TAP OR SWIPE: INTERACTION'S IMPACT ON COGNITIVE LOAD AND REWARDS IN A MOBILE MENTAL MATH GAME

Patrick Jost, Sebastian Rangger and Andreas Künz
Human-Centred-Technologies Research Centre, FHV University of Applied Sciences, Dornbirn, Austria

ABSTRACT

With the growing prevalence of mobile apps for self-directed learning, educational games increasingly find their place in everyday routines, becoming accessible to a broad audience. Despite the growing ease of content creation by artificial intelligence computing, the challenge of designing effective and engaging Serious Games remains, particularly in managing cognitive resources and ensuring quality engagement, notably influenced by the game's interaction modalities. This study explores these challenges within the context of a casual mobile mental arithmetic game, investigating the differential impacts of tap and swipe interaction variants on cognitive load and reward-based engagement. The study presents the findings of an international field study on Google Play. In a between-group design, the two casual interaction paradigms were compared regarding their impact on practice performance, cognitive load and effect on classic casual game rewarding represented through points, leaderboards and badges. The findings show that tap interaction can optimise cognitive load with a better mental math practice performance than the more indirect swipe gesture. A combination of elementary tap interaction with point rank and interaction precision badges indicates to enhance practice motivation. The results are synthesised into interaction design recommendations for casual mental math mobile games.

KEYWORDS

Mobile Game-Based Learning, Mental Math Training, Casual Game Interaction Design, Cognitive Load, Playing Engagement, Serious Game, Google Play Store, Field Experiment

1. BACKGROUND AND RESEARCH AIMS

The integration of engaging mobile apps for self-directed learning has become prevalent in educational practices, facilitated by advancements and increased accessibility of artificial intelligence (AI) technologies. AI enables swift, generative creation of visual and auditory representations, simplifying the development of educational games for platforms like the Google Play Store (Liu & Chilton, 2022; Anantrasirichai & Bull, 2022; Jost, 2021; Louie et al., 2020). Such game-based learning experiences can reach a broad audience, integrating learning into everyday routines, for example, as a time-filler activity during commutes (Grothues et al., 2022; Mäyrä & Alha, 2020).

Utilising free game assets and AI's generative potential, non-experts, including educators, can create casual learning games for essential skills like mathematics. Despite the developing ease of asset creation, challenges persist in creating effective and engaging Serious Games (SGs) that aim beyond entertainment (Dörner et al., 2016). Special attention must be paid to cognitive resources and the game's entertaining quality when designing mobile SGs for mental arithmetic expertise. Both aspects are influenced by a digital game's interaction modalities (Isbister & Hodent, 2022) and can thereby affect the game's efficacy and engagement quality.

Research indicates that, for example, the interaction in Virtual Reality (VR) mental math training games can impact cognitive load more than less physically demanding gestures on a mobile device (Jost et al., 2020; Sweller, 2020). However, impact differences on cognitive resources and rewarding between much more similar interaction variations on a smartphone device, such as touch tapping or swiping, are less researched in mental arithmetic practice games.

This paper's research investigates the potential differences between these interaction variants in a mobile mental math learning game designed for casual, self-directed playing. The study examined the effects of interaction on cognitive load and engagement through rewards between tap and swipe gestures in a mobile mental arithmetic game called "Mental Math Ball," created with free assets and published on the Google Play Store for a two-month field study.

1.1 Interaction and Rewarding in Educational Math Games

Casual games, characterised by simple rules, brief sessions, and the potential for rapid proficiency through moderate to high challenge levels, are popular among inexperienced players and all age demographics (Grothues et al., 2022; Juul, 2010; Pizzo, 2023). Research in math practice Serious Games (SGs) covers a broad range of scenarios to understand learning efficacy and engagement qualities. Simplistic and direct interaction paradigms have been found to be more effective learning approaches in SGs, avoiding extraneous cognitive load (Chatain et al., 2022; Jost et al., 2020).

While most math learning game studies focus on the personal computer platform and respective interaction paradigms (Pan et al., 2022), mobile learning is associated with positive effects on mathematics achievement (Güler et al., 2022). Detailed insights into different mobile interaction variants could help identify sources of extraneous cognitive load (Sweller, 2020) that impair learning efficacy or engagement quality.

Besides intrinsic motivation from playing a digital SG that inherently includes interaction variation, extrinsic rewards can enhance engagement. Simple reward strategies like points, badges, and leaderboards (PBL) are particularly suited to casual games (Y. Chou, 2019; Deterding, 2012; Sailer et al., 2017; Werbach & Hunter, 2015). However, their benefits on motivation and learning achievement are controversially discussed in educational scenarios. Points can enhance motivation by gauging progress and competence (Hamari et al., 2014; Mekler et al., 2017), badges provide visual proof of success and boost a sense of capability and autonomy (Abramovich et al., 2013; Nicholson, 2015), and leaderboards introduce a competitive aspect to invigorate students inclined towards social comparisons (Hamari et al., 2014; Landers, 2014).

PBLs, when combined as a rewarding system in math SGs, enhance performance and engagement by introducing competition, supporting narratives, and providing adaptivity (Ariffin et al., 2022; Atin et al., 2022; Ortiz Rojas et al., 2016). However, their effectiveness varies among students and can shift focus towards extrinsic rewards rather than intrinsic learning (Jagušt et al., 2018; Mekler et al., 2017; Nicholson, 2015; Sanmugam et al., 2016). Not achieving certain rewards can cause frustration, negatively affecting engagement (C. C. Chou & He, 2017; McDaniel et al., 2012).

PBLs can instil engagement by accomplishment through mastering SG challenges and allow for social influence when sharing badges or leaderboard states (Y. Chou, 2019; Isbister & Hodent, 2022). Expert control over interaction variation connects to these core motivational drivers. For a comprehensive investigation into the impact of common interaction paradigms in mobile math learning games, research must consider both interaction's effects on cognitive resources and on casual game rewarding systems.

1.2 Research Objectives

The focus of this research is consequently to investigate the impacts of common mobile interaction design paradigms, the tap and the swipe gesture, to learn about differences in cognitive load and effects on rewarding by a points, badges and leaderboard system. Using established measures of perceived cognitive load and in-game metrics that assess interaction efficiency and playing engagement by frequency of voluntary playing/replaying, a mobile research game is created and deployed in an international field test in the Google Play Store. The research objectives of this field study were thereby twofold:

1. Investigating the impact of tap versus swipe interaction paradigms on cognitive load and performance in a casual mental arithmetic practice game.
2. Investigating the impact of tap versus swipe interaction paradigms on extrinsic motivation by a PBL reward system in a casual mental arithmetic practice game.

2. EMPIRICAL RESEARCH APPROACH

2.1 Creating and Configuring the Mobile Mental Arithmetic Practice Game

The game Mental Math Ball (MMB) was developed as a smartphone game for Android using the Unity game engine. It features two different ways of interaction but has otherwise an entirely identical structure. Unity is a suitable choice for research work due to its extensive library of assets and the ability to publish cross-platform builds from a single code base. These freely available assets can also be combined and expanded with AI-generated content, making it useful for non-game experts in creating educational games. The main learning goal of MMB is to enhance mental arithmetic skills through step-by-step practice. It starts with basic operations such as addition and subtraction, progresses to multiplication and division, and later includes exponentiation and root extraction. The game's structure allows for alternating arithmetic tasks while maintaining a consistent level of difficulty within each level.

Table 1. Mental arithmetic exercises developed with upper secondary school mathematics teachers

Operation	*Range*	*Restrictions*	*Example*
Addition	Summands: 30 – 250	Max. summand = 250	235 + 34
Subtraction	Minuend, subtrahend between: 30 – 250	Max. minuend and subtrahend = 250	63 - 112
Multiplication	Factors between: 1 – 250	Max. multiplicand = 20; Product divisible by 10	120 x 15
Division	Dividend between: 1 – 250 Divisor between: 1 – 100	Max. divisor = 100; Without a remainder	192 : 96
Exponentiation	Base between: 1 – 30	Max. exponent = 2	8^2
Square root	Radicand: 1 – 900	Only integer results	$\sqrt{121}$

These mental arithmetic equations, developed with upper secondary math teachers (Table 1), structure practice objectives for 16+ learners across a progression of difficulty levels. The game includes visual and auditory feedback, with exercises divided into three levels: addition/subtraction, multiplication/division, and exponentiation/root extraction. To keep practices manageable and goal-focused on smartphones, each level lasts 2 minutes, with a complete round taking 6 minutes. This offers an efficient, progressive structure that suits a mobile learning environment.

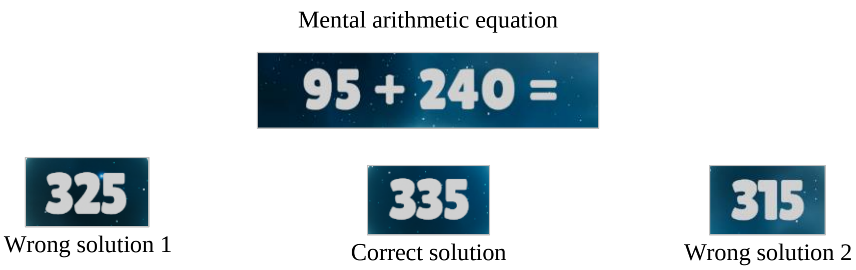

Figure 1. Addition task from the mental arithmetic game - Level 1.
Correct result and two slightly modified incorrect results

Figure 1 displays a level 1 arithmetic problem from the learning game, featuring three solutions - one correct and two modified. For addition/subtraction and multiplication, incorrect results varied by a randomly added number between -20 and 20. The correct solution's placement was also randomised. For low or single-digit results, common in division and root extraction, a number between -3 and 3 was added for closer approximations.

Tap Swipe

Figure 2. The game instruction illustrates and explains their respective interaction variant to the players. Group I (left) was explained the typing gesture, group II (right) the swipe interaction

In the actual practice phase of the learning game, elements of extrinsic motivation, such as the score display, are utilised. Initially, players are given a detailed introduction to the game mechanics, the learning objectives, and the manner of practising mental arithmetic. This also includes an explanation and illustration of the specific game interaction (Figure 2), scoring mechanics, and a description of the game levels. The introductory screen clarifies the individual arithmetic tasks, explains the three levels, their duration (2 min.), and the goal mechanism, which involves throwing the ball through the centre of the ring with the correct result, avoiding the two incorrect options. Scoring is established as gaining a point for correct results and losing a point for incorrect ones. From this screen, players can initiate the practice phase with an "Ok, let's play" button.

Figure 3. Mental Math Ball – addition in level one. Use of Unity's 3D engine with the soccer ball as a rigid body, realistic dimensions and mass, and eleven-metre distance to the goal rings

To maintain focus on the learning objective and minimise base cognitive load, the basic visual and auditory exercise scenario is deliberately minimalistic. A quiet, ambient night scene serves as the game's backdrop during the practice phase (Figure 3). The educational game leverages the 3D environment provided by the Unity game engine, which visually and physically simulates a three-dimensional world. The game environment incorporates the "rigidbody" component to implement spatial-physical conditions according to natural laws, allowing the ball to fly along a trajectory based on its mass and acceleration. The Unity engine interprets units as meters, facilitating the design of a realistic, three-dimensional scenario.

However, the first PBL element to be recognised in the practice phase is the scoring system, which, together with the structuring into levels, provides immediate feedback to players (Figure 3, bottom left and right). The point system connects the learning objective with the game objective by gaining a point for a correct calculation solution, but also deducting a point for an incorrect solution. The easily recognisable progress and the clear goal of achieving a high number of points fulfil general prerequisites for promoting motivation through the game activity (cf. flow theory; Nakamura & Csikszentmihalyi, 2020).

Tap Swipe

Figure 4. Illustration of the two interaction variants - tap and swipe - for throwing the ball into the goal with the correct calculation solution

Group I players use a tapping gesture to throw the ball at the correct mental arithmetic solution (Figure 4). The force of the throw is calculated based on the tap's location. Conversely, the swipe group 'kicks' the ball into the goal ring, with the trajectory determined by the swipe's speed and direction, using Unity's Rigidbody.AddForce(). The ball's specifications match an official FIFA soccer ball (size 5; 22 cm diameter, 450 grams), and its trajectory is computed by Unity's Nvidia PhysX Engine. Visual and audio cues provide feedback, and the game's performance is optimised for older smartphones. Invisible collider objects trigger scoring, animation, and precision calculation for the sniper badge reward.

2.2 Research Design, Hypotheses and Data Collection

The research design, as displayed in Figure 5, corresponds to a between-group field study for which each participant was randomly assigned to an interaction variant group. Group I was playing with the tap interaction, while Group II was assigned the swipe variant. Players stayed in their corresponding league also in potential replays of the game and were not aware of the existence of the other interaction variation.

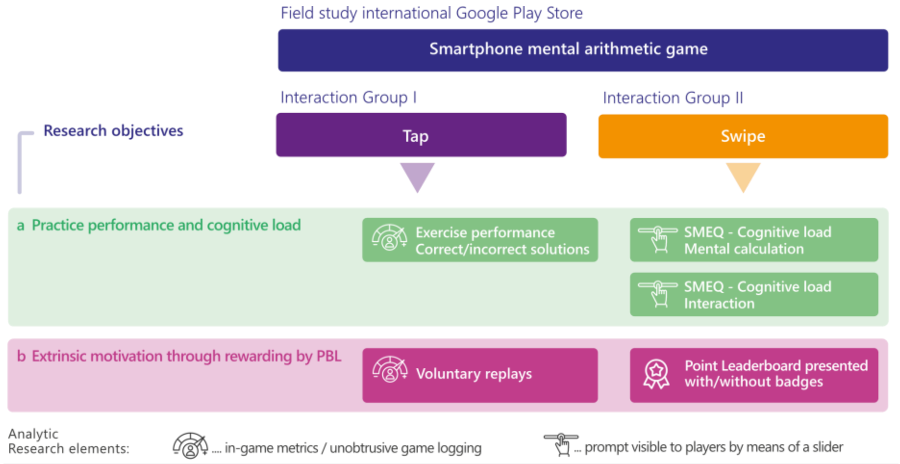

Figure 5. Experimental design for investigating interaction's effects in mobile mental math practice games

The MMB game recorded players' scores and the precision of throws, measured by the ball's distance from the ring's centre, unnoticeable for players during the practice phase (cf. stealth assessment; Ifenthaler & Kim, 2019; Ke & Shute, 2015). After this phase, players rated perceived cognitive load of the mental math equations and the interaction gesture individually via the Subjective Mental-Effort Question Scale (SMEQ), validated for reliability and sensitivity (Rubio et al., 2004; Sauro & Dumas, 2009; So et al., 2017; Verwey & Veltman, 1996; Zijlstra & Doorn, 1985), using a 0-150 slider input. Individual feedback on math equation and interaction variant informs about players' awareness of cognitive load origins and allows comparison with further interaction variations.

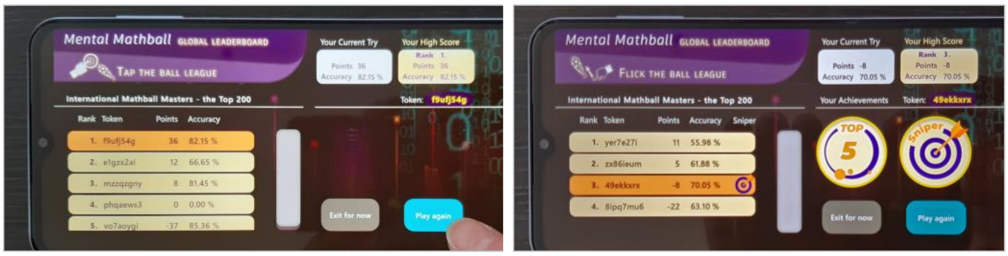

Figure 6. PBL reward system – point leaderboard and badges. Left: leaderboard of the tap gesture league without badge awarding. Right: the swipe gesture league in the variation with badge rewards (rank/sniper badge)

The SMEQ feedback was only displayed after the first game round and was required to access the leaderboard screen, showing the point leaderboard with or without badges. A condition randomly allocated at the game start and kept for players during all successive playing. If one was in the group showing badges,

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badges were awarded for top 200, 100, 50, 10, and 5 ranks and for over 70% average hit accuracy as a sniper badge (Figure 6). From this screen, players could exit or voluntarily play another round, the latter being the metric to evaluate interaction variation impact PBL rewarding. In accordance with the research objectives, it was hypothesised that there would be a difference between the interaction groups regarding practice performance, cognitive load and effects on PBL rewards. Respectively, the null hypotheses for the field study were established as:

H_{0a1}: 'There is no significant difference in mental arithmetic practice performance between playing the smartphone mental arithmetic game using either tap or swipe gestures.'

H_{0a2}: 'There is no significant difference in the perceived cognitive load from solving the mental arithmetic tasks between playing the smartphone mental arithmetic game using either tap or swipe gestures.'

H_{0a3}: 'There is no significant difference in the perceived cognitive load from throwing the ball at the correct result between playing the smartphone mental arithmetic game using either tap or swipe gestures.'

H_{0b1}: 'There is no significant difference between the tap and swipe gestures in their effect on extrinsic rewarding through point leaderboards awarding no badges in the smartphone mental arithmetic game.'

H_{0b2}: 'There is no significant difference between the tap and swipe gestures in their effect on extrinsic rewarding through point leaderboards awarding rank and precision badges in the smartphone mental arithmetic game.'

The MMB game was internationally released on the Google Play Store for a two-month field study. An international Google Ad managed by the researchers adjusted daily budgets weekly between 70 to 280 NOK. Aiming for 300 valid unique plays per interaction group, we anticipated a 90% dropout rate, following trends in similar studies (Jost, 2021). The game was compatible with 4,493 devices and available in 177 countries. Players were informed about privacy, data collection, and research objectives before installation. Gameplay data, collected anonymously, referenced by a generated token and securely transferred via https, complied with EU General Data Protection. Only after informed consent could participants proceed to play the game.

3. RESULTS

3.1 Field Study Participation

In the two months, the game was installed by 11716 individuals on 1144 devices, with 99% on smartphones, and 1% on tablets. Of these, 892 played at least once, representing an expected dropout rate of 93%. Seven datasets were excluded due to non-serious attempts; three entries were removed due to interaction variant changes only possible through deleting and reinstalling the app. Valid participants included 757 who completed the first round and 135 who initially quit but later played valid rounds. Out of those completing the first round, 396 provided valid feedback. 152 inauthentic feedback entries, made only to access the leaderboard, were discarded. Such entries, identified from log analysis, showed setting min/max scale values in mostly three or fewer seconds while not reflecting on the questions.

Table 2. Participant distribution of the two-month field study

	n	*Quota*	*Tap*	*Swipe*
Installations from Google Play Store	11716	100%	-	-
Valid unique players	892	7.61%	-	-
Valid complete first round plays	757	6.46%	418	339
Valid feedback in the post-practice screen (SMEQ)	396	3.38%	225	171

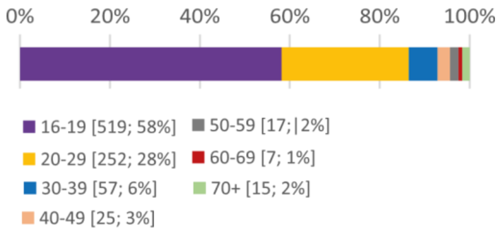

Figure 7. Distribution of valid participations by age group

Players' age group distribution (Figure 7) showed that over 50% of participants were under 20, and 86.5% were under 30 years old. This data, based on self-reports, is not verifiable for authenticity, but a mainly young audience is expected.

3.2 Interaction Impact on Math Practice Performance and Cognitive Load

The collected data did not show a consistent normal distribution for the dependent variables tested, according to Shapiro-Wilk (1965). Therefore, for the hypothesis tests of the analytical questions, the distribution medians of the groups (typing/wiping) were tested for differences using Mann-Whitney *U* analysis ($\alpha = 0.05$) as recommended by Field (2017). To address analytical question a, only first successful playthroughs ($n = 757$) were evaluated. This approach ensured comparison of interaction variants was free from hidden practice effects.

Table 3. Significant median differences in exercise performance between tap/swipe interaction. [*CI* = 95% confidence interval]

		Tap	*Swipe*	*U*	*z*	*p*	*r*
	n	418	339				
Total score	*Mdn* *CI*	19 18 – 21	11 10 – 13	55930.0	-5.0	< .001	-.18
Correct solutions	*Mdn* *CI*	34 32 – 36	22 20 – 24	40039.5	-10.3	< .001	-.37
False Solutions	*Mdn* *CI*	10 10 – 11	7 7 – 8	53046.5	-6.0	< .001	-.22

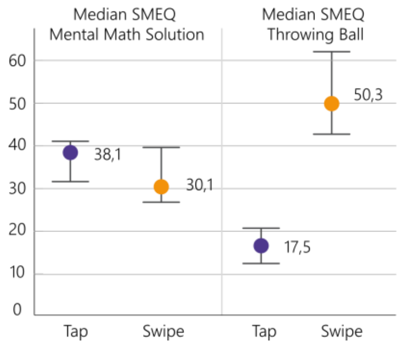

Figure 8. Significant cognitive load difference in throwing balls between interaction variants (right)

Statistical analysis revealed significant differences in practice performance between swipe and tap interaction groups in total points and correctly/incorrectly solved mental arithmetic tasks (Table 3). Those using swipe gesture had lower median performance (*Mdn* = 11) than the tap group (*Mdn* = 19). This extends to correct solutions, with the swipe group scoring fewer (*Mdn* = 22) than the tap group (*Mdn* = 34), while throwing fewer balls at incorrect solutions (*Mdn* = 7 vs. *Mdn* = 10). The effect sizes (*r*) for these differences were small, but a medium effect size (> 0.3) was indicated for correct solutions (Cohen, 1988; Field, 2017). Analysis of SMEQ feedback on perceived cognitive load (Figure 8; $n = 225$ tap; 171 swipe) showed the swipe interaction introduced significantly more perceived cognitive load (*Mdn* = 50.3, *CI 95%* = 41.9 – 61.8) than the tap interaction (*Mdn* = 17.5, *CI 95%* = 12.4 – 21.4), $U = 1128.2$, $z = 8.38$, $p = < .01$, $r = .42$. However, no significant difference in perception was observed in solving the math equation, $U = 17647.5$, $z = -1.41$, $p = .159$. Data analysis suggests rejecting H_{0a1} and H_{0a3} due to significant performance differences and differing cognitive load perception regarding interaction variant, while H_{0a2} is to retain as cognitive load of solving math equation was perceived not differently by both groups.

3.3 Interaction Impact on Extrinsic Motivation by PBL Rewarding

By statistical analysis of authentic game participations ($n = 892$), players who didn't receive badge rewards ($n = 511$) across tapping and swiping interactions were compared. The only reward for these players was a global leaderboard entry (Figure 6 left). Players who received badges were then also analysed regarding differences (n = 381) to evaluate the impact differences of interaction types on reward-based motivation introducing badges. These players could gain rank badges (leaderboard position) and sniper badges (precision of ball throwing), as shown in Figure 6 (right).

U-test analysis revealed that without badges, the tap interaction group replayed less frequently (*Mdn* = 1.00) than the swipe group (*Mdn* = 1.50). However, with badges awarded, tap group replay frequency increased (*Mdn* = 1.50), while the swipe group decreased (*Mdn* = 1.00), eliminating the significant difference (Table 4).

Table 4. Significant difference between tap/swipe interaction without rewards; no difference with performance and precision badges. [*CI* = 95% confidence interval]

	Tap [no badges]	*Swipe [no badges]*	*U*	*z*	*p*	*r*
n	289	222				
Mdn	1.0	1.5	26612.5	-3.7	< .001	-.16
CI 95%	1 – 1	1 – 2				
Maximum	115	39				
	Tap [with badges]	*Swipe [with badges]*	*U*	*z*	*p*	
n	186	195				
Mdn	1.5	1.0	35872.0	-1.39	.164	
CI 95%	1 – 2	1 – 2				
Maximum	149	24				

Statistical results suggest rejecting null hypothesis H_{0b1} due to significant differences in game repetition without badges. However, no differences were found when badges were used; thus, analysis suggests retaining H_{0b2}.

4. DISCUSSION

4.1 Implications for Interaction Design in Casual Math Practice Games

When interpreting the results regarding common interaction modality impact differences in mobile math practice games, two main design implications can be observed.

First, mental arithmetic practice games can be optimised regarding math training performance and cognitive load by preferring tap over swipe interaction. Confirming prior studies that investigated math training games with more diverse and complex interaction paradigms (Jost et al., 2020), the more direct interaction with fewer degrees of freedom proved to be more supportive for math practice in a learning game. While designing the interaction by tap gesture can, therefore, optimise cognitive load to focus on the math-solving problem, no considerable drawbacks to a casual game's practice motivation quality were found in this field study.

Second, combining simple tapping gestures with reward-oriented motivational drivers including badges, can augment engagement in casual mental arithmetic games. The simple executability of the tapping gesture proved well-suited to be combined with reward-oriented motivational drivers in the form of badges. For instance, a precision badge in mental arithmetic practice games, which, as in the present study, connects the interaction with the learning objective, can support playing engagement. Due to the low complexity of the tapping gesture, frustration caused by the interaction modality is more unlikely, and the incentive effect of the reward badges is in the foreground, helping to keep focus on the overall learning aim of gaining mental arithmetic expertise. In that, the results support the findings of previous studies raising awareness of negative impacts of frustration and distraction when introducing badges (C. C. Chou & He, 2017; McDaniel et al., 2012) by leading to consider less intricate interaction paradigms in casual mental math practice games.

4.2 Limitations and Further Research Trails

The study offered insights into interaction effects and research-oriented game design. Voluntary participation facilitated a valid sample in this international Google Play Store field study, though freedom brought limitations, such as participant uncertainty. The game, distributed internationally but only in English, may have been played by those who misunderstood instructions. Another limitation is the reduced control over game context; extreme values can be logged, but subtle contextual influences could affect group differences. Self-reported endgame analytics may contain untruthful responses. Future controlled studies should further explore these findings. The

Google Ads campaign and smaller ad budgets may have biased the sample nationally due to uncontrolled ad placements.

5. CONCLUSION

The reported result from the two-month field study confirmed previous studies that found impacts from interaction on cognitive load and practice performance in math training games. The study expanded towards investigating the detailed impact between the common casual mobile game interaction paradigms tap and swipe. During the two-month field study on the international Google Play Store, players of the mental math game perceived more cognitive load and had lower practice performance from interacting with the swipe gesture compared to the more direct tap interaction. Results also showed that while players with the tap gesture were initially less inclined to replay the game when only a leaderboard was shown for extrinsic motivation, introducing rank and interaction precision badges as rewards negated this disadvantage compared to the more indirect swipe gesture. Ultimately, the findings showed that less intricate interaction paradigms can be utilised for optimising math learning performance and cognitive load in casual mental math training games while not considerably impeding practice motivation. In particular, a combination with badges has shown to support motivational quality, improving replayability when utilising a tap interaction paradigm. Future studies are encouraged to investigate further combinatory pathways of elementary mobile interaction in combination with badge rewarding in casual mental math practice game scenarios.

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