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Playing solo, against rivals, or in a team? Exploring individual, competitive, and cooperative dynamics in gamified digital education

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ABSTRACT

While gamification is increasingly applied in education, research rarely compares distinct social dynamics and evaluates their cognitive, emotional, and motivational impact in a learning context. This study examines the effects of social gamification in education using a digital learning platform and a randomized controlled trial (RCT). Following research standards (CONSORT, Cochrane Collaboration, EVAT©), we compared individual, competitive, and cooperative gamification modes to assess the impact of social dynamics on nursing undergraduate students (n = 42). We analyzed participant characteristics (sociodemographics, gaming habits, player traits) alongside cognitive (learning, engagement, eye-tracking visual attention), emotional (facial emotion recognition), and motivational (intrinsic motivation) outcomes. Participants in the individual mode showed significantly higher eye-tracking visual attention than those in competition or cooperation modes. Social gamification appeared to reduce attention, likely due to cognitive overload from digital multitasking and distractions. Given the rise of the attention economy, individual gamified sessions may better sustain focus, aligning with trends toward personalized digital learning. Digital social gamification may not mirror the benefits of in-person interaction. The absence of significant differences in outcomes beyond visual attention may stem from contextual factors—such as weak social traits, low gaming interest, and health-related backgrounds—suggesting effective gamified strategies must align with learner profiles and context.

1. Introduction

Gamification involves incorporating game elements into non-game settings, distinguishing it from conventional games [1,2]. It is recognized for its versatility, and it is frequently implemented in areas such as education [3]. The primary goal of gamification is to create game-like experiences in real-world contexts, including classrooms and workplaces [4,5], either through a single-player format that encourages independent interaction or a multiplayer setting that incorporates social dynamics [6].

Early gamification centered on basic elements for individual experiences, but online platforms have driven a shift toward gamified multiplayer environments, where users interact, collaborate, and compete in shared virtual spaces [7]. Games can facilitate distinct social dynamics that positively impact cognitive, emotional, and motivational processes [8]. Multiplayer gameplay can be classified as competitive, where players aim for personal success; collaborative, where individual success is replaced by group achievement; and cooperative, where players pursue personal goals within a group, benefiting from mutual support [9–11]. Concerning the orientation of social values, competition promotes "proself" or individualistic behavior, whereas collaboration and cooperation encourage more "prosocial" and altruistic behaviors [12].

Systematic reviews on gamification in education indicate that achievement and progression are the most frequently used game elements, whereas social aspects are limited or primarily centered on competition [13,14]. While the effectiveness of positive and negative reinforcement in enhancing desired behaviors has been widely studied

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in single-player interactions, its impact on multiplayer cognitive tasks is unexplored in the literature [15]. Therefore, knowing that social aspects play a vital role in educational settings, shaping students' academic involvement and psychological well-being [16], we aimed to address the literature gap by investigating the social dynamics of gamification, comparing the differing effects of multiplayer (competition and cooperation) and single-player gamification in education.

Both collaborative and cooperative modes align with a "prosocial" orientation [12][17]. Nonetheless, collaborative learning emphasizes group performance through open-ended tasks, qualitative methods, and group consensus-building, whereas cooperative learning – rooted in more individualistic cultures – relies on quantitative methods and structured, closed-ended tasks to foster positive interdependence by linking individual performance to group success [17]. This randomized controlled trial (RCT) employed quantitative evaluation using objective measures across intervention groups (IG) within a gamified platform, with individual-level assessments during the intervention rather than group-level analysis. Thus, we focused on the cooperative mode (IGCoop) in lieu of collaboration and compared it with competitive multiplayer (IGComp) and single-player modes (IGSolo).

This RCT builds on gamified learning theory and gamification science by isolating game elements to examine their influence on psychological and behavioral states [5,18]. We focused on points, the most commonly used and flexible game element in educational gamification, as they function as an assessment tool and provide progress-based feedback [18,19]. Given its adaptability across interaction formats, we implemented the same game element (points) across single-player, competitive, and cooperative multiplayer modes, each designed with distinct dynamics to encourage individual performance (points with no social comparison), competition (a ranking displaying the best point scores), or cooperation (points earned by the group through individual contributions), respectively. This approach allowed us to evaluate the impact of the different interventions on cognitive, emotional, and motivational outcomes in education.

Given the scarcity of experimental research comparing distinct gamified social components in cognitive contexts [15] and digital learning [20], we sought to examine how single-player (IGSolo) and different multiplayer modes (IGComp and IGCoop) affect education. Despite the growing use of social gamification, few studies directly compare single-player, competitive, and cooperative modes or examine their combined cognitive, emotional, and motivational effects. This gap limits understanding of how different social dynamics shape learning in digital environments. Accordingly, the present study was designed to provide clearer evidence on when social gamification influences cognition, emotions, and motivation in educational processes, thereby informing the design of more effective gamified interventions.

1.1. Cognitive, emotional, and motivational interplay

Cognition is influenced by emotions and motivation, which shape behavior and determine stimulus prioritization [21]. Gamification enhances cognition by triggering emotions like joy or fear, serving as a motivational catalyst [22]. We selected specific cognitive (learning, engagement, and visual attention), emotional (neutral emotions), and motivational (intrinsic motivation) outcomes as dependent variables, based on previously adapted protocols [23,24] and supported by prior studies where gamification has shown effectiveness, as detailed in the following sections. We formulated hypotheses, detailed below, for each dependent variable by first comparing single-player and multiplayer modes, followed by comparisons distinguishing between the two multiplayer conditions – competitive and cooperative. Fig. 1 illustrates the three domains and the specific outcomes examined within each.

1.1.1. Cognition

Cognition involves the brain's ability to process, acquire, and represent knowledge about oneself and the surrounding world, shaping

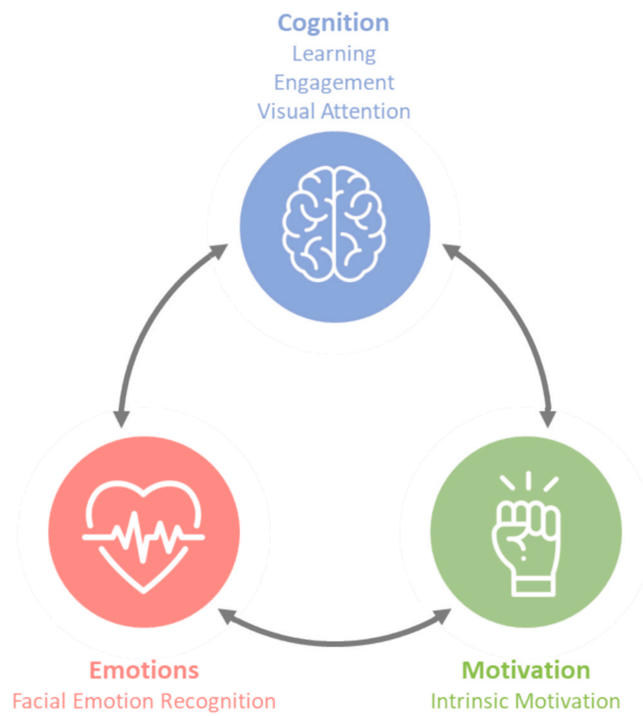

Fig. 1. Cognition, emotions, and motivation.

behavior in response to this information [25,26]. Learning is a cognitive process that refers to the development of new skills, knowledge, behaviors, values, and attitudes [27]. Assessments formulated by lecturers are commonly regarded as valid and reliable tools for assessing student learning outcomes [28,29]. Engagement can be viewed as another process that encompasses behavioral (participation and interaction), emotional (interest, enjoyment, and value), and cognitive (investment and self-regulation) dimensions related to students' involvement in learning [30–32]. From a cognitive perspective, engagement reflects the learner's mental effort and commitment during the educational process to understanding and acquiring knowledge, which can be measured through performance indicators such as correct responses in assessments [32,33]. Taking that into consideration, engagement may refer to assessments that are not graded and therefore differ from learning performance in that they lack an evaluative component, but they are similar in their cognitive role in supporting the learning process.

Finally, attention is another cognitive process that plays a crucial role in selecting, processing, and prioritizing information, directly impacting education [34,35]. Eye-tracking technology is widely used in educational settings as an objective method to analyze visual attention by monitoring gaze patterns on screens [36], enabling the identification of focus areas or specific regions of interest [37]. Mind wandering, which disrupts external visual processing, is associated with changes in gaze behavior – such as fewer and more dispersed fixations – indicating a redirection of attention from the task to unrelated thoughts and areas [38]. By tracking gaze points, researchers can assess attention levels, where a higher number of recorded samples indicates sustained focus and reduced mind wandering [39].

Gamification can enhance learning [5,18,40], cognitive engagement [41], and visual attention [42,43]. Cognitive processes are shaped through social dynamics, with knowledge emerging from socially mediated experiences, as social factors and human relations play a crucial role in cognitive and educational development [44,45]. Regarding social dynamics, both competition [46,47] and cooperation [48,49] can foster cognition in educational settings. Thus, firstly, we hypothesize that multiplayer gamification (competition and cooperation) will have a greater cognitive impact on learning, cognitive engagement, and visual attention than single-player mode. Also, the cooperative mode tends to yield better educational outcomes than competition [20]. In gamified learning contexts, cooperation can enhance social relatedness more effectively than competition [50], which, in turn, plays a key role in supporting cognitive processes, perceived learning outcomes, and student satisfaction in educational settings [51,52]. Therefore, secondly, we hypothesize that cooperative interactions will outperform competitive ones in multiplayer settings across the cognitive outcomes. These expectations about cognition are presented as hypothesis one (H1) related to learning, hypothesis two (H2) concerning cognitive engagement, and hypothesis three (H3) regarding visual attention.

1.1.2. Emotions

Emotions, shaped by biological reactions and mental states, are subjective experiences that significantly influence cognition [53]. Emotions emerge from person–situation interactions relevant to one's active goals, triggering flexible multisystem responses that often alter the interaction and generate object-specific response tendencies [54]. Emotions vary in valence (positive or negative) and arousal level (activating or deactivating), reflecting their pleasantness and physiological intensity [55]. Studies suggest a universal recognition of basic emotions – anger, fear, happiness, sadness, disgust, and surprise [56]. Facial expression analysis via webcams provides an objective method to assess these emotions, capturing physical reactions to screen stimuli [57,58].

Gamification fosters emotional variations, evoking happiness through enjoyment while also triggering emotions like fear or sadness, which can drive persistence despite challenges [22]. Emotions are influenced by social aspects, arising from interactions, shaped by norms and goals, expressed in social contexts, and reciprocally influencing others [59]. Humans are social learners, and, from birth, emotions learned through social dynamics are crucial for cognitive and affective growth [60]. Thus, firstly, we hypothesize that multiplayer gamification (competition and cooperation) will generate greater emotional variation than single-player mode, leading to fewer neutral emotions. Moreover, as competition tends to heighten physiological arousal and emotional intensity in gameplay [61], we expect competitive interaction to surpass cooperative interaction in multiplayer settings with more emotional variation and lower neutral emotions. These expectations about emotions are presented as hypothesis four (H4).

1.1.3. Motivation

Motivation, as a concept explaining human behavior through actions aimed at fulfilling needs and achieving goals, leads students to tackle challenges in educational settings [62]. 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 [63,64]. 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 [65]. The Interest/Enjoyment subscale of the Post-Experimental Intrinsic Motivation Inventory (PEIMI), derived from SDT, is a validated tool for assessing intrinsic motivation [66].

Gamification plays a key role in enhancing intrinsic motivation [67]. In SDT, relatedness is a crucial factor, as social dynamics positively influence intrinsic motivation [64]. Social features play a crucial role in enhancing students' intrinsic motivation, which can be supported through gamification in educational settings [68]. A meta-analysis found that educational gamification significantly enhanced students' sense of relatedness, tied to intrinsic motivation, likely due to a fostered sense of belonging and strengthened team community [69]. Therefore, we hypothesize that multiplayer gamification (competition and cooperation) will foster higher intrinsic motivation than single-player mode. Additionally, since SDT emphasizes relatedness as the need for social connection, which is strongly associated with participation and cooperative behavior [70], we expect cooperative interaction to surpass competitive interaction in multiplayer settings, reflecting variations in the hypothesis. These expectations about motivation are presented as hypothesis five (H5). Table 1 presents all the hypotheses proposed in this RCT.

2. Materials and methods

We implemented a RCT with a between-subjects design, featuring three IG. It is important to note that this study followed a RCT design, with participants randomly assigned to different interventions rather than to a non-active control group, aligning with a parallel-group trial framework within the RCT scope [71]. A digital course was embedded within a gamified digital learning platform, which we tailored into three unique versions incorporating different game elements, setting distinct IG: IGSolo used just "points" with no social dynamic, IGComp included "points and competition" though a leaderboard showing the best scores, and IGCoop featured "points and cooperation" with points accumulated by the group from individual contributions.

To ensure transparency and rigor, we followed three established RCT guidelines. We adhered to the Consolidated Standards of Reporting Trials (CONSORT) guidelines for a clear organization and presentation of data [72,73]. We also followed the Cochrane Collaboration's recommendations to keep internal validity and mitigate bias [71]. Finally, we used the External Validity Assessment Tool (EVAT©) to consider external validity, regarding the generalizability and replicability of our findings [74]. While the Cochrane Collaboration and EVAT© guidelines are primarily designed for systematic reviews, their application in this study was essential for establishing robust internal and external validity, thereby enhancing the overall quality and reliability of our RCT research and reporting.

Table 1
Research variables, groups, and hypotheses.

Domains	Dependent variables	Hypotheses	Hypotheses description
Cognition	Learning	H1	IGSolo will exhibit lower performance in Learning, compared to IGComp and CGCoop, while IGCoop will exhibit higher performance in Learning, compared to IGComp (IGSolo < IGComp < IGCoop)
	Cognitive Engagement	H2	IGSolo will exhibit lower performance in Cognitive Engagement, compared to IGComp and IGCoop, while IGCoop will exhibit higher performance in Cognitive Engagement, compared to IGComp (IGSolo < IGComp < IGCoop)
	Visual Attention	H3	IGSolo will exhibit lower performance in Visual Attention, compared to IGComp and CGCoop, while IGCoop will exhibit higher performance in Visual Attention, compared to IGComp (IGSolo < IGComp < IGCoop)
Emotions	FER (Neutral Emotions)	H4	IGSolo will exhibit higher Neutral Emotions, compared to IGComp and CGCoop, while IGComp will exhibit lower Neutral Emotions, compared to IGCoop (IGComp < IGCoop < IGSolo)
Motivation	Intrinsic Motivation	H5	IGSolo will exhibit lower performance in Intrinsic Motivation, compared to IGComp and CGCoop, while IGCoop will exhibit higher performance in Intrinsic, compared to IGComp (IGSolo < IGComp < IGCoop)

2.1. Participants

To establish sample size for a One-Way Analysis of Variance, an a priori power analysis with F tests family (ANOVA: Fixed effects, omnibus, one-way) was conducted using G*Power v.3.1.9.4 [75]. Assuming an effect size of f = 0.50, a power of 0.80, and an alpha level of 0.05, the estimated sample size was N = 42 for three groups. Regarding the selected effect size, we considered it large, in line with a recent meta-analysis on gamification in education, which reported a significant overall large effect on students' learning outcomes [76]. We included 42 participants in the final analysis from 61 individuals initially enrolled in the Anatomy and Physiology course of the Nursing Undergraduate program at a local University in Lisbon, Portugal. Eligibility criteria required participants to be undergraduate students without any self-reported major disabilities or diagnosed mental health conditions. The exclusions occurred for several reasons: two participants withdrew from the course, 16 failed to attend the experiment, and one faced webcam-related technical issues. Additionally, an outlier was identified in one variable and removed for that measure, while the case was kept in the remaining variables since analyses were independent, with further details provided in Section 3 (Results).

The remaining participants were distributed into three groups: IGSolo (n = 15), IGComp (n = 13), and IGCoop (n = 14). A detailed overview of participant allocation and the different phases of the RCT is provided in Fig. 2, which includes the CONSORT Flow Diagram. Approval of the study was granted by the local Ethics Committee, and all participants provided informed consent before participating in the research.

The effects of gamification are influenced by both individual and situational factors [40]. Characteristics such as player traits and gaming habits [77,78] influence how individuals interact with gamified environments. To account for these variables, this study incorporated participants' profiles as control factors. Data on participants' profiles were collected through a sociodemographic questionnaire (SQ), the Game Habits Questionnaire (GHQ), the Player Traits Questionnaire (PTQ), and the pretest of the Learning Performance Assessment (LPA). The SQ gathered information on age, gender, marital status, education level, and nationality, while the GHQ assessed weekly gaming activity. Additionally, the PTQ, a validated instrument with a substantial sample base [77–79], was used to evaluate player preferences, behaviors, and motivations. The PTQ consists of 25 items rated on a 7-point Likert scale, ranging from strongly agree to strongly disagree, and generates scores across five player orientations: Social, Aesthetic, Narrative, Challenge, and Goal. Social Orientation measures a preference for interactive and collaborative play. Aesthetic Orientation focuses on the enjoyment of visual and auditory game elements, Narrative Orientation reflects an affinity for engaging storylines, Challenge Orientation evaluates the preference for difficult, fast-paced gameplay, and Goal Orientation assesses motivation driven by measurable achievements and task completion. Finally, prior knowledge concerning the Anatomy and Physiology course of the Nursing Undergraduate program was assessed using the pretest of LPA, consisting of 15 multiple-choice questions, further detailed in Section 2.2 (Instruments and Measures).

To control potential confounding effects from several variables, a Two-Step Cluster Analysis was performed, asking for three clusters and including the variables Age, Gender, Nationality, Game Habits, Player Traits (Social Orientation, Aesthetic Orientation, Narrative Orientation, Challenge Orientation, and Goal Orientation), and a pretest measure of LPA. Later, considering the participants' profiles on these variables, they were randomly allocated to the three IG. Thus, potential effects were balanced.

The final participant sample comprised 42 undergraduate students (38 women and 4 men) aged between 18 and 22 (M = 18.4, SD = 0.939). Sociodemographic details of the participants are illustrated in Table 2.

Regarding one of the experimentally controlled variables, Table 3 shows the participants' game habits in terms of the time they spent playing games per week. A Kruskal-Wallis test confirmed no significant differences in game habits across the groups ($\chi 2$ (2) = 2.372, p = 0.305).

As previously referred, the player traits were also control variables. Descriptive statistics of the player traits across the groups are in Table 4. The closer the value is to one, the more orientation to the profile, indicating the percentage of that orientation within the player trait (e.g., 1 equals 100 %). As expected, a One-Way Multivariate Analysis of Variance (MANOVA) indicated no statistically significant differences across the groups [Social: F(2, 39) = 0.320, p = 0.728; partial $\eta 2$ = 0.016; Aesthetic: F(2, 39) = 0.388, p = 0.681; partial η 2 = 0.020; Narrative: F(2, 39) = 0.511, p = 0.604; partial $\eta 2$ = 0.026; Challenge: F (2, 39) = 1.180, p = 0.318; partial $\eta 2$ = 0.057; Goal: F(2, 39) = 0.683, p = 0.511; partial $\eta 2$ = 0.034].

Finally, descriptive statistics of the LPA's pretest measure across the groups are presented in Table 5. Again, since this variable was also experimentally controlled, a One-Way ANOVA analysis revealed no significant differences across the groups (F(2, 39) = 0.693, p = 0.506; partial $\eta 2$ = 0.034).

2.2. Instruments and measures

2.2.1. Learning – learning performance assessment

Learning performance was measured using two assessment tests, collectively referred to as the Learning Performance Assessment (LPA). Each test included 15 multiple-choice questions based on the content covered in a 45-minute Anatomy and Physiology video lecture (e.g., "What formula is used to define blood pressure?"). The questions were designed by the course lecturers, who also led the teaching activities and had prior experience evaluating the same student cohort. This approach ensured alignment between the assessments and the course objectives and content, offering consistency through expert insight and familiarity with student performance. Lecturer-developed exams of this kind are generally considered valid and reliable measures of learning achievement [28,29]. These assessments were conducted at two points: before the course as a pre-test and after the course as a post-test, both administered on paper. To minimize potential bias, participants were not given feedback on the correct answers. Learning performance was quantified as the difference between the scores on the post-test and pre-test. The pre-test was also used as a control variable to form the IG, ensuring more homogeneous groups.

2.2.2. Cognitive engagement – exercises

Engagement was evaluated based on established research in e-learning, which associates cognitive engagement with a learner's psychological investment and effort, quantified through the number of correct responses [32,33]. Criterion-related validity reflects how well a measure corresponds with recognized benchmarks, while reliability refers to the stability of results when measurements are repeated under similar conditions [80]. To support the validity and reliability of our data, we assessed engagement using an approach previously employed in a comparable study on gamification in education. Students were provided with 12 multiple-choice questions designed to assess content from a 45-minute video lecture on Anatomy and Physiology (e.g., "What is the usual orientation of the cardiac electrical axis in the frontal plane?"). Cognitive engagement was determined by analyzing the number of exercises attempted and correctly answered, serving as indicators of participants' psychological involvement.

2.2.3. Visual attention – webcam-based eye tracking

Screen focus can be measured through eye-tracking technology, where a greater number of gaze data – indicating how often participants were detected looking at the screen – reflects sustained visual attention and decreased mind wandering associated with non-screen focus [39]. Therefore, we opted to assess attention using eye-tracking technology to determine whether participants maintained their focus on the screen throughout the course or shifted their attention elsewhere. Webcam-

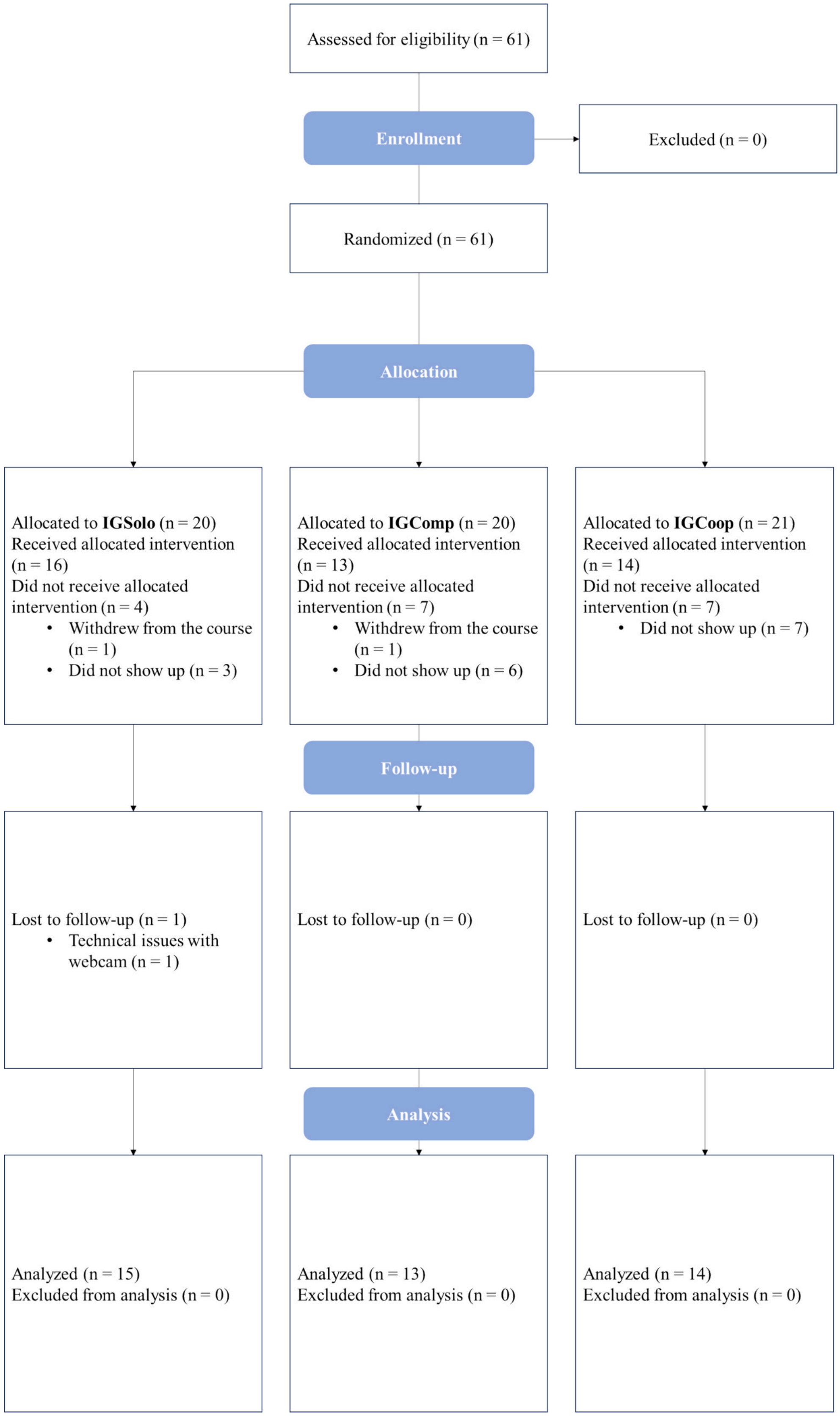

Fig. 2. CONSORT flow diagram.

Table 2
Sociodemographic characteristics of the sample (N = 42).

Variable	*N*	%
Gender		
Woman	38	90.5
Man	4	9.5
Marital Status		
Single	42	100.0
Age (years)		
18	32	76.2
19	7	16.7
20	1	2.4
22	2	4.8
Education		
Secondary	42	100.0
Nationality		
Portugal	37	88.1
Other	4	11.9

Table 3
Game habits in hours per week (N = 42).

Variable	*N*	%
Gaming Habits		
Dońt play	15	35.7
1 to 10	25	59.5
11 to 20	1	2.4
More than 20	1	2.4

Table 4
Descriptive statistics of the player traits across the groups (N = 42).

	IGCoop		*IGComp*		*IGSolo*	
	M	*SD*	*M*	*SD*	*M*	*SD*
Social	0.5921	0.15715	0.5646	0.23468	0.6233	0.18745
Aesthetic	0.6543	0.25355	0.6185	0.24477	0.5733	0.24561
Narrative	0.5000	0.18170	0.4223	0.18917	0.4747	0.23102
Challenges	0.6586	0.25038	0.5515	0.20448	0.6753	0.22408
Goal	0.6979	0.22046	0.6154	0.16328	0.6653	0.16278

Table 5
Descriptive statistics of the pretest measure of the Learning Performance Assessment (N = 42).

	IGCoop		*IGComp*		*IGSolo*	
	M	*SD*	*M*	*SD*	*M*	*SD*
Pretest LPA	4.5714	1.69680	5.4615	1.98391	5.0667	2.18654

Note. LPA = Learning Performance Assessment.

based eye-tracking, such as WebGazer, has demonstrated adequate levels of accuracy and precision for this type of measurement [39]. These accuracy and precision indicators correspond to the broader constructs of measurement validity and reliability, supporting the consistency and reproducibility of findings [81]. The Webgazer (v 3.1.2) eye-tracking system was used, with gaze time recorded as the key outcome measure [82,83]. While not as precise as infrared eye-tracking systems, WebGazer offers a convenient, webcam-based alternative that effectively captures gaze patterns, making it a practical choice for studies aiming to track participants' attention direction [84]. The course duration varied per participant, as the video lecture was fixed in length, but the exercises had no time limit. To account for differences in gaze time due to extended course duration, we analyzed the proportion of screen-viewing seconds relative to each participant's total course time, yielding a percentage from 0 to 100. This method enabled the assessment of visual attention on interfaces, aiming to validate the participants' attentional focus on the screen.

2.2.4. Facial emotion recognition – webcam-based Morphcast

An alternative and more objective method for assessing emotions, beyond traditional questionnaires, involves analyzing facial expressions [57]. FER employs machine learning algorithms to identify and track facial features, detect variations in facial landmarks over time, and categorize emotions using classifiers trained on labeled facial expression datasets [85]. The validity of FER pertains to its ability to correctly detect emotional states as defined by psychological frameworks, whereas reliability involves the stability of these detections across different moments, settings, individuals, and contexts [86]. Automated analysis of facial expressions has demonstrated alignment with electromyography (EMG) results, supporting its convergent validity, and has shown consistent ratings across various conditions, indicating strong reliability [87]. In this study, we used the webcam-based FER software Morphcast, which detects emotions such as anger, disgust, fear, happiness, sadness, surprise, and neutral [88]. Given that gamification can elicit a broad spectrum of emotions, including both positive and negative affective states [22], we focused on the proportion of neutral emotions. A ceiling effect arises when many participants begin with high scores, limiting the assessment of variations or intervention impact [89]. As participants watched the same 45-minute lecture, we analyzed FER without segmenting video moments, which were identical and dominated the intervention, likely causing uniformly emotional scores. Instead, we focused on interactive moments – transitions, exercises, and session start/end – where there was more active interaction. The neutral-to-other emotion ratio indicates emotional variability, as more neutral emotions reflect fewer other emotions, and vice versa.

2.2.5. Motivation – post-experimental intrinsic motivation inventory

To assess motivation, we employed a questionnaire grounded in SDT [64]. Specifically, intrinsic motivation was measured using the Interest/Enjoyment scale from the PEIMI, a validated instrument for the Portuguese population, demonstrating strong construct validity through the high Adjusted Goodness of Fit Index (AGFI), Comparative Fit Index (CFI), and Tucker-Lewis Index (TLI) values (all above 0.93) across multiple model structures, along with solid reliability indicated by Cronbach's alpha values ranging from 0.82 to 0.91 [66]. This scale consists of seven statements (e.g., "I enjoyed doing this activity very much"), with participants rating their agreement on a 7-point Likert scale. The PEIMI was administered digitally both before and after the intervention, with the variable calculated as the difference between post-test and pre-test scores, assessing changes in intrinsic motivation from the start to the end of the course.

2.3. Procedure

At the beginning of the term, participants were informed about the study and asked to provide informed consent if they agreed to take part. Following this, they completed the SQ, GHQ, PTQ, and LPA (pre-test) during a regular Anatomy and Physiology class in which all students were seated at desks with no individual desktop computer, 90 days before the commencement of the intervention. The 90-day waiting period was due to the course lecturers' view that the subject matter would be more relevant to students later in the semester, based on the structure of the Nursing program's pedagogical calendar. The data collected from these assessments were used to group participants into clusters, with each individual assigned a unique identifier to ensure anonymity. Participants within each cluster were then randomly allocated to different IG. After 90 days, participants were assigned to one of three group sessions, each lasting 90 min and conducted within the same week. To minimize bias in the randomization process and deviations from intended interventions [71], participants remained unaware of their group allocations.

Each session began with an instructor asking participants to complete the PEIMI pre-test digitally on their respective individual desktop computers. Next, each participant received a unique login to access the digital learning platform locally. They then engaged with three modules, each featuring a 15-minute video lecture (totaling 45 min), a PDF containing the professor's presentation, and four multiple-choice questions (12 exercises in total). The sessions took place in a dimly lit university computer lab with minimal distractions. While all participants viewed the course simultaneously, each had an individual computer equipped with headphones. Throughout the interaction with the gamified digital learning platform – including video viewing and answering exercises – both eye-tracking and FER applications collected data via webcam. After completing the digital course, participants responded to the PEIMI post-test. Fig. 3 illustrates the group session setup.

Finally, a week after the final group session, all participants returned to complete the paper-based post-test LPA, in the same settings as the pre-test of LPA (during a regular Anatomy and Physiology class, with all students seated at desks with no individual desktop computers. Fig. 4 visually illustrates these procedures.

2.3.1. *Gamified digital learning platform*

To ensure a controlled experimental environment, we designed a gamified digital learning platform based on gamified learning theory and gamification science [5,18]. This platform, previously tested and validated in feasibility and pilot studies [90], served as both a flexible educational system and a controlled framework for examining the effects of different game elements on cognition, emotions, and motivation. The platform incorporates Webgazer 3.1.2 for eye-tracking [83] and Morphcast 1.16 v1.3 for FER [85]. Figs. 5–10 illustrate the user interfaces for IGSolo, IGComp, and IGCoop.

2.3.2. *Gamification settings*

For this study, we developed three distinct versions of the gamified digital learning environment, each tailored to correspond with a specific group session. These versions integrated course materials, including video lectures and practice activities, structured within different course modules covering various topics. Across all groups, participants were expected to engage in specific actions: 1) start the course; 2) begin the video lecture; 3) complete the video lecture; 4) accurately answer classroom exercises with minimal attempts; 5) finish all course modules; and 6) complete the course.

These predefined behaviors formed the basis for the reward mechanisms implemented in the IG, where points were distributed based on adherence to these expected actions. The gamification design process involved the strategic manipulation of variables within a digital system to encourage participants toward more effective and goal-oriented behaviors [4]. For example, the system prompted participants to focus on answering exercises correctly rather than relying on guessing, as incorrect responses resulted in no rewards. The point system, user interface, and visual elements varied across the groups, as described below.

2.3.2.1. IGSolo. In the "solo points" version of the digital learning platform, the user interface displayed a dynamic numerical score reflecting the total points accumulated. Since no social components were included and points were awarded based solely on individual performance within the gamified digital learning platform, this condition was defined by its individual and single-player nature. Additionally, it featured a detailed history of all points earned, providing participants with a clear overview of their progress. Figs. 5 and 6 illustrate the interfaces for this group.

2.3.2.2. IGComp. In the "competitive points" version of the digital learning platform, the user interface showcased a real-time, dynamic numerical score reflecting each participant's total accumulated points. Absolute leaderboards motivate top scorers but can discourage lower-ranked students, while relative leaderboards, showing partial scores, help reduce this discouragement [91]. Lower-ranked players often prefer anonymous leaderboards to avoid embarrassment [92]. To address this, we used a selective, anonymous leaderboard that updated automatically, displaying only the participants' scores and the top five while protecting participants' identities. The interface also included a detailed points history, allowing participants to track their progress. Figs. 7 and 8 illustrate the interfaces for this group.

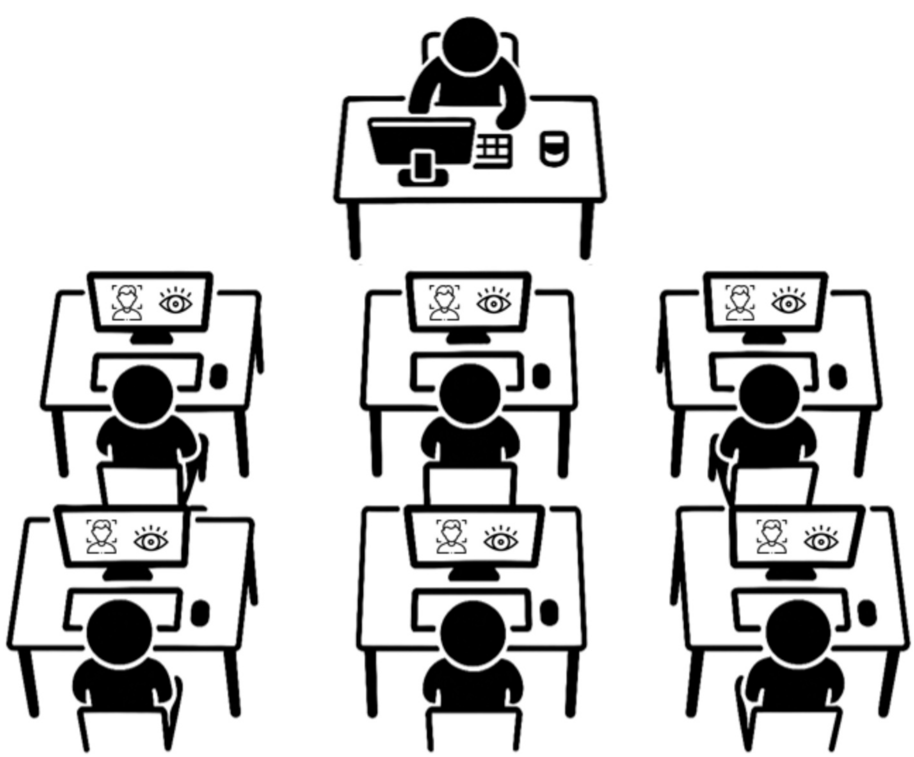

Fig. 3. Group session setting.

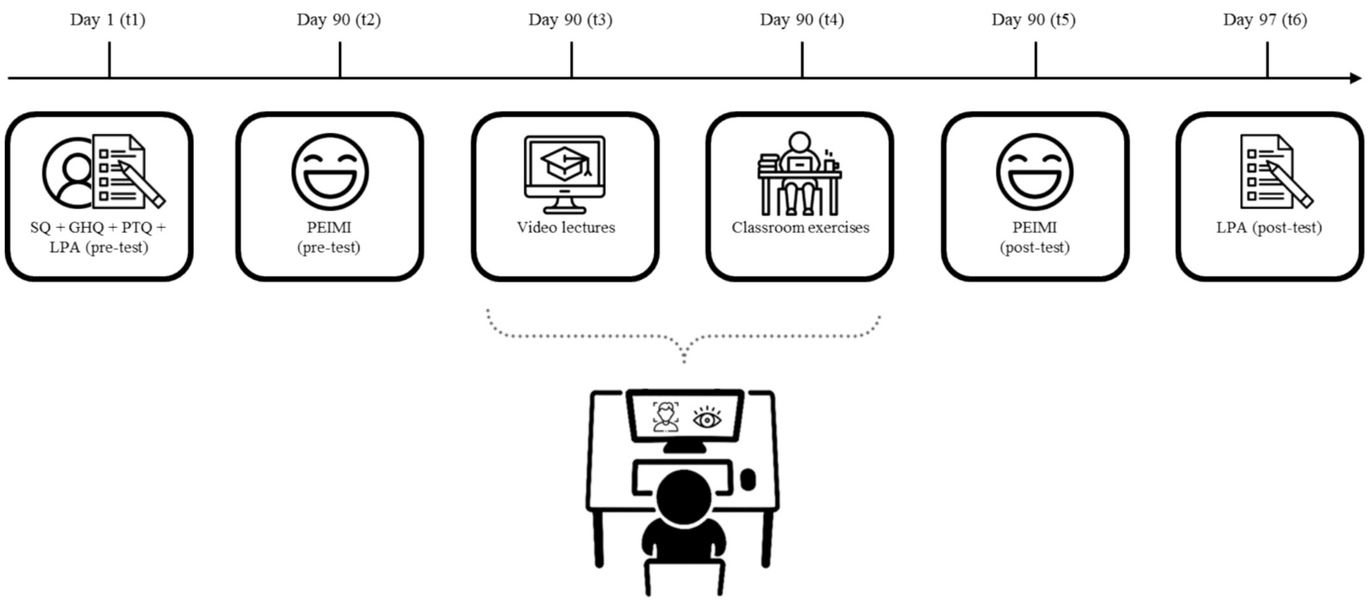

Fig. 4. Research procedure.

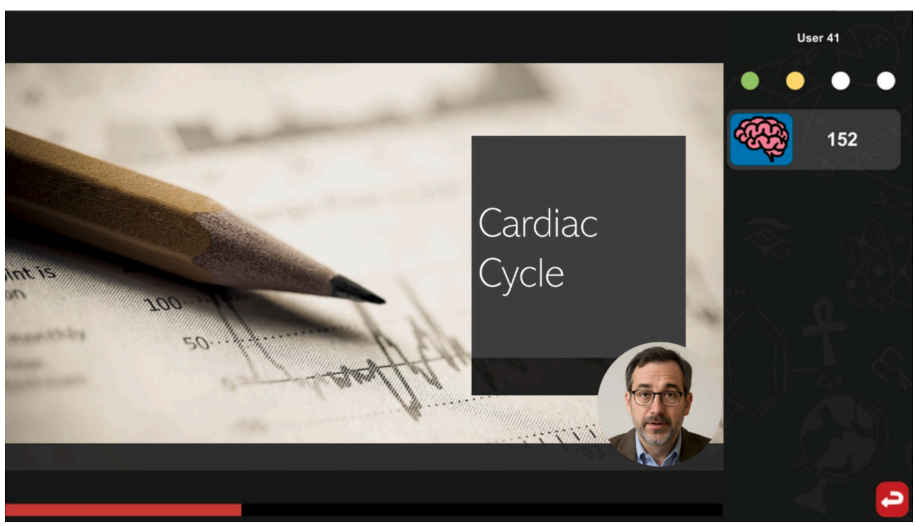

Fig. 5. Gamified digital learning platform – video interface (IGSolo).

2.3.2.3. IGCoop. Cooperative multiplayer games involve players pursuing individual goals while benefiting the group [11]. In educational settings, while competition emerges from the belief that one's success depends on others' failure, cooperation stems from the perception that achievement is only possible through shared success [93]. Given that majority-vote systems can effectively foster cooperation [94], we developed a system in which exercises displayed the percentage of peers' choices for each option, allowing participants to follow the majority or influence it with correct answers. The group earned points if the majority was correct; otherwise, no points were awarded. In this version of the platform, the interface displayed a real-time group score and a progress bar with milestones, updating automatically to show collective progress. A detailed points history also allowed participants to track their group's achievements. Figs. 9 and 10 illustrate the interfaces for this group.

2.4. Data analysis

Data analyses were performed using IBM Statistical Package for the Social Sciences (SPSS) 29. The grouping variable was gamification type, with three categories: two social (cooperation – IGCoop – and competition – IGComp) and one non-social (IGSolo).

Response variables were participants' LPA, PEIMI, Cognitive Engagement, Neutral Emotions experienced, and Visual Attention. As mentioned above, LPA and PEIMI were assessed twice, previously and after performing the task. We calculated the difference between the post-test and the pre-test measures for these variables and considered the difference variable in the analysis. Concerning Cognitive Engagement, the number of correct answers was analyzed. Regarding the emotions experienced, we registered the proportion of each emotion for every second (anger, fear, happiness, sadness, surprise, and neutral emotion) and calculated the average proportion for each emotion. We calculated proportions to account for variability in course duration across participants, as some may take longer to complete the questions. Using raw emotion data could lead to significant inconsistencies. As described in Section 2.2 (Instruments and Measures), we only considered Neutral Emotions (average proportion) in the analysis, as a lower proportion of neutral emotion means a higher proportion of other emotions and vice

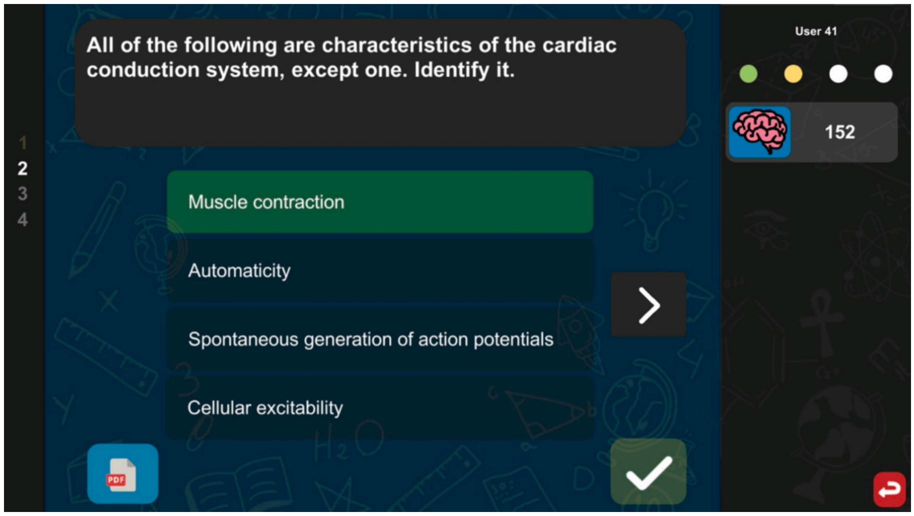

Fig. 6. Gamified digital learning platform – exercises interface (IGSolo).

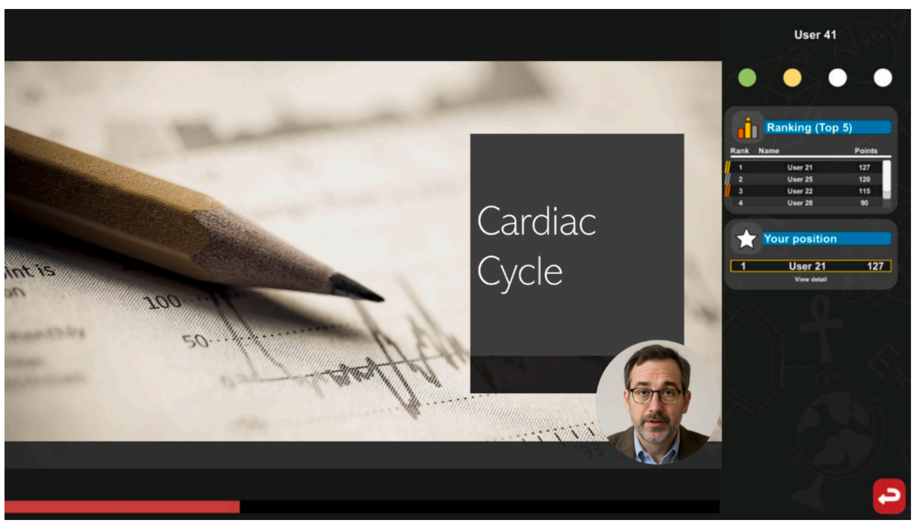

Fig. 7. Gamified digital learning platform – video interface (IGComp).

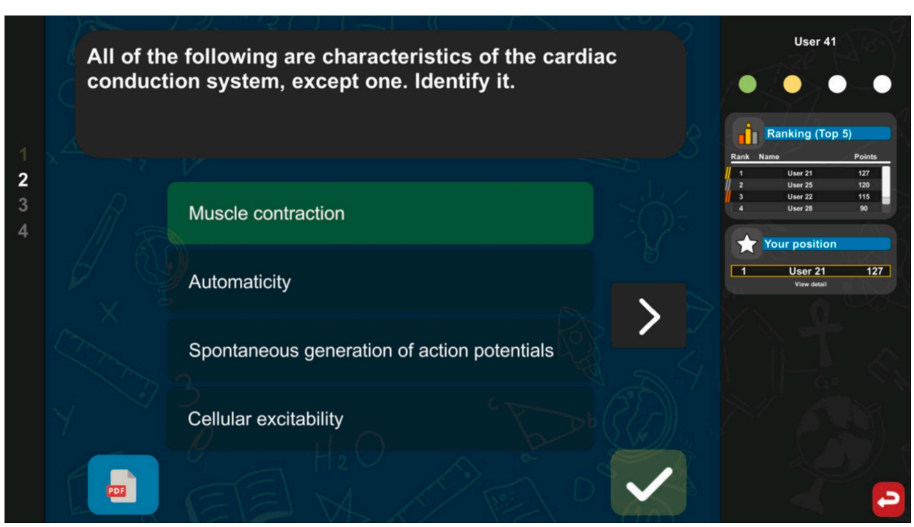

Fig. 8. Gamified digital learning platform – exercises interface (IGComp).

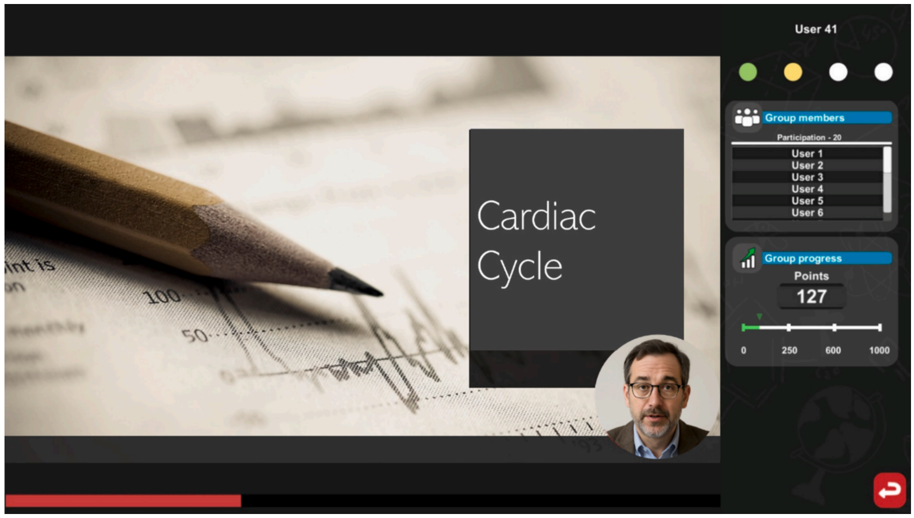

Fig. 9. Gamified digital learning platform – video interface (IGCoop).

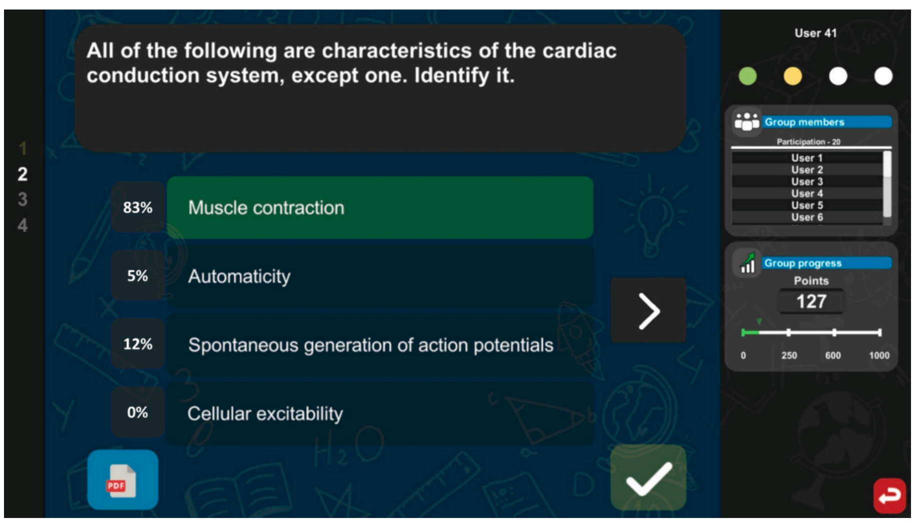

Fig. 10. Gamified digital learning platform – exercises interface (IGCoop).

versa. Also, we analyzed the percentage of Visual Attention during the execution of the task to account for varying course durations – due to fixed-length video lectures and untimed exercises – measuring visual attention as the percentage of screen-viewing time relative to each participant's total session, allowing for standardized assessment of attentional focus.

Considering that only two moderate bivariate correlations between the response variables were statistically significant, a Multivariate Analysis of Variance (MANOVA) was disregarded, and a One-Way Analysis of Variance (ANOVA) was conducted for each response variable, with alpha Bonferroni adjustment, by dividing the original 0.05 threshold per five separate One-Way ANOVAs(in this case, after correction, $\alpha = 0.01$). Concerning Visual Attention, an outlier was identified in case ID = 9 (z = -4.98). Therefore, we removed the value in Visual Attention but maintained the case, since each analysis was independent of the others.

Concerning the ANOVA assumptions, Cognitive Engagement and Visual Attention were not normally distributed in IGCoop and IGSolo. However, ANOVA is robust if non-normality is due to asymmetry of the distribution in place rather than the existence of outliers [95,96]. The homogeneity of variance of the response variable was met, except for Visual Attention. So, for this variable, we opted for Welch's correction.

3. Results

Descriptive statistics of the response variables across the gamification groups can be found in Table 6.

As mentioned above, the assumption of homogeneity of variance was fulfilled for four dependent variables [PEIMI: $F(2, 39) = 0.410$, $p = 0.667$; Cognitive Engagement: $F(2, 39) = 0.384$, $p = 0.067$; LPA: $F(2, 39) = 0.879$, $p = 0.423$; Neutral Emotions: $F(2, 39) = 0.543$, $p = 0.585$; Visual Attention: $F(2, 38) = 3.524$, $p = 0.039$].

Table 7 features the results of the series of One-Way ANOVAs. To avoid inflation of Type I error, an alpha Bonferroni adjustment was used, and only results with p-values below 0.01 were considered statistically significant. As a result of this adjustment, statistically significant differences among groups were found only in Visual Attention. In this regard, the type of gamification explains 47.8 % of the variability in Visual Attention.

Later, multiple pairwise comparisons were conducted to identify differences between the groups in Visual Attention, since it was the only variable with significant differences. Because of the heterogeneity of variance, the Games-Howell Test was more adequate. It showed significant differences between IGCoop and IGSolo (I.C. 95 %] −1.310, −0.367 [; $p < 0.001$), and between IGComp and IGSolo (I.C. 95 %]

Table 6
Descriptive statistics of the response variables across the gamification groups.

	Gamification Groups	M	SD	N
PEIMI	IGCoop	−0.4993	0.98567	14
	IGComp	−0.5700	0.91489	13
	IGSolo	0.2667	0.96396	15
	Total	−0.2476	1.01078	42
Cognitive Engagement	IGCoop	6.71	2.199	14
	IGComp	7.46	1.984	13
	IGSolo	7.33	1.397	15
	Total	7.17	1.860	42
LPA	IGCoop	2.3571	4.10641	14
	IGComp	4.3846	3.06970	13
	IGSolo	2.5333	4.40562	15
	Total	3.0476	3.94445	42
Neutral Emotions	IGCoop	34.7700	12.96272	14
	IGComp	26.9485	9.41720	13
	IGSolo	23.8473	10.54276	15
	Total	28.4481	11.80222	42
Visual Attention	IGCoop	97.921900	0.5678369	13
	IGComp	97.982669	0.2717500	13
	IGSolo	98.761993	0.3861965	15
	Total	98.248520	0.5723630	41

Note. PEIMI = Post-Experimental Intrinsic Motivation Inventory; LPA = Learning Performance Assessment.

Table 7
One-Way ANOVA for each response variable.

Variable	Sum of squares	df, df	Mean square	F	Sig.	η^2
PEIMI	6.205	2, 39	3.103	3.391	0.044	0.148
Engagement	4.412	2, 39	2.206	0.626	0.540	0.031
LPA	33.880	2, 39	16.940	1.094	0.345	0.053
Neutral Emotions	906.272	2, 39	453.136	3.678	0.034	0.159
Visual Attention	–	2, 23,550	–	20.928	< 0.001	0.478

Note. Bonferroni correction of alpha (α = 0.01. Welch's F Test was used for Visual Attention due to heterogeneity of variance. PEIMI = Post-Experimental Intrinsic Motivation Inventory; LPA = Learning Performance Assessment.

−1.091, −0.468 [; $p < 0.001$), with the average of Visual Attention being higher in IGSolo compared to the others. The comparison between IGCoop and IGComp was non-significant (I.C. 95 %] −0.508, 0.387 [; $p = 0.936$).

3.1. Summary of hypotheses and findings

In H1 (Learning), we hypothesized that IGSolo would show the lowest LPA, compared to IGComp and IGCoop, and IGCoop would outperform IGComp. This hypothesis was not supported, as no significant group differences emerged.

Concerning H2 (Cognitive Engagement), we expected IGSolo to show the lowest engagement, and IGCoop to have the highest one, compared to IGComp. This hypothesis was not supported, as there were no significant group differences.

Regarding H3 (Visual Attention), we anticipated that IGSolo would demonstrate the lowest visual attention, and IGCoop would show the highest attention, compared to IGComp. This was not supported, but contradicting expectations, IGSolo had significantly higher visual attention compared to the other groups.

In H4 (FER), we expected IGSolo to exhibit the highest proportion of neutral emotions, and IGComp would show the lowest neutral emotion levels, compared to IGCoop. This was not supported, as no significant differences were found.

Finally, concerning H5 (Intrinsic Motivation), we anticipated IGSolo would yield the lowest PEIMI scores, and IGCoop would show the highest scores, compared to IGComp. Since no significant differences were observed, the hypothesis was not supported.

4. Discussion

This study used an innovative gamified digital learning platform grounded in gamified learning theory and gamification science [5,18,23,90] to investigate the effects of single-player and multiplayer modes (competition and cooperation) on cognitive (learning performance, cognitive engagement, webcam-monitored visual attention), emotional (FER), and motivational (intrinsic motivation) outcomes in a digital education setting. Our findings unexpectedly contradict hypothesis H3, showing that individual gamification (IGSolo) had a significantly greater impact on Visual Attention than social modes (IGComp and IGCoop). With no other significant differences observed, the remaining hypotheses were rejected. In this discussion, we first explore possible explanations for this outcome in Visual Attention and related variables. Next, we address the absence of significant findings in other measures. Finally, we offer a critical analysis of the implications for contemporary digital education. Table 8 illustrates the results of all hypotheses.

4.1. Increased social component, less attention

Gamification can enhance attention [42,43] and perception [40] – two associated processes [97] - by increasing exposure to diverse game-

Table 8
Hypotheses Results.

Domains	Dependent variables	Hypotheses	Hypotheses description	Results
Cognition	Learning	H1	IGSolo will exhibit lower performance in Learning, compared to IGComp and CGCoop, while IGCoop will exhibit higher performance in Learning, compared to IGComp	☒
	Cognitive Engagement	H2	IGSolo will exhibit lower performance in Cognitive Engagement, compared to IGComp and CGCoop, while IGCoop will exhibit higher performance in Cognitive Engagement, compared to IGComp	☒
	Visual Attention	H3	IGSolo will exhibit lower performance in Visual Attention, compared to IGComp and CGCoop, while IGCoop will exhibit higher performance in Visual Attention, compared to IGComp	⚠☒
Emotions	FER (Neutral Emotions)	H4	IGSolo will exhibit higher Neutral Emotions, compared to IGComp and CGCoop, while IGComp will exhibit lower Neutral Emotions, compared to IGCoop	☒
Motivation	Intrinsic Motivation	H5	IGSolo will exhibit lower performance in Intrinsic Motivation, compared to IGComp and CGCoop, while IGCoop will exhibit higher performance in Intrinsic, compared to IGComp	☒

Note. ⚠=Divergent from hypothesis; ☒=Hypothesis not supported.

based stimuli. Social stimuli can activate cognitive processes [98], leading us to hypothesize that social dynamics in competition or cooperation modes could enhance visual attention. However, our results showed the opposite, suggesting that visual attention was higher in the group without social game elements (IGSolo).

This previous context may be explained by two interrelated phenomena: 1) social dynamics in multimedia learning require more cognitive demand due to the need to process multiple stimuli; and 2) external and internal distractions, where factors disrupt focus on the primary task.

4.1.1. Social dynamics in multimedia learning

With digital media's rise, constant attentional competition and multitasking – managing multiple tasks during media use – are linked to reduced working and episodic memory, likely due to sustained attention failures and increased mind wandering [99]. The orienting network filters sensory input, prioritizes information, and maintains focus, but can also split attention between stimuli, like multitasking, lowering focus on the main task [100]. The cognitive theory of multimedia learning states that humans process verbal and visual information through separate, limited channels, needing active effort to select, organize, and integrate content with prior knowledge for meaningful learning [101]. Multimedia learning requires learners to monitor and regulate emotional, motivational, and cognitive processes [102]. Multitasking connects to multimedia learning through media use and to social learning, as behavior is shaped by interactions, with social context influencing media use [103].

Digital social multitasking is the common practice of using technology during social dynamics, where people perform multiple activities at once [104]. Although participants did not engage in conversation during the experiment, performing tasks within a social dynamic where others may influence individual actions, can affect individual behavior and cognitive processes [105–107], as earning points could change the leaderboard position (competition mode) or enhancing the group score (cooperation). Social dynamics can shape individual behavior by enabling actions such as individualistic, competitive, or cooperative ones – similar to social dilemmas, where decisions are made in contexts where each person's choices can affect others and, in turn, influence their action [108–110].

In the competitive and cooperative modes of this study, participants viewed their performance as tied to others (competition) or the group (cooperation), creating social dynamics where the context could influence behavior and cognition, as individual outcomes could shift the overall point structure and, in turn, demand further actions – such as increased effort driven by the desire to win or collaborate with the team. Therefore, the social dynamics present in competitive and cooperative modes may have created a context that influenced individual behavior and increased cognitive demands, diminishing the visual attention of the main task, as social stimuli are associated with greater cognitive effort [111] and social cues can be linked to elevated cognitive load [112]. Through social multitasking and multimedia and social learning concepts, we can infer that social context and dynamics shape experiences [44], impacting cognitive resources for focus [113] and sustained attention [114]. Thus, our results show that, regarding visual attention, social dynamics added cognitive demand, pulling attention from the main screen task.

4.1.2. External and internal distractions

Attention acts as a gateway between information and learning, categorized as external/internal and on-topic/off-topic, with off-topic attention from either source linked to distractions [115]. Learning and memory rely on sustained attention and resisting distractions; however, students often face external distractions like phones, social media, noise, objects, and social distractors [116]. Research shows social stimuli get preferential cognitive processing, as eye-tracking revealed visual social distractors captured attention more than non-social ones, while memory accuracy for target positions dropped with social stimuli [117]. Likewise, auditory distractions from classroom noise, often social, cause interference and annoyance, making it harder and more unpleasant for students to reach learning goals [118]. Thus, social elements unrelated to learning can act as external distractions, hindering goal-directed tasks [119] and possibly explaining reduced visual attention in IGComp and IGCoop.

While peers add to external distractions, internal ones in education are also significant, arising from cognitive states (e.g., difficult or boring tasks), motivational and emotional factors (e.g., interest, excitement), and behaviors (e.g., frequent smartphone use) [120]. Internal distractions, studied via gaze patterns and eye-tracking, are linked to more mind-wandering and less visual attention during tasks [121]. Our results showed PEIMI and Neutral Emotion tend to be significant, as the p-value was below 0.5, but, after applying the Bonferroni adjustment (correct alpha = 0.01), these results were not statistically significant, even though such correction may yield overly conservative outcomes [96,122]. Thus, considering the trend toward significance and analyzing the descriptive data in Table 6, it suggests that IGSolo had positive intrinsic motivation and low neutral emotions. Boosting intrinsic motivation improves attitudes toward academic tasks, raising effort and reducing boredom [123]. Neutral emotions may reflect a slight negative bias, linked to reduced interest or enthusiasm [124]. Motivational and emotional issues, like boredom, low interest, and low self-efficacy, are key causes of internal distraction in education [125]. Thus, as IGSolo showed higher Visual Attention than IGComp and IGCoop, with positive intrinsic motivation and low neutral emotions, these findings may reflect lower internal distractions and increased focus, with less mind-wandering. Nonetheless, this analysis should be viewed as an insight rather than an inferential statistical conclusion, as the result approached but did not reach significance. Further research is needed to better understand the relationship between intrinsic motivation, neutral emotions, internal distraction, and visual attention in educational settings.

4.2. The role of context in gamification effectiveness

Variables like player traits and game habits [77,78], culture [126], and gender [127] can significantly shape participants' gamification experience, potentially influencing learning outcomes [128,129]. Individual and contextual factors may have significantly influenced our findings and should be considered when assessing generalizability and transportability for external validity [130], as those variables likely shaped the outcomes and affected how results apply to broader undergraduate populations. Taking this into consideration, it is essential to first acknowledge that the context of this research, represented by the modest sample drawn from a single Portuguese university's nursing program, should be considered when interpreting our findings.

Regarding player traits, most participants in our study showed challenge, goal, and aesthetic orientations, with no predominant inclination toward social orientation. While challenge-oriented individuals seek tasks that affirm their competence, goal-oriented players are drawn to activities that offer clear progress markers, and aesthetic-oriented players enjoy visual and auditory elements; the social-oriented, characterized by a preference for interaction and collaborative play [77,78], was not dominant. This may help explain the absence of significant cognitive outcomes related to learning and engagement, as social dynamics in IG, like competition and cooperation, may have had a limited impact due to the participants' low interest in socially driven gameplay, shown by their player traits. In other words, since participants were less influenced by social factors, the competitive and cooperative conditions may have failed to produce effects distinct from the individual mode. Based on social value orientation theory, individuals may prioritize self-benefit (individualist), outperforming others (competitive), or collective outcomes (pro-social, including cooperative orientations) [108–110]. Social value orientation can influence student behavior in learning contexts [131], potentially shaping how educational interactions happen, as it affects how people relate to one another [132]. Thus, the lack of social traits in our sample may reflect a stronger individualist orientation, with fewer participants displaying competitive or cooperative tendencies, possibly explaining why the social modes had little influence on learning and engagement outcomes.

In terms of culture, gender, and gaming habits, the sample primarily consisted of Portuguese female nursing students with low gaming activity (most of them do not play or play under 10 h per week), which may explain the absence of group differences in learning and engagement. Video games gained widespread popularity in the 1980s [133], during a time when the computer industry and gaming culture were predominantly male-oriented [134], likely shaping the experiences of individuals born during or after that decade. In Portugal, this scenario was not different, and computer games gained popularity in the 1980 s during the country's transition from authoritarian rule, but media discourse – shaped by traditional gender roles and perceived biological differences – cast men as naturally aligned with technology, excluding women and reinforcing masculine norms in tech spaces [135]. These narratives persist today, with women underrepresented in gaming, potentially due to their general lack of interest or, more critically, due to stereotypes, hypersexualized avatars, and online harassment, all contributing to reduced participation and negative psychological impacts such as lower self-esteem and adverse comparisons [136]. This cultural context is evident in the participants' gaming habits, as most reported little to no playing, suggesting a broader disconnect between Portuguese women and gaming culture that persists until today. Still, despite ongoing gender challenges, women hold a growing presence in the industry [137], reinforcing the need for balanced representation in both practice and research.

Although men continue to report more gaming activity – especially on consoles and PCs [138] – gender should not limit inclusion in educational gamification research. Additionally, educational background may also explain the limited gaming involvement. As nursing students in a health-focused program, participants may favor leisure activities that align with well-being. Research shows that health-related students are more active during free time and more likely to translate health motivation into behavior [139]. While video games can yield health benefits and drawbacks, they are often perceived as sedentary or unhealthy, which may lead to avoidance [140]. Thus, participants' limited gaming may reflect health-centered values, influencing their interest in gamification. As a result, given that interest plays a key role in engagement and learning [141,142], participants' limited interest in games may have reduced the effectiveness of the intervention.

Combined, all these factors likely contributed to uniform outcomes across gamified conditions, consistent with a floor effect, as, in behavioral science, floor and ceiling effects occur when tests are too difficult or easy, positing participants at the extremes, producing limited variability and affecting interpretation [143]. Similarly, in this study, low gaming exposure with no social player trait dominance – enhanced by culture, gender, and educational background – may have dampened the gamification effect, minimizing its cognitive impact on learning and engagement across all groups. In other words, since most participants were not potentially interested in the way the gamified experience was implemented, its effect was likely insufficient to influence the outcomes. This is comparable to a floor effect, where, for instance, both a pre- and post-test are too challenging, and the intervention fails to produce measurable performance improvements. Additionally, it is important to highlight that although we discussed trends in intrinsic motivation and neutral emotions related to internal distraction, and visual attention – particularly the near-significant results for intrinsic motivation and neutral emotions in IGSolo – these effects did not reach statistical significance. This may be linked to the same contextual factors that affected learning and engagement outcomes discussed here, as motivation and emotions play a key role in shaping cognitive outcomes in educational settings [144]. That is, such contextual factors could have reduced gamification's overall impact, limiting also its effect to significantly motivate participants or trigger emotional responses beyond neutrality.

4.3. Contemporary digital education implications and recommendations

Our findings may reflect a modern educational trend favoring gamified digital learning that captures attention through greater individualization [145]. Integrating digital technologies into education has reshaped learning, creating a dynamic, flexible, and globally accessible higher education environment, free from time and place constraints [146].

The concept of scaffolding stems from Vygotsky's sociocultural theory, which posits that development and learning are shaped by interactions among the individual, others, and the cultural context, where a learner's ability to close the gap between actual and potential performance depends on the support or resources available [147,148]. In contemporary digital education, technology-enhanced scaffolding supports learning by facilitating group coordination, promoting knowledge elaboration, enabling feedback through programmed responses, improving interaction with peers and content, and providing access to inquiry tools aligned with students' interests [149].

Digital education supports self-directed learning, shifting from content-centered methods to placing learners in a central, responsible role [150,151], enabling more personalized education, with methods and content adapting to each learner's needs [152]. Gamification and personalized experiences become adaptive by tailoring virtual agents, content, and assessments to individuals, further enhanced by artificial intelligence (AI), providing real-time feedback, assessing strengths and weaknesses, and adjusting strategies accordingly [153–155]. Gamification and game-based interventions also enable learning through simulations, allowing exploration, practice, and skill-building in safe virtual environments [156]. Our visual attention results indicate that digital gamification functioned as a technology-enhanced scaffolding tool that improved participants' attention, but only in the individual mode. The non-social element of points worked as automated feedback and progress tracking and proved more effective for sustaining attention without social dynamics of competition and cooperation, suggesting that gamification may be particularly useful for supporting individualized learning, especially in contemporary settings like online courses where students follow more individualized paths [157].

Nonetheless, while social components are also essential for scaffolding learning [147,148], the competitive and cooperative modes in our study did not significantly enhance cognitive, emotional, or motivational outcomes – showing that social gamification should not replace social components within universities. Learning in social contexts remains vital, with instructors modeling behaviors and encouraging autonomy, while knowledge grows through social dynamics and shared experiences [44]. Social factors are key in education, as peer networks support student satisfaction and involvement [158]. Social cognition, involving language, memory, and learning, fosters connections and improves communication [159]. Social connectedness boosts student well-being, lowering loneliness, which is related to anxiety, stress, and depression [160]. Social elements deeply shape education and wider society, and universities, as social institutions, should promote societal and cultural growth [161]. Therefore, the absence of significant results in the social conditions suggests that the benefits of social components should not be expected to transfer directly to online settings as substitutes for in-person experiences. Our findings indicate no cognitive, motivational, or emotional gains from digital social modes alone, at least in short digital courses, highlighting the importance of preserving physical presence and real-world interaction in educational contexts, balancing with digital environments [162].

As previously discussed, contextual factors must be considered when implementing gamification in educational settings, since outcomes may vary depending on participant characteristics [5,78]. Understanding students' profiles – including sociodemographic data, gaming habits, and player traits – is essential for tailoring gamification to better support their motivation, interests, and needs [163]. In our case, the sample consisted mostly of Portuguese female nursing students with low gaming frequency (most played less than 10 h per week) and a preference for challenge, goal orientation, and aesthetics. For such a profile, a more playful and less structured approach, compared to rigid game-like systems [164], may be more effective. Emphasizing fun, spontaneity, and positivity through playful design [165] may better engage these learners, moving beyond the sole reliance on incentives and feedback [166]. For instance, course dynamics could include narrative-based roleplay and quest-style activities, potentially combining online and offline formats to foster a balanced and engaging learning experience that connects digital tools with real-world interaction.

To sum up, our results are most directly generalizable to short, points-based digital courses implemented in higher education cohorts similar to ours, namely undergraduate health-related programs composed predominantly of young adult students with low gaming frequency and no strong social player orientation. In such contexts, our data suggest that individual gamification may be particularly effective for sustaining visual attention, whereas the addition of competitive or cooperative elements may introduce cognitive demands and distractions that do not necessarily translate into cognitive, emotional, or motivational gains. Thus, from a micro perspective, our findings suggest education need not always be social, as individual dynamics better capture visual attention in short digital courses. Therefore, short, individually gamified sessions may effectively capture attention in university settings, especially in today's digital age, where attention is constantly challenged by competing stimuli [167]. However, in-person social interactions remain essential and should not be replaced entirely by digital environments, since socially gamified digital formats may not yield the expected benefits, as represented by the lack of results of social groups in our research.

Concerning real-life applications, these results indicate that instructors and instructional designers working with comparable student profiles may prioritize brief, individually gamified modules – using simple point-based feedback – when the main objective is to support focused attention in digital learning. In other populations (e.g., students with stronger social or gaming orientations, different cultural backgrounds, or other disciplines), social gamification may operate differently, and targeted empirical testing is needed before broad implementation. With that in mind, when it is possible, it is essential to assess the specific context of each educational setting before applying gamification strategies, ensuring a more effective and meaningful learning experience.

5. Conclusion

This study examined the effects of gamification on cognitive (learning, cognitive engagement, and visual attention), emotional (neutral emotions), and motivational (intrinsic motivation) outcomes in digital education, revealing that individual learning settings (IGSolo) fostered higher visual attention compared to social modes (IGComp and IGCoop). Contrary to our hypothesis, social dynamics in competition and cooperation modes did not enhance visual attention, potentially due to cognitive demands associated with digital social multitasking and internal and external distractions. The lack of significant differences in the remaining outcomes may be attributed to contextual factors, such as the absence of dominant social player traits, low gaming habits, and interest, and the participants' background in health-related education – all of which may have reduced the effectiveness of the gamification intervention, resembling a floor effect.

Broader trends in digital education are also addressed in light of current advancements in digital education, where increased personalization and self-regulated learning are becoming more prevalent. Given the growing influence of the attention economy and the prevalence of digital distractions, our study introduces a novel perspective to social gamification research by demonstrating how integrating short and individual gamified learning sessions could serve as a valuable strategy for sustaining student attention in complex university settings. While social dynamics remain vital for scaffolding learning, cognitive development, well-being, and meaningful interpersonal connections, our findings suggest that digital social gamification elements may not serve as effective substitutes. Therefore, careful consideration of contextual variables, such as the characteristics of our sample, is essential when interpreting, designing, and applying gamified interventions to ensure meaningful and effective educational experiences.

6. Limitations and future research

It is essential to note, for proper contextualization, that contextual variables likely influenced our results and should be considered when evaluating their generalizability and external validity [130]. Despite meeting the requirements for statistical significance by using G*Power v.3.1.9.4 [75] – shown in the Materials and Methods Section, the sample was relatively small and drawn from a single Portuguese university's nursing program. This context remains crucial for interpreting our findings.

Also, participants were mostly women aged 18–22 (M = 18.4, SD = 0.939), born in Portugal, with little gaming experience (under 10 h weekly or none), and a dominant preference for goal-oriented player traits. Contextual and individual factors shape gamification outcomes [40,77,78,126,168]. Thus, these sociodemographic and behavioral details are important for interpreting results, as different contexts may yield different outcomes. Future studies should test this gamified platform in more diverse populations to examine the impact on participants with stronger social orientations.

Voluntary recruitment, while ethically and pedagogically necessary, improves validity and reliability in social research by increasing the likelihood of sincere responses and reducing the risk of misleading information often given by unwilling participants [169]. On the other hand, voluntary recruitment introduces non-participation bias [170]. Following Cochrane guidelines [71], this presents a risk of bias from deviations and missing data, as some participants withdrew or were absent on the intervention day. However, these deviations likely had little impact, as all participants had equal enrollment opportunities, and absences were evenly spread. Since university courses often track attendance and require participation [171], future studies should test individual and social gamification in compulsory courses, offering insights closer to real-world education than voluntary settings.

Gamification applies game elements to create playful learning experiences [172]. This study used points, the most common game element in education [14], for their simplicity and adaptability to social modes. Yet, gamification offers many design options [173,174]. A previous RCT using the same platform found that points, badges, and challenges combined improved undergraduate learning more than isolated elements or no gamification [24] offering ideas for adapting social modes. Social modes could also include other dynamics, such as direct player-versus-player (PVP) competition [175] or cooperative team roles with specific responsibilities [176]. Competition and cooperation can be blended to promote teamwork against external challenges [177]. Another variation, collaborative mode, replaces individual success with group goals, enabling shared annotations, ideas, and decisions [178]. This research focused on points, competition, and cooperation, but future studies should test different individual and social elements to find the most effective strategies. Indeed, our gamified digital learning platform was specifically designed to support both competitive and cooperative modes, enabling the investigation of potential combined effects of these social dynamics in educational contexts. However, due to sample size limitations, we chose to allocate participants into three groups only, rather than adding a fourth group. Introducing an additional condition would have significantly reduced the number of participants per group, potentially compromising statistical power. Therefore, we encourage future studies to explore the combined impact of competitive and cooperative dynamics – made possible through our gamified platform – on cognitive, emotional, and motivational outcomes in educational settings.

Webcam-based eye-tracking, though less precise, is scalable and cost-effective for adaptive online learning [179]. Similarly, webcam-based FER is a practical, low-cost alternative to manual analysis [85,180]. With a need for more objective measures of learning's cognitive, emotional, and motivational aspects [181], these methods help fill research gaps. However, their accuracy is limited, and future research could adopt advanced technologies. Infrared eye-tracking, though more precise, is expensive and confined to labs, limiting real-world use [39]. Additionally, emotional states can be assessed through neurophysiological methods such as electroencephalography (EEG), functional magnetic resonance imaging (fMRI), and transcranial magnetic stimulation (rTMS), offering greater precision [182,183]. Future work should explore these tools to enhance studies of social educational gamification.

Lastly, it is vital to consider moderating and mediating factors in gamified learning and gamification science theories, supporting our platform and protocol [5,18]. However, our sample size limited statistical power, reducing our ability to analyze social gamification across multiple outcomes with moderating and mediating factors. Future research should explore how participant characteristics (e.g., socio-demographics, gaming habits, player traits) moderate effects, and assess the mediating roles of cognitive engagement, visual attention, FER, and intrinsic motivation on learning. Examining moderation and mediation could offer deeper insights into how social gamification dynamics influence education.

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Ethics approval and Informed Consent

The study was conducted following the Ethics Committee of Universidade Católica Portuguesa (project 210 – 24/07/2024). Informed consent was obtained from all subjects involved in the study.

CRediT authorship contribution statement

Franz Coelho: Writing – original draft, Visualization, Software, Resources, Methodology, Investigation, Funding acquisition, Conceptualization. **Belén Rando:** Formal analysis, Data curation. **Rafael Bernardes:** Resources. **Patrícia Pontífice-Sousa:** Resources. **Daniel Gonçalves:** Writing – review & editing, Validation, Supervision, Project administration, Methodology, Conceptualization. **Ana Maria Abreu:** Writing – review & editing, Validation, Supervision, Resources, Project administration, Methodology, Funding acquisition, Conceptualization.

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Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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