

The Influence of Social Competition and Maths Anxiety on Game Performance

André Almo¹, Maíra Amaral¹, Mariana Rocha¹, Attracta Brennan², and Pierpaolo Dondio¹

¹Technological University Dublin, Dublin, Ireland

²University of Galway, Galway, Ireland

andre.almo@tudublin.ie

maira.amaral@tudublin.ie

mariana.rocha@tudublin.ie

attracta.brennan@universityofgalway.ie

pierpaolo.dondio@tudublin.ie

Abstract: Digital Game-Based Learning (DGBL) uses serious games to deliver educational content. DGBL has the potential to aid children's development of maths skills, providing educators with alternatives to traditional mathematics teaching. However, the efficacy of serious games can be affected by their attributes, including whether they are single or multi-player. While competition in a multi-player environment may enhance players' interest and motivation, potential social pressure may lead to anxiety and affect performance. In maths education, there are additional challenges. Mathematics Anxiety (MA), the negative emotional response to mathematics, may interact with game features and impact players' experience. This study assesses players' performance in a digital maths game called 'Seven Spells' across two different game modes (*vs. Human* and *vs. CPU*), and it also investigates whether MA levels impacted players' performance. 43 children from two classes in an Irish primary school participated in this study. Each class played a different game mode of the 'Seven Spells' game, one group playing against computer-controlled characters (*vs. CPU*) and the other playing against their classmates (*vs. Human*). The game mechanics were identical between the two competition game modes. The children completed the modified Abbreviated Mathematics Anxiety Scale (mAMAS) and a mathematics questionnaire before participating in the intervention, which included 4 sessions. They also participated in a focus group session at the end of the intervention. Data on their gameplay were collected throughout the first three sessions and analysed through multiple linear regression models to investigate possible connections between MA, maths knowledge, game modes and game performance. The results of the multiple linear regressions indicate that game performance was positively influenced by the duration of gameplay and the complexity of moves — measured by the number of moves and cards used — while being negatively affected by MA. However, a significant interaction between MA and the competition game mode was observed, suggesting that MA had a more pronounced negative impact on players in the *vs. Human* game mode compared to the *vs. CPU* game mode.

Keywords: Digital Game-based Learning, Primary School, Mathematics Anxiety, Competition.

1. Introduction

Digital Game-Based Learning (DGBL) is an active, student-centred problem-based learning approach in which digital games are used as tools for teaching and learning (Theofylaktos et al., 2018; Vanbecelaere et al., 2020). DGBL has been shown to optimise learning, positively influencing concentration, information assimilation and retention (Moyer-Packenham et al., 2019; Vanbecelaere et al., 2020). Additionally, DGBL mathematics interventions are perceived as more enjoyable than traditional paper-based mathematics exercises and typically show positive effects on arithmetic performance (Castellar et al., 2015, Vanbecelaere et al., 2020).

Games have several design elements that may influence learning (Moyer-Packenham et al., 2019), including whether they are single or multi-player. Playing against a human opponent or against a computer can affect immersion, flow, enjoyment and presence, all of which are relevant for digital learning and player motivation (Weibel et al., 2008). Among other factors, competition is indeed experienced in different ways when a player is facing a human opponent or a computerised one (Cagiltay et al., 2015). Even though competition can enhance a player's motivation and lead to better learning outcomes (Cagiltay et al., 2015), this game element can also reduce performance and increase anxiety (Cagiltay et al., 2015). In the context of mathematics, Mathematics Anxiety (MA), which is defined as a set of negative feelings such as nervousness and dread associated with mathematics learning, could indeed negatively affect mathematics performance (Buratta et al., 2019, Carey et al., 2017, Krinzinger et al., 2009). To investigate the relationship between different game modes, MA levels and game performance, this research investigates the connections between gameplay characteristics, maths knowledge, MA levels and player performance within a digital maths game ('Seven Spells') in two competition modes: *vs. Human* and *vs. Computer-Controlled Characters (vs. CPU)*. The research questions for this study are:

1. What factors influence player performance in the digital maths game ‘Seven Spells’?
2. Do specific factors affect player performance differently depending on the competition game mode?

Given the negative effects that MA might have on mathematics performance, we hypothesised that MA would be a significant factor negatively associated with game performance, while the complexity of the moves executed by players would significantly increase game performance. Moreover, due to the potential difference in the way competition is perceived in the two different game modes, we expect that the effect of MA could vary according to the game mode played.

2. Methods

2.1 Research Design

This study recruited two 3rd classes from a primary school based in Dublin, Ireland, comprising students aged 9 to 10 years old. Only students whose guardians/parents permitted participation in the study were included. Classes were visited in four sessions; twice per week, during school hours. Each session lasted one hour. Table 1 details the experimental design, displaying the activities performed in each session.

Table 1: Experimental design

	Session 1	Session 2	Session 3	Session 4
Activities	Questionnaires	Game review	Game review	Focus group
	Game tutorial	Game session	Game session	
	Game session			

In Session 1, the students completed the modified Abbreviated Mathematics Anxiety Scale (mAMAS) (Carey et al., 2017) and a maths fluency test. Students were then introduced to the ‘Seven Spells’ game, which they played on tablet devices provided by the research team. The research team also delivered an in-person tutorial explaining the game and advising the students during their first gameplay. The two 3rd classes played the same game, but in different competition modes: one group competed against CPU (*vs. CPU* group) whilst the other group competed against their classmates (*vs. Human* group). During Sessions 2 and 3, the researchers reminded students of the game’s rules through a guided game match and students played again. During Session 4, the students were invited to attend a focus group discussion on their overall game experience.

2.2 Participants and Data Collection

The total sample for this study comprised 43 3rd class students. Data on the students’ MA levels and maths performance before playing the DGBL intervention were gathered and inputted into an anonymised dataset, in compliance with the General Data Protection Regulations (GDPR). Students played the ‘Seven Spells’ game using randomly generated usernames. Data cleaning was necessary to remove students who did not participate in all four sessions and/or did not answer questions on the mAMAS scale (incomplete data). The final number of students whose data was included in the analyses is shown in Table 2.

Table 2: Number of students included in the analyses of each variable (complete data).

Variable	vs. CPU	vs. Human	Total
Mathematics test	21	22	43
MA levels	21	20	41

Data was analysed to investigate possible correlations between the game’s distinct competition modes, player performance, and MA levels. Data was password-protected, and only participant researchers could access it.

Maths fluency. The students’ maths fluency was identified through a short mathematics test aligned with the content covered both by the ‘Seven Spells’ game and the Irish Mathematics curriculum for 3rd class. They were given ten minutes to complete the questionnaire. In the data analysis, the number of mathematics errors (ME) was captured with omissions (i.e. questions not answered) being counted as errors.

Mathematics Anxiety (MA). The modified Abbreviated Mathematics Anxiety Scale (mAMAS) (Carey et al., 2017) was used to measure the students’ MA. In this questionnaire, the students answered nine questions about

situations involving mathematics learning. using a 5-point Likert scale to indicate their feelings: 1: 'Low anxiety'; 2: 'Some anxiety'; 3: 'Moderate anxiety'; 4: 'Quite a bit of anxiety'; 5: 'High anxiety'), along with a simple emoji to better illustrate that feeling. The minimum possible score for the mAMAS questionnaire is 9, which would indicate low MA. The maximum possible score of 45 points would indicate high levels of MA.

Focus groups. Students from each group were recruited to participate in 2 focus groups (one per group) in Session 4. These focus groups aimed to elicit the students' points of view, motivations and perceptions regarding 'Seven Spells'. To achieve this in a non-directive way, the moderator created a set of open-ended questions (Gibson, 2007). To make better use of the students' potential to generate rich debate, only five to six students were included in each focus group due to their age (9-10 years old). Gibson, 2007 recommends using small focus group numbers when working with younger children (6-10 years). The following questions were asked to both groups: "What did you think about the game?"; "What maths concepts did you learn while playing Seven Spells?"; "Did the game make you feel less anxious about maths?". One question differed depending on the group: the *vs. CPU* group was asked: "How do you feel about playing against the computer characters?", while the *vs. Human* group was asked: "How do you feel about playing against your classmates?".

2.3 The 'Seven Spells' Game

The digital maths game 'Seven Spells' was used to deliver the DGBL intervention. To play, the students needed to understand the concept of even and odd numbers, prime numbers, multiples, intervals, symbols (such as less-than and greater-than (" $<$ ", " $>$ ")) and intervals. The aim of the game is to capture the opponents' cards by using the players' own cards. Cards can be classified as 'number cards' (the blue and red cards in Figure 1) or 'spell cards' (the yellow cards in Figure 1). Spell cards are used to capture or modify number cards displayed on the board. To capture a card, a player must match cards that carry the same number. There are also 'special' number cards: the 'Total' card (capable of capturing multiple opponent cards, as long as they sum up to the number shown on the 'Total' card) and the 'Max' card (which captures any card whose number is equal or lower than the number shown on the 'Max' card). During their turn, players can use as many cards as they want, combining numbers, arithmetic operations, and number properties to capture the highest amount of cards. After completing their moves, players press the 'GO' button to earn points for their actions. It is then the opponent's turn to play next.

To win, players must reach or surpass 100 points. If the player who started the match achieves or exceeds 100 points first, their opponent has one more turn. If the opponent surpasses the starting player's score, they win; if not, the first player wins.

Although the rules and gameplay are similar, there are some differences between the two competition game modes. When playing *vs. CPU*, a storyline element is connected to a reward system. In the story, the player is part of a fictional martial arts academy where they learn the art of number fighting. They must face distinct characters to advance through different-coloured belts, with characters from the next belt being stronger than those having a belt of a lower rank. It is only when the players defeat an opponent that they can face the next opponent. After defeating all opponents in a particular level, the player is rewarded with a belt matching that level's colour. When playing the *vs. Human* mode, players have to choose an opponent within their class and create a match in an online lobby. The invited classmate can then join this match.



Figure 1: "Seven Spells" gameplay - *vs. CPU*.

2.4 In-game Variables Considered in the Study

By collecting and processing game logs, we computed various indicators of game performance. The variables were computed for each move that a player executed. The move-level in-game variables include:

- **Number of opponent cards** - The number of opponent cards that can be captured by the player in that turn.
- **Maximum achievable points** - The maximum number of points that the player can achieve in that turn. It is a theoretical number of points that the player can be awarded through the ‘best’ possible combination of moves.
- **Stack size** - The number of the player’s own cards used to execute a move. A higher number of cards being used suggests a higher complexity of moves in that turn.
- **Total cards available** - The total number of cards available for the player to use in their moves in a turn.
- **Incremental move** - An incremental number for the moves of each player. The variable is introduced to control for a learning effect, where players execute more complex and precise moves as they play more.
- **Optimality score.** This score measures the quality of each player's moves performance and is equal to the number of actual points scored by the player in a turn, divided by the maximum achievable points. This measure ranges from 0 to 1, with 1 being perfect optimality, meaning that the player scored the maximum amount of points possible for that turn. Optimality represents a measure of game performance and it is used as the target outcome variable in our regression models.

$$Optimality = \frac{Number\ of\ points}{Maximum\ achievable\ points}$$

We also collected the game mode being played: *vs. CPU* or *vs. Human*.

2.5 Quantitative Data Analysis

Data analysis was carried out using R. Descriptive and inferential statistics were used to draw conclusions about the effect of MA and other variables on the players’ performance in the ‘Seven Spells’ game in distinct game modes. Regarding the inferential statistics tests, a set of multiple linear regression models was carried out considering the optimality of each move as the target variable; as predictors, this study considered the players’ level of MA and the in-game variables described in section 2.4, including the number of opponent cards, maximum achievable points, stack size, total cards available and incremental moves.

3. Results

3.1 Descriptive Statistics for Mathematics Anxiety & Mathematics Errors

MA values collected before the DGBL intervention were considered for both the *vs. CPU* (MA_{CPU}) and the *vs. Human* (MA_H) groups. The values of both groups together are referred to as MA_{CPU+H} (Table 3).

Table 3: Descriptive statistics of MA.

Variable	Description	N	Mean	SD
MA_{CPU}	MA in the <i>vs CPU</i> group	21	17.14	7.95
MA_H	MA in the <i>vs Human</i> group	20	21.75	7.09
MA_{CPU+H}	MA in both groups	41	19.39	7.80

Mathematics Errors (ME) collected before the intervention were considered for both the *vs. CPU* (ME_{CPU}) and the *vs. Human* (ME_H) groups. The values of both groups together are referred to as ME_{CPU+H} (Table 4).

Table 4: Descriptive statistics of ME.

Variable	Description	N	Mean	SD
ME_{CPU}	ME in the <i>vs CPU</i> group	21	12.43	9.38
ME_H	ME in the <i>vs Human</i> group	22	11.68	7.97
ME_{CPU+H}	ME in both groups	43	12.05	8.59

3.2 Multiple Linear Regression

A multiple linear regression analysis was conducted to identify the relationship between game performance (measured by optimality of moves) and a set of predictors represented by MA, the set of in-game variables described in section 2.4 and the game mode, represented by a categorical variable with two possible levels: vs. *Human* or vs. *CPU*. A total of 3875 moves were collected from the game logs.

Table 5 shows the results obtained. *MA* was a significantly negative factor, showing how a higher level of *MA* decreased the optimality of a player's moves. The variable *incremental move* was significant and positive, suggesting that players were getting better the more they played. *Stack size* was also significant and positively associated, meaning that larger and more complex moves increased game performance. Finally, the control in-game variable, *maximum number of achievable points*, was significant, suggesting how the optimality of a move increased when there were more points available to capture. The R-squared value for the model was 0.2406, suggesting a moderate level of fit for the model. The variable *game mode* was not significant, showing how there were no significant differences in optimality across the two game modes.

Table 5: Linear regression coefficients (both game modes).

Coefficients				
	Estimate	Standard Error	t-value	Pr(> t)
<i>Intercept</i>	0.5750435	0.0613538	9.373	< 2e-16 ***
<i>ME</i>	-0.0002430	0.0011195	-0.217	0.82817
<i>Incremental move</i>	0.0015602	0.0002552	6.113	1.21e-09 ***
<i>MA level</i>	-0.0036764	0.0012461	-2.950	0.00322 **
<i>Game mode = Human</i>	-0.0252745	0.0187479	-1.348	0.17780
<i>Maximum achievable points</i>	-0.0061532	0.0006561	-9.379	< 2e-16 ***
<i>Stack size</i>	0.0826504	0.0049369	16.741	< 2e-16 ***
<i>Total cards available</i>	-0.0060673	0.0038093	-1.593	0.11141
<i>Number of opponent cards</i>	-0.0014115	0.0071558	-0.197	0.84366

We then fitted the same model for the vs. *CPU* and vs. *Human* game mode data separately. In the vs. *CPU* game mode, *MA* ceased to be a significant factor, whereas the in-game variables - incremental move, stack size, and maximum number of points - remained significant, consistent with the model fitted using data from both game modes (see Table 6). The multiple R-squared was 0.1981, lower than that of the model fitted on all the data.

Table 6: Linear regression coefficients (vs CPU mode).

Coefficients				
	Estimate	Standard Error	t-value	Pr(> t)
<i>Intercept</i>	0.4520127	0.0896796	5.040	5.48e-07 ***
<i>ME</i>	-0.0002351	0.0013084	-0.180	0.857
<i>Incremental moves</i>	0.0014337	0.0002810	5.103	3.97e-07 ***
<i>MA level</i>	-0.0023759	0.0015327	-1.550	0.121
<i>Maximum achievable points</i>	-0.0066158	0.0008738	-7.571	8.14e-14 ***
<i>Stack size</i>	0.0857383	0.0067286	12.742	< 2e-16 ***
<i>Total cards available</i>	-0.0007567	0.0051220	-0.148	0.883
<i>Number of opponent cards</i>	0.0096095	0.0117563	0.817	0.414

In contrast, a model fitted only using game data from the *vs Human* game mode (Table 7) showed how MA was strongly significant, with a coefficient of $\beta_{MA} = -6.61 * 10^{-3}$, almost twice the size of the coefficient computed using the data from both game modes ($\beta_{MA} = -3.67 * 10^{-3}$, see Table 6). Once more, *incremental moves*, *maximum achievable points* and *stack size* were significant factors. The multiple R-squared was 0.2747, exceeding the values observed in the two preceding models.

Table 7: Linear regression coefficients (vs. Human game mode).

Coefficients				
	Estimate	Standard Error	t-value	Pr(> t)
<i>Intercept</i>	0.7195637	0.0903635	7.963	8.45e-15 ***
<i>ME</i>	-0.0009067	0.0022966	-0.395	0.693122
<i>Incremental moves</i>	0.0025835	0.0007225	3.576	0.000377***
<i>MA</i>	-0.0061942	0.0022159	-2.795	0.005350 **
<i>Maximum achievable points</i>	-0.0050291	0.0009919	-5.070	5.30e-07 ***
<i>Stack size</i>	0.0771627	0.0072745	10.607	< 2e-16 ***
<i>Total cards available</i>	-0.0143471	0.0056819	-2.525	0.011824 *
<i>Number of opponent cards</i>	-0.0122425	0.0094350	-1.298	0.194935

As MA showed significance in the *vs. Human* mode but not in the *vs. CPU* mode, we explored the possibility of a significant interaction between MA and game mode by performing a multiple linear regression to assess the interaction effect between these two variables. The results in Table 8 show a significant interaction between MA and game mode at a 0.05 confidence level. The direction of the interaction is shown in Figure 2, suggesting that MA had a stronger negative impact on performance in the *vs. Human* game mode. The multiple R-squared value was 0.2426, slightly higher than the model without interaction (Table 6).

Table 8: Linear regression coefficients (MA and game mode).

Coefficients				
	Estimate	Standard Error	t-value	Pr(> t)
<i>Intercept</i>	0.5308061	0.0615147	8.629	< 2e-16 ***
<i>Incremental moves</i>	0.0016373	0.0002493	6.566	6.83e-11 ***
<i>MA</i>	-0.0023753	0.0011311	-2.100	0.0359 *
<i>Game mode = Human</i>	0.0669650	0.0454827	1.472	0.1411
<i>Maximum achievable points</i>	-0.0060389	0.0006459	-9.350	< 2e-16 ***
<i>Number of opponent cards</i>	-0.0008633	0.0070940	-0.122	0.9032
<i>Stack size</i>	0.0833005	0.0048711	17.101	< 2e-16 ***
<i>Total cards available</i>	-0.0057731	0.0037237	-1.550	0.1212
<i>MA * Game Mode = Human</i>	-0.0044325	0.0021444	-2.067	0.0389 *

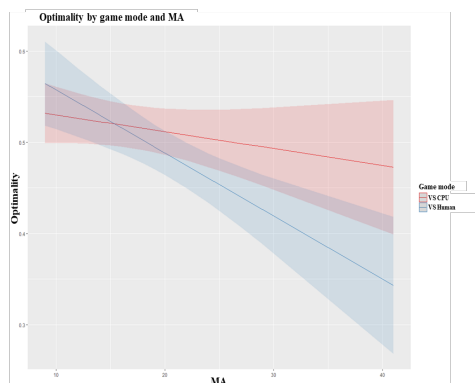


Figure 2: Optimality by game mode and MA.

3.3 Focus Groups

A review of the focus group feedback showed that the students provided positive remarks regarding their experience, describing it as fun and beneficial to their learning. They also mentioned various mathematics topics they practised during gameplay, such as multiplication, addition, prime numbers, and symbols.

In the *vs. CPU* group, the students expressed appreciation for the fantasy martial arts setting, particularly noting the progressive levels marked by different coloured belts: One student remarked; “I like the way there's a bunch of different belts, so it's like you are doing jiu-jitsu and you're fighting people and the more people you fight and win, the more you get a higher belt”. Another mentioned, “You started with an easy-peasy belt, and you got upper belts and it got harder”. Overall, students enjoyed this game mode, commenting: “I liked the way that people were robots, but they act like real people”.

Meanwhile, students in the *vs. Human* group emphasised the competitive aspect against their classmates. One student said; “I like the fact that I've been beating everybody whenever playing the game. I am really good at the game and I really like it”. Another student mentioned: “You are able to go against people and beat them because you are good at maths”. However, they also acknowledged a negative social aspect, with one student expressing: “but it's also bad, because you don't want to see them getting upset, but then you can cheer them up by helping them win against someone else”.

4. Discussion and Conclusions

This study investigated the relationship between different playing modes, psychological factors and students' performance in ‘Seven Spells’, a digital maths game. The results of a linear regression analysis showed several in-game variables as significant predictors of game performance and indicated a distinction in how MA levels impact performance based on the game mode (*vs. Human* or *vs. CPU*) being played.

When considering both game modes as one group, the linear regression identified MA, incremental moves and stack size as significant coefficients for the target variable (optimality). Whilst MA had a negative effect on optimality, incremental moves and stack size affected optimality positively. Considering MA, this suggests that students who feel anxious about maths have lower performance in the ‘Seven Spells’ game. Regarding incremental moves, this result indicates that as the students played ‘Seven Spells’ for longer durations, their performance in the game improved. Finally, the positive correlation between stack size and optimality points out that players who use more cards in their moves have a better performance. In this analysis, game mode was not significant after controlling for all other factors.

When considering just the *vs. CPU* game mode, the linear regression produced similar results: incremental moves and stack size remained statistically significant and positively influenced optimality. However, MA was not a significant coefficient. When repeating the linear regression for the *vs. Human* mode, the results for incremental moves and stack size did not change, while MA showed a significant and negative effect on optimality, the strongest effect among the models considered. This difference suggests that MA had a different effect on players' performance depending on the game mode, with a higher negative impact when students compete against one another (*vs. Human*), as opposed to playing against the computer (*vs. CPU*).

To further investigate the potential link between MA and the different competition game modes, we fitted a linear regression to examine the interaction between MA and game mode. The interaction was found to be significant, confirming that MA had a negative impact solely in the *vs. Human* competition game mode.

Given that MA encompasses the social experience of doing maths (Rooney, 2014), this study offers additional insights into serious games focused on maths. The presence of a competitive element, especially in scenarios involving two human players, may trigger anxiety, particularly related to MA within its social context, thereby negatively affecting performance (Cagiltay et al., 2015; Rooney, 2014). This highlights the need for maths games to consider MA and the experience of maths-anxious players (Dondio, Gusev and Rocha, 2023).

In the *vs. Human* focus group discussion, some players mentioned concern over potentially upsetting their classmates if they were to win a match. This hints at a possible increase in anxiety due to the competitive component/aspect of the game (Cagiltay et al., 2015).

Concerns about potentially irritating other players did not arise during the focus group discussion in the *vs. CPU* group, as these players were solely competing against computer-controlled characters. These results may suggest that players of the *vs. Human* competition game mode potentially experienced some attributes of social

anxiety, characterised by fear/apprehension of social interactions and negative social outcomes (Belzer et al., 2005). Since social anxiety can also impact students' concentration and academic performance (Leigh et al., 2021), this raises the possibility of an interaction between social anxiety and MA, with one potentially influencing the other and both negatively impacting students' performance.

This study has several limitations, mainly the low number of students involved in the experiment and the differences between game modes. The small sample - due to the number of available classes and students missing sessions and/or not answering all questionnaire questions - had an impact on data significance. A further issue with the present dataset is that students from the *vs. Human* group had a higher baseline MA than those in the *vs. CPU* group. Moreover, the two competition game modes evaluated in this study have additional differences other than having human or computer-controlled opponents. The *vs. CPU* mode incorporates a storyline element and a reward system. The inclusion of a reward mechanism, serving as a motivational tool, could potentially introduce a confounding factor. Furthermore, the two competition game modes have a fundamental difference in terms of the ease with which students could start a match. The *vs. CPU* players could start a match against the computer at any time, while the *vs. Human* players needed to set up a match with another human player. As a result, students assigned to the *vs. CPU* group engaged in more gameplay sessions. Additionally, games against human players tended to be longer as players took more time to execute their moves, and communication between the two players during the match was infrequent.

Further research should include larger sample sizes to better investigate how MA and different competition game modes, in addition to their potential interactions, influence students' performance in 'Seven Spells'. The current study establishes links between the aforementioned factors and highlights shortcomings in the existing experimental design, mainly regarding students' playtime. These limitations will be addressed in a redesigned version, informed by the findings of this study.

Acknowledgements

This work was conducted with the financial support of the Science Foundation Ireland Centre for Research Training in Digitally-Enhanced Reality (d-real) under Grant No. 18/CRT/6224.

References

- Buratta, L. et al. (2019) "Mathematics Anxiety and Cognitive Performance in Adolescent Students", *Psychiatria Danubina*, Vol 31, Suppl 3, pp 479-485.
- Cagiltay, N. E., Ozcelik, E. and Ozcelik, N. S. (2015) "The effect of competition on learning in games", *Computers & Education*, Vol 87, pp 35-41. doi: 10.1016/j.compedu.2015.04.001.
- Carey, E. et al. (2017) "The Modified Abbreviated Math Anxiety Scale: A Valid and Reliable Instrument for Use with Children". *Frontiers in Psychology*, Vol 8.
- Castellar, E. et al. (2015) "Cognitive abilities, digital games and arithmetic performance enhancement: A study comparing the effects of a math game and paper exercises". *Computers & Education*, Vol 85, pp 123-133.
- Dondio, P., Gusev, V. and Rocha, M. (2023) "Do games reduce maths anxiety? A meta-analysis", *Computers & Education*, Vol 194, p 104650. <https://doi.org/10.1016/j.compedu.2022.104650>.
- Gibson, F. (2007) "Conducting focus groups with children and young people: strategies for success", *Journal of Research in Nursing*, Vol 12, Suppl 5, pp 473-483. doi: 10.1177/1744987107079791.
- Krinzinger, H., Kaufmann, L. and Willmes, K. (2009) "Math Anxiety and Math Ability in Early Primary School Years". *Journal of Psychoeducational Assessment*, Vol 27, Suppl 3, pp 206-225.
- Moyer-Packenham, P. et al. (2019) "How design features in digital math games support learning and mathematics connections". *Computers in Human Behavior*, Vol 91, pp 316-332.
- Rooney, P. (2014) "A Theoretical Framework for Serious Game Design". *International Journal of Game-Based Learning*, Vol 2, pp 41-60.
- Theofylaktos, A., Lampropoulos, G., Siakas, K. (2018) "Digital Game-based Learning and Serious Games in Education". *International Journal of Advances in Scientific Research and Engineering*, Vol 4, pp 139-144. doi: 10.31695/IJASRE.2018.33016.
- Vanbecelaere, S. (2020) "The effects of two digital educational games on cognitive and non-cognitive math and reading outcomes". *Computers & Education*, Vol 143, 103680.
- Weibel, D. (2008) "Playing online games against computer- vs. human-controlled opponents: Effects on presence, flow, and enjoyment". *Computers in Human Behavior*, Vol 24, Suppl 5, pp 2274-2291. doi: <https://doi.org/10.1016/j.chb.2007.11.002>.
- Wu, S. (2012) "Math Anxiety in Second and Third Graders and Its Relation to Mathematics Achievement", *Frontiers in Psychology*, Vol 3, 162.

Belzer, K. D., McKee, M. B. and Liebowitz, M. R. (2005). "Social anxiety disorder: Current perspectives on diagnosis and treatment". *Primary Psychiatry*, Vol 12, Suppl 11, pp 35–48.

Leigh E., Chiu K., Clark D.M. (2021) "Is concentration an indirect link between social anxiety and educational achievement in adolescents?" *PLoS ONE*, Vol 16, Suppl 5: e0249952. <https://doi.org/10.1371/journal.pone.0249952>