The Role of Gamification in Learning Transfer: Does Early Skill Learning Predict Performance in Complex Tasks?

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Abstract: Gamification is widely employed in digital education to enhance engagement and motivation, yet its effectiveness in promoting cognitive skill transfer remains debated. This study investigated whether early learning efficiency in foundational levels (L1–L4) predicts performance in more complex tasks (L5–L8) within a physics-based educational game, and whether gamification moderates this transfer process. Ninety-four secondary school students were randomly assigned to either a gamified ($n = 49$) or standard ($n = 45$) training condition. Performance outcomes included overall efficiency, average points per attempt, and conceptual learning gains. Independent Welch's t-tests revealed no significant group differences across these metrics (all $p > .05$, $ds < 0.12$), suggesting a high degree of performance equivalence between the gamified and standard conditions. Regression analyses indicated that early learning efficiency significantly predicted later performance in Level 5 ($\beta = 0.611$, $p < .001$) and Level 7 ($\beta = 0.427$, $p = .017$), but not in Levels 6 and 8. A composite model across Levels 5–8 confirmed a generalized transfer effect ($\beta = 0.405$, $p = .002$, $R^2 = .10$), emphasizing the critical role of foundational skill acquisition in complex problem-solving. Gamification did not significantly moderate this overall transfer relationship. However, a notable exception emerged at Level 7: a significant interaction ($\beta = 0.762$, $p = .031$) suggested that gamification enhanced transfer under conditions of heightened conceptual complexity, likely by supporting adaptive learning processes. No significant trajectory effects were observed across successive levels, with participants maintaining relatively stable performance. Further analysis of foundational levels revealed that strategic variation and cognitive challenge in Levels 2, 3, and 4 contributed most strongly to later success, whereas simple introductory practice in Level 1 was insufficient. These findings indicate that while gamification alone does not universally improve learning transfer, it may selectively facilitate skill adaptation when learners face novel or disruptive challenges. The results highlight the importance of scaffolded instructional design, emphasizing task complexity and strategic engagement during early learning stages, and suggest that gamification should be deployed adaptively rather than uniformly to optimize educational outcomes.

Keywords: Gamification, Learning transfer, Skill acquisition, Cognitive flexibility, Educational psychology, Instructional design

1. Theoretical Framework

Foundations of Learning Transfer. The ability to transfer acquired skills and knowledge to novel contexts is regarded as a central challenge in education and cognitive science. In an increasingly complex and dynamic world, fostering learning transfer is critical for preparing learners not merely to perform routine tasks, but to adapt and innovate in unfamiliar situations.

Learning transfer, the process of applying knowledge or skills acquired in one context to new, often more complex situations, is widely recognized as a core objective of education. The foundational work of Perkins and Salomon (1987, 1988, 1989, 2012) distinguishes between near transfer and far transfer, based on the degree of similarity between learning and application contexts. Near transfer involves the effortless application of well-practiced skills in similar environments through "low-road transfer," relying on extensive practice and automaticity. Far transfer, by contrast, requires conscious abstraction and recontextualization, termed "high-road transfer," and demands metacognitive reflection, cognitive flexibility, and the active construction of connections between prior learning and novel situations (Salomon & Perkins, 1987; Perkins & Salomon, 1989).

Perkins and Salomon's detect–elect–connect model (2012) further refines the understanding of high-road transfer as a deliberate cognitive process, emphasizing the learner's active role in detecting potential applicability, electing to engage prior knowledge, and connecting it meaningfully to new tasks. Critically, transfer is not a guaranteed consequence of learning but a complex phenomenon requiring intentional educational design. To foster transfer, Perkins and Salomon (1988) propose two complementary strategies: hugging, designing learning experiences closely aligned with real-world applications to support low-road transfer; and bridging, encouraging learners to reflect on the generalizability of their knowledge, thus supporting high-road transfer.

Game-Based Learning and Cognitive Development. Building on these theoretical foundations, recent research has increasingly highlighted game-based learning (GBL) as a powerful medium for promoting cognitive development and transfer. Games offer dynamic environments for feedback, exploration, and simulation, each serving critical roles in facilitating deeper learning. Feedback loops, as identified by Garris et al. (2002), provide immediate and informative responses to learner actions, sustaining engagement and promoting refinement of understanding. Hamari et al. (2016) further confirmed that the perceived challenge inherent in GBL environments significantly predicts learning outcomes, mediated through heightened cognitive engagement.

The exploratory nature of games supports active meaning-making. Gee (2007) emphasized that well-designed games encourage players to navigate complex systems, fostering systems thinking and conceptual understanding. Simulation-based learning extends these benefits by offering risk-free environments in which theoretical knowledge can be applied to realistic problems (Kumar & Sherwood, 2007). Recent findings by Sounthornwiboon et al. (2025) demonstrated that simulation games not only improved conceptual learning but also enhanced cognitive processing skills, including problem-solving and decision-making.

Empirical evidence from Ke et al. (2016) and Pratama and Setyaningrum (2018) illustrates that game-based learning can scaffold the progression from affective engagement (curiosity and challenge) to deep cognitive engagement (strategic thinking and conceptual understanding), ultimately supporting critical thinking and reflective learning processes. GBL environments thus provide fertile grounds for promoting the kind of metacognitive activity necessary for high-road transfer.

Gamification, Motivation, and Cognitive Load. While game-based learning and gamification share common elements, gamification specifically refers to the integration of game mechanics in non-game contexts to enhance engagement (Deterding et al., 2011). Underpinned by Self-Determination Theory (SDT) (Ryan & Deci, 2000), effective gamification aims to fulfill basic psychological needs for autonomy, competence, and relatedness. Empirical studies demonstrate that choice-driven mechanics (Luarn et al., 2023), adaptive feedback systems (Sailer et al., 2017), and social interaction features (Kam & Umar, 2018) align gamified environments with these motivational needs, thereby fostering intrinsic motivation and deeper engagement.

A comprehensive review by Ortiz-Rojas, Chiluiza, and Valcke (2017) supports these findings, identifying consistent short-term engagement effects across diverse gamified learning environments, though with mixed results for long-term performance improvements.

Nevertheless, empirical findings underscore that the impact of gamification is highly context-dependent. Domínguez et al. (2013) and Hanus and Fox (2015) reported that while gamification initially enhanced engagement, overemphasis on external rewards, such as points and badges, eventually led to frustration, distraction, and diminished intrinsic motivation. Similarly, Fung et al. (2024) highlighted that gamification tends to be more effective in structured STEM contexts but can be counterproductive in informal learning environments.

Further complicating the picture, Deci et al. (1999) found that extrinsic rewards tied to performance can undermine intrinsic motivation, reinforcing the need for carefully balanced gamification designs that prioritize psychological meaningfulness over superficial incentives. Kam and Umar (2018) additionally warned that excessive gamification elements could increase extraneous cognitive load, particularly in cognitively demanding domains like STEM, thereby hindering rather than helping learning.

Conditions Supporting Gamified Learning Transfer. Recent research identifies specific conditions under which gamification can successfully support learning transfer. Chen et al. (2022) demonstrated that gamified flipped learning environments, when carefully aligned with meaningful learning tasks, can optimize cognitive load management by reducing extraneous distractions and enhancing intrinsic engagement. Similarly, Baah et al. (2024) confirmed that gamified courses designed with clear instructions and immediate feedback effectively minimized cognitive distractions, fostering greater cognitive investment and engagement.

Meta-analyses further support these findings. Wouters, van Oostendorp, and van der Spek (2013) found that serious games promote both near and far transfer when design features such as feedback, scaffolding, and reflective activities are embedded. They emphasize the importance of contextual alignment, where game environments closely mirror real-world application settings, to facilitate "hugging" transfer. Mayer (2019) complements this perspective, applying the Cognitive Theory of Multimedia Learning (CTML) to highlight the role of coherence, signaling, and spatial contiguity in minimizing cognitive overload and enhancing generative processing, both critical for successful transfer.

Both Wouters et al. and Mayer converge on the principle that feedback loops, cognitive load management, and contextual or conceptual alignment are central mechanisms mediating the relationship between gamification and learning transfer. Poorly designed systems that violate these principles risk cognitive overload and motivational decline, ultimately hindering the very learning outcomes gamification seeks to promote (Mayer, 2019).

Summary. In sum, the literature demonstrates that gamification and game-based learning can substantially support learning transfer when grounded in cognitive, motivational, and instructional principles. Alignment with SDT needs, careful cognitive load management, provision of feedback and reflection opportunities, and contextual relevance emerge as critical design imperatives. Conversely, gamification that relies excessively on extrinsic incentives or adds cognitive complexity without pedagogical justification can impair both motivation and transfer. Building on the frameworks articulated by Perkins and Salomon, and drawing on empirical insights from Wouters, Mayer, Chen, Baah, Ortiz, and others, the present study investigates the extent to which early learning efficiency in gamified foundational tasks predicts successful performance in more complex transfer tasks, and explores the moderating role of gamification design quality.

2. Methods

Participants. The research data presented in this study was collected through direct recruitment of school classes, despite the app being publicly available. This approach allowed for (a) greater control over session conditions and (b) increased commitment to completing the pre- and post-tests. Each participating class received an incentive of 300 CHF for the class fund to encourage full participation. In total, 170 secondary school students from nine classes initially took part in the study. The sample included 71 male and 73 female students, with 26 not specifying gender. Grade levels ranged from 6th to 9th grade: 10 students from 6th grade, 25 from 7th grade, 76 from 8th grade, and 34 from 9th grade, with 25 not indicating grade level. The average age was 13.66 years (SD = 0.79; range = 11–16).For the present analyses, only students who completed both the pre- and post-test assessments and full gameplay data were included. This resulted in a final sample of 94 students (mean age = 13.48 years, SD = 1.01), with 55.2% identifying as female (n = 48), 41.4% as male (n = 36), and 3.4% as diverse (n = 3). Group assignment was randomized, resulting in 49 participants in the gamified condition and 45 in the standard condition. No group assignment data was missing.

Study Design. The study employed a between-subjects design to investigate whether early learning efficiency in a digital physics-based game predicts later performance on complex tasks, and whether gamification moderates this transfer. Participants were randomly assigned to either the gamified or standard condition, ensuring equivalence in group characteristics.

Physics comprehension was measured using quizzes administered before and after the learning sessions. In contrast to earlier iterations of the learning environment, no motivation questionnaire was employed in this study, focusing the analyses exclusively on cognitive learning outcomes.

Digital Learning Environment: Basketball Physics Challenge. The learning environment was a web-based educational game called *Basketball Physics Challenge*, developed using HTML5, CSS, and JavaScript, with backend logging via PHP and mySQL. To ensure privacy compliance, no cookies were used. The game ran on desktop and mobile devices, ensuring usability for school learners.

The game simulated a basketball shooting task in which players used a virtual cannon to adjust physical parameters (e.g., angle, initial velocity) in order to shoot a ball through a basket. Across successive levels, players encountered increasingly complex environmental manipulations requiring deeper engagement with physical principles such as force, motion, and trajectory.

Two versions of the game were developed:

- The **gamified version** featured points systems, timers, visual progress indicators, and playful graphical elements designed to foster motivation and engagement.
- The **standard version** presented identical physics tasks but without additional gamification elements, emphasizing clarity and cognitive focus without external incentives.

Both versions shared the same core physics content and task structure, allowing direct comparison of the effects of gamification on learning outcomes.

Figure 1: Level 7 (magnetism). Left: gamified version. Right: standard version. Level with strongest gamification effect

Level Structure and Cognitive Progression. The game included eight sequential levels that scaffolded learning from basic procedural skills to complex adaptive tasks:

- **Foundational levels (L1–L4):** These initial levels emphasized isolated control of motor-physics parameters. Level 1 served as a basic motor warm-up focusing on simple shooting mechanics. Levels 2 to 4 introduced systematic variation: Level 2 altered launch heights, Level 3 constrained launch angles (fixed 30°), and Level 4 required adaptation to steeper angles (fixed 60°). These foundational levels aimed to build procedural fluency and strategic flexibility.
- **Complex levels (L5–L8):** The later levels integrated previously isolated skills under novel or conceptually demanding conditions. Level 5 required the simultaneous adjustment of angle and speed. Level 6 introduced reduced gravity conditions simulating lunar environments. Level 7 incorporated magnetic field interference selectively affecting iron projectiles. Level 8 presented underwater physics, altering ball dynamics through fluid resistance.

The level design was grounded in a competency model derived from international curricula, particularly referencing the Swiss *Lehrplan 21* (NT.5.1.3.b). This ensured that the cognitive progression aligned with educational standards on force and motion, focusing on the development of transferable problem-solving skills.

Learning Task and Quiz Structure. Learning outcomes were assessed using an 8-item multiple-choice physics quiz administered both before and after the gameplay sessions. The quiz was specifically developed for this study to evaluate not only factual knowledge but also deeper conceptual understanding and the prevalence of persistent misconceptions in fundamental physics domains.

Each item addressed a key concept that is frequently misunderstood by learners, including initial velocity, motion and trajectory, throwing angles, gravitational effects, friction and air resistance, as well as material-dependent forces in magnetic and fluid environments. Correct answers contributed one point each toward a composite physics comprehension score, with no penalties for incorrect responses. The total score thus ranged from 0 to 8 points.

The quiz design was informed by cognitive science research on common misconceptions in physics learning, drawing upon frameworks such as those developed by McDermott and Redish (1999) and the PISA science literacy standards. Special emphasis was placed on constructing distractors that represented scientifically plausible but incorrect reasoning, allowing for a more precise identification of conceptual errors related to force dynamics, motion, environmental resistance, and material interactions.

By integrating both straightforward factual recall and diagnostic misconception targeting, the quiz provided a robust measure of participants' conceptual grasp and the extent to which gameplay interventions facilitated the correction of misunderstandings.

Data Collection and Performance Metrics. In-game performance metrics—including successful hits, total attempts, time to completion, and accumulated points (where applicable)— were automatically logged by the backend system. These behavioral data allowed for detailed analyses of learning efficiency and task mastery. Statistical analyses focused on four main aspects: First, Welch's t-tests were used to compare learning outcomes between the gamified and standard conditions. Second, linear regression models examined the predictive relationship between foundational learning efficiency and later performance in complex tasks. Third, interaction terms were included to test whether gamification moderated this transfer effect. Finally, linear mixed-effects models were employed to assess performance trajectories across levels. All tests were two-tailed with an alpha level of 0.05.

3. Results

Learning Outcomes Across Groups. To examine differences between the gamified and standard training conditions, independent Welch's t-tests were conducted on three primary outcome measures: overall gameplay efficiency (Levels 1–8), average points per attempt, and quiz learning gains. Across all measures, no statistically significant group differences were observed. Participants in the gamified group ($M = 0.439$, $SD = 0.123$) and the standard group ($M = 0.440$, $SD = 0.149$) achieved nearly identical efficiency scores, $t(85.68) = –0.05$, $p = .962$, with a negligible effect size ($d = –0.01$, 95% CI [–0.42, 0.40]). Similarly, no significant differences were found for average points per attempt, $t(85.47) = –0.58$, $p = .565$, $d = –0.12$, or for quiz learning gains, $t(87.89) = 0.52$, $p = .606$, $d = 0.11$. These results suggest a high degree of performance equivalence between the two instructional conditions.

Generalized Transfer from Foundational to Complex Tasks. To assess generalized skill transfer, a composite score representing complex task performance (Levels 5–8) was regressed on early foundational efficiency (Basis_Effizienz, averaged across Levels 1–4). The analysis revealed a statistically significant positive relationship, $F(1, 92) = 10.52$, $p = .0016$, $R^2 = .10$, $\beta = 0.405$, indicating that higher early efficiency was associated with better subsequent complex task performance. When instructional condition (gamified vs. standard) and its interaction with foundational efficiency were added to the model, the overall model remained significant, $F(3, 90) = 4.39$, $p = .0062$. However, neither the interaction effect ($\beta = 0.391$, $p = .121$) nor the main effect of foundational efficiency ($\beta = 0.202$, $p = .266$) remained individually significant, suggesting that the transfer effect occurred similarly across both groups.

Level-Specific Transfer Patterns. Further regression analyses were conducted separately for each complex task level. Foundational efficiency significantly predicted performance in Level 5, $F(1, 92) = 16.85$, $p < .001$, $R^2 \approx 0.155$, $\beta = 0.611$, and in Level 7, $F(1, 92) = 5.86$, $p = .017$, $R^2 \approx 0.06$, $\beta = 0.427$. No significant predictive relationships were found for Level 6 ($F(1, 92) = 1.20$, $p = .276$) or Level 8 ($F(1, 92) = 1.44$, $p = .234$). Moderation analyses revealed that gamification significantly enhanced the transfer relationship at Level 7 ($\beta = 0.762$, $p = .031$), while no significant moderation effects were observed for Levels 5, 6, or 8. This suggests that gamification may support skill adaptation particularly under conditions of increased conceptual complexity.

Efficiency Trajectories Across Levels. To explore the progression of learning efficiency across the eight game levels, a linear mixed-effects model was fitted with Level (1–8), Group (Gamified vs. Standard), and their interaction as fixed effects. No significant main effect of Level ($\beta = –0.0036$, $SE = 0.0057$, $t = –0.64$) or Group ($\beta = 0.0373$, $SE = 0.0463$, $t = 0.81$) was found, nor a significant Level × Group interaction ($\beta = –0.0080$, $SE = 0.0082$, $t = –0.98$).

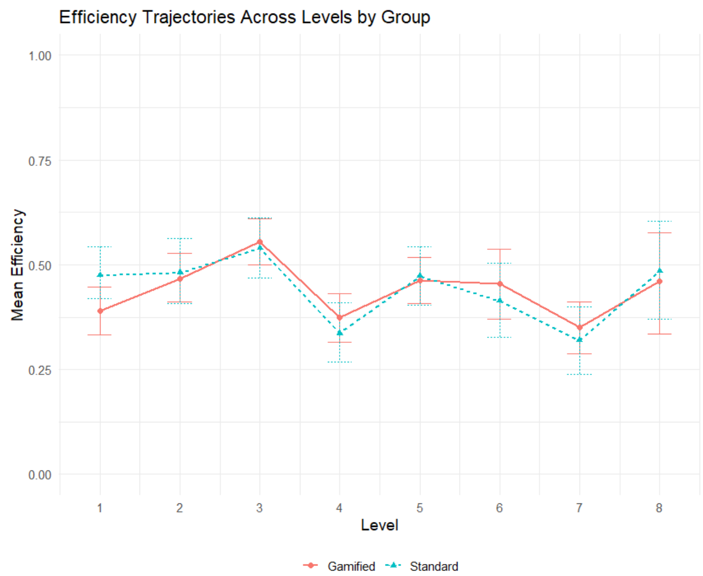

Figure 1: Efficiency trajectories across game levels for both groups

As shown in Figure 1, both groups demonstrated relatively stable levels of efficiency across the sequence of game levels. No significant upward or downward trend was identified. This finding indicates that neither instructional condition engendered differential learning curves across the progression of complexity.

Contributions of Individual Foundational Levels. Finally, a multiple linear regression model assessed the differentiated contributions of efficiencies in foundational Levels 1–4 to overall complex task performance (Levels 5–8). The model revealed an excellent fit, $F(4, 90) = 10{,}340$, $p < .001$, Adjusted $R^2 = 0.998$. Levels 2, 3, and 4 contributed significantly to later success (L2_effizienz: $\beta = 0.233$, $p = .010$; L3_effizienz: $\beta = 0.282$, $p < .001$; L4_effizienz: $\beta = 0.281$, $p = .003$), while Level 1 efficiency did not ($\beta = 0.145$, $p = .161$). These findings suggest that strategic complexity and task variation during foundational training were crucial in promoting transfer to more complex challenges.

4. Discussion

This study investigated whether early learning efficiency in foundational game levels (L1–L4) predicts performance in subsequent complex challenges (L5–L8), and whether gamification moderates this transfer process. The results offer differentiated insights into mechanisms of skill acquisition, transfer, and the conditional role of gamified instructional design.

First, analyses revealed no significant differences between the gamified and standard groups across overall gameplay efficiency, average points per attempt, or quiz learning gains. These findings confirm that, despite its motivational appeal, gamification did not inherently enhance learning outcomes relative to a standard training condition. This aligns with previous critiques suggesting that gamification, when implemented superficially, may increase engagement without necessarily improving cognitive outcomes (Domínguez et al., 2013; Hanus & Fox, 2015).

However, closer examination of transfer processes revealed that early learning efficiency robustly predicted later complex task performance, particularly for Levels 5 and 7. In Level 5, which required the integration of angle and speed control, early proficiency in foundational tasks significantly supported learners' ability to generalize isolated physics principles under increased task demands. Similarly, Level 7, introducing a magnetic field that altered material behavior, exhibited a significant predictive relationship, but with an important addition: the relationship between early learning efficiency and later performance was significantly stronger for gamified learners. This suggests that gamification may contribute positively when learners face novel, disruptive conditions that demand cognitive flexibility. Gamified environments might have supported exploratory learning strategies or sustained attention.

However, the absence of a consistent gamification effect across all complex tasks suggests that gamification alone may not sufficiently scaffold the cognitive processes required for more routine or procedurally similar tasks. Where task demands do not fundamentally disrupt established strategies, intrinsic motivation and existing skill schemas may suffice, rendering additional motivational scaffolds less impactful.

In contrast, no significant predictive relationships were found for Levels 6 and 8, which introduced substantial environmental deviations such as reduced gravity and underwater physics. The absence of transfer in these tasks suggests that procedural skills acquired in the foundational stages were insufficient when the environmental context diverged substantially from initial learning conditions. This observation is consistent with theories of far transfer (Perkins & Salomon, 1992), which posit that applying knowledge to dissimilar contexts demands deliberate abstraction and reasoning, processes that were not explicitly scaffolded within the present training design.

The linear mixed-effects analysis of efficiency trajectories further corroborated the stability of performance across the eight levels. Neither a main effect of level nor group was detected, nor an interaction between the two. This suggests that participants, after an initial phase of skill acquisition, reached a performance plateau that persisted. Such stability may reflect early mastery of core mechanics without substantial cognitive elaboration.

Further analysis of the contributions of individual foundational levels revealed important nuances. Efficiencies in Levels 2, 3, and 4 emerged as significant predictors of later complex performance, whereas Level 1, a basic introductory exercise, did not. This pattern underscores the critical importance of practice quality. Foundational tasks that introduced strategic variations and constraints—such as adjustments in launch height and constrained angle modulation—fostered stronger skill transfer than simple repetition. The observed effects support the theoretical distinction between low-road and high-road transfer mechanisms proposed by Perkins and Salomon (1992), highlighting that task variability, complexity, and cognitive engagement are necessary conditions for promoting the abstraction and flexible application of learned skills.

The differentiated contributions of foundational levels emphasize that effective transfer is not merely a function of exposure but depends on strategically designed early experiences. Levels 2–4, through structured variation and cognitive challenge, scaffolded strategic thinking processes necessary for both near transfer, as evidenced in Level 5, and more flexible adaptation under novel conditions, as evidenced in Level 7.

Taken together, these findings illustrate that gamification, while not universally beneficial, may enhance transfer when learners encounter tasks that require adaptation rather than routine application. Gamification's potential thus appears to be context-dependent, emerging particularly in situations where learners face conceptual disruptions that challenge their existing skillsets.

From an instructional design perspective, these findings suggest that gamification should be used selectively in learning environments where adaptive reasoning and transfer are explicitly targeted. Educators and developers should combine gamified elements with scaffolded challenges and reflective prompts to optimize engagement and skill generalization.

This study contributes to growing evidence that early-stage learning quality—not mere exposure—is key to complex task performance. It highlights the need for instructional designs that go beyond shallow engagement and promote cognitively rich experiences. While gamification can support learners under specific cognitive demands, its blanket use is unlikely to yield consistent benefits. These results call for rethinking gamification strategies: rather than relying on universal engagement mechanics, future implementations should respond to task complexity and learner needs. The study thus offers empirical insights and practical guidance for the targeted, evidence-based integration of gamification into digital learning environments.

Implications for Instructional Design. The present findings carry important implications for the instructional design of game-based learning environments. First, the results suggest that not all forms of practice are equally effective in promoting transfer. Foundational experiences must be designed to incrementally build complexity and foster cognitive engagement rather than merely facilitating rote repetition. Strategic task variation, involving constraints and decision-making demands, appears essential for developing flexible, transferable competencies.

Moreover, while gamification did not consistently enhance performance across all tasks, it demonstrated a supportive effect under conditions of heightened cognitive load and task novelty. Thus, gamification elements should not be uniformly applied but rather targeted selectively to scaffold learner motivation and adaptation when instructional challenges intensify. This suggests that adaptive gamification strategies—responsive to learner needs and task characteristics—may be more effective than static designs.

Limitations and Future Research. Several limitations of this study should be acknowledged. The sample size, while sufficient for detecting medium-sized effects, limits the generalizability of the findings. Additionally, transfer was assessed in a near-immediate timeframe, precluding conclusions about the durability of learning over longer periods. The study also focused exclusively on a physics-based game environment, which may limit applicability to other knowledge domains.

Future research should address these limitations by investigating longitudinal transfer trajectories in gamified and non-gamified contexts, exploring adaptive gamification designs that adjust challenge dynamically based on learner performance, and systematically examining mechanisms for fostering high-road transfer through explicit abstraction, reflection, and metacognitive scaffolding.

Ethics declaration*:* This study was conducted in accordance with institutional and national ethical guidelines. Formal ethical approval was not required, as the research involved non-invasive educational interventions within school settings. Informed consent was obtained from all participants and their legal guardians. Participation was voluntary, and all data were anonymised prior to analysis.

AI declaration*:* AI tools (ChatGPT, OpenAI) were used to support academic editing, linguistic refinement, and formatting assistance during the preparation of this manuscript. The authors reviewed and verified all content to ensure scientific accuracy and originality. No AI-generated content was accepted without human oversight or critical assessment.

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