International Journal of Serious Games

ISSN: 2384-8766
https://journal.seriousgamessociety.org/

Article

Investigating the Effects of Feedback Modality on Sustained Attention and Performance in a Serious Game, A Pilot Study

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Keywords:

Sustained attention
Serious games
Feedback control system
Auditory feedback
Tactile feedback
Visual feedback

Received: December 2024
Accepted: August 2025
Published: October 2025
DOI: 10.17083/88v16n77

Abstract

Research has shown that serious games can improve cognitive functions, particularly attention. Feedback, a key component in serious games, is typically delivered through various modalities such as auditory, visual, and tactile channels. This study investigates how different feedback modalities (auditory, visual, and tactile) affect sustained attention during a 12-session training period in a sample of 19 participants. A custom-built Android car racing game was used to test four groups: auditory feedback, visual feedback, tactile feedback, and a control group with no feedback. We analysed participants' sustained attention through correct responses and errors, using both statistical methods and the Hidden Markov Model (HMM) to track behavioural patterns. While the three feedback, groups showed no significant differences in correct responses, the auditory feedback group made the fewest errors, while the visual and tactile groups showed the most improvement over time in error reduction. HMM results suggested that feedback modalities did not significantly influence path choices between target and non-target cars but did affect the precision of those decisions. These findings highlight the potential of feedback in serious games to improve sustained attention, addressing a gap in the literature and offering insights for future cognitive training interventions.

1. Introduction

The effectiveness of computer games in enhancing cognitive functions, particularly in areas like attention, relies on various factors such as design elements, interactivity, and user engagement [1]. These features become even more critical when used for rehabilitation or cognitive enhancement, especially for improving attention [2] [3]. Attention, the ability to allocate mental resources efficiently, is a fundamental cognitive process studied extensively in neuroscience and psychology [4]. It plays a key role in managing awareness, vigilance, and executive control and is essential for maintaining focus on relevant information while filtering out distractions [5] [6].

One promising approach for enhancing attention is through serious games, which are games designed not just for entertainment but for educational or rehabilitative purposes [7] [8]. These games simulate real-world scenarios and allow players to engage in activities where they can interactively apply and practice skills. Such environments provide unique opportunities to explore how sustained attention impacts how people process relevant and irrelevant information [9] [10]. Additionally, serious game adaptive learning systems can be tailored to individual learning needs, making them effective tools for cognitive enhancement [11].

A crucial element in serious games is feedback, which guides users' actions and performance through various responses [12]. Feedback is typically categorised based on the sensory modality it uses: auditory, visual, or tactile [13]. Each feedback type has its characteristics, tactile feedback, for example, is less detailed but less disruptive than visual or auditory feedback, which may offer more information but can interrupt user focus [14] [15]. Understanding the delivery mode of feedback messages is essential, as it can influence how effectively users engage with the game and process information [16] [17].

Research has mostly focused on comparing auditory and visual feedback in serious games, often finding that while more disruptive, visual feedback tends to be more effective in fostering understanding and self-regulation [18] [19]. To understand how different feedback modalities impact cognitive engagement, we reviewed prior studies focusing on auditory, visual, and tactile feedback in serious games. This review emphasised peer-reviewed literature examining the suitability of feedback modalities for tasks needing sustained attention, providing a basis for our investigation. However, studies have been inconclusive about the ideal balance between these modalities, particularly regarding their long-term effects during extended training periods [20]. There's also a gap in research on how all three feedback modalities, auditory, visual, and tactile, affect performance in serious games. Previous studies have not fully explored whether feedback helps increase correct responses or decreases errors over time or how it interacts with the duration of training [21].

The choice of a racing game as the focus of this study is particularly relevant due to its ability to simulate real-world scenarios that require rapid decision-making and attentional control. Racing games demand high levels of cognitive engagement, as players must process multiple stimuli while managing their speed and trajectory. This dynamic environment provides a unique opportunity to examine how different feedback modalities influence cognitive functions such as spatial awareness and reaction times. Furthermore, the immediate feedback loops in racing games allow for real-time assessment of how auditory, visual, and tactile cues impact player behaviour and decision-making. As such, this study utilises a racing game to explore the effectiveness of various feedback modalities, highlighting their potential role in enhancing attentional processes in an engaging and interactive format.

This study aims to address these gaps by investigating how different feedback modalities—auditory, visual, and tactile—impact sustained attention and performance in a custom-designed Android-based serious game. Specifically, we focus on understanding the positive and negative effects of each feedback type during a task requiring sustained attention [22]. It is worth noting that negative feedback doesn’t always reduce confidence. In settings like leaderboards, falling behind can feel discouraging initially but often creates positive peer pressure, encouraging players to improve. This study examines these potential effects of negative feedback on sustained attention and performance.

This study examines how auditory, visual, and tactile feedback modalities influence sustained attention during a 12-session training period in a serious game. Attention is operationalized as the ability to maintain focus on target cars (measured by correct responses/positive scores) and suppress distractions (measured by commission errors/negative scores). By analyzing these metrics, we assess whether feedback type differentially enhances attentional control or reduces lapses.

Given the exploratory nature of this investigation and the small sample size (n = 19), we employ Hidden Markov Models (HMM) to analyze the cognitive processes underlying feedback-driven decision-making. This approach is methodologically justified through three key evidence-based considerations:

1. Longitudinal Small-Sample Precedent: Haines et al. [23] demonstrated that intensive repeated measures (e.g., 15 participants × sessions) can reliably model cognitive dynamics, establishing that observation density outweighs participant count for temporal analysis. Our design aligns with this approach, using 19 participants × 12 sessions = 228 observations.
2. HMM Robustness for Sparse Data: Visser & Speekenbrink [24] demonstrated that HMMs reliably recover transition parameters from limited behavioral observations, validating their use for small-sample studies. Their R package (depmixS4) has proven effective in extracting meaningful patterns from sparse datasets with observation densities comparable to ours (228 observations for 6 parameters = 38 observations/parameter), confirming methodological suitability for our n=19 sample.
3. Cognitive Modeling Validation: Wang et al. [25] demonstrated the effectiveness of HMMs in modeling sequential patterns in dynamic environments, validating their utility for analyzing behavioral sequences in interactive tasks, while Rabiner [26] established their theoretical foundation for analyzing hidden states from observable actions - precisely matching our gameplay paradigm.

A custom-built Android car racing game was developed as the experimental tool for this study. The game incorporates key design elements, including clear goals (e.g., maximizing positive interactions), structured rules (e.g., avoiding non-target cars), and a feedback system integrated into the gameplay. These components form the backbone of the serious game, enabling controlled experiments on attentional engagement and feedback modalities

The HMM is particularly well-suited for modelling sequential decision-making processes, allowing us to track how players' decisions evolve in response to different feedback types. By inferring hidden cognitive states based on observable behaviours, HMM provides a deeper understanding of the underlying processes that guide players' interactions with the game. This probabilistic approach accounts for variability in how different feedback modalities impact attentional shifts, facilitating a nuanced analysis of feedback effectiveness. Ultimately, the use of HMM allows us to model the temporal dynamics of attention, offering insights into the immediate and sustained effects of auditory, visual, and tactile feedback on player performance.

In this study, sustained attention is operationalized through behavioural indicators commonly used in attentional research. These include correct responses (positive scores), commission errors (negative scores), and reaction times, all of which reflect participants' ability to maintain focus on relevant stimuli and inhibit responses to distractions over time. Additionally, participants’ decision-making patterns, measured through transitions between bands containing target and non-target cars, were analysed using a Hidden Markov Model (HMM) to capture deeper cognitive shifts associated with attentional control.

1.1 Conceptual Framework

Attention is a critical cognitive function that allows individuals to process relevant information while filtering out distractions. In the context of serious games, attention is particularly important as players must navigate complex environments and make quick decisions based on feedback.

Our framework integrates three evidence-based components:

1. Feedback modality effects [13][17][19], where auditory, visual, or tactile cues differentially guide attention;
2. Attentional state modulation [5][6][27], where players shift between focused and distracted states, is well-documented in tasks requiring sustained attention. Esterman et al. [27] specifically traced these transitions in feedback-rich environments, providing a neural basis for how modalities like auditory cues stabilize attention; and
3. Longitudinal training efficacy [23], with repeated sessions reinforcing learning.

Research shows:

- Visual feedback enhances self-regulation despite disruption [4][5],
- Auditory cues prompt rapid responses [6][7], and
- Tactile inputs minimize interference [8][9].

These findings inform our experimental design (Figure 1), which tracks attention through target/non-target discrimination across 12 gameplay sessions, with performance metrics quantifying attentional efficiency.

This study aims to explore these dynamics by addressing:

- **RQ1: How feedback modalities differentially impact sustained attention (correct responses/errors);**
- **RQ2: Whether modalities differ in immediate vs. sustained effects;**
- **RQ3: How HMM reveals latent decision patterns despite overt behavior.**

The framework specifically examines:

- How modalities *immediately* vs. *gradually* affect attention (RQ1/RQ2)
- Latent decision patterns revealed by HMM (RQ3)
- Practical applications for serious game design

By situating this research in established literature, we clarify feedback's role in cognitive performance and identify applications for serious game design.

the experimental design of the pilot study (Figure 1) illustrates our training protocol with 12 sessions. Each 30-minute session contained three standardized phases: initiation interface, race scenario with modality-specific feedback (see Methods 2.5), and performance scoring. Feedback implementations were: auditory (tone cues), tactile (vibration patterns), or visual (on-screen text), with conditions randomized across participants.

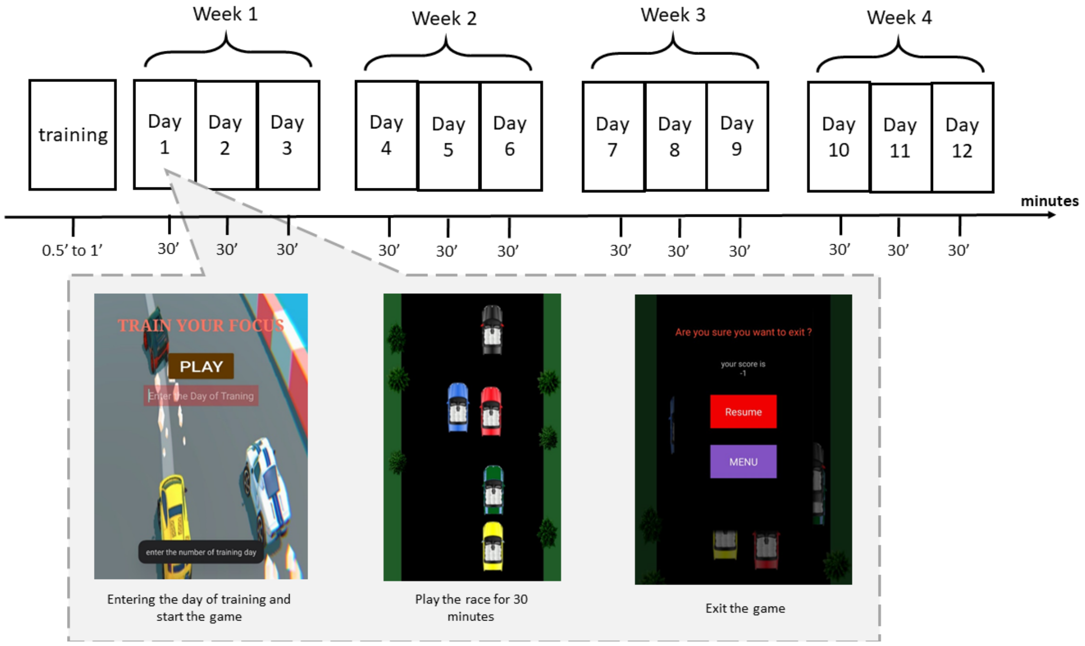

Figure 1. The experimental design of the pilot study

In Section 2: Methods and Material, we detail the methodology employed to investigate the effects of feedback modality on sustained attention and performance. Section 2.1 describes the participant demographics, including age, gender, and health status, to contextualize the study sample. Section 2.2 outlines the experimental design, focusing on the 12-session training protocol, the custom-built Android car racing game, and the randomization of feedback conditions. Section 2.3 explains the game mechanics and difficulty levels, emphasizing the simplified controls and the rationale behind the four-band track structure. Section 2.4 specifies the rules of the game, such as target and non-target car interactions, to clarify the attentional demands placed on participants.

Section 2.5 elaborates on the three feedback modalities—auditory, visual, and tactile—and their implementation in the game, including the control group setup. Section 2.6 details the data measurement process, covering automated logging of touch inputs, scores, and movement transitions, which were critical for both statistical and sequential behavioral analysis. Section 2.7 discusses the statistical methods, including ANOVA, used to evaluate performance metrics (positive/negative scores) across feedback types and training days. Finally, Section 2.8 introduces the Hidden Markov Model (HMM), explaining its application for analyzing latent decision-making patterns and transition probabilities between attentional states.

Section 3 presents the results. Section 3.1 provides statistical findings, including comparisons of positive/negative scores across feedback groups and training days, supported by bar graphs and heatmaps. Section 3.2 reports the HMM analysis, visualizing transition probabilities and band-selection tendencies, with figures illustrating state dynamics for each feedback group.

Section 4 interprets these results, linking auditory feedback's immediate error reduction to rapid cognitive adjustments, while visual/tactile feedback's gradual effects are tied to higher informational load. The HMM's null findings for strategic changes are contrasted with its utility in modeling precision improvements.

Section 5 synthesizes the conclusions, highlighting implications for serious game design and proposing future research directions, such as multimodal feedback studies and clinical applications.

To further clarify the theoretical structure linking feedback modality to attention and performance, Figure 2 presents a workflow diagram of modality-attention interaction within the context of serious gaming. This diagram synthesizes how sensory feedback influences transitions between attentional states, modelled via a Hidden Markov Model (HMM), and how these states yield behavioural outcomes over time. This visual representation provides a bridge between the conceptual framework and the experimental design by highlighting the mechanisms underlying feedback-driven cognitive modulation.

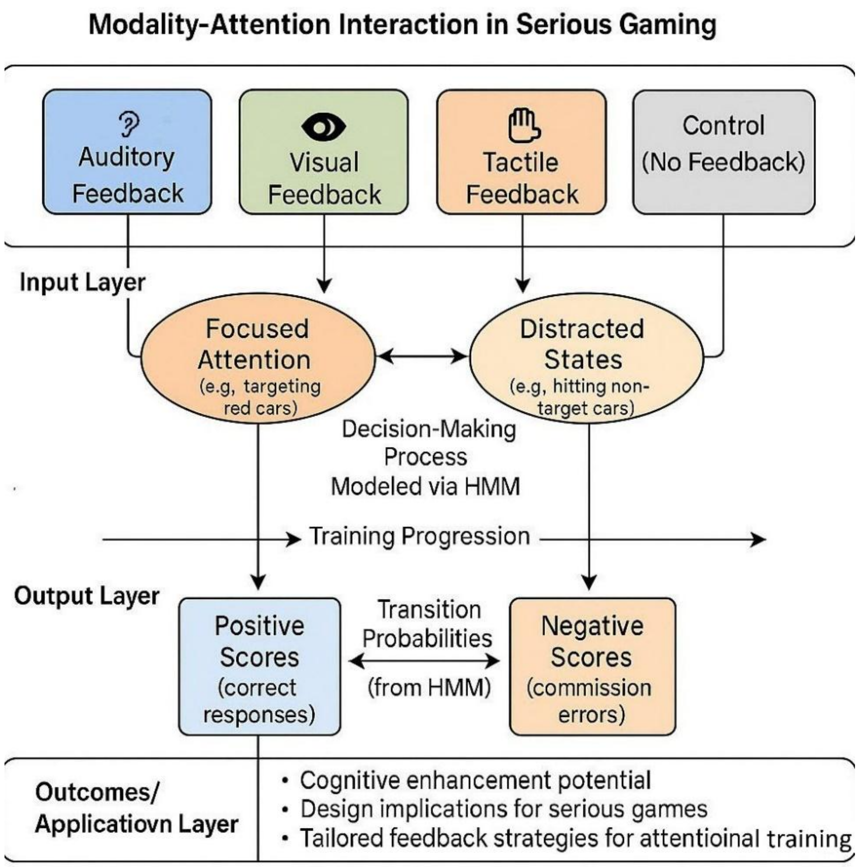

Figure 2. Modality-Attention Interaction in Serious Gaming. A conceptual diagram illustrating how different feedback modalities (auditory, visual, tactile, control) influence attentional states (focused vs. distracted) during gameplay, modelled using a Hidden Markov Model (HMM). Transitions between attentional states affect training outcomes, represented by positive and negative scores, with implications for cognitive enhancement and serious game design

2. Methods and Material

2.1 Participants

Nineteen healthy female participants voluntarily took part in the study. All participants were right-handed and had a mean age of 22.36 ± 2.1 years. They reported no history of neurological disorders and were fully informed about the experiment's procedures, providing written consent prior to participation. Table 1 provides the descriptive statistics for the participants, including age, gender distribution, and years of education.

Table 1. Participant demographics.

Variable	Mean ± SD
Number of Participants	19
Gender	Female
Handedness	Right-handed
Age (years)	22.36 ± 2.1
Neurological Disorders	None reported

While homogeneous samples are methodologically justified for initial controlled experiments [28], our results require validation in broader populations.

2.2 Experimental Design

To achieve the objectives of this research, a custom-built car racing game, developed on the Android platform, was used as the experimental tool. This game diverged from conventional racing titles by integrating specific rules to challenge sustained attention.

The experiment consisted of 12 sessions over four weeks, with three sessions each week. Each session lasted 30 minutes. The initial training session took place on the first day, allowing participants to familiarise themselves with the game mechanics and performance evaluation. This introductory session lasted approximately 30 seconds to 1 minute, during which participants learned the fundamental rules.

Participants controlled a green race car using both hands; the car's dimensions were approximately 3/20 of the screen width and 1/5 of the screen height.

The primary goal was to maximise the number of interactions with target cars (red) while minimising encounters with non-target cars (blue, black, and yellow). The appearance of these cars followed a random pattern, with equal frequency for each type, ensuring balanced gameplay experience across all participants.

To monitor gameplay duration, a timer was implemented within the game. At the end of each 30-minute session, a notification prompted players to exit the game, displaying a message indicating that the time was complete. The game recorded performance data, which was saved as an Excel file on the participants' devices for subsequent analysis.

Participants were allowed to choose any three days within the week and any time of day to engage in the game. They were encouraged to select times when they were adequately rested and able to maintain concentration throughout the session. This design aimed to create an optimal environment for improving capacities of sustained attention.

2.3 Game mechanics and Difficulty levels

The custom-built Android car racing game was developed using Android Studio and designed with simplified controls to maintain attentional focus on decision-making rather than motor coordination. The game featured three difficulty levels, which differed based on the speed of incoming vehicles. Participants selected their preferred difficulty level during the initial training session and continued with that same level throughout the 12 training sessions to ensure consistency in cognitive load across time.

The game interface divided the screen vertically into two equal regions. To control the green car, participants used either thumb to tap on the left or right side of the screen:

- A tap on the right side moved the car one band to the right (e.g., from Band 1 to Band 2).
- A tap on the left side moved the car one band to the left (e.g., from Band 3 to Band 2).

The track consisted of four horizontal bands, and the green car could switch bands in real-time based on these touch inputs. This setup allowed for intuitive interaction and real-time responses, which were crucial for attentional engagement.

2.4 Rules of the Game

The game features specific rules designed to enhance attentional demands and create a challenging environment for participants. Players controlled the green car's movement across four bands of the track by touching the screen. The car could switch between these bands in response to user input.

- Target Cars (Red): Successfully passing over a red car resulted in a positive score, rewarding players for making correct choices.
- Non-Target Cars (Blue, Black, Yellow): Passing over these cars led to point deductions, encouraging players to avoid them to minimise errors.

The game environment simulated real-life driving scenarios, where quick decision-making is essential. Players were tasked with navigating the bands, making rapid decisions on which cars to interact with while maintaining sustained attention on the overall goal of maximising positive encounters and minimising errors.

2.5 Feedback Modalities

Three distinct feedback modalities were incorporated into the game: auditory, visual, and tactile.

- Visual feedback was delivered via on-screen text: the word “Positive” in green appeared when players successfully interacted with a target (red) car, while “Negative” in red was shown after encountering a non-target car.
- Auditory feedback consisted of two distinct sound cues: a coin sound for correct responses and a car horn for incorrect ones, played immediately after the player's action.
- Tactile feedback involved vibration patterns: a short triple vibration for correct interactions and a longer, more intense vibration for incorrect ones.

This combination of feedback modalities was chosen to investigate their respective impacts on sustained attention and performance, facilitating a nuanced understanding of how different forms of feedback can enhance cognitive training in a gaming context.

The control group was maintained in the same configuration as the experimental groups but did not receive any feedback. This consistent setup allowed us to isolate the effects of auditory, visual, and tactile feedback on performance, as the control group participants completed the tasks without external guidance.

2.6 Data Measurement

To evaluate attentional engagement and decision-making performance during gameplay, multiple metrics were systematically recorded using built-in data logging functions within the Android Studio environment. These metrics served as the primary dependent variables in the study and were used for both statistical and sequential behavioral analysis.

2.6.1 Automated Data Logging and File Structure

The game was designed to automatically log all interaction data in real time and export it as an Excel (.xls) file after each session. Each file captured the player's full session history, including:

- Screen touch coordinates
- Time stamps for each input
- The current and resulting band positions
- The type of car (target or non-target) in each band during transitions
- Score changes associated with each interaction

These data allowed for the reconstruction of each player’s full decision sequence over the course of the game, enabling detailed behavioral modeling using statistical and probabilistic methods (e.g., HMM).

2.6.2 Touch and Movement Control Tracking

The game interface was designed for intuitive two-thumb control by dividing the screen vertically into two equal regions. Participants controlled the green race car by tapping on either side of the screen:

- Tapping the right half moved the car one band to the right.
- Tapping the left half moved it one band to the left.

The track consisted of four parallel bands. Each tap resulted in an immediate lateral movement between adjacent bands, which was logged as a transition. These transitions were recorded along with the type of cars (target or non-target) present in both the origin and destination bands, allowing analysis of decision-making under attentional load.

Each touch was time-stamped to the second, enabling the precise calculation of reaction times and decision latency. This helped evaluate how quickly participants responded to changing visual stimuli, especially as difficulty increased through faster car speeds at higher levels.

In addition to logging transitions and timing, the system recorded the positions of all visible cars and the green player-controlled car at the moment of each touch. This allowed for synchronized tracking of participant responses within the evolving game environment and provided a detailed dataset for analyzing navigational patterns and attentional accuracy over time.

2.6.3 Positive Score

Positive scores were recorded when participants successfully interacted with target objects during the task, indicating successful attentional control and goal-directed behaviour. This metric is commonly used to assess correct responses in cognitive tasks that involve attentional engagement. In line with the research on attention systems [5], positive scores in this study reflect the participants' ability to effectively allocate mental resources to relevant stimuli and avoid distractions, demonstrating successful cognitive control.

2.6.4 Negative Score

Negative scores (or commission errors) were recorded when participants interacted with non-target objects during the task, indicating attentional lapses or failures in cognitive control. Commission errors reflect instances where participants mistakenly responded to stimuli that were not relevant to the task, representing impulsive actions or a failure to maintain attention.

The use of commission errors as a metric for measuring attention is well-established in cognitive research, particularly in tasks like the Sustained Attention to Response Task (SART). In SART, participants are required to withhold responses to non-target stimuli, and commission errors occur when they fail to do so, highlighting lapses in sustained attention and cognitive control. The relevance of commission errors has been revisited and strengthened by studies that link SART performance with daily-life cognitive failures, making this metric a valuable tool for understanding real-world attentional lapses [23].

By applying this metric in our study, we aim to capture the cognitive processes associated with attention lapses and impulsivity, similar to how SART tracks sustained attention. Negative scores provide insight into the participant's ability to filter out irrelevant stimuli and maintain focus during the task, particularly in the context of different feedback modalities. This approach allows us to evaluate how feedback influences not only correct responses but also the reduction of errors, further enhancing our understanding of its impact on attentional control.

2.6.5 Movement Counters

A series of counters tracked the number of movements between different bands of the road based on the colour of cars encountered. These counters recorded transitions from target to non-target cars and vice versa, helping to elucidate participants' decision-making processes. For example:

- 1t-2t: Counts movements from band 1 with a target car to band 2 with a target car.
- 1n-2t: Counts movements from band 1 with a non-target car to band 2 with a target car.
- 3n-4n: Counts movements from band 3 with a non-target car to band 4 with a non-target car.

By analysing these diverse metrics, we aimed to develop a comprehensive understanding of how different feedback modalities influenced participants' attentional performance and decision-making during gameplay. The combination of scores, position data, and movement counters allowed for a nuanced analysis of cognitive engagement, providing valuable insights into the effectiveness of the serious game in enhancing attention.

2.7 Statistical Analysis

The data were subjected to Analysis of Variance (ANOVA) to evaluate significant differences between training days and feedback types concerning the recorded measures. Feedback type and training duration acted as independent variables, while positive and negative scores served as dependent variables. Statistical analyses were conducted at a significance level of 5%. The post hoc tests were repeated measures of two-way ANOVA, with matched values organized into sub-columns for clarity.

2.8 Hidden Markov Model (HMM)

The Hidden Markov Model (HMM) serves as a probabilistic framework for analysing the sequential data obtained from participant movements throughout the gameplay. In this study, the model was utilized to understand the decision-making processes of participants as they navigated the game and encountered various target and non-target cars.

The model was constructed with:

- 8 discrete states (4 bands × 2 car types: target/non-target)
- Deterministic observations: Actual band transitions (e.g., Band 1 → Band 2)

Transition probabilities calculated using:

$$a_{ij} = \frac{Number\ of\ transitions\ from\ state\ i\ to\ j}{Total\ transitions}$$

The HMM is characterized by a set of hidden states, each representing a distinct band on the road where the cars are positioned. Specifically, there are four bands, with each band containing either a target (red car) or a non-target (blue, black, or yellow car). Participants' choices regarding which band to move to next were analysed through their recorded transitions between these states.

To construct the HMM, we defined two types of states for each band:

- Target States: These states are associated with the presence of a red car; which participants aim to interact with positively to gain points.
- Non-Target States: These states correspond to the presence of blue, black, or yellow cars, which participants seek to avoid to minimize errors.
- Transitions: All possible band shifts between these states, totalling 24 unique probabilities (Figures 7–10).

In gameplay terms:

- Target states represent focused attention (correctly prioritizing red cars)
- Non-target states reflect attentional lapses (failing to avoid distractors)
- Transitions model how feedback modalities reinforce or disrupt these states (e.g., auditory cues may increase transitions toward targets).

The transitions between states were modelled as probabilistic events, where the likelihood of moving from one band to another depended on the current state and the feedback received. This allowed us to examine how different feedback modalities might influence participants' decisions regarding path selection. For example, a transition from Band 1 (non-target) → Band 2 (target) would increment the 1n→2t counter, reflecting a recovery from distraction to focused attention.

Data collected during gameplay included the frequency of transitions between bands based on the colour of the cars encountered, which was used to calculate the transition probabilities. For example, if a participant moved from a non-target band to a target band, the corresponding counter for that transition would increase, reflecting the participant's decision-making process.

By analysing the transition probabilities, we aimed to determine whether the type of feedback provided (auditory, visual, or tactile) significantly affected the participants' choices in selecting their paths. The insights gained from the HMM analysis contribute to understanding the impact of feedback modalities on cognitive processes, specifically in the context of sustained attention and performance in serious games.

This design aligns with established HMM applications in attention research [25], including Visser & Speekenbrink's [24] validation of HMMs for behavioral data with limited observations, where:

- States map to measurable cognitive conditions (focused/distracted)
- Transitions quantify feedback’s impact on attentional stability
- The 4-band × 2-type structure captures task-specific demands

Furthermore, the HMM analysis enables us to visualise the dynamics of participants' movements over time, offering a clear representation of how feedback influences behaviour in a gaming environment. This approach not only enhances our understanding of attentional mechanisms but also provides a methodological framework for future research exploring feedback effects in various task settings.

While alternative modelling approaches exist (e.g., reinforcement learning models or dynamic Bayesian networks), the HMM was uniquely suited for our research questions because:

- It is state-transition architecture directly mirrors theoretical constructs of attentional shifting [5].
- It handles sparse observation sequences common in behavioural studies [24].
- It has established validity for decoding latent cognitive states from discrete actions [26].

Future studies comparing HMM performance against other modelling frameworks could provide additional methodological insights.

Figure 3. Game interface used in the experiment and designation of different road sections or "bands" in the serious game, to tracking participants' choices and feedback during the task.

3. Results

In this part, the results of statistical analysis as well as HMM implementation are described. For statistical analysis, the effect of training time (first day in comparison to the last day) and feedback types on positive and negative scores were investigated. Performance metrics (positive/negative scores) were analysed as indicators of attentional engagement, where higher positive scores reflect improved focus on targets, and reduced negative scores indicate fewer attentional lapses.

3.1 Statistical analysis

Firstly, the statistical results are presented using plots and tables. Secondly, a total summation is presented dividing the results into three sections: feedback impact, time of training impact, and feedback and time of training combined.

As shown in Figure 3, all four groups of our study approximately had the same range of positive scores at the beginning of training. After 12 days of training, the control group (i.e., the group with no feedback) witnessed a decline, while all three types of feedback groups led to a slight improvement at the end of the last day compared to the first day. Among these three groups, the visual and tactile feedback groups showed a slightly higher improvement. However, these changes were not statistically significant ($p > 0.05$), indicating that while feedback may aid performance, the effect was not strong enough to be conclusive.

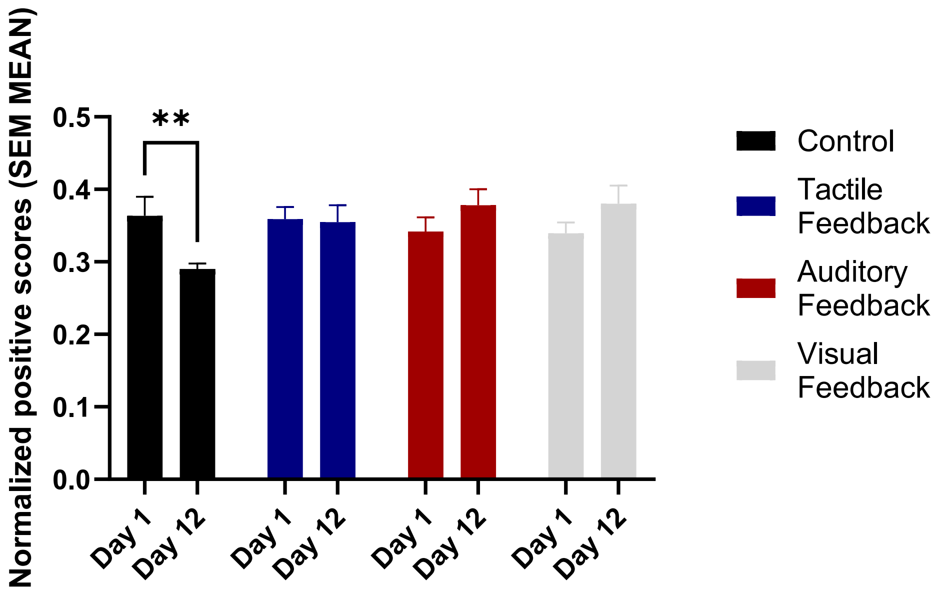

Figure 4. Bar graph comparing normalized positive scores (± SEM) on Day 1 and Day 12 of training across four feedback groups.

Figure 4 compares negative scores (commission errors) across the four groups on the first and last days of training. Unlike positive scores, the four groups had different levels of negative scores on the first day of training. The value of negative scores decreased on the last day compared to the first day in all groups. However, this reduction in the visual and tactile feedback groups was higher than in the other groups, suggesting a more pronounced effect of these feedback modalities on error reduction.

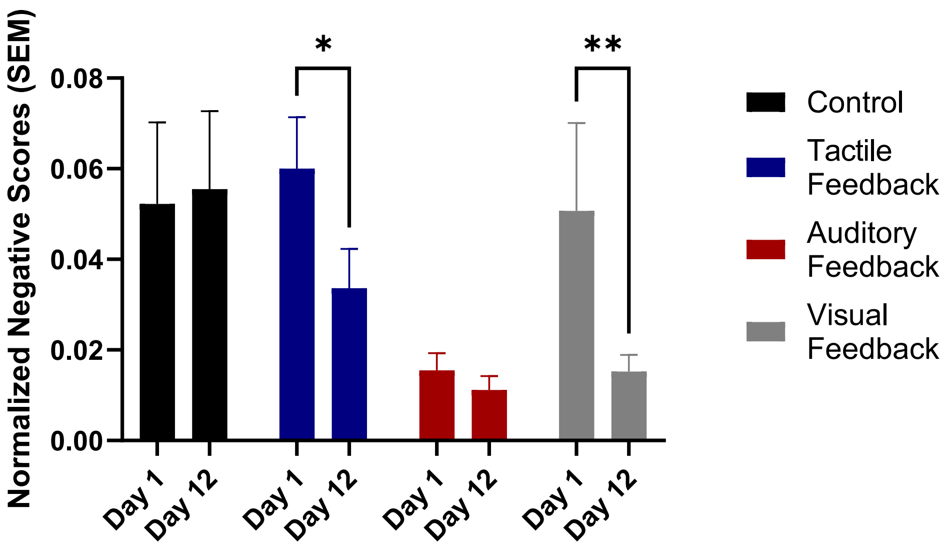

Figure 5. Bar graph comparing normalized positive scores (± SEM) on Day 1 and Day 12 of training across four feedback groups.

To see the pattern of changes in positive and negative scores over all training days, Figures 5 and 6 show a heatmap of scores over 12 days in four groups. The colour spectrum shown in Figure 5 contains the whole procedure of positive scores over 12 days of training. Positive scores in the control group experienced a reduction throughout the 12 days. Positive scores in the auditory feedback group experienced irregular changes over the 12 days of training and approximately stayed the same, while visual and tactile feedback groups had a significant increase in earning positive points, indicating a potential benefit of these feedback types over time.

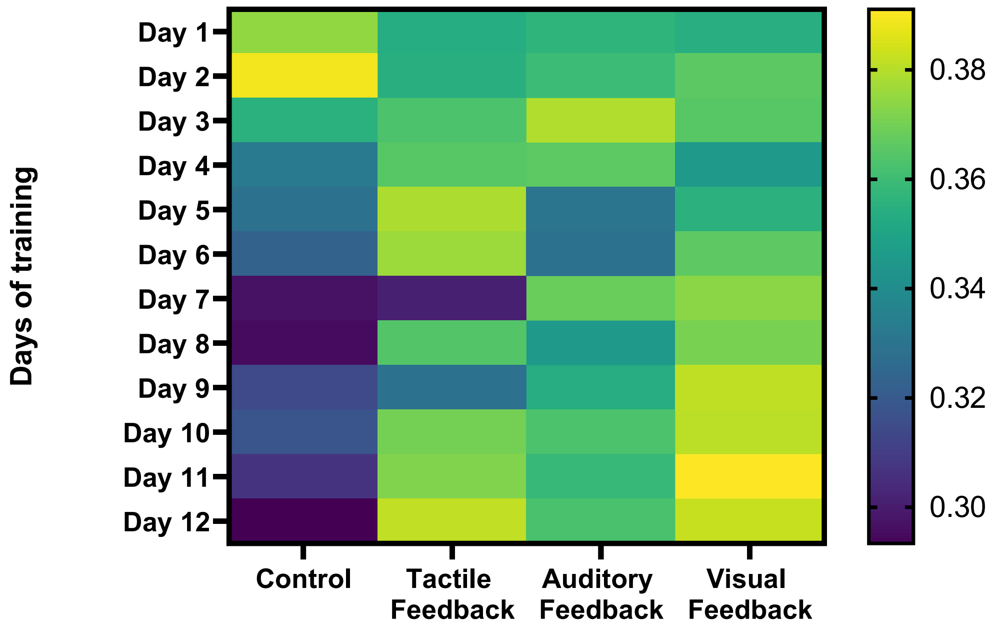

Figure 6. Heat map of normalized positive scores across 12 days of training in four feedback groups.

The colour spectrum shown in Figure 6 contains the whole procedure of negative scores over 12 training days. Negative scores in the control group experienced irregular changes over the 12 days and remained approximately the same. Visual and tactile feedback groups experienced a drastic drop in commission errors, while negative scores in the auditory feedback group slightly decreased over the total training days. The notable point is the level of negative points in the auditory feedback group, which is completely different from other groups from the first to the last session.

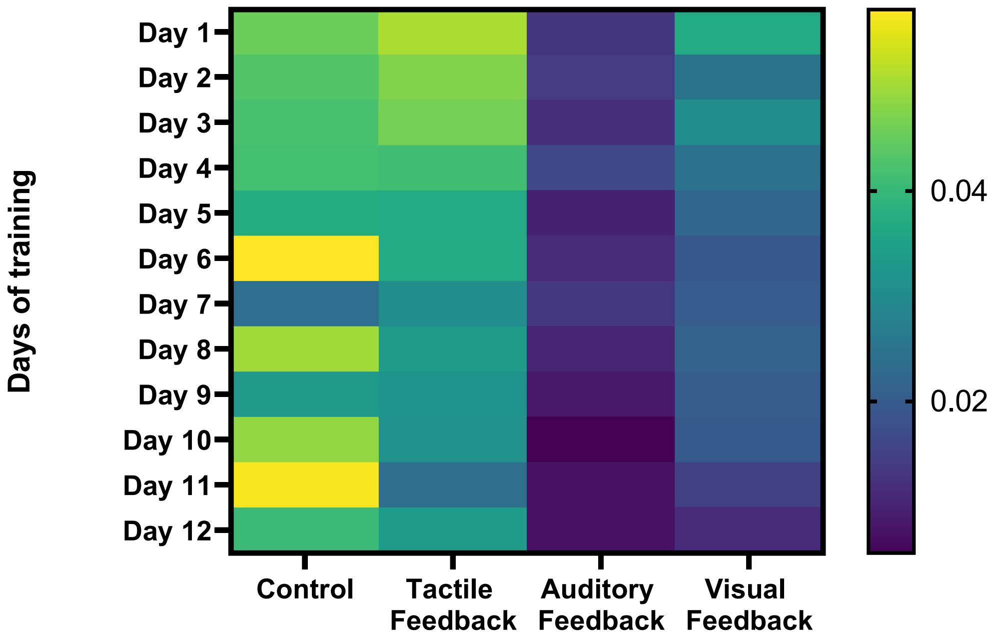

Figure 7. Heat map of normalized negative scores across 12 days of training in four feedback groups.

Table 2 shows the statistical results of positive scores on the first and last day of training. As it shows, applying different feedbacks and training days does not have an effect on improving the achievement of more positive scores. Yet there is a meaningful relation ($p < 0.05$) between days of training and different feedbacks, suggesting that although the feedback did not significantly enhance scores, time allowed for gradual learning.

Table 2. Statistical significance of positive scores comparing Day 1 and Day 12 using a two-way ANOVA test.

Source of Variation	% of total variation	P value	P value summary	Significant?
Row Factor (Feedbacks)	0.0002450	0.9890	ns	No
Column Factor (Days of training)	7.701	0.5457	ns	No
Row Factor x Column Factor	21.31	0.0082	**	Yes
Subject	52.19	0.0274	*	Yes

Table 3 provides the statistical values of the comparison of negative scores (commission errors) on day 1 and day 12 of training. This result suggests that the effectiveness of types of feedback applied in the game is statistically significant ($p < 0.01$). The effectiveness of days of training in decreasing commission errors is not meaningful; however, the effects can be observed in the results. In addition, statistical significance is found between the days of training and the feedbacks.

Table 3. Statistical significance of negative scores comparing Day 1 and Day 12 using a two-way ANOVA test.

Source of Variation	% of total variation	P value	P value summary	Significant?
Row Factor (Feedbacks)	6.303	0.0080	**	Yes
Column Factor (Days of training)	25.23	0.1068	ns	No
Row Factor x Column Factor	6.532	0.0526	ns	No
Subject	52.20	0.0015	**	Yes

In the following, Table 4 and 5 are provided to resent the statistical results of positive and negative scores through the entire days of training.

Table 4 provides the statistics of positive scores over 12 days of training. As it can be seen, the impact of feedback and days of training is not statistically meaningful ($p > 0.05$). However, the impact can be seen in the results, especially in applying different feedbacks. On the other hand, the relationship between different feedbacks and training days is statistically significant ($p < 0.05$).

Table 4. Statistical significance of positive scores across 12 days of training using a one-way ANOVA test, highlighting the significance levels for each feedback group over the training period.

Source of Variation	% of total variation	P value	P value summary	Significant?
Row Factor (Feedbacks)	2.335	0.2633	ns	No
Column Factor (Days of training)	5.927	0.6851	ns	No
Row Factor x Column Factor	7.337	0.0800	ns	No
Subject	58.77	<0.0001	****	Yes

Table 5 contains the statistics of the procedure of changes in the negative scores through all 12 days of training. The effectiveness of all 12 sessions is statistically significant ($p < 0.01$). While the effect of feedback was observed in the decrease of commission errors, it is not statistically meaningful. At last, there was no connection between the days of training and types of feedback in the decrease of the negative score.

Table 5. Statistical significance of negative scores across 12 days of training using a one-way ANOVA test, highlighting the significance levels for each feedback group throughout the training period.

Source of Variation	% of total variation	P value	P value summary	Significant?
Row Factor (Feedbacks)	5.586	0.0549	ns	No
Column Factor (Days of training)	25.81	0.0469	ns	No
Row Factor x Column Factor	4.039	0.8145	*	Yes
Subject	38.36	<0.0001	****	Yes

3.1.1 Feedback impact

On one side, the effect of the three types of feedback applied in the study showed that feedback can prevent the drawbacks of earning positive scores. The visual and tactile feedback groups presented slightly more progress in earning positive points. However, the impact of feedback on positive scores was not significant.

On the other side, feedback showed better results in the reduction of negative scores. Statistical analysis pointed out that visual and tactile feedback had a drastic decrease in negative scores in comparison with the first day. Also, auditory feedback presented its quick impact. This group had a significant difference from other groups in commission errors from the start and stayed approximately the same until the end of the experiment.

3.1.2 Time of training impact

Time of training had no specific effect on increasing or decreasing positive and negative scores per se. Yet, small impacts can be observed in the reduction of commission errors. Although all groups improved over time, the auditory feedback group showed the most pronounced improvements, indicating that time allowed participants to refine their skills in responding to feedback.

3.1.3 Feedback and Time of Training Combined

Comparing the first and last day of training, the statistical analysis presented that the influence of applying feedback and time of training collectively demonstrated a significant impact on earning more positive scores. On the other hand, it didn't show any specific signs of reduction in commission errors. However, considering the whole 12 days of training, the collective impact of time and feedback showed significant effects on alleviating commission errors.

Addressing our first research question (*How do feedback modalities affect attention?*), statistical analysis revealed:

- Feedback type significantly impacted negative scores (commission errors; $p = 0.008$, Table 3), with auditory feedback showing the strongest reduction.
- Positive scores were unaffected by feedback alone ($p > 0.05$, Table 2), but the interaction between feedback and training time was significant ($p = 0.008$), suggesting visual/tactile groups improved gradually (Figure 3).

For our second question (*Immediate vs. sustained impacts?*):

- Auditory feedback's error reduction was evident early (Day 1 vs. Day 12, Figure 4), while visual/tactile groups required longer training (heatmaps, Figures 5–6).
- Training duration alone had no main effect ($p = 0.11$, Table 3) but interacted with feedback ($p = 0.008$)

Key statistical findings:

- Auditory feedback reduced commission errors significantly vs. control ($p = 0.008$, Table 3), with the lowest baseline errors (Figure 4).
- Visual/tactile feedback groups showed the steepest decline in errors over time (Figures 5–6), though between-group differences were non-significant ($p > 0.05$).
- Positive scores remained stable across feedback groups ($p = 0.26$, Table 2), but the control group declined (Figure 3).
- Feedback × training time interaction was significant for both positive scores ($p = 0.008$) and errors ($p = 0.053$, Table 3), highlighting temporal dynamics.

3.2 HMM Analysis

A detailed examination of movements between four defined roads in four groups was conducted. The results suggested that the feedback had no significant effect on how the roads were chosen for the next move. The HMM analysis revealed no significant differences in transition probabilities between the four feedback groups. There were some visible differences between the proportion of different stages (e.g., 3n-2n and 3t-2t) in all four groups at the same time. This significance is based on situations that the algorithm provided for black, blue, and red car appearances. Due to that, the significant gaps in the proportion of stages are not related to the HMM and the purpose of this study.

In total, by considering just destination in HMM, the visual and auditory feedback groups had a greater tendency to choose target roads compared to other groups. However, the difference was not significantly visible. Figures 7, 8, 9, and 10, respectively, show HMM extracted for auditory, visual, tactile, and control groups. In these figures, the numbers on the arrows show the probability of choosing the next state from the current state. Figure 11 shows diagram-based information on HMM for the four study groups. Results reported in this figure reveal that different types of feedback have no influence on the band selection and all three feedback groups and the control group followed approximately the same pattern of movement facing the target and non-target cars. The difference between the probability of some transitions is because of the difference in the appearance of target and non-target cars. The probability of the appearance of the target car (red car) is one-third compared to the non-target car (blue, black, and yellow cars).

The HMM analysis showed that while there were some behavioural differences between groups, these did not translate into significant changes in decision-making patterns. Auditory feedback appeared to encourage a tendency to move toward target cars; however, this tendency was not robust enough to demonstrate statistically significant effects in the transitions captured by the HMM.

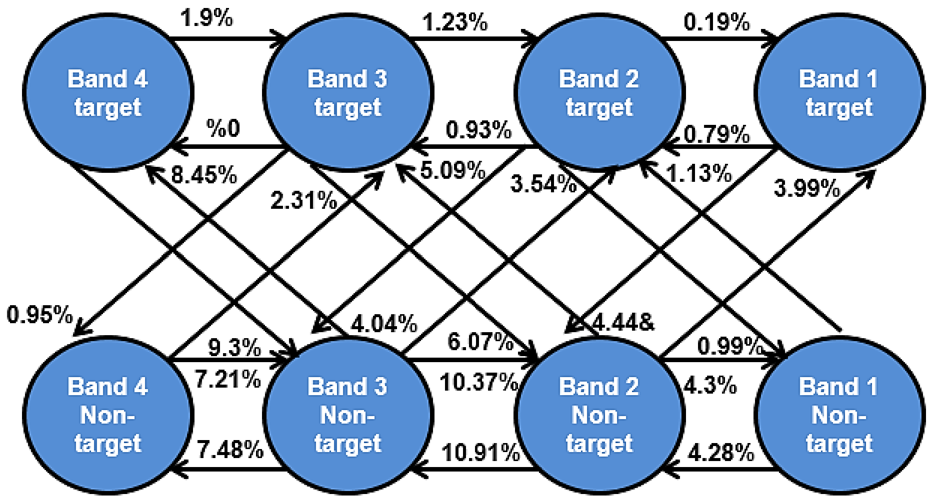

Figure 8. Hidden Markov Model (HMM) for auditory feedback. This figure illustrates the state transitions and probabilities associated with the auditory feedback condition, providing insights into the cognitive processes and decision-making patterns of participants during the task.

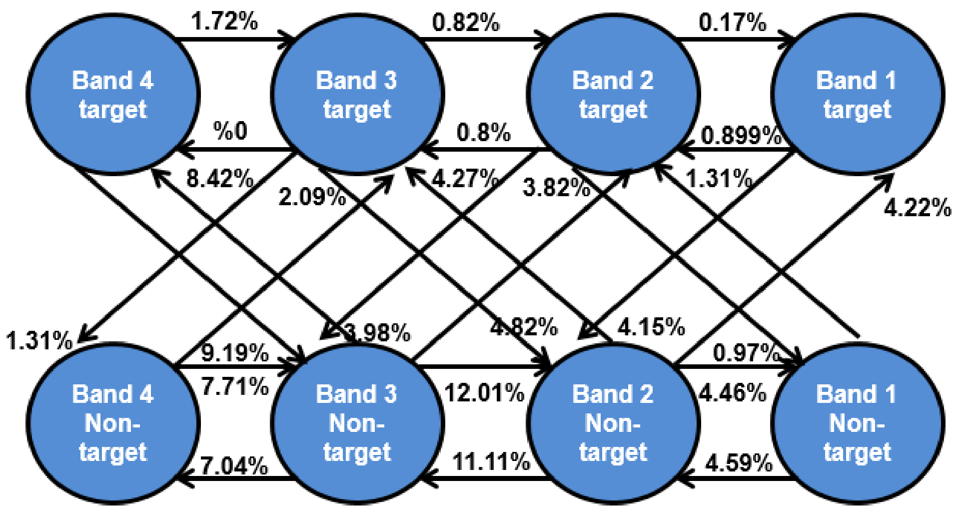

Figure 9. Hidden Markov Model (HMM) for visual feedback. The numbers on the arrows indicate the probabilities of transitioning to the next state from the current state, illustrating the cognitive processes and decision-making patterns of participants when utilizing visual feedback during the task.

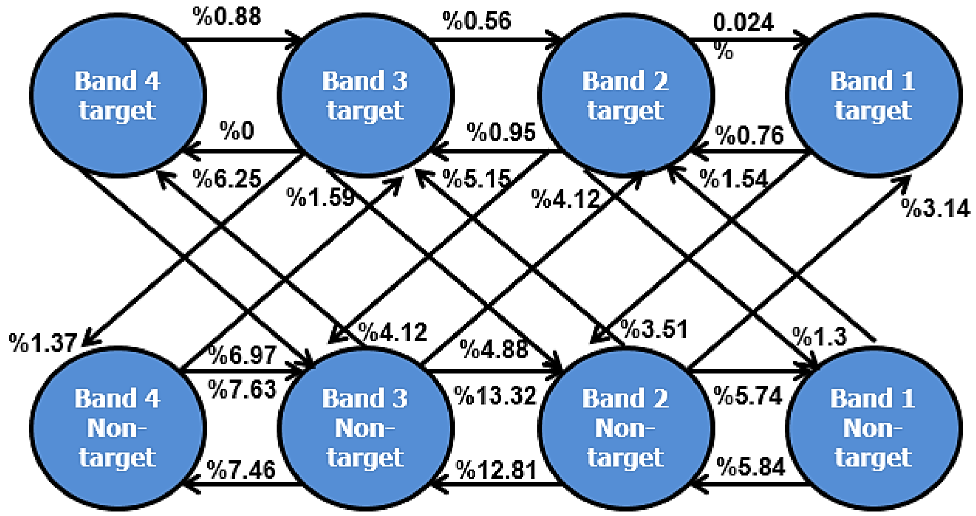

Figure 10. Hidden Markov Model (HMM) for tactile feedback. The numbers on the arrows represent the probabilities of transitioning to the next state from the current state, illustrating the cognitive processes and decision-making patterns of participants while utilizing tactile feedback during the task.

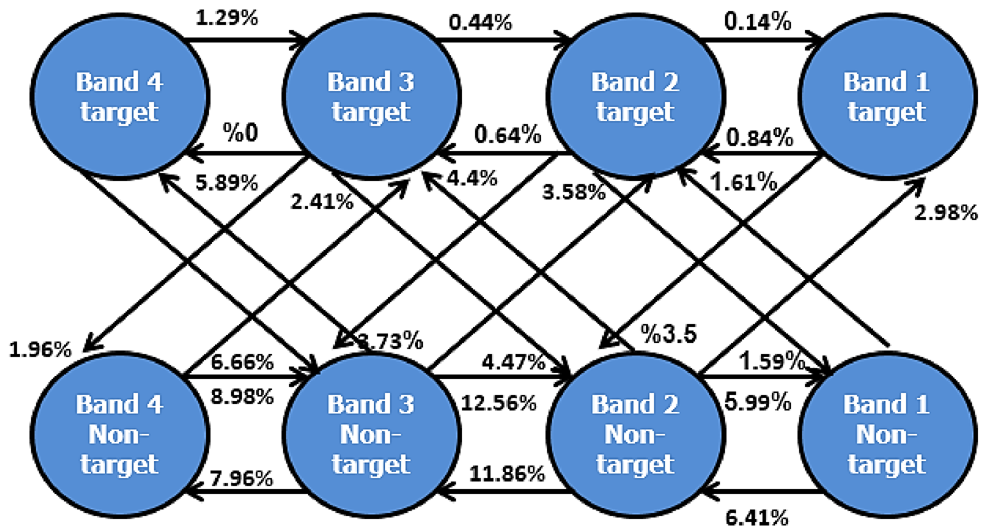

Figure 11. Hidden Markov Model (HMM) for the control group. The numbers on the arrows indicate the probabilities of transitioning to the next state from the current state, illustrating the decision-making patterns of participants in the absence of feedback during the task.

Due to the large number of probabilities to compare, all the probabilities of the four hidden Markov models are represented in the bar graph in Figure 11 As can be seen, the probability of choosing the next band in all four groups follows the same trend and does not depend on the feedback applied in the game. However, there are some slight differences between the groups in their choice of the next path.

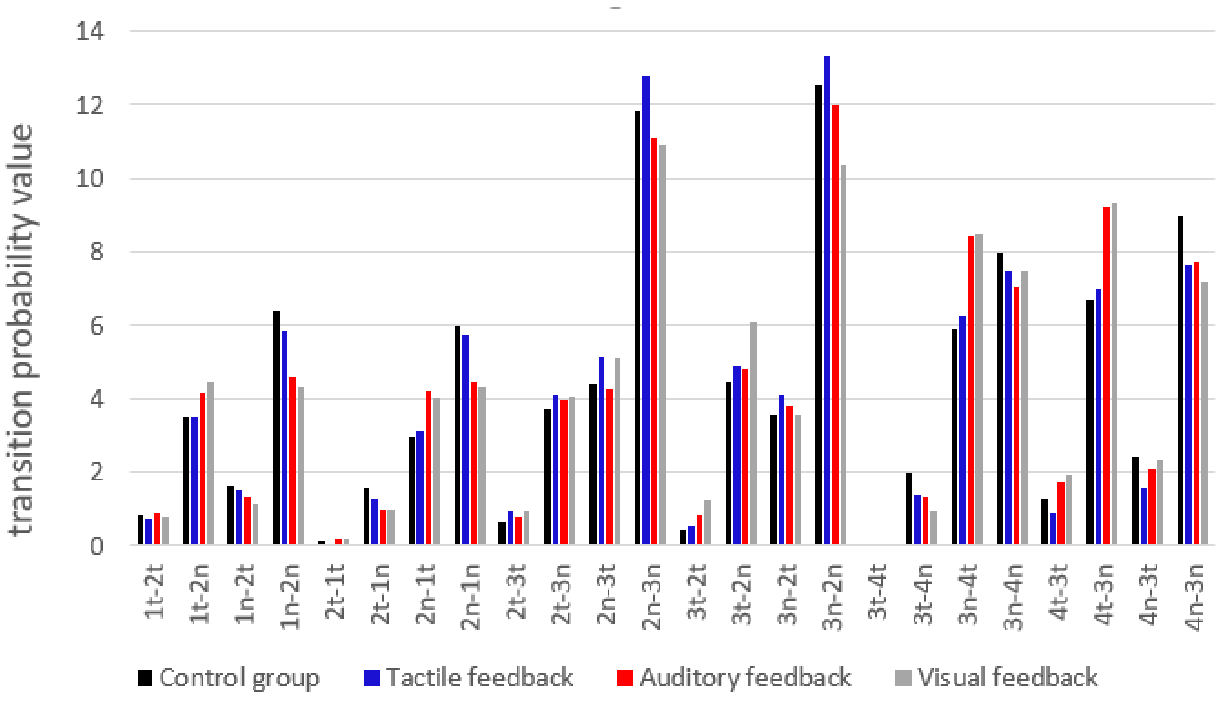

Figure 12. Comparison of transition probability values in Hidden Markov Models (HMMs) extracted for the four study groups. The figure displays transition probabilities for each band, where: 1t = band 1 with a target car, 1n = band 1 with a non-target car, 2t = band 2 with a target car, 2n = band 2 with a non-target car, 3t = band 3 with a target car, 3n = band 3 with a non-target car, 4t = band 4 with a target car, and 4n = band 4 with a non-target car

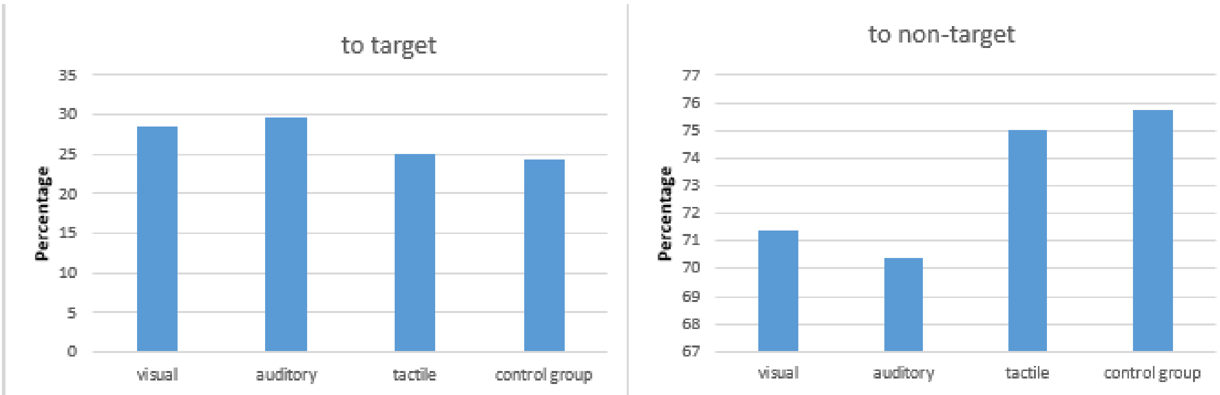

Figure 13. Percentage of participants choosing target versus non-target bands in their next move across the four groups. This figure illustrates the distribution of choices made by participants, highlighting differences in decision-making patterns among the auditory, visual, tactile, and control groups.

Figure 12 shows that auditory and visual feedback group studies have more correct choices for their next move, respectively.

The HMM analysis (Figures 7–11) directly tested whether feedback modalities influenced participants' latent decision-making strategies (RQ3). While transition probabilities showed no significant differences between groups ($p > 0.05$), two subtle patterns emerged:

- Target Band Preference**:** Auditory/visual groups exhibited marginally higher transitions to target bands (Figure 12), suggesting feedback may implicitly sharpen attentional focus without altering overall path-selection *strategies*.
- Precision vs. Strategy**:** The HMM's null findings align with our statistical results (Section 3.1), confirming that feedback primarily enhanced decision-making *precision* (reducing errors) rather than restructuring *strategic* band-hopping sequences. This dissociation reflects HMMs' sensitivity to macro-level behavioral patterns, which remained stable despite feedback interventions. Methodologically, Wang et al. [25] demonstrated the robustness of HMMs in modeling sequential patterns within dynamic systems, such as sports video recognition, where macro-level structural behaviors persist despite micro-level variations. Similarly, Rabiner [26] established HMMs' theoretical utility for decoding latent states from observable actions in sequential tasks. Together, these studies validate that while micro-level metrics (e.g., reaction times, errors) may fluctuate with interventions like feedback, HMMs reliably capture persistent strategic frameworks in interactive tasks—consistent with our observation of unchanged transition probabilities between attentional states.

4. Discussion

Our research demonstrated a direct relationship between feedback delivery during gameplay and training duration, impacting both positive scores and error reduction.

Additionally, our results confirmed the effect of feedback on functionality and completed the analysis outcome, specifically focusing on the effectiveness of decreasing commission errors. The effectiveness of time allocated to training was noticeable, with different impacts observed across the three types of feedback. Results should be interpreted in context of the study's homogeneous sample (healthy young females).

Auditory feedback demonstrated a strong early effect on sustained attention, as reflected by reduced commission errors. This suggests participants more quickly focused on task-relevant stimuli and inhibited incorrect responses without requiring extended training. This result aligns with prior research indicating that auditory stimuli are processed more quickly by the brain, leading to immediate cognitive adjustments. A study found that auditory attention allows for rapid responses to auditory cues, which supports the swift impact of auditory feedback observed in our study [29]. In contrast, visual feedback led to a reduction in commission errors, but only after a longer training duration. Previous studies showed that while visual feedback is often more informative, it can disrupt attentional processes, requiring more time for its benefits to emerge [22][30].

Tactile feedback, though less detailed than visual feedback, also required an extended period for participants to adjust. Aus der Wieschen et al. (2016) suggest that tactile feedback, due to its limited informational content, requires more time to be effective but is less disruptive than visual feedback [15]. At the end of the training period, a less significant decrease in commission errors was observed for tactile feedback compared to the auditory and visual feedback groups. This suggests that while tactile feedback has a lower cognitive load, its simpler nature may delay improvements in performance.

These findings align with our operationalization of attention as the ability to maintain focus on targets (reflected in positive scores) while suppressing distractions (reflected in reduced commission errors), bridging gameplay performance to cognitive outcomes.

Overall, the findings suggest that if sufficient training time is not provided, auditory feedback may produce better results than visual feedback, particularly in tasks requiring sustained attention and performance improvement. The greater disruption caused by visual feedback likely necessitates more training time to achieve effectiveness in transmitting information, while auditory feedback's lower disruption facilitates faster progress.

Our HMM model revealed that the three types of feedback had no significant impact on band selection. This result indicates that influencing path choices cannot rely solely on feedback messages that do not provide directional guidance. However, both the auditory and visual feedback groups exhibited a greater tendency to select target bands, suggesting that informative feedback related to movement direction could enhance decision-making. This is consistent with findings from a study that highlighted the role of feedback in guiding user behaviour during decision-making processes [31]. The use of HMM enabled us to model the sequential decision-making processes of players, offering deeper insights into how feedback influences their attentional shifts and performance over time.

The HMM results (Section 3.2) complement our statistical findings by revealing a dissociation between feedback's effects on *performance* (reduced errors) and *decision-making* (unchanged band transitions). This implies that auditory/visual feedback enhanced participants' ability to discriminate targets (attentional focus) but did not alter their macro-level navigation strategy—a nuance consistent with attentional control theory [5].

For serious games targeting strategic attention shifts, future designs might integrate directional feedback (e.g., spatialized auditory cues or visual arrows) to explicitly guide path selection, as non-directional feedback alone may insufficiently reshape decision habits.

These findings not only provide insights into how to utilize each type of feedback effectively in serious games but also suggest avenues for further research into the effects of feedback combinations. The results are based on a small sample of 19 participants, indicating that future research with larger datasets could yield more robust conclusions. While this limitation has not impacted the primary outcomes of the study, future work should focus on exploring the effects of various feedback combinations on individual performance in serious games, particularly in educational settings where serious games are used as cognitive training tools. In addition, while the HMM provided theoretically grounded insights into attentional dynamics, future research could benefit from comparing its performance against alternative modelling approaches (e.g., reinforcement learning models or recurrent neural networks) to identify optimal analytical frameworks for feedback modality research.

Furthermore, the implications of these findings extend to educational contexts, as understanding how feedback influences attention can inform the design of serious games aimed at enhancing learning outcomes. By leveraging the insights gained from this research, educators and game designers can create more effective serious games that promote sustained attention and improve cognitive functions among learners.

Our findings are based on a homogeneous sample of young adult females, which limits generalizability. Sex differences in cognitive processing are well-documented [32]and attentional capacity varies significantly across the lifespan [33]. Future studies should include gender-balanced, age-diverse, and clinical populations (e.g., ADHD, where feedback modality effects differ; [34]).

5. Conclusions

Attention plays a fundamental role in cognitive functioning, and serious games present a valuable platform for enhancing attentional capabilities through carefully designed feedback systems. This study examined how different feedback modalities - auditory, visual, and tactile - influence performance in an attention-demanding racing game over a 12-session training period.

The findings reveal several key insights about feedback's role in attentional training.
While all feedback types helped maintain performance levels, they demonstrated distinct

temporal patterns in their effects. Auditory feedback showed immediate benefits in reducing errors, suggesting its effectiveness for rapid response tasks. In contrast, visual and tactile feedback led to more gradual but sustained improvements, indicating their potential for long-term attentional training. Importantly, feedback modalities influenced the precision of decisions rather than the strategic choices between targets and non-targets. Notably, HMM analysis revealed that feedback modalities improved precision (reducing errors) without significantly altering strategic choices (band transitions), underscoring the need for targeted feedback designs to influence higher-level decision-making.

These results carry significant implications for serious game design and cognitive training applications. Game developers and educators should carefully consider the temporal dynamics of different feedback types when designing training programs. Auditory feedback may be most suitable for tasks requiring quick reactions, while visual and tactile feedback could be preferred for developing sustained attention. The findings also highlight the potential of serious games as customizable training tools that can adapt feedback modalities to specific cognitive objectives.

Future research directions emerging from this study include investigating optimal combinations of feedback modalities, examining longer-term training effects, and exploring applications in clinical populations with attention deficits. Additionally, studies with larger sample sizes could further validate these findings and potentially reveal more nuanced patterns of interaction between feedback types and individual differences in attentional processing. Also, Methodologically, comparative studies examining different computational modelling approaches would help establish best practices for analysing attentional processes in serious games.

By advancing our understanding of how different feedback modalities shape attentional performance, this research contributes to the development of more effective serious games for cognitive enhancement. The findings provide a foundation for designing targeted interventions that can be tailored to specific training goals and user needs in both educational and therapeutic contexts.

Critical next steps include: (1) replication in larger, gender-balanced samples to assess potential sex differences in feedback effectiveness; (2) extension to broader age ranges to examine developmental trajectories; and (3) application in clinical populations with attention deficits (e.g., ADHD) to test therapeutic potential.

Acknowledgments

The authors received no specific funding for this work.

Conflicts of interest

Authors have no conflict of interest to declare.

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