Developing ACT-R Model for Key Concept Recall in a Multilayered K-12 Educational Game

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Abstract: Educational games, while widely used to enhance engagement and motivation, often struggle to balance instructional content with compelling gameplay. Although integrating learning and gameplay within a unified structure is theoretically effective, it presents practical challenges in achieving both high engagement and instructional impact. To address this, the current study introduces an intertwined Multilayered Educational Game – Computer-based Framework (iMEG C-Framework) and an ACT-R cognitive model to simulate the recall process. These models will be evaluated across three instructional conditions (Traditional Learning, Classic Educational Game, and iMEG) targeting K–12 students in both short- and long-term memory tasks. Cognitive modeling is particularly valuable in K–12 contexts where large-scale studies are often difficult. The iMEG framework separates game mechanics, instructional content, and feedback to create a more adaptive and organized learning experience. ACT-R modeling supports analysis of how students encode, store, and retrieve key concepts, enabling real-time adaptive feedback and instructional refinement. A within-subjects experiment will be conducted with 39 seventh-grade students across three counterbalanced conditions, each involving a 75-minute session on board game design, followed by retention assessments one and seven days later. By combining experimental data with ACT-R modeling, this study explores predictive capabilities and the impact of different game-based learning structures on student trajectories, contributing to the design of motivation-driven learning environments in K–12 education.

Keywords: ACT-R modelling, Game-Based learning, Motivation-Based learning, K-12 learning environments

1. Introduction

Over the past two decades, game-based learning has gained recognition as a strategy to enhance motivation, engagement, and learning outcomes in K–12 education (Boyle et al., 2016). Well-designed games can foster deeper understanding and persistence, especially among students who struggle in traditional settings (Plass et al., 2015). However, many still fail to produce measurable academic gains. A key issue is the blending of entertainment and instructional goals, which can lead to cognitive overload or superficial engagement (Parthasarathy & Mittal, 2023). This is further complicated by a disconnect between educators and designers. Educators may lack technical skills to build interactive systems, while developers may lack pedagogical knowledge (Roungas, 2015). As a result, many games remain ineffective or impractical for classroom use.

To be more specific about the learning processes involved in game-based learning, it is important to recognize that understanding how games influence memory requires more than a surface-level examination of engagement or enjoyment; it involves analysing the structural elements that shape cognitive processing (Mayer, 2019). From educational games designed to enhance learning outcomes (Clark et al., 2016), to non-educational games that foster incidental memory gains (Bavelier & Green, 2019), and gamified systems that overlay game-like features onto instruction (Deterding et al., 2011), each environment engages memory through distinct mechanisms. Research shows that memory-based educational games support vocabulary learning and retention using techniques like visual cues, mnemonics, and pattern recognition. Evidence includes improved recall through card games (Razali et al., 2017), long-term memory gains from digital mnemonic tasks (Heidari et al., 2023), and vocabulary development through games like Scrabble and memory grids (Halpern & Wai, 2007; Sivakumar, 2022). Collectively, these findings highlight the potential of such games to strengthen encoding, retrieval, and long-term retention (Fung & Oyibo, 2024).

While these games offer strong learning potential, merging gameplay with instructional content remains challenging. According to Self-Determination Theory, this integration can increase intrinsic motivation and engagement (Cook & Artino, 2016), but developing unified games often demands significant time and resources, limiting scalability (Christopoulos, 2023). Moreover, such games are typically designed for specific subjects, restricting their broader applicability despite demonstrated effectiveness (Young et al., 2012).

Building on these insights, this study introduces an ACT-R modeling approach within the iMEG C-Framework to examine how separating gameplay, instruction, and feedback into distinct layers affects learning. The framework can enhance instructional clarity and cognitive efficiency, while the ACT-R model simulates encoding, retrieval, and decay to provide real-time insights into memory. Together, they enable dynamic personalization and promote collaboration across education, design, and learning science.

This study addresses two central research questions:

RQ1- How does the iMEG C-Framework compare to traditional and classic game-based designs in supporting memory encoding and retrieval?

RQ2- To what extent can the ACT-R model accurately predict learners' memory performance across different educational game structures?

2. Theoretical Background: ACT-R Model

ACT-R modeling (Anderson & Lebiere, 2014) forms the core theoretical framework of this study, simulating key cognitive processes such as memory encoding, retrieval, and decision-making. Using real-time learner data, it enables adaptive feedback and iterative refinement of instructional strategies to better match individual learning trajectories. The model tracks how memory strength changes with repeated exposure and how retrieval probability varies over time. Each game mechanic and its examples are represented as memory chunks, with activation levels computed using ACT-R's standard equations.

$$m = \ln\left(\sum_{i=1}^{n}\left(t_i^{-d_i}\right)\right) \tag{1}$$

where m is the memory activation, t_i represents the time since the *i*-th encoding event, and d_i denotes the decay rate specific to each encoding. The decay rate following each encoding is modeled dynamically as a function of prior activation, following the equation:

$$d_i = a + c \times m_{i-1} \tag{2}$$

where a is a baseline decay constant, c is a scaling parameter controlling how decay changes with prior memory strength, and m_{i-1} represents the activation before the *i*-th exposure. The probability of successful retrieval at any testing point is modeled using a logistic retrieval function:

$$p_r = \frac{1}{1 + e^{\frac{\tau - m}{s}}} \tag{3}$$

where P_r is the probability of retrieval, τ is the retrieval threshold, and s is the noise parameter reflecting individual variability in retrieval success. Currently, the model is theoretical, with no simulations or fitted parameters. After the experiment, it will be implemented in ACT-R to calibrate based on data and assess how different instructional conditions impact short- and long-term memory retention, as well as how the model can capture these effects.

3. Experiment Design

All instructional content and game-based materials in this study were developed using Articulate Storyline (version 3.20) to ensure consistency and interactivity across conditions. Each learning condition—Traditional, Classic Educational Game, and iMEG—was implemented as a standalone module. The study includes 39 seventh-grade students (balanced by gender) from private middle schools, randomly assigned to one of the three conditions using a between-subjects design. The experiment consists of three main phases: a pretest phase, a learning (encoding) phase, and a posttest (retrieval) phase. In the pretest phase, all participants complete a 15-item multiple-choice test to assess prior knowledge of board game mechanics. In the learning phase, each group receives a different instructional intervention based on their assigned condition. Finally, in the retrieval phase, participants complete two post-tests: one 15-item test administered 24 hours after the learning session to measure short-term retention, and another identical test given seven days later to assess long-term memory. This design enables comparisons of learning effectiveness across instructional formats and time intervals.

3.1 Traditional Condition Design

In the traditional learning condition, participants begin with an initial study phase (Exposure 1) by reviewing slides that define ten game mechanics, each paired with three illustrated examples, spending one minute per slide to support encoding. In the second phase (Exposure 2), they complete a 15-item multiple-choice quiz within 10 minutes, receiving 10-second corrective feedback for incorrect answers and retaining access to definitions throughout. This is followed by two more sets of 8 multiple-choice questions (3 minutes each), during which no definitions are available, encouraging retrieval practice without support. After each quiz, unresolved questions and correct answers are shown for feedback.

Figure 1: Sample image from Exposure 1, used across all three conditions

3.2 Classic Educational Game Condition Design

In the classic educational game condition, participants begin with the same initial study phase (Exposure 1) as in the traditional condition, reviewing slides on ten game mechanics and examples for one minute each. In Exposure 2, they complete three rounds of a memory-based matching game. The first round (Blitz Race) is a 10-minute 5×6 Match Pairs game with access to definitions and examples (Figure 2, left) with retaining access to definitions throughout. The second and third rounds (Bullet Races) use a 4×4 grid with 3-minute limits and no access to definitions, promoting retrieval-based learning. After each round, unresolved pairs and correct answers are shown for feedback.

3.3 iMEG Condition Design

In the iMEG condition, participants begin with the same initial study phase (Exposure 1) as the other groups, reviewing slides on ten board game mechanics with three examples each, spending one minute per slide. In the second phase (Exposure 2), participants will engage in three rounds of memory-based matching games, like the classic design (Section 3.2), but using a neutral theme, matching animals to their corresponding foods, instead of board game mechanics (Figure 2, right). At the start of each round, participants will be given three initial attempt opportunities to match pairs. To earn additional attempt opportunities, two for each correct answer, participants must answer a multiple-choice question (timer will pause during responding) similar to those used in the traditional condition. If a participant answers incorrectly, the correct answer will be displayed for five seconds before they return to the matching task. This structure is designed to separate the gameplay experience from the instructional content.

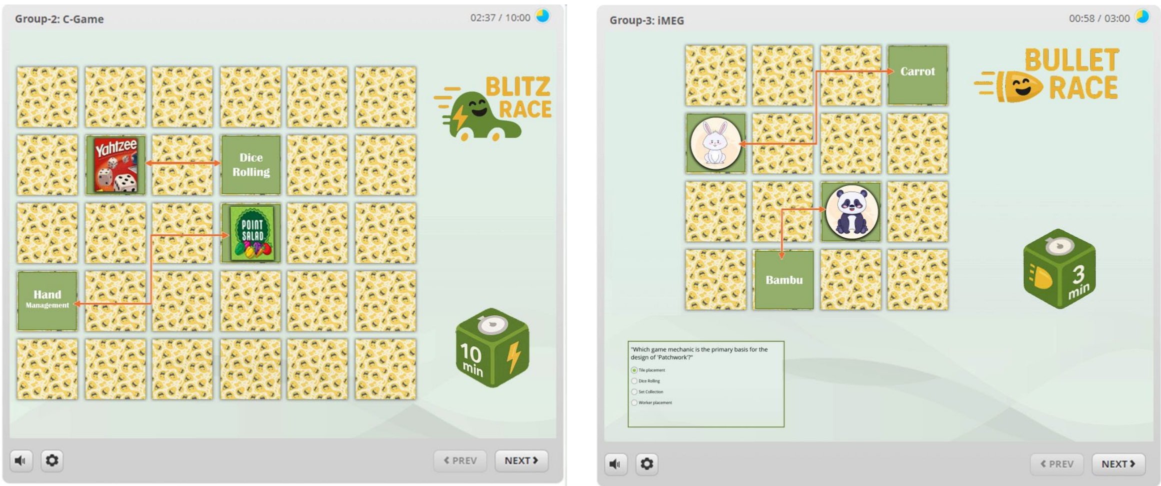

Figure 2: Blitz section of Classic Game Design (left) and Bullet section of iMEG Framework Design (Right)

3.4 Mapping Experimental Design to ACT-R Model

To bridge the experimental design with computational modeling, Figure 3 presents the conceptual flow of the ACT-R based memory model underlying this study. The diagram maps how participants move from initial study exposure to multiple phases of practice, with corresponding updates in memory activation after each learning event. Following the learning phases, memory decay is applied over one- and seven-day intervals to simulate the natural forgetting process, and retrieval probability is predicted based on the resulting activation values.

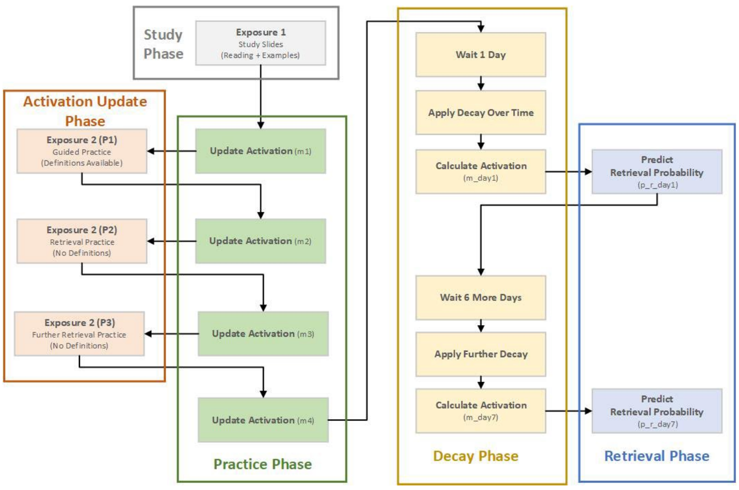

Figure 3: Conceptual flow of the ACT-R memory model showing exposure, activation updates, decay over time, and retrieval prediction

4. Conclusion

This study introduces a novel approach to understanding memory processes in educational game environments by integrating the ACT-R cognitive architecture with the iMEG C-Framework. By structurally separating gameplay, instruction, and feedback, the iMEG framework aims to reduce cognitive load and promote more effective memory encoding and retrieval. The use of ACT-R modeling enables simulation and prediction of learners' cognitive performance, offering a foundation for adaptive learning design. Together, these contributions represent a step toward more theoretically grounded and scalable educational game development for K–12 learners.

5. Future Work and Limitations

While the proposed framework and model are promising, this study remains in the implementation and validation phase. No formal simulation results are currently available, and model parameters have not yet been empirically calibrated. Future work will involve analyzing the experimental data from the three instructional conditions to fit and validate the ACT-R model. Additionally, the generalizability of findings is limited by the specific subject matter and grade level (seventh-grade students). Expanding the framework to different content areas and learner populations, as well as exploring affective and motivational variables through extended modeling, are important directions for future research.

Ethics Declaration: This study involved the design and evaluation of instructional materials for seventh-grade students using de-identified, anonymized procedures and did not collect any personal or sensitive data. As such, formal ethical clearance was not required. The research was conducted in accordance with institutional guidelines for educational research with minors.

AI Declaration: During the preparation of this manuscript, the authors used GPT-4 for grammar and clarity checks. No content was generated by the AI tool beyond surface-level editorial suggestions. All substantive content, analysis, and interpretations were developed by the authors, who take full responsibility for the final work.

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