

Keywords Gamification · Interdisciplinary projects · Media in education · Digital learning · Human–computer interaction

Introduction

Gamification involves integrating game elements into non-game contexts and is distinct from traditional gameplay (Deterding et al., 2011, 2013). Its purpose is to transform real-world scenarios such as classrooms or workplaces into game-like

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environments (Landers et al., 2018). Known for its adaptability, gamification is widely applied in fields like education (Oliveira et al., 2023).

Research on gamification in education—spanning general education (from basic to higher levels, including courses and training) (Koivisto & Hamari, 2019; Majuri et al., 2018; Sailer & Homner, 2020), e-learning in higher education (Khaldi et al., 2023; Smiderle et al., 2020; van Roy & Zaman, 2018), and cognitive processes such as learning and executive functions (Coelho & Abreu, 2025; Lumsden et al., 2016; Vermeir et al., 2020; Wouters et al., 2013)—shows promise but identifies several limitations, including: (1) Lack of theoretical models complicating comparisons across settings; (2) Unexplained success factors, especially in cognitive outcomes; (3) Study heterogeneity, raising questions on gamification's effectiveness; (4) Small sample sizes limiting generalizability; (5) Non-validated instruments, vulnerable to subjectivity and social desirability biases; (6) Few studies using physiological and neural measures to reduce subjectivity; and (7) Lack of research considering individual and contextual participant factors, despite evidence that these variables may influence gamification outcomes. To address these issues, we have designed a study protocol and gamified digital platform with webcam-based eye-tracking and facial emotion recognition (FER), refined through usability, feasibility, and pilot studies (Coelho et al., 2023, 2024), now applied in this randomized controlled trial (RCT).

Educational gamification involves integrating game elements into learning environments; however, studies often combine multiple elements to influence various outcomes, making it challenging to isolate and assess the effect of each element individually (Mazarakis & Bräuer, 2023). For instance, using points, badges, and leaderboards in educational settings increased perceived competence, autonomy, and relatedness, resulting in better performance and achievement (Zainuddin, 2018). Another study testing gamification through badges, leaderboards, and performance graphs found that these elements improved competence satisfaction and task meaningfulness, while avatars, stories, and teammates enhanced feelings of social relatedness (Sailer et al., 2017). Leaderboards showed a strong impact in a brainstorming task, working as a goal-setting tool that boosted idea generation and performance (Landers et al., 2017a, 2017b), and outperformed game elements of cooperation and badges in boosting learning performance (Puritat, 2019). In contrast, badges increased engagement in a networking app within a university (Hamari, 2017) and enhanced self-testing behavior in learning environments, which is related to improved test outcomes (Denny et al., 2018). However, another study found no improvement in motivation, activity, or performance with badges, but noted that learners preferred private badges over public visibility ones (Kyewski & Krämer, 2018). Further, game elements like badges, avatars, progress bars, and thumbs-ups supported engagement in online discussions (Ding et al., 2017). Yet, another study found that motivation effects varied across avatars, progress, timer, score, ranking, and badges, depending on learner profiles and initial motivation levels (Reyssier et al., 2022). Finally, a study comparing competition, collaboration, and adaptive gamification found only the adaptive setup—combining narrative and performance-based personalization—significantly improved student outcomes, suggesting that simple game elements may not be sufficient to impact education (Jagušt et al., 2018).

Considering this frequent use of multiple game elements in gamification research, which makes it challenging to identify the specific effects on education, this RCT extends gamified learning theory and gamification science, isolating game elements to elicit psychological and behavioral states (Landers, 2014; Landers et al., 2018). We selected the game elements "points", "badges", and "challenges" due to their frequent use and mixed research outcomes on learning impact, yielding positive, mixed, and negative results (Majuri et al., 2018). Points and badges serve as assessment tools in gamification, providing progress-based feedback, while challenges set specific goals, like marking task completion on a map of activities (Landers, 2014; Toda et al., 2019). Examining two distinct assessment elements (points and badges) allowed us to explore differences despite their similarities. Previous findings suggest multiple game elements enhance cognitive task performance (Groening & Binnewies, 2021), while isolated elements, like points or badges alone, have been criticized for lacking a true game-like experience, as it is essential to incorporate various game elements that evoke different emotions and motivations to effectively engage users in the experience (Chou, 2019). Also, compared to isolated elements, the combination of points, badges, and leaderboards was most effective in enhancing intrinsic motivation and reducing amotivation, likely due to the richer interaction of elements in a unified system (Leitão et al., 2022). Thus, we cogitate that combining elements would amplify isolated effects, and we aimed to compare the results of individual versus combined elements (points + badges + challenges) on different cognitive, emotional, and motivational outcomes.

Cognition is shaped by emotions and motivation, which influence behavior and determine the prioritization of stimuli (Madan, 2017). Gamification can boost cognition by eliciting emotions like happiness or fear, acting as a motivational driver for behavior (Mullins & Sabherwal, 2020). This RCT incorporated isolated and combined game elements to assess gamification's impact on the interconnected domains of cognition, emotions, and motivation within an educational context. We chose several outcomes within these domains with proven significance in prior studies, seeking to replicate findings through this RCT while addressing the six literature gaps previously identified. Figure 1 presents the three domains along with the specific outcomes analyzed within each one.

Cognition

`Cognition encompasses brain functions and mental processes involved in acquiring and representing knowledge about ourselves and the world, as well as how this knowledge influences behavior (D'Esposito et al., 2012; Kihlstrom & Park, 2018). Beyond these processes, learning is the process of acquiring knowledge and new skills, behaviors, values, and attitudes (Gross, 2020). In an educational context, game elements have been employed to enhance learning performance (Landers, 2014; Landers et al., 2018), so we state our first hypothesis (H1) that gamification will enhance learning.

In educational contexts, engagement involves students' active participation and connection to learning (Hu & Li, 2017)**.** Engagement interlinks cognition, behavior,

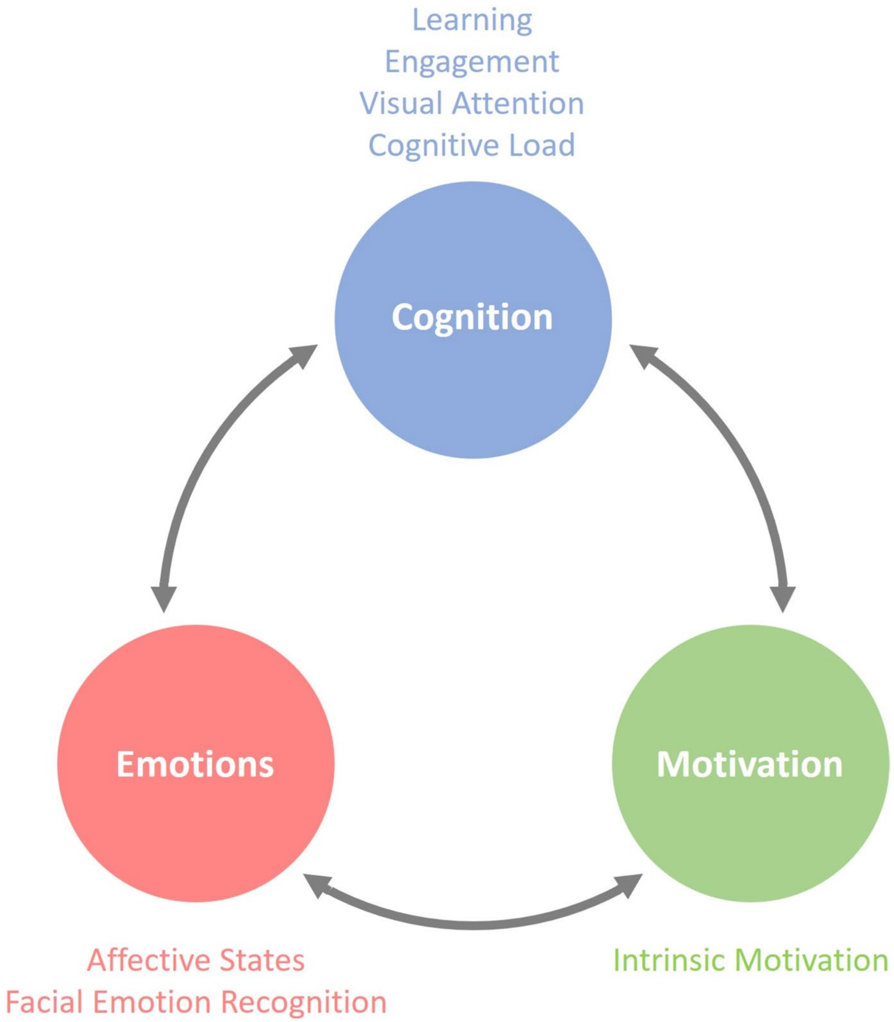

Fig. 1 Cognition, emotions, and motivation

and emotions, including optimized thinking, on-task focus, and the affective connection to tasks (Reeve et al., 2020; Wong & Liem, 2022). Cognitively, engagement involves assessing the learner's psychological investment and effort in understanding, learning, and acquiring knowledge and skills, such as the number of correct answers given by students (Bouchrika et al., 2021). Gamification effectively enhances user engagement in educational systems (Chans & Portuguez Castro, 2021), so we state our second hypothesis (H2) that gamification will enhance engagement.

Attention is essential for selecting, processing, and prioritizing information, directly influencing learning (Oberauer, 2019; Rueda et al., 2023). Eye-tracking gathers visual attention data by tracking eye movements on screens (Wang et al., 2020), allowing measurement of focus on specific screen areas, or areas of interest (Borys & Plechawska-Wójcik, 2017). Mind wandering, which reduces external visual processing, links to altered gaze patterns (Faber et al., 2020), and can be assessed by tracking gaze points, with more samples indicating sustained attention and less mind wandering (Hutt et al., 2024). Gamification can enhance visuospatial attention and focus during cognitive tasks (Olfers & Band, 2018; Scharinger et al., 2023). Thus, we state our third hypothesis (H3) that gamification will enhance visual attention by increasing screen-directed gaze, as measured through eye-tracking.

Digital technology fosters new learning opportunities through interactive applications, but irrelevant design elements can increase the cognitive load (Skulmowski & Xu, 2022). Cognitive load comprises three types (Leppink et al., 2013; Timothy et al., 2023): (1) intrinsic load, tied to task difficulty; (2) extraneous load, from instructional information not essential for learning; and (3) germane load, from activities enhancing long-term knowledge structures. In digital environments, the extraneous load is further subdivided for precision (Andersen & Makransky, 2021): (1) instruction, connected to contextual learning elements; (2) interaction, related to user engagement with the system; and (3) environment, concerning the digital learning space. Game elements in learning may increase cognitive load overall (Turan et al., 2016), add extraneous load temporarily (Chen et al., 2022), and make tasks more demanding (Vermeir et al., 2020). Nonetheless, these contradictory findings may result from the inconsistent and careless design of many gamification studies investigating cognitive load, as making learning more interesting can reduce cognitive load, enhance concept memorization, and ultimately improve academic performance by fostering a more intuitive learning experience (Baah et al., 2024). When gamified learning platforms are appropriately aligned with educational tasks, they reduce cognitive load and simplify complex concepts, enhancing student performance (Wang & Kartika Sari, 2024), while supporting cognitive skills development, and improving the overall learning experience (Gong et al., 2025). Therefore, we state our fourth hypothesis (H4) that gamification will reduce cognitive load.

Emotions

Emotions are subjective experiences characterized by biological reactions and mental states (Luo & Yu, 2015), systematically impacting cognitive processes (L. Li et al., 2020). They may vary along two dimensions: arousal (emotional activation, low to high) and valence (emotion quality, negative to positive) (Lang, 1995; Sutton et al., 2019). Research suggests a degree of universality in expressing and recognizing basic emotions—anger, fear, happiness, sadness, disgust, and surprise (Keltner et al., 2019). These emotions align within a two-dimensional framework of arousal and valence, with happiness, for instance, mapped as high arousal and positive valence (Hamann, 2012). An objective way to assess these emotions is via facial expression analysis using webcams, capturing physical responses to screen stimuli (Küntzler et al., 2021; Ninaus et al., 2019). Gamification can enhance cognitive performance by increasing arousal and positive valence (Gabana et al., 2017), thus we state our fifth hypothesis (H5) that gamification will enhance arousal and positive valence. However, gamification may also evoke emotions beyond happiness, like fear or sadness, motivating persistence despite setbacks (Mullins & Sabherwal, 2020). Thus, we state our sixth hypothesis (H6) that gamification will evoke a wider proportion of basic emotions, resulting in a lower proportion of neutral emotions.

Motivation

Motivation, as a concept explaining human behavior through actions aimed at fulfilling needs and achieving goals, empowers students to tackle challenges in educational settings (Gopalan et al., 2017). Self-Determination Theory (SDT) posits that motivation varies from amotivation to extrinsic and intrinsic motivation, depending on the alignment between personal needs and external influences (Ryan & Deci, 2000, 2020). The theory is central to understanding intrinsic motivation, which involves engaging in activities for inherent satisfaction and interest, in contrast to extrinsic motivation, which is driven by achieving external rewards or avoiding punishment (Di Domenico & Ryan, 2017). Gamification is relevant here, as it can enhance intrinsic motivation (Treiblmaier & Putz, 2020), tied to satisfaction and well-being (Ryan & Deci, 2020), thus positively impacting learning (Pietarinen et al., 2014). Therefore, we state our seventh hypothesis (H7) that gamification will increase intrinsic motivation.

Research objectives, variables, groups and hypotheses

Our study primarily aimed to examine game elements' impact on undergraduate students, comparing groups experiencing either isolated game elements, all elements combined, or none. The independent variable, based on the learning environment (the game element used), formed four intervention groups—IG (IGPoints: points; IGBadges: badges; IGChallenges: challenges; IGAll: points + badges + challenges) and one control group—CG—with no game elements. Within the groups, we measured four outcomes (dependent variables) related to cognition (learning, engagement, visual attention, and cognitive load), three related to emotions (affective states—i.e., arousal and valence—and FER), and one related to motivation (intrinsic motivation). As previously discussed, given gamification's potential to influence all outcomes, our seven hypotheses state that gamification (IG) will have a greater impact on the dependent variables than the absence of it (CG). Additionally, we propose that combining multiple game elements will amplify the effects of gamification, as existing evidence suggests that multiple game elements improve cognitive task performance and motivation (Groening & Binnewies, 2021; Leitão et al., 2022) and that combining different game elements creates a more enjoyable gamified experience (Chou, 2019). Thus, our seven hypotheses were each divided into three variations, structured to examine both the isolated impact of individual game elements and their combined effect, comparing with a non-gamified condition. By doing so, this study investigates how isolated and combined game elements affect cognition, emotions, and motivation, assessing gamification's potential to enrich education. Figure 2 and Table 1 present the variables, groups, and hypotheses.

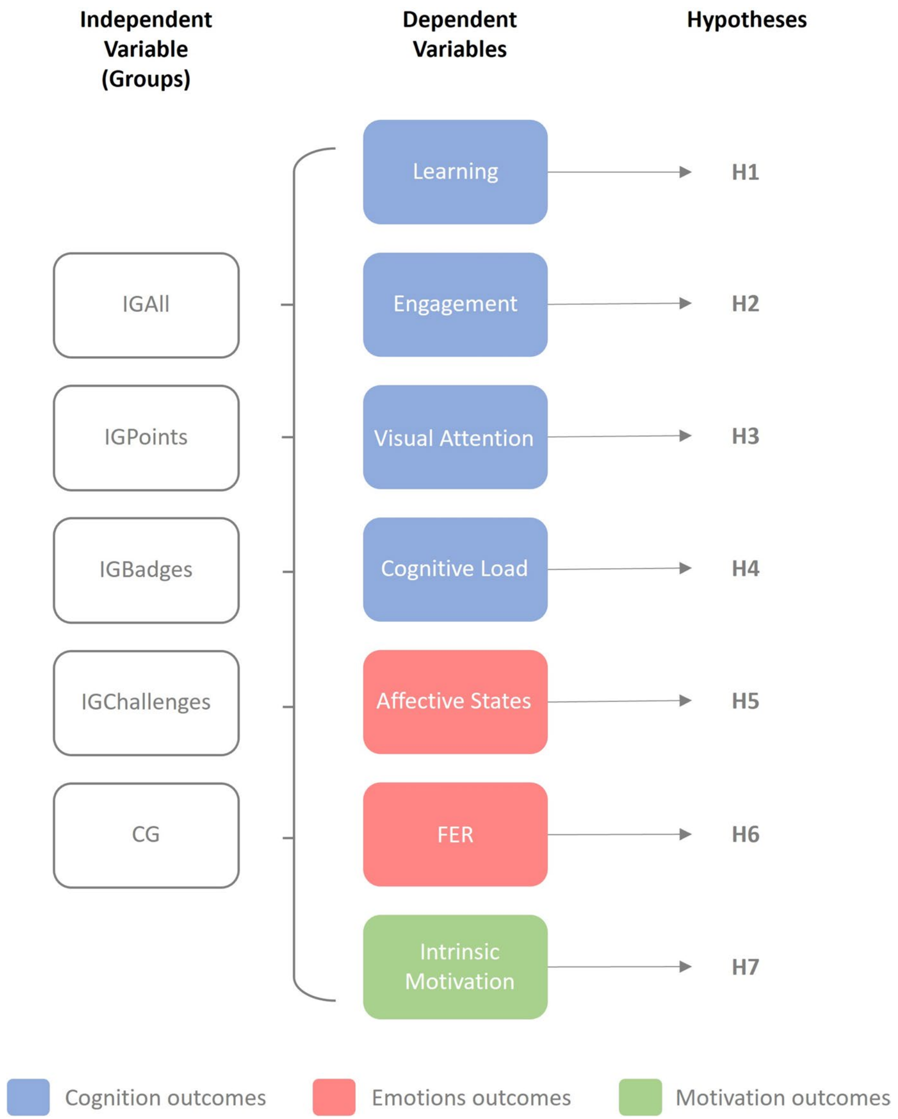

Fig. 2 Research variables, groups, and hypotheses

Table 1 Research variables, groups, and hypotheses

Domain	Dependent variable	Group	Hypotheses	Hypotheses description
Cognition	Learning	IGAll	H1a	IGAll will exhibit the highest learning performance among all groups
		IGPoints + IGBadges + IGChallenges	H1b	The groups are hypothesized to show higher learning performance compared to CG
		CG	H1c	CG is expected to demonstrate the lowest performance among all groups
	Engagement	IGAll	H2a	IGAll will exhibit the highest engagement among all groups
		IGPoints + IGBadges + IGChallenges	H2b	The groups are hypothesized to show higher engagement compared to CG
		CG	H2c	CG is expected to demonstrate the lowest engagement among all groups
	Visual attention	IGAll	H3a	IGAll will exhibit the highest visual attention among all groups
		IGPoints + IGBadges + IGChallenges	H3b	The groups are hypothesized to show higher visual attention compared to CG
		CG	H3c	CG is expected to demonstrate the lowest visual attention among all groups
	Cognitive load	IGAll	H4a	IGAll will exhibit the lowest cognitive load among all groups
		IGPoints + IGBadges + IGChallenges	H4b	The groups are hypothesized to show lower cognitive load compared to CG
		CG	H4c	CG is expected to demonstrate the highest cognitive load among all groups
Emotions	Affective states	IGAll	H5a	IGAll will exhibit the highest arousal and positive valence among all groups
		IGPoints + IGBadges + IGChallenges	H5b	The groups are hypothesized to show higher positive valence and arousal compared to CG
		CG	H5c	CG is expected to demonstrate the lowest arousal and positive valence among all groups
	FER	IGAll	H6a	IGAll will exhibit the lowest score of neutral emotion among all groups
		IGPoints + IGBadges + IGChallenges	H6b	The groups are hypothesized to show lower scores of neutral emotions compared to CG
		CG	H6c	CG is expected to demonstrate the highest score of neutral emotion among all groups
Motivation	Intrinsic motivation	IGAll	H7a	IGAll will exhibit the highest score of intrinsic motivation among all groups
		IGPoints + IGBadges + IGChallenges	H7b	The groups are hypothesized to show higher intrinsic motivation compared to CG
		CG	H7c	CG is expected to demonstrate the lowest intrinsic motivation among all groups

Material and methods

Research design and quality

We adopted an experimental between-subject RCT design with four different IG and one CG to verify the impact of digital gamification on the cognition, emotions, and motivation of undergraduate students within an educational context. We nested a digital course within a developed gamified digital learning platform, which underwent adaptation into four distinct versions featuring various embedded game elements representing the IG (IGPoints: "points", IGBadges: "badges", IGChallenges: "challenges", and IGAll: "points + badges + challenges"). The group devoid of embedded game elements represented the CG.

To ensure the quality and transparency of our research, we followed three established guidelines for RCT. Firstly, we adhered to the Consolidated Standards of Reporting Trials (CONSORT) (Falci & Marques, 2015; Schulz et al., 2010), for clear reporting and structuring of data. We incorporated the recommendations of the Cochrane Collaboration (Higgins et al., 2023) for robust bias assessment and internal validity analysis. We also employed the External Validity Assessment Tool (EVAT©) to evaluate the model and external validity, analyzing the generalizability and replicability of our findings (Khorsan & Crawford, 2014). While the latter two guidelines (Cochrane Collaboration and EVAT©) are particularly relevant for systematic reviews, these assessments are crucial for establishing the internal and external validity of data, ultimately strengthening the quality of RCT research and reporting.

Participants

An a priori power analysis was computed using G*Power v.3.1.9.4 and F tests for MANOVA (Faul et al., 2007). We considered a medium effect size ($f^2(V) = 0.09$), a power of 0.80, and an alpha of 0.05 for five groups and eight response variables. It yielded a sample size $N = 80$. Concerning the effect size selected, a recent meta-analysis on gamification in education found a significant overall large effect on students' learning outcomes (Li et al., 2023). Despite these findings, we considered it more appropriate to adopt a more conservative approach, accounting for contextual differences and variability in outcome measurements, thereby enhancing the replicability of this study design. Taking into account the sample size obtained in the power analysis and the possibility of losing elements of the sample, we recruited $N = 89$ participants from the Anatomy and Physiology course of the Nursing Undergraduate program at a local University in Lisbon, Portugal. The students were recruited during the first elective semester (September 2023). Eligibility criteria consisted of participants who were undergraduate students without self-reported serious disabilities or diagnosed mental health issues. This study received approval from the local Ethics Committee, and all the participants signed an informed consent form before the study.

Gamification is subject to both individual and contextual influences, but, as highlighted in the Introduction, there is a lack of research addressing these individual and contextual factors, despite evidence showing that motivational processes can vary significantly among learners—revealing a key gap in the literature (Koivisto & Hamari, 2019; van Roy & Zaman, 2018). Factors such as culture (Ćwil & Howe, 2020), age (Marston & del Carmen Miranda Duro, 2020), game habits, and player traits (Tondello & Nacke, 2019; Tondello et al., 2019) can significantly impact the interaction between participants and gamified experience. Thus, in this study, the participants' profiles were used as control variables to ensure a more homogeneous allocation based on their characteristics. Participants' profiles were retrieved through the application of a sociodemographic questionnaire (SQ), which included variables such as gender, marital status, age, education, and nationality, along with the Game Habits Questionnaire (GHQ), which assessed the weekly time dedicated to playing games. Additionally, we employed the player traits questionnaire (PTQ) (Tondello & Nacke, 2019; Tondello et al., 2019), a widely validated questionnaire with a large sample of respondents (Tondello et al., 2018), to discern individual player preferences, motivations, and behaviors. The PTQ consists of 25 items answered on a 7-point Likert scale (from totally agree to totally disagree). Based on the results, users receive a score from five distinct player orientations (Social, Aesthetic, Narrative, Challenge, and Goal Orientations), ranging from 0 to 1. According to the literature (Tondello & Nacke, 2019; Tondello et al., 2019), Social Orientation involves a preference for playing with others, motivated by the need for meaningful interactions. Aesthetic Orientation reflects a preference for enjoying game graphics, sound, and art, driven by a desire for exploration and autonomy. Narrative orientation reflects a preference for complex game stories, motivated by an openness to experience and a natural enjoyment of narratives. Challenge orientation is characterized by a preference for fast-paced, difficult gameplay that satisfies the need for competence. Finally, Goal Orientation involves a preference for completing quests and tasks, focusing on measurable progress and task completion. After clustering the participants by their participants' profiles, they were randomly assigned to one of the five groups, according to the learning environment independent variable. A blank participants' profile questionnaire is available as Appendix A in the Open Science Framework (OSF) project link provided in the reference list (Coelho et al., 2025b).

From the initial recruitment of 89 participants, only 82 were included in this study. Five exclusions occurred due to three participants not attending the in-person class, one participant leaving the class prematurely, and one participant encountering issues with the webcam applications during the experiment. Two additional participants were excluded due to their status as multivariate outliers during statistical analysis. The final formation of the five groups were IGPoints ($n=16$), IGBadges ($n=16$), IGChallenges ($n=15$), IGAll ($n=18$), and CG ($n=17$). Figure 3 illustrates the CONSORT Flow Diagram with all the phases of the RCT and allocation groups.

The final sample comprised 82 undergraduate students (72 women and 10 men) with ages ranging from 17 to 30 ($M=18.67$, $SD=1.89$). Table 2 shows the sociodemographic characteristics of participants.

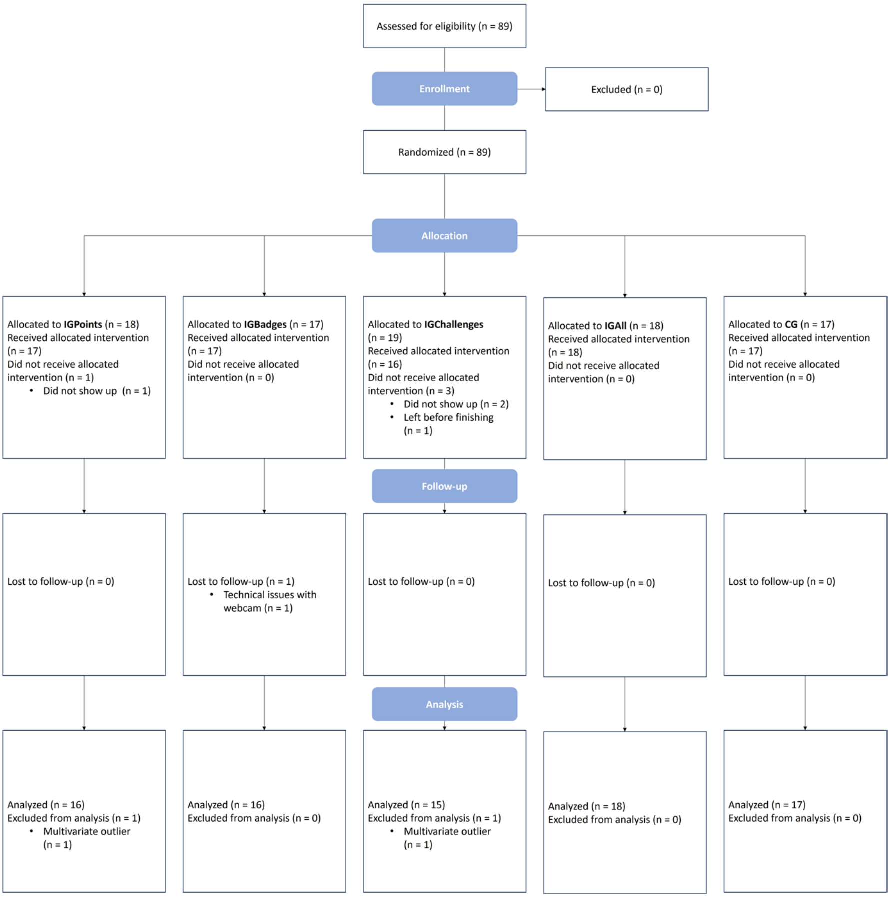

Fig. 3 CONSORT flow diagram

Regarding the game habits of the participants, Table 3 features time per week dedicated to playing games across the groups of the learning environment. The results of a Fisher's Exact Test indicated no significant association between the learning environment and the game habits ($p = 0.976$). So, the distribution of that type of habit is similar across the groups.

Also, Table 4 shows descriptive statistics of the player traits across the groups. The closer the value to one, the more orientation to the profile. As mentioned above, these player profiles were experimentally controlled to ensure no differences among the five groups of learning environment. In fact, a One-Way Multivariate Analysis of Variance (MANOVA) showed no statistically significant differences among the groups [Social: $F(4, 77) = 0.137$, $p = 0.968$, partial $\eta 2 = 0.007$; Aesthetic: $F(4, 77) = 0.203$, $p = 0.936$, partial $\eta 2 = 0.010$; Narrative: $F(4, 77) = 0.339$, $p = 0.851$, partial $\eta 2 = 0.017$; Challenges: $F(4, 77) = 0.303$, $p = 0.875$, partial $\eta 2 = 0.015$; Goal: $F(4, 77) = 0.257$, $p = 0.905$, partial $\eta 2 = 0.013$].

Table 2 Sociodemographic characteristics of the sample (N = 82)

Variables	Percentage
Gender	
Man	12.2
Woman	87.8
Marital status	
Single	97.6
Other	2.4
Age (years)	
17–18	70.7
19–20	24.4
21–30	4.9
Education	
Secondary	96.3
Bachelor	3.7
Nationality	
Portugal	89.0
Brazil	7.3
Other	3.7

Table 3 Crosstabulation of game habits in hours per week and learning environments (percentages)

	CG	IGPoints	IGBadges	IGChallenges	IGAll	Total
Don't play	29.4	31.3	31.3	33.3	27.8	30.5
1 to 10	58.8	56.3	56.3	66.7	61.1	59.8
11 to 20	11.8	12.5	12.5	0.0	11.1	9.8
Total	100.0	100.0	100.0	100.0	100.0	100.0

Table 4 Descriptive statistics of the player traits across the learning environments

	CG		IGPoints		IGBadges		IGChallenges		IGAll	
	M	SD	M	SD	M	SD	M	SD	M	SD
Social	0.599	0.236	0.592	0.181	0.606	0.227	0.634	0.233	0.626	0.217
Aesthetic	0.652	0.144	0.646	0.308	0.609	0.246	0.671	0.144	0.621	0.216
Narrative	0.569	0.194	0.607	0.272	0.535	0.244	0.540	0.176	0.579	0.183
Challenges	0.731	0.155	0.716	0.169	0.681	0.140	0.683	0.171	0.700	0.180
Goal	0.733	0.145	0.712	0.134	0.727	0.181	0.707	0.130	0.680	0.174

Instruments and measures

Learning (learning performance assessment)

The evaluation of learning performance involved two exams, i.e., the Learning Performance Assessment (LPA), both consisting of identical 10 multiple-choice questions addressing the content presented in a 60-min video lecture on Anatomy and Physiology (e.g., “Which of these options cannot be assessed using the electrocardiogram?”). The questions were crafted by the lecturers and instructors of the course, the same lecturers who conducted the instructional activities and had previously assessed the same student cohort in past years. This procedure ensured the alignment of the assessment with the instructional objectives and subject content, bringing consistency based on expert judgment (in this case, lecturers and instructors) and maintaining familiarity with student performance patterns. This type of lecturer-made exam is considered a valid and reliable measure of learning performance (Considine et al., 2005; Magdalena et al., 2023). These exams were administered before and after the course, serving as the pre-test and post-test, respectively. The pre-test was conducted digitally, while the post-test took the form of a paper-based assessment. To prevent bias, no feedback on correct answers was provided. A change score was calculated given the difference between the post-test and pre-test scores. The output of this variable is analyzed in Sect. “Results” as Learning Performance.

Engagement (home exercises)

Engagement was assessed based on existing e-learning literature, linking cognitive engagement to the learner’s psychological investment and effort, measured by the number of correct answers (Bouchrika et al., 2021), particularly during the home phase, which was a voluntary period within the experimental design. Criterion-related validity indicates alignment with established standards, while reliability might concern the consistency of measurements under repeated conditions (Karnia, 2024). Thus, we measured engagement using a method previously applied in a similar study on gamification in educational settings, aiming to ensure valid and reliable data. Eighty different multiple-choice questions addressing the content presented in a 60-min video lecture on Anatomy and Physiology (e.g., “which of these processes is not related to hemostasis?”) were made available for the students. The students had access to the gamified digital learning platform at home and could answer the questions in their own time. The assessment of engagement was made by determining the number of home exercises completed and correctly answered, which served as indicators of participants’ psychological investment. The output of this variable, analyzed in Sect. “Results”, is Engagement.

Visual attention (webcam-based eye tracking)

Screen focus can be assessed through eye-tracking, with a higher number of gaze points (i.e., how many times it captured the participants looking at the screen) indicating sustained visual attention and reduced mind wandering, related to non-screen focus, with webcam-based eye-tracking like WebGazer showing sufficient accuracy and precision for this purpose (Hutt et al., 2024). Eye-tracking accuracy and precision measures align with the broader concepts of validity and reliability, ensuring consistent and replicable results (Carter & Luke, 2020). Thus, we chose to assess attention using eye-tracking technology to determine whether participants remained focused on the screen throughout the course or lost attentional focus by looking elsewhere. We used the Webgazer (v 3.1.2) eye-tracking system and considered as outcome of the number of gaze points from the eye-tracking (Papoutsaki et al., 2016). Although less precise than infrared eye-tracking, WebGazer is an easily portable, webcam-based solution suitable for gaze patterns, being a feasible option for experiments focused on identifying where participants direct their attention (Slim et al., 2024). This approach involves gauging visual attention on interfaces, intending to validate the attentional focus on the screen. The output of this variable is analyzed in Sect. "Results" as Visual Attention.

Cognitive load (cognitive load questionnaire)

The Cognitive Load Questionnaire (CLQ) is based on a cognitive load measurement, which originally assessed intrinsic load (task difficulty), extraneous load (unnecessary instructional information), and germane load (learning activities aiding knowledge development), demonstrating acceptable construct validity, with a Comparative Fit Index (CFI) of 0.965 and a Tucker-Lewis Index (TLI) of 0.947, as confirmed by Confirmatory Factor Analysis (CFA) for a three-factor model, showing reliability with Cronbach's alpha values ranging from 0.75 to 0.82. (Leppink et al., 2013). In its adaptation to virtual environments, extraneous load was subdivided into instruction, interaction, and environment to provide a more precise assessment of digital learning environments, further supporting its construct validity with CFI and TLI scores of 1.00, confirmed through CFA, and demonstrating reliability via Rasch analysis, with coefficients ranging from 0.81 to 0.85 (Andersen & Makransky, 2021). We used this adapted version, designed for digital learning environments, which included 18 statements covering intrinsic (e.g., "the topic of this class was very complex"), extraneous—considering instruction, interaction, and environment (e.g., "the elements in the digital platform environment made learning very unclear"), and germane load (e.g., "the class really improved my understanding of the concepts and definitions covered"). Given the absence of a validated version in Portuguese, the instrument was translated and back-translated according to recommendations (Beaton et al., 2000; Klotz et al., 2023) to ensure linguistic and conceptual similarity. Participants rated their agreement with each statement on an 11-point Likert scale. CLQ was administered digitally once as a post-test following the in-person course. The output of this variable is analyzed in Sect. "Results" as Cognitive Load.

Affective states (self-assessment manikin)

To assess self-reported sensory experience, we used the Self-Assessment Manikin (SAM) pictographic scale, a widely employed tool for measuring subjective emotional responses (Bynion & Feldner, 2017; Sutton et al., 2019). SAM is a non-verbal scale that quickly gauges valence (from unpleasant to pleasant) and arousal (from calm to aroused) linked to an individual's emotional reaction (Franco et al., 2021). The SAM scale has been widely used across diverse cultural contexts to reliably measure the valence and arousal dimensions of emotion (Branco et al., 2023; Lemos et al., 2024). Thus, we chose this tool to ensure criterion-related validity by aligning with established standards and to guarantee reliability through consistent measurements under repeated conditions (Karnia, 2024). In a 10-point Likert scale, the leftmost end (unpleasant and calm) is rated 1, while the rightmost (pleasant and aroused) is rated 10. The SAM was administered digitally during both the pre- and post-tests. The variable was calculated as the difference between the post-test and pre-test scores. The outputs of this variable are analyzed in Sect. "Results" as Valence and Arousal.

Facial emotion recognition (webcam-based morphcast)

A different and more objective approach to assessing emotions, beyond conventional questionnaires, entails the scrutiny of facial expressions (Küntzler et al., 2021). FER uses machine learning algorithms to detect and track facial features, monitor changes in facial landmarks over time, and classify them into emotion categories based on classifiers trained with tagged facial expression databases (Dupré, 2021). FER validity refers to how accurately the emotion recognition identifies the intended emotional states based on psychological theory, while reliability concerns the consistency of emotions across times, locations, participants, and conditions (Mattioli & Cabitza, 2024). Automated facial expression analysis has shown convergent validity with electromyography (EMG) measures and reliability in rating concordance across conditions (Beringer et al., 2019). We used the webcam-based FER software Morphcast, which measures emotions of anger, disgust, fear, happiness, sadness, surprise, and neutral (Dupré et al., 2020). For this research, we considered the proportion of neutral emotions, as gamification can evoke a range of emotions, such as sadness and happiness (Mullins & Sabherwal, 2020), making the neutral-to-other emotion ratio a useful measure for detecting emotional fluctuations beyond neutrality. The higher the proportion of neutral emotion, the lower the proportion of the other emotions and vice versa. The output of this variable is analyzed in Sect. "Results" as the Proportion of Neutral Emotion.

Motivation (post-experimental intrinsic motivation inventory)

Our selection for gauging motivation involved the utilization of a questionnaire rooted in SDT (Ryan & Deci, 2020). For measuring intrinsic motivation, we employed the Interest/Enjoyment scale of the Post-Experimental Intrinsic Motivation Inventory (PEIMI) questionnaire, which has been validated for the Portuguese population, demonstrating acceptable overall construct validity with Adjusted Goodness of Fit Index (AGFI), CFI, and TLI values above 0.93 across Multidimensional, Second-Order, and Bi-Factor Models, along with satisfactory reliability reflected by Cronbach's alpha values ranging from 0.82 to 0.91 (Monteiro et al., 2015). The scale comprises seven statements (e.g., "I enjoyed doing this activity very much"), and participants indicate their level of agreement on a 7-point Likert scale for each statement. The PEIMI was administered digitally during both the pre-test and post-test. The variable was calculated as the difference between the post-test and pre-test scores. The output of this variable is analyzed in Sect. "Results" as Interest/Enjoyment.

Procedure

Participants completed the SQ, the GHQ, and the PTQ during a regular Anatomy and Physiology class 60 days before the beginning of the RCT. After utilizing data from the SQ, GHQ, and PTQ, we clustered them and then we randomly allocated, enrolled, and assigned participants to interventions using a numbered system, ensuring anonymity. The variables considered for pairing the participants in the different groups included age, gender, nationality, game habits, and scores on each of the five distinct player traits (Social, Aesthetic, Narrative, Challenge, and Goal Orientations). Subsequently, after 60 days, participants were allocated to five different group sessions, each lasting two hours, conducted in the same week. To mitigate the bias of the randomization process and deviations from intended interventions (Higgins et al., 2023), participants remained unaware of their group assignments.

During each group session, an instructor requested participants to provide informed consent (previously digitally sent) and complete the pre-tests outlined earlier, consisting of the LPA the SAM test, and the PEIMI questionnaire. Subsequently, each participant was provided with a unique login to locally access the digital learning platform, wherein they watched five modules, each containing a 12-min video lecture, a PDF with the professor's presentation, and two multiple-choice questions, amounting to a total of 60 min of video content and 10 multiple-choice questions as classroom exercises. These classroom exercises were not

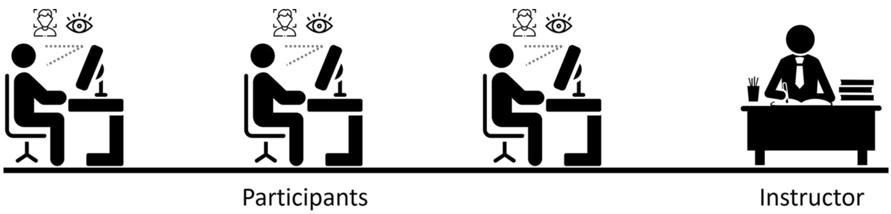

Fig. 4 Group session setting
Note. This figure is for illustrative purposes only, as each group session took place in a classroom with a similar setup, but featuring 20 available computers where participants were distributed

used for measurement purposes but were solely intended for system and course practice. The course viewing took place in a dimly lit computer lab at the local University, with minimal distractions. All participants simultaneously viewed the course but on separate individual computers equipped with headphones. While engaging with the gamified digital learning platform, including course viewing, and answering questions, both eye-tracking and FER applications collected data via webcam. Figure 4 illustrates the group's session setting. After the digital course, participants responded to some of the post-tests, namely the SAM test, the PEIMI questionnaire, and the CLQ.

Upon the conclusion of all group sessions within the same week, participants were individually supplied with a link to access the digital learning platform online, along with their login credentials for continuing the course. Over six days, they had the opportunity to revisit the video lectures and the 10 classroom exercises they had previously completed. Additionally, there were 80 more multiple-choice questions related to the 60-min video content as home exercises to facilitate further practice and study of the subject. Following these six days, online access to the digital learning platform was restricted, and all students went to the University for the paper-based post-test LPA. A visual representation of these procedures is provided in Fig. 5.

Gamified digital learning platform

To conduct our experiment within a controlled environment, we developed a gamified digital learning platform built upon gamified learning theory and gamification science (Landers, 2014; Landers et al., 2018). This platform was tested and validated in previous feasibility and pilot studies (Coelho et al., 2023, 2024) and functioned as an adaptable educational system and a controlled setting to assess the influence of various game elements on cognition, emotions, and motivation. Integrated into this platform are the applications for eye-tracking Webgazer 3.1.2

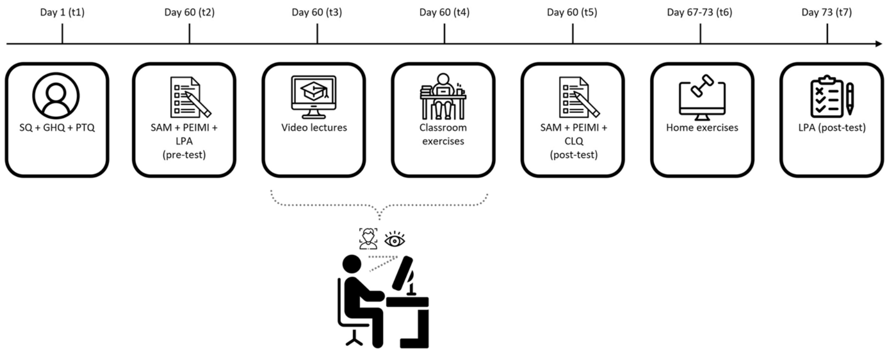

Fig. 5 Research procedure

Fig. 6 Gamified digital learning platform—video lectures interface (IGAll)
Note. IGPoints could just see the game element of "Points". IGChallenges could just see the game element of "Challenges". IGBadges could just see the game element of "Badges". IGAll could see all the game elements, as shown in the figure

(Papoutsaki et al., 2016) and for FER Morphcast 1.16 v1.3 (Dupré, 2021). Figures 6 and 7 depict the interfaces for video lectures and exercises, respectively (for IGAll, i.e., with all the game elements presented).

Gamification settings

To conduct this research, we created five distinct editions of the gamified digital learning environment, each edition corresponding to each group session. Each edition incorporated the course materials, such as video lectures and practice activities within distinct course modules with different subjects. Within all the groups, participants were expected to follow specific behaviors: (1) initiate the course; (2) commence the video lecture; (3) complete the video lecture; (4) provide correct responses to classroom exercises with minimal attempts; (5) provide correct responses to home exercises with minimal attempts; (6) complete the course modules; and (7) conclude the course. These anticipated behaviors served as the basis for rewarding participants in the IG under different game element settings, wherein points, badges, or completed challenges were allocated for meeting the expected behaviors. The process of gamification design included the manipulation of variables using a digital system to encourage participants toward improved and more

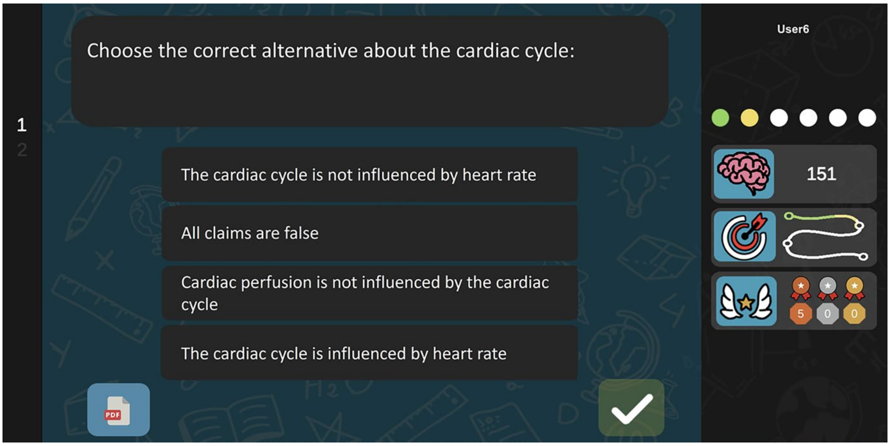

Fig. 7 Gamified digital learning platform—exercises interface (IGAll)

desirable behaviors (Coelho & Abreu, 2023), e.g., it was expected that participants would be encouraged (with points, badges, or challenges) to invest effort in producing accurate answers to exercises rather than resorting to guessing, as errors led to reduced or no rewards. In the version encompassing all game elements (IGAll), users had access to all three user interfaces and visual components, as shown in Figs. 6 and 7. The configuration without any game elements (CG) only included the course materials within the gamified digital learning platform. We chose to illustrate only the IGAll interface here, as it represents the most complete version, but detailed interfaces for all groups are available in Appendix B, accessible through the OSF project link listed in the references (Coelho et al., 2025b). The user interface and visual components for the IG are described below.

Points Within the digital learning platform's "points" version, a user interface with visual components showcased the total points earned, along with a comprehensive history of all acquired points. The points were represented by a progressive numerical score.

Badges In the "badges" version of the digital learning platform, a user interface with visual components displayed the total number of badges earned, along with a detailed history of all acquired badges. Participants had the chance to earn bronze, silver, or golden badges based on their progress, but there was no required information on how to achieve them.

Challenges The "challenges" version incorporated diverse visual components, providing users with the capability to review completed challenges and obtain information about upcoming challenges, such as "answer 10 questions without making a mistake."

Data analysis

A One-Way Multivariate Analysis of Variance (MANOVA) was computed, considering the learning environment as the independent variable (four gamified environments and one without any gamified element) and eight response variables, since MANOVA allows to control the inflation of Type I error when several dependent variables are analyzed (Tabachnick & Fidell, 2013). As mentioned above, the learning environment variable divided participants into five groups: IGPoints, IGBadges, IGChallenges, IGAll, and CG. The response variables were: Valence, Arousal, Interest/Enjoyment, Cognitive Load, Learning Performance, Engagement in Home Exercises, Visual Attention, and Proportion of Neutral Emotion.

Regarding MANOVA assumptions, the independence of observations was assumed. Mahalanobis distances and leverage values were calculated using multivariate linear regression and the response variables as predictors. The critical χ^2 value for Mahalanobis distance when eight variable dependents are analyzed is $\chi^2 = 26.12$ ($\alpha = 0.001$). Taking into account this criterion and Leverage values, two multivariate outliers were identified and excluded from the analysis (case 47: MAH = 27.017, LEV = 0.326; case 74: MAH = 42.456, LEV = 0.511 (Marôco, 2023).

Shapiro–Wilk tests revealed non-normal data for several dependent variables and groups of learning environments before and after excluding the multivariate outliers. Nevertheless, MANOVA is robust when non-normality is due to an asymmetric distribution in comparison to the presence of outliers (Tabachnick & Fidell, 2013), allowing us to proceed with this analysis.

Matrix scatter plots were performed for the five groups to verify linearity. Since the scatter plots with all variables did not allow observing the distribution of the data, we created graphs for variable subsets, but the problem persisted in several graphs that showed no clear patterns.

Aiming to assess potential multicollinearity among dependent variables, we used the criterion of moderate bivariate correlations of about 0.60, suggested by Tabachnick and Fidell (2013) and all the correlations were lower.

Concerning the homogeneity of the variance–covariance matrices across the learning environments, results showed that the assumption was fulfilled [Box's M = 148.403; $F(144, 10{,}509.316) = 0.791$, $p = 0.969$).

After the MANOVA, univariate ANOVA Tests were performed for each response variable. Subsequent post-hoc tests were calculated when statistically significant differences were observed in an univariate F test.

Results

Table 5 shows descriptive statistics for each learning environment and each response variable.

One-way MANOVA analysis revealed an effect of the learning environment on the response variables [Roy's Largest Root = 0.318; $F(8, 73) = 2.902$, $p = 0.007$; partial $\eta^2 = 0.241$)]. As mentioned in the data analysis, the assumption of the

Table 5 Descriptive statistics for each learning environment

	Learning environment	M	SD	N
Valence	CG	− 0.2353	1.34766	17
	IGPoints	− 0.3125	2.27211	16
	IGBadges	− 0.0625	1.38894	16
	IGChallenges	0.0667	1.57963	15
	IGAll	− 0.1667	1.65387	18
	Total	− 0.1463	1.64145	82
Arousal	CG	0.0000	1.17260	17
	IGPoints	0.0625	2.11246	16
	IGBadges	− 0.1875	1.79699	16
	IGChallenges	0.4000	1.45406	15
	IGAll	0.1667	1.61791	18
	Total	0.0854	1.62694	82
Interest/enjoyment	CG	− 0.7982	1.28977	17
	IGPoints	− 0.3744	1.10622	16
	IGBadges	− 0.1519	0.98290	16
	IGChallenges	− 0.0287	1.03527	15
	IGAll	− 0.2061	1.12829	18
	Total	− 0.3187	1.12219	82
Cognitive load	CG	17.9376	4.57016	17
	IGPoints	16.8956	4.20976	16
	IGBadges	21.2019	4.86110	16
	IGChallenges	16.5620	4.40956	15
	IGAll	16.5094	3.87113	18
	Total	17.8061	4.62545	82
Learning performance	CG	1.18	1.741	17
	IGPoints	2.06	2.081	16
	IGBadges	2.44	1.711	16
	IGChallenges	2.60	1.454	15
	IGAll	3.28	2.024	18
	Total	2.32	1.917	82
Engagement in home exercises	CG	44.47	37.229	17
	IGPoints	41.19	38.704	16
	IGBadges	55.19	38.016	16
	IGChallenges	50.67	35.752	15
	IGAll	48.33	37.360	18
	Total	47.90	36.824	82
Visual attention	CG	54,434.76	7497.966	17
	IGPoints	50,741.31	4044.928	16
	IGBadges	47,612.69	7658.168	16
	IGChallenges	50,791.53	7480.631	15
	IGAll	51,636.28	6938.218	18
	Total	51,102.21	7043.726	82

Table 5 (continued)

	Learning environment	M	SD	N
Proportion of neutral emotion	CG	0.3129	0.16197	17
	IGPoints	0.2600	0.12340	16
	IGBadges	0.2012	0.11413	16
	IGChallenges	0.2860	0.12900	15
	IGAll	0.2444	0.14431	18
	Total	0.2609	0.13824	82

homogeneity of the variance–covariance matrices across the learning environments was fulfilled [Box's M = 148.403; F(144, 10,509.316) = 0.791, p = 0.969).

Regarding univariate one-way ANOVA for each dependent variable, the assumption of homogeneity of variance was fulfilled too [Valence: F(4, 77) = 0.637, p = 0.612, partial η^2 = 0.006; Arousal: F(4, 77) = 0.593, p = 0.668, partial η^2 = 0.014; Interest/Enjoyment: F(4, 77) = 0.420, p = 0.794, partial η^2 = 0.058; Cognitive Load: F(4, 77) = 0.159, p = 0.958, partial η^2 = 0.145; Learning Performance: F(4, 77) = 0.669, p = 0.616, partial η^2 = 0.138; Engagement in Home Exercises: F(4, 77) = 0.180, p = 0.948, partial η^2 = 0.017; Visual Attention: F(4, 77) = 1.965, p = 0.108, partial η^2 = 0.098; Proportion of Neutral Emotion: F(4, 77) = 0.825, p = 0.513, partial η^2 = 0.076]. We found statistical differences in Cognitive Load and Learning Performance among different element groups (Table 6).

According to Post-hoc Tukey's Tests, comparison of Cognitive Load's means between IGBadges and IGPoints tend to significance (I.C. 95%) − 0.026, 8.638; p = 0.052), while comparison between IGBadges and IGChallenges and between IGBadges and IGAll are statistically significant (IGBadges *vs* IGChallenges: I.C. 95% 0.236, 9.044; p = 0.034; IGBadges *vs* IGAll: I.C. 95% 0.482, 8.903; p = 0.021). In both cases, the Cognitive Load's mean is higher in the IGBadges group. Also, when the mean of Learning Performance in CG is compared to the mean in IGAll, there is a significant difference (I.C. 95% − 3.83, − 0.38; p = 0.009), with a higher value in IGAll. The other comparisons are non-significant.

Since we found significant differences in Cognitive Load, and this measure results from five subscales, descriptive statistics for each dimension of Cognitive Load across the Learning Environments allow for more detailed analysis. These statistics are presented in Table 7.

Summary of hypotheses and findings

In summary, our seven hypotheses proposed that gamification (IG) would produce greater effects on the dependent variables compared to its absence (CG). Furthermore, we hypothesized that the combination of multiple game elements (IGAll)

Table 6 Univariate F tests for each dependent variable with (4, 77) df

Variable	Hypoth. sum of squares	Error sum of squares	Hypoth mean square	Error mean square	F	Sig	Partial η^2
Valence	1.377	216.867	0.344	2.816	0.122	0.974	0.006
Arousal	2.927	211.475	0.732	2.746	0.266	0.899	0.014
Interest/enjoyment	5.894	96.110	1.474	1.248	1.181	0.326	0.058
Cognitive load	251.539	1481.443	62.885	19.240	3.269	**0.016**	0.145
Learning performance	41.199	256.557	10.300	3.332	3.091	**0.020**	0.138
Engagement in home exercises	1888.776	107,948.444	472.194	1401.928	0.337	0.852	0.017
Visual attention	392,294,794.197	3,626,445,177.278	98,073,698.549	47,096,690.614	2.082	0.091	0.098
Proportion of neutral emotion	0.117	1.431	0.029	0.019	1.579	0.188	0.076

Table 7 Descriptive statistics of the cognitive load's dimensions across the learning environments

	CG		IGPoints		IGBadgets		IGChallenges		IGAll	
	M	SD	M	SD	M	SD	M	SD	M	SD
IL	5.667	1.780	5.688	2.761	6.329	1.648	5.245	2.083	5.567	2.108
EL_INS	2.173	1.631	1.444	1.479	2.675	1.673	1.467	1.463	1.796	1.369
EL_INT	1.352	1.646	0.766	1.120	2.267	2.027	0.847	0.987	0.634	0.815
EL_E	0.868	1.379	0.891	1.304	2.316	1.765	0.968	1.398	0.824	1.011
GL	7.476	1.789	7.969	2.298	7.462	2.137	7.767	1.554	7.611	1.488

IL intrinsic load, *EL_INS* extrinsic load_instruction, *EL_INT* extrinsic load_interaction, *EL_E* extrinsic load_environment, *GL* germane load

would amplify these effects, outperforming the individual gamification groups (IGPoints, IGBadges, and IGChallenges).

In H1 (Learning Performance), we hypothesized that IGAll would show the highest performance (H1a), the other IG (IGPoints, IGBadges, IGChallenges) would outperform the CG (H1b), and the CG would perform the lowest (H1c). This hypothesis was partially supported, as IGAll significantly outperformed CG (supporting H1a), but the other IG did not outperform the CG, rejecting H1b and H1c.

Concerning H2 (Engagement), we expected IGAll to show the highest engagement (H2a), followed by the other IG outperforming CG (H2b), and CG with the lowest engagement (H2c). These hypotheses were not supported, as no significant group differences emerged.

Regarding H3 (Visual Attention), we anticipated IGAll would demonstrate the highest visual attention (H3a), other IG would score higher than CG (H3b), and CG would show the lowest attention (H3c). No significant differences were found, rejecting all hypotheses.

For H4 (Cognitive Load), we hypothesized that IGAll would show the lowest cognitive load (H4a), other IG would have lower scores than CG (H4b), and CG would show the highest load (H4c). These were not supported, but contradicting expectations, IGBadges had the highest cognitive load among all groups.

Focusing on H5 (Affective States), we predicted IGAll would produce the highest arousal and positive valence (H5a), followed by the other IG outperforming CG (H5b), and CG showing the lowest scores (H5c). No significant differences were found, rejecting all hypotheses.

About H6 (FER), we expected IGAll to exhibit the lowest proportion of neutral emotions (H6a), followed by other IG performing better than CG (H6b), and CG showing the highest neutral emotion levels (H6c). These were not supported, as no significant differences were found.

Finally, about H7 (Intrinsic Motivation), we anticipated IGAll would yield the highest interest/enjoyment scores (H7a), with the other IG scoring higher than CG (H7b), and CG showing the lowest scores (H7c). No significant differences were observed, so the hypotheses were not supported.

Discussion

This study introduced a novel gamified digital learning platform based on a theoretical framework and an RCT protocol, refined through usability, feasibility, and pilot studies (Coelho et al., 2023, 2024). This research examines the individual and combined effects of the game elements points, badges, and challenges, contrasted with a control group lacking these elements. The RCT assessed the gamified digital learning platform's impact on cognitive, emotional, and motivational outcomes, including learning performance, engagement, webcam-monitored visual attention, cognitive load, affective states, FER, and intrinsic motivation.

As stated in Sect. "Introduction", more game elements improve cognitive task performance and motivation (Groening & Binnewies, 2021; Leitão et al., 2022), and isolated elements like points or badges have been critiqued for failing to create an enjoyable experience, as engaging users effectively requires diverse elements that elicit different emotions and motivations (Chou, 2019). Our results support hypothesis H1a (refer to Table 6 for Learning Performance data and Post-hoc Tukey's Tests), indicating that integrating all game elements enhances learning performance compared to other IG and CG groups. Contrary to hypotheses H4a, H4b, and H4c (refer to Table 6 for Cognitive Load data and Post-hoc Tukey's Tests), however, a single element (IGBadge) notably raised cognitive load, more so than IGPoints, IGChallenges, or the combined IGAll. No other significant differences emerged, leading to the rejection of other hypotheses. Table 8 illustrates the results of all hypotheses.

Gamification and education

Our study was based on the theory of gamified learning and gamification science (Landers, 2014; Landers et al., 2017a, 2018), which offers frameworks for examining gamification's educational potential by analyzing individual game elements along with psychological and contextual factors. However, our findings suggest a more complex interaction that enriches these theories and the field of gamification in education. Results indicate that the combined effects of game elements are more impactful than isolated analysis reveals. Effective gamified interventions should adopt a holistic approach, where complementary game elements are strategically integrated to enhance overall learning impact. While isolated game elements serve as valuable tools for experimental research evaluation, educators must recognize that their impact within real-world educational contexts may differ when combined with other elements. According to the theory of gamified learning (Landers, 2014), points and badges function as assessment elements, tracking accomplishments and progress, while challenges serve to define rules and goals, offering guidance on progress. Thus, a deeper understanding of these individual components within our gamification framework is essential for clarifying their role in the observed learning gains.

In using game elements like points, learners and teachers must demonstrate that objectives meet set competency levels for their programs (Ray et al., 2022).

Table 8 Hypotheses results

Domain	Dependent variable	Group	Hypotheses	Hypotheses description	Results
Cognition	Learning	IGAll	H1a	IGAll will exhibit the highest learning performance among all groups	☑
		IGPoints + IGBadges + IGChallenges	H1b	The groups are hypothesized to show higher learning performance compared to CG	☒
		CG	H1c	CG is expected to demonstrate the lowest performance among all groups	☒
	Engagement	IGAll	H2a	IGAll will exhibit the highest engagement among all groups	☒
		IGPoints + IGBadges + IGChallenges	H2b	The groups are hypothesized to show higher engagement compared to CG	☒
		CG	H2c	CG is expected to demonstrate the lowest engagement among all groups	☒
	Visual attention	IGAll	H3a	IGAll will exhibit the highest visual attention among all groups	☒
		IGPoints + IGBadges + IGChallenges	H3b	The groups are hypothesized to show higher visual attention compared to CG	☒
		CG	H3c	CG is expected to demonstrate the lowest visual attention among all groups	☒
	Cognitive load	IGAll	H4a	IGAll will exhibit the lowest cognitive load among all groups	⚠ ☒
		IGPoints + IGBadges + IGChallenges	H4b	The groups are hypothesized to show lower cognitive load compared to CG	⚠ ☒
		CG	H4c	CG is expected to demonstrate the highest cognitive load among all groups	⚠ ☒

Table 8 (continued)

Domain	Dependent variable	Group	Hypotheses	Hypotheses description	Results
Emotions	Affective states	IGAll	H5a	IGAll will exhibit the highest arousal and positive valence among all groups	☒
		IGPoints + IGBadges + IGChallenges	H5b	The groups are hypothesized to show higher positive valence and arousal compared to CG	☒
		CG	H5c	CG is expected to demonstrate the lowest arousal and positive valence among all groups	☒
	FER	IGAll	H6a	IGAll will exhibit the lowest score of neutral emotion among all groups	☒
		IGPoints + IGBadges + IGChallenges	H6b	The groups are hypothesized to show lower scores of neutral emotions compared to CG	☒
		CG	H6c	CG is expected to demonstrate the highest score of neutral emotion among all groups	☒
Motivation	Intrinsic motivation	IGAll	H7a	IGAll will exhibit the highest score of intrinsic motivation among all groups	☒
		IGPoints + IGBadges + IGChallenges	H7b	The groups are hypothesized to show higher intrinsic motivation compared to CG	☒
		CG	H7c	CG is expected to demonstrate the lowest intrinsic motivation among all groups	☒

☑ = Supported hypothesis; ⚠ = Divergent from hypothesis; ☒ = Hypothesis not supported

Research shows points in courses can increase task completion but do not correlate with improved final learning performance (Nicholas Filipiak et al., 2010). Another study found that points in a gamified learning platform enhanced students' enjoyment and playfulness (hedonic perception) without affecting perceived usefulness (utilitarian perception), while the perceived value of points also declined over time (Berglund & Jedel, 2023). Adding points in assessments reduced response speed without improving accuracy (Attali & Arieli-Attali, 2015). Together, this research suggests that points alone provide performance benefits, even though with limited effect.

Studies on isolated badges as a game element have shown mixed results. One study found that badges did not significantly improve activity or performance in an online course compared to a control group, likely due to insufficient motivational impact, the voluntary nature of quizzes, and the long interval between badge awards and exams, which lessened their effect as extrinsic rewards (Kyewski & Krämer, 2018). Another study did not report any significant differences in time spent in the course or learning outcomes with or without badges, although badges indirectly improved learning by increasing time on task (Tahir et al., 2022). Additionally, badges boosted engagement with out-of-class work and academic performance, driven primarily by extrinsic motivation rather than intrinsic enjoyment (Dicheva et al., 2020).

According to the Dynamic Model for Gamification of Learning (DMGL), points and badges are game mechanics focused on data representation and algorithms, while challenges involve both mechanics and dynamics, with behavior adapting to player inputs over time (Kim & Lee, 2015). This adds more complexity to challenges as they involve goal-setting, task resolution, and sustained effort (Klock et al., 2020). Challenges are strong predictors of learning outcomes (Sasupilli & Bokil, 2022) and promote goal-oriented learning (Durmaz et al., 2022; Pangaribuan, 2022). Flow theory suggests that challenges maintain engagement by balancing difficulty to prevent boredom and avoid frustration (Chapman et al., 2023; Csikszentmihalyi, 2000). Challenges and skills (physical, intellectual, and knowledge-based) are essential for experiencing flow in gameplay, with competition and conflict acting as primary mechanisms to create challenges, whether against others or oneself (Sasupilli & Bokil, 2022). Challenge-based gamification also supports constructivist learning by fostering active, collaborative, and experiential learning (Kaya & Ercag, 2023).

When points, badges, and challenges were combined, there was a significant positive impact on learning performance. Points and badges offered feedback and tracked progress, while challenges set clear goals, motivating learners and enhancing outcomes. When all three elements (points, badges, and challenges) were combined, we found a substantial positive effect on learning performance. Although individual elements may lack strong effects, the combined use appears beneficial, aligning with studies showing that combining goal-setting with feedback boosts sustained attention, motivation, and task engagement (Robison et al., 2021), which are associated with increased learning performance (Kokoç et al., 2020). Moreover, blending goal-setting with assessment has been shown to improve learning (Papanthymou & Darra, 2022). These findings highlight a synergistic effect where assessment and feedback elements (points, badges) amplify goal-setting (challenges), thereby enhancing learning outcomes.

Learning can be influenced by engagement (Hu & Razlog, 2023), visual attention (King et al., 2023), cognitive load (Hadie et al., 2018), emotions (Reyna García et al., 2023), and motivation (Bredenkamp et al., 2022). Gamification similarly impacts these factors, enhancing engagement (Lyons et al., 2023), visual attention (Lu et al., 2021), cognitive load (Chen et al., 2022), emotions (Mullins & Sabherwal, 2020), and motivation (Huseinović, 2024). Our findings indicate that IGAll achieved higher learning outcomes, with no single variable (engagement, visual attention, cognitive load, emotions, motivation) standing out, suggesting a possible cumulative effect from these variables. Likewise, the combined elements in IGAll thus boosted the gamification impact beyond what individual elements might achieve.

Learner characteristics and contextual conditions

Aspects like age (Marston & del Carmen Miranda Duro, 2020), game habits, and player traits (Tondello & Nacke, 2019; Tondello et al., 2019), and cultural background (Ćwil & Howe, 2020), can significantly shape participants' gamification experience, potentially influencing learning outcomes (Lucardie, 2014; Wei et al., 2023). Individual and contextual factors may have significantly influenced our findings and should be considered when assessing generalizability and transportability for external validity (Findley et al., 2021), as variables such as player traits, culture, gender, gaming habits, educational background, and age likely shaped the outcomes and affect how results apply to broader undergraduate populations.

Concerning player traits, our participants, mainly challenge- and goal-oriented, benefited from gameplay aligning with these traits: challenge-oriented players seek competence-affirming tasks, while goal-oriented players prefer tasks that allow measurable progress (Tondello & Nacke, 2019; Tondello et al., 2019). Points and badges function as assessment elements in gamification by offering feedback based on progress, whereas challenges establish clear goals, such as tracking task completion within an activity map (Landers, 2014; Toda et al., 2019). This alignment between players' traits and the combined use of these elements likely contributed to the enhanced learning outcomes in IGAll, where all game elements were combined.

Nonetheless, regarding culture, gender, and gaming habits, our sample primarily consisted of Portuguese women with low or no gaming activity (under 10 h per week), which may have influenced the absence of significant effects in other study variables. In Portugal, computer games gained popularity in the 1980s as the country transitioned from its 1970s authoritarian regime, but media narratives—shaped by longstanding gender norms and beliefs in biological differences—framed men as inherently drawn to technology, excluding women from gaming culture and reinforcing masculinity as the default in tech representation (Lima et al., 2022). These patterns persist today, with women still underrepresented in gaming due to stereotypes, hypersexualized avatars, and harassment, contributing to decreased participation and negative well-being effects, such as low self-esteem and harmful social comparisons (Lopez-Fernandez et al., 2019). Additionally, this could reflect gendered leisure preferences, as studies indicate boys are typically motivated by competence and mastery—traits reinforced by video games—whereas girls more often prioritize social interaction and show stronger attachment to peers (Elsen et al., 2024; Tichon & Tornqvist, 2016). This potential cultural factor is evident in our participants' gaming habits, as most reported little to no gaming activity, highlighting a possible disconnect between Portuguese women and gaming, represented in our sample. However, it is important to highlight that, despite persistent gender challenges in gaming, women hold a strong presence in the industry (Entertainment Software Association, 2022), highlighting the equal relevance of both genders to gaming and academic research, even though boys typically game more, particularly on consoles and PCs (Leonhardt & Overå, 2021).

Regarding educational background, it is another factor that may have contributed to the absence of significant effects in variables other than learning, as they were nursing students enrolled in a health-related program. Research showed that participation in health education courses was positively linked to students' physical activity during leisure time and influenced how fitness and health-related motivations translated into actual engagement in physical activity (Sukys et al., 2019). Although video games can yield both positive and negative health outcomes, they can be perceived as unhealthy behavior (Agans et al., 2022). Therefore, students' low gaming habits may reflect a preference for health-related interests, influencing their leisure behavior and shaping their orientation toward gaming and motivation for gamification.

Lastly, when it comes to age, participants were 17 to 30 years old ($M = 18.67$), with over 95% between 17 and 20, reflecting a generation immersed in digital technology, where video games are a regular part of daily life (Coelho & Abreu, 2025). Childhood socialization influences adult behavior (Evans et al., 2018), making those raised in digitally saturated environments with frequent exposure to screens and video games more inclined to pursue similar digital experiences in adulthood (Yun, 2023). This digital familiarity may have contributed to participants' ease of use and adherence to the platform, but it could have triggered the novelty effect, playing a significant role in influencing the study's outcomes.

From novelty effect to sustainable impact in human–computer interaction

Human–Computer Interaction (HCI) is a multidisciplinary field focused on designing and understanding human–computer interaction (Rapp, 2023). As computers are now widespread in workplaces (Coelho & Abreu, 2023) and schools (Ahn & Clegg, 2018), analyzing these interactions has become essential. Interactive multimedia, designed with HCI principles, enhances university education by providing user-friendly digital learning options suited for diverse age groups (Al Mahdi et al., 2019). Effective learning technology design, according to HCI literature, must incorporate both design thinking and learning theories, emphasizing the social and contextual aspects of learning environments when introducing new technologies, complementing traditional teaching methods rather than replacing them (Ahn & Clegg, 2018).

The novelty effect, which occurs when a new system or modifications are introduced into an environment, often leads to temporarily increased interest (Koch et al., 2018). Initial curiosity and the desire to understand a system's functionality drive early user engagement (Shin et al., 2019). Feasibility and pilot studies (Coelho et al., 2023, 2024) for this RCT highlighted that the gamified digital platform was perceived as innovative, marking a distinct educational approach for students. As university courses in this study are typically taught in on-site classes, our preliminary findings suggest that digital elements positively impact student perception of pedagogy. We thus hypothesize two scenarios.

Employing a unified gamified learning platform for all groups likely equalized the novelty effect across IG and CG groups, as both encountered the same new system, while only game elements varied. This consistency may have reduced the perceived novelty impact of gamification itself, explaining the lack of significant effects favoring IG over CG. While digital tools like computers, smartphones, and interactive boards can boost student engagement, this may arise from the novelty effect, as students are generally unaccustomed to using such tools in traditional classrooms (Kopinska, 2020). Thus, using the same platform, though crucial for isolating gamification effects, may have unintentionally overshadowed gamification's specific effects.

Moreover, students often experience a surge in engagement when first introduced to gamified systems, but this enthusiasm usually fades as the novelty wears off and activity drops (Tsay et al., 2020). Gamification itself can act as a novelty effect, which may be short-lived rather than enduring (Hamari et al., 2014). Initial excitement from game elements can decline over time (Hanus & Fox, 2015). Therefore, the gamified platform's novelty, especially in IGAll with more game elements, may have amplified perceived interest, partially explaining IGAll's learning gains. Novel additions to a system can create temporary interest boosts (Koch et al., 2018), which may have influenced IGAll outcomes.

While new technologies can initially boost motivation through the novelty effect, this impact fades over time (Jeno et al., 2019), making continuous innovation vital to sustaining engagement. Emotional design in multimedia learning materials can enhance learning (Heidig et al., 2015), and gamification adds cognitive and emotional dimensions to digital experiences, increasing design effectiveness (Mullins & Sabherwal, 2020). Although isolated game elements may be interesting for research purposes (Landers, 2014), effective gamification should go beyond standalone elements to align with pedagogical strategies, ideally through iterative design that corrects flaws, embeds content into the curriculum, and maintains engagement beyond novelty, creating a habit-driven, meaningful experience. For example, by creating a gamified experience based on participants' player traits, as the traits can influence motivation and enjoyment (Tondello & Nacke, 2019; Tondello et al., 2019).

Novelty effects and extrinsic rewards can initially boost motivation and interest, but this increase is often short-lived, with engagement declining as learners become more familiar with the gamified experience (Ratinho & Martins, 2023). To sustain gamification's impact on learning, it is essential to design meaningful gamified experiences aligned with instructional goals and learners' psychological needs, related to intrinsic motivation, like autonomy, mastery, relatedness, purpose, and flow, promoting long-term engagement, and ensuring both effectiveness and meaningful learning (Li et al., 2024). Nonetheless, the interaction between intrinsic and extrinsic motivation revealed that extrinsic rewards harmed academic performance in highly intrinsically motivated students, but improved it for those with low intrinsic motivation (Liu et al., 2020). Additionally, while autonomy—linked to intrinsic motivation—enhanced learning across cultures, the positive effect of rewards on memory was stronger for Chinese than Dutch participants, indicating that cultural factors can influence the impact of extrinsic motivation (Zhang et al., 2025). Different game elements can stimulate distinct types of motivation—for example, points and badges may promote extrinsic motivation through external regulation, while missions and challenges can enhance intrinsic motivation by supporting learner autonomy (John et al., 2023). Thus, in our study, the group exposed to all game elements (IGAll) likely benefited from both intrinsic and extrinsic motivational triggers, since points and badges promoted more external regulation, while challenges offered autonomous goal setting. Although no significant results emerged for intrinsic motivation alone, the combination of intrinsic and extrinsic motivation may have contributed to the observed learning outcomes, which should be sustained and incremented to overcome the novelty period.

Our intervention measured only short-term effects due to the limited course duration, and there is a need for gamification designs that extend beyond novelty. Sustainable gamification requires well-crafted, personalized systems that integrate evolving challenges, collaborative activities, meaningful narratives, and regular updates to foster a lasting sense of ownership, skill development, and engagement (Huang et al., 2024). Thus, to achieve this, designers and researchers should consider learners' individual and cultural traits, together with holistic pedagogical strategies, aligning game elements with both intrinsic and extrinsic motivations to foster meaningful engagement and lasting educational impact. Sustaining novelty should also require ongoing updates, such as adding new game elements, adjusting reward systems, refreshing challenges, and strengthening social features—since social interaction also plays a vital role in supporting students' intrinsic motivation in educational gamification (Luarn et al., 2023).

Multimedia learning and cognitive load

Multimedia learning and cognitive load theories are essential to understanding digital learning, and examining how multimedia design, content type, format, and individual differences impact learning (Mutlu-Bayraktar et al., 2019). Cognitive load plays a key role in virtual learning environments, as complexity can affect learning (Andersen & Makransky, 2021). Cognitive load increases with unnecessary learning demands (Sweller et al., 2019). Extrinsic cognitive load arises from extraneous demands due to unnecessary design, intrinsic cognitive load from material complexity, and germane cognitive load from activities that help build knowledge in memory (Klepsch et al., 2017; Krieglstein et al., 2022; Leppink et al., 2013; Sweller et al., 2019; Timothy et al., 2023). Gamification may alter cognitive load by introducing new environmental stimuli into the learning experience (Chen et al., 2022).

Unexpectedly, only IGBadges increased cognitive load compared to other IG, indicating badges alone caused this effect, as it was neutralized in IGAll, counter to our hypotheses. Table 7 data shows IGBadges had higher intrinsic and extrinsic load scores, suggesting that badges added task and presentation complexity, impacting instructional and environmental factors. Badges may shift focus excessively toward earning them, reducing attention to main tasks (Almeida et al., 2023), and, by linking tasks to external rewards, decreasing interest and enjoyment (Diefenbach & Müssig, 2019). Missing potential badges can also cause frustration, which is tied to a higher cognitive load (Novak et al., 2023; Toda et al., 2018). Surprising stimuli can distract, disrupting cognition and working memory, ultimately affecting cognitive load (Skulmowski & Xu, 2022; Sweller et al., 2019; Wessel et al., 2016). With badges that might appear unexpectedly, participants' awareness of potentially better rewards (e.g., bronze versus gold) may increase desire, reducing task focus, and increasing distraction and frustration, ultimately impacting cognitive load. In contrast, points lacked potential gain awareness, while challenges allowed participants to see potential gains upfront, letting them plan effort, potentially reducing frustration and not increasing cognitive load.

Badges can be used to represent varying levels of achievement for a task (e.g., bronze, silver, or gold) (Ahmad et al., 2020), but they may function as controlling rewards by promoting specific actions while limiting them to predefined objectives, which can influence and potentially restrict learning processes (Hanus & Fox, 2015; Reyssier et al., 2022). Our badge system lacked clear achievement criteria (since goals were tied only to the game element of challenges in IGChallenges or IGAll), being earned unexpectedly and failing to promote goal-setting behavior, potentially limiting their impact (Denny et al., 2018). Therefore, by confining learners to predefined objectives that lacked transparency, the badges may have acted as irrelevant distractors, as it was difficult to discern how or when they were earned. Additionally, an achievement using indexical icons, such as a running rabbit to suggest speed, may enhance clarity and user motivation compared to generic symbols like stars (Matallaoui, 2018). User-centered design must align with the task's cognitive demands to maintain data quality and interest, as inaccurately chosen game elements can raise irrelevant cognitive load by complicating stimulus interpretation or inducing anxiety (Khaleghi et al., 2021). Thus, using uniform star icons for all badges—without specific descriptions or feedback tied to the cognitive task—may have reduced their transparency and increased cognitive load by presenting stimuli that were difficult to interpret. Also, high cognitive load relates to perceived usability (including usefulness, ease of use, and enjoyment), which is directly associated with learning intention and attitudes (Wu et al., 2022). When designing game elements for digital learning platforms, usability must be prioritized, aiming to reduce cognitive load and facilitate learning, by using methods like heuristic evaluation (e.g., the 10 Usability Heuristics for User Interface Design), which identifies design flaws through a low-cost, simple, and iterative process applicable in early development and evaluation stages., supporting system improvement and refinement (Benaida, 2023; Nielsen, 1994; Nielsen & Molich, 1990).

Curiously, IGBadge showed the highest cognitive load and low visual attention compared to the other groups (though not statistically significant), consistent with studies showing high cognitive load reduces visual attention and correct responses, impacting information processing (Mahjoob & Anderson, 2023). Cognitive load diverts attentional resources, particularly when working memory requires updates and maintenance (Singh & Schubert, 2021). Visual fatigue, linked to cognitive load, affects memory and experience in virtual environments (Souchet et al., 2022). Both cognitive load and visual fatigue harm working memory and overall experience, affecting learning and linking visual attention to cognitive load (Singh & Schubert, 2021; Souchet et al., 2022). Additionally, high cognitive load is tied to mind wandering, which reduces external information processing and influences gaze behaviors (Faber et al., 2020; Krimsky et al., 2017). Mind wandering, measured by eye-tracking gaze samples for screen attention (Hutt et al., 2024), matches our visual attention method. Given the connection between visual attention and cognitive load (Mahjoob & Anderson, 2023; Singh & Schubert, 2021; Souchet et al., 2022), IGBadges' high cognitive load and low visual attention suggest potential mind wandering or visual fatigue, warranting further investigation.

Finally, IGAll did not raise cognitive load, despite achieving higher learning outcomes, as the combined game elements enriched the course experience and facilitated learning. In contrast, using only badges increased cognitive load without improving learning, suggesting that effective gamification for learning and cognitive load depends less on the number of elements and more on how they interact within a system. This highlights the need for thoughtful gamification design that considers element interplay.

Educational implications and recommendations

Understanding individual and contextual factors before educational gamification implementation is essential, as these shape user experiences and learning outcomes (Lucardie, 2014; Wei et al., 2023). Addressing these factors through intrinsic and extrinsic motivational cues can help engage diverse learners—intrinsic motivation benefits those already motivated, while extrinsic rewards aid those less motivated (Liu et al., 2020). Game elements should be selected accordingly, such as points and badges to support extrinsic motivation and challenges to enhance intrinsic motivation (John et al., 2023). Also, goal-setting and feedback mechanisms improve learning outcomes and should be central to gamification design (Papanthymou & Darra, 2022). Designers, researchers, and educators must also consider the novelty effect, which can spark initial interest but often fade as users adapt to the system (Ratinho & Martins, 2023). Sustained interest requires adaptive systems with evolving tasks, collaboration, narrative, and regular updates to build ownership and skills (Huang et al., 2024). Gamification should align pedagogy with design, as cognitive load is related to unnecessary learning demands (Sweller et al., 2019). Also, usability principles and heuristic evaluations help improve interface clarity (Benaida, 2023; Nielsen, 1994; Nielsen & Molich, 1990), potentially avoiding the increase of cognitive load. Our findings showed that badges need to be more effectively designed, with clear goal criteria (Denny et al., 2018), and meaningful, context-relevant visuals—for instance, indexical icons that reflect the task rather than generic symbols

(Matallaoui, 2018)—as ambiguous designs may obscure achievement meaning and add an interpretive burden.

Conclusions

This study demonstrated that gamification can enhance learning when game elements are thoughtfully integrated rather than used in isolation. Using a RCT, we found that combining elements like points, badges, and challenges significantly improved learning outcomes, while isolated use—especially badges—raised cognitive load without improving performance. These results highlight the need to align gamified systems with educational objectives, considering individual and contextual differences. Effective design should also use game elements to leverage both intrinsic and extrinsic motivational drivers, incorporate goal-setting and feedback, consider usability principles, and address the novelty effect by designing adaptive, engaging, and regularly updated systems. Also, relevant visual cues and defined achievement criteria are essential for creating impactful game elements, especially badges.

Limitations and future research

Contextual and individual factors can influence gamification outcomes (Ćwil & Howe, 2020; Marston & del Carmen Miranda Duro, 2020; Tondello & Nacke, 2019; Tondello et al., 2019). Our study involved mainly women aged 17 to 20, nursing students, born in Portugal, who played less than 10 h weekly or not at all, with challenge and goal orientation as predominant traits. As stated in our discussion, these characteristics should be considered when interpreting results, as they may vary in other contexts. Additionally, our sample was selected due convenience of professors available to collaborate within the university and calendar constraints, which made us select the nursing program to apply the research. Future research should apply this RCT's gamified digital learning platform in diverse settings to assess impact differences.

We selected specific game elements due to debates on their learning impact, as they can yield varied results (Majuri et al., 2018). Following the gamified learning theory (Landers, 2014), focused on two assessment elements (points and badges) with an alternative element (challenge) to assess outcomes, configuring four setups: points, badges, challenges, and all combined, which we limited to examine scope. Modifications to these elements could influence outcomes, suggesting the need for diverse gamification configurations within theoretical frameworks like gamified learning (Landers, 2014). Based on a specific game element categorization for gamification (Klock et al., 2020), a recent systematic review (Coelho et al., 2025a) showed cognitive-focused game-based studies typically use nine elements, often the same seven (emotions, feedback, single-player, narrative, choice, level, signposting), limiting comparative potential. Future research should employ consistent game elements to support cross-study comparisons or explore new elements to expand gamification's research boundaries. Additionally, by reflecting on the insights presented in Sect. "Educational implications and recommendations", we encourage educators and researchers to explore the design of game elements through a more holistic lens—considering everything from contextual variables to system usability—to deepen the investigation of their distinct effects in educational settings.

Given that the novelty effect (Tsay et al., 2020) may have influenced our results, future studies should explore whether the learning gains and lack of significant effects in other outcomes persist over longer educational durations or differ across instructional methods. Gamification targets various cognitive outcomes, such as satisfaction and flow (Coelho et al., 2025a), both linked to learning. Satisfaction is vital in online education, affecting performance, retention, and graduation rates (Martin & Bolliger, 2022), while flow (intense focus and enjoyment during challenging tasks) (Chapman et al., 2023; Csikszentmihalyi, 2000), enhances engagement and learning (Miles et al., 2023). Our IGAll learning gains might relate to satisfaction and flow, although not measured here. We suggest assessing these in future studies, utilizing tools like the Online Learning Satisfaction (OLS) framework (Martin & Bolliger, 2022) for satisfaction and GameFlow (Sweetser & Wyeth, 2005) to gauge flow.

Regarding instruments and measurements, the CLQ was translated and back-translated following recommendations (Beaton et al., 2000; Klotz et al., 2023) from a source instrument with demonstrated validity and reliability (Andersen & Makransky, 2021), due to the lack of a validated Portuguese version. Recognizing that cultural and linguistic differences impact measurement precision, it remains crucial to validate instruments for specific populations to ensure reliability and cross-cultural equivalence, facilitating comparisons across diverse groups in global health research (Zhao et al., 2024). We encourage future studies to undertake full validation of the cognitive load instrument in Portuguese.

In terms of visual attention, infrared eye-tracking is more accurate than webcam systems (Burton et al., 2014), but its high cost and limited availability restrict it mainly to lab settings, limiting its practical application in real-world learning (Hutt et al., 2024). Webcam eye-tracking, while less precise, offers greater scalability and potential for adaptive online learning. Given the link between cognitive load and visual attention (Souchet et al., 2022), further investigation using infrared eye-tracking could deepen understanding of the relationships between cognitive load, visual attention, mind wandering, and visual fatigue in multimedia learning (Faber et al., 2020; Hutt et al., 2024; Krimsky et al., 2017; Mahjoob & Anderson, 2023; Singh & Schubert, 2021; Souchet et al., 2022).

Moreover, the link between emotions and cognition is key in gamification, as game elements trigger emotions that affect cognitive processing (Mullins & Sabherwal, 2020). We used webcam-based FER, a scalable and cost-effective method compared to manual FER (Dupré, 2021; Kumar & Anitha Sheela, 2022). However, as this approach depends on physical expressions, the system algorithm, and the image database, it may introduce bias, inaccuracy, and miscategorization (Howell et al., 2024), potentially contributing to the non-significant emotional findings in this study. Emotions can be assessed through neurophysiological methods like electroencephalography (EEG), functional magnetic resonance imaging (fMRI), and transcranial magnetic stimulation (rTMS), offering precise data on emotional states (Alexander et al., 2021; Boukarras et al., 2024). Thus, further research should explore neurophysiological-emotional correlates in educational gamification.

Finally, we recognize the importance of considering moderator and mediator factors in gamified learning and gamification science theories underlying our platform and protocol (Landers, 2014; Landers et al., 2018). However, our sample size limited statistical power for such analyses, given the comparison of four gamified learning forms against a control group across multiple outcomes. We noted a link between the gamified intervention (IGAll) and learning outcomes. Based on these theories, we recommend future studies to explore gamification's impact, analyzing the moderation of participant profiles (sociodemographic data, game habits, player traits) and the mediation effects of engagement, visual attention, cognitive load, affective states, FER, and intrinsic motivation in learning outcomes, to better understand gamification's educational impact.

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Declarations

Conflict of interest On behalf of all authors, the corresponding author states that there is no conflict of interest.

Ethical approval This study received approval from the local Ethics Committee, and all the participants signed an informed consent form before the study.

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