Received: 2 January 2023 | Accepted: 14 September 2023

DOI: 10.1111/bjet.13395

ORIGINAL ARTICLE

British Journal of Educational Technology BERA

In-game performance: The role of students' socio-economic status, self-efficacy and situational interest in an augmented reality game

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Funding information
European Union's EU Framework Programme for Research and Innovation Horizon 2020 [grant no 812716]

Digital games are widely used in education to motivate students for science. Additionally, augmented reality (AR) is increasingly used in education. However, recent research indicates that these technologies might not be equally beneficial for students with different background characteristics. Moreover, students with different backgrounds may differ in their self-efficacy and interest when playing games and this could lead to differences in performance. Given the increased use of games and immersive technologies in education, it is important to gain a better understanding of the effectiveness of games for different student groups. This study focused on the role of students' socio-economic status (SES) and examined whether SES was associated with in-game performance and whether interest and self-efficacy mediated potential associations between SES and in-game performance. Since log data are increasingly used to predict learning outcomes and can provide valuable insights into individual behaviour, in-game performance was assessed with the use of log data. In total, 276 early secondary school students participated in this study. The results indicate that SES has no direct or indirect effect through self-efficacy and interest on in-game performance. However, a lower self-efficacy increased the likelihood to drop out of the game. These findings suggest that students from different socio-economic backgrounds are equally interested and self-efficacious while playing the game and that their performance is not affected by their background. The affordances of AR as an immersive learning environment might be motivating enough to help mitigate possible SES differences in students.

KEYWORDS

at-risk students, game-based learning, immersive technologies for learning, interest, learning analytics, self-efficacy

Practitioner notes

What is already known about this topic

- Digital games are an effective tool to increase motivation and learning outcomes of students.
- Students' self-efficacy and situational interest influence learning outcomes and in-game performance.
- It is unclear whether digital games are equally effective for students with different socio-economic status.

What this paper adds

- Socio-economic status (SES) of students does not affect in-game performance.
- Students with different SES are equally interested and self-efficacious.
- Lower self-efficacy and lower school track influence the likelihood of dropout.

Implications for practice and/or policy

- Socio-economic status does not fortify the possible performance differences between students and games can be utilized as a learning tool that motivates all students equally.
- There are students who do not optimally benefit when games are implemented in education and who may need additional support.

INTRODUCTION

Games are widely used in education and have been shown to increase students' motivation for learning (Lamb et al., 2018; Zainuddin et al., 2020) since they provide a safe environment for failure (Plass et al., 2020). Additionally, games enable students to explore scenarios that would not be possible in a traditional classroom environment (Klopfer & Thompson, 2020), which can be particularly beneficial in science, technology, engineering and mathematics (STEM) education. Recent technologies such as augmented reality (AR) are increasingly being used to develop simulation games for students, due to the advances in mobile devices supporting AR that are broadly available (Blattgerste et al., 2021). Recent reviews have shown that AR is increasingly accessible for young students (Radu, 2014) and as such it is expected to become more popular in education (Garzón et al., 2019). Augmented reality has been shown to increase students' understanding of spatial and conceptual knowledge, to increase motivation and also to direct attention (Radu, 2014). Moreover, immersive technologies like AR can increase situational interest, self-efficacy and therefore performance through an increased feeling of presence (Makransky & Petersen, 2021). Over the last decades, an abundant number of studies has demonstrated the effectiveness of games in education (eg, Riopel et al., 2019; Vogel et al., 2006; Wouters et al., 2013), and more recently, researchers have shown increased interest in using log data to predict students' learning outcomes through their in-game performance (Alonso-Fernández et al., 2019). Given the increase in the use of immersive technologies and games in education, it is important to understand whether all students can benefit from this. However, a recent meta-analysis indicated that limited attention has been paid towards individual differences in the effectiveness of games (Arztmann et al., 2022). This meta-analysis has provided preliminary support for the hypothesis that games may be less effective for students with lower socio-economic status (SES). If that is indeed the case, the widespread use of games in education may exacerbate existing differences between different socio-economic groups. Given the scarcity of studies on the differential effects for students with different SES, more research is needed.

Socio-economic status differences in in-game performance may be due to differences between students in their interest in games and their self-efficacy while playing games. That is, interest and self-efficacy have been found to be associated with students' SES (Demanet & Van Houtte, 2019; Engels et al., 2020; Li et al., 2021) and predictive of in-game performance (Hsu et al., 2018; Wang et al., 2022).

To gain more insights into SES differences in in-game performance and the factors that may be underlying these differences, we aim to investigate whether the in-game performance differs for students with different socio-economic backgrounds, and whether these effects may be explained by students' interest in the game and their self-efficacy beliefs. In other words, the main contribution of this paper is to provide a more comprehensive understanding of the influence of SES on game performance through students' self-efficacy and interest.

LITERATURE REVIEW

Socio-economic status

The influence of SES in education and its role in replicating class inequalities has been recognized by scholars since a long time (see eg, Bourdieu & Passeron, 1990) and has been shown in many empirical studies to be still relevant today (eg, Leest et al., 2020; Morgan et al., 2016; Verhaeghe et al., 2018). Socio-economic status is usually defined through an individual's education, occupation or income (Sirin, 2005). Parental SES directly influences a family's material affluence (Currie et al., 2008) and, as such, is associated with children's access to home resources and home learning environment (Betancur et al., 2018; Mullis et al., 2020). As a result, children with lower SES backgrounds on average show lower precursor abilities (eg, lower literacy) necessary for later academic achievement (Krajewski & Schneider, 2009; Verhaeghe et al., 2018), due to which many of them start their educational career with a disadvantage. These disadvantages subsequently cause differences in performance throughout their educational career. That is, on average, students from lower SES backgrounds tend to have lower academic performance compared with more advantaged students (Leest et al., 2020; Wiederkehr et al., 2015). As such, there are persistent achievement gaps between children with lower and higher SES backgrounds (Morgan et al., 2016). Moreover, low SES has also been found to be associated with long-term educational outcomes, as a low SES contributes to a higher risk of school failure and early school leaving (European Agency for Special Needs, 2019).

Socio-economic status and (game) performance

Prior research on the role of SES in education mostly focused on SES differences in traditional school tasks. The meta-analysis by Arztmann et al. (2022) cautiously suggested that SES may also be predictive of performance in the context of game-based learning. Although there were too few studies reporting students' SES, preliminary evidence from this meta-analysis suggests that low SES students may benefit less from the use of games in class, and hence their in-game performance may be lower than the performance of their higher SES classmates. Since technologies such as educational games are widely implemented as educational tools nowadays (Lamb et al., 2018; Zainuddin et al., 2020), it is important to know whether these are equally beneficial for every student or whether this implementation may add to the structural inequalities. If that is in fact the case, implementation needs to be considered carefully and additional measures may need to be taken to ensure all students are able to use the technology in such a way that it benefits their learning.

Prior research on traditional classroom tasks has shown that the effectiveness of teaching strategies or interventions can vary for students with different SES (eg, Li et al., 2021). Likewise, it may also be that the use of games in classrooms might have a similar differential effect for students with different SES backgrounds. However, thus far it is unclear whether games may also be differentially effective for students with different SES. As yet, it has been shown that games can increase the social participation (Hanghøj et al., 2018), and increase prosocial behaviour of students with lower SES backgrounds (Harrington & O'Connell, 2016).

One of the affordances of digital games is the opportunity to use log data as an objective performance measure for learning analytics (Shute et al., 2015) since it provides detailed information about students' learning (Debeer et al., 2021). Log data can be used to assess learning outcomes of students without needing assessments on paper (Alonso-Fernández et al., 2019) and can give detailed insights into underlying attentional processes of the individual learner (Wang et al., 2022). To our knowledge, thus far no study has investigated how students' SES is associated with students' in-game performance. Therefore, we will use the log data of the present study to distinguish three game performance indicators: *time-on-task, number of mistakes* and *dropout*.

Interest and self-efficacy

Socio-economic status differences in-game performance might be explained by interest and self-efficacy, as prior research suggested that children's SES is associated with interest and self-efficacy in school (Demanet & Van Houtte, 2019; Jansen et al., 2016; Li et al., 2021; Parker et al., 2021). Moreover, interest and self-efficacy have in turn been found to be predictive of performance (Nuutila et al., 2020; Wiederkehr et al., 2015).

Interest is defined as an individual's engagement with and motivation for a certain content (Renninger & Hidi, 2019) and is important for continued task engagement (Hidi & Renninger, 2006). Interest can develop from situational interest (focused attention to and affective reaction to a triggered stimuli) to (sustained) individual interest (the predisposition to reengage with a certain content again) (Hidi & Renninger, 2006). Situational interest has been found to predict performance in traditional learning tasks (Jansen et al., 2016; Nuutila et al., 2020). For in-game performance, however, the results are not as congruent. Poor in-game performance seems to be related to decreasing situational interest (Rodríguez-Aflecht et al., 2018). Situational interest was also found to predict in-game performance and transferred knowledge, but only for female students (Nietfeld, 2020). Kiili et al. (2021) did not find any effect of situational interest on in-game performance, but they did find a relation of students' interest to overall learning gains.

Self-efficacy is defined as the individual's belief of their ability to perform well. It can affect choices, effort and persistence (Bandura, 1977; Schunk & DiBenedetto, 2020). As such, higher self-efficacy can lead to better performance in any given task or domain (Bandura, 1977). Compared with less-efficacious students, those with a strong sense of self-efficacy for learning and performing tend to be more engaged in learning tasks, expend more effort to succeed, are more persistent when they encounter difficulties and achieve at higher levels (Schunk & DiBenedetto, 2020). Self-efficacy has also been found to influence in-game behaviour (Hsu et al., 2018; Wang et al., 2022). Whereas players with high self-efficacy tend to be able to master relevant game mechanics (Hsu et al., 2018; Wang et al., 2022), players with low self-efficacy tend to focus on other cues such as remaining time, possibly due to a lack of self-confidence to successfully finish a game (Hsu et al., 2018).

Impact of socio-economic status on interest and self-efficacy

Interest and self-efficacy beliefs are both important motivational constructs that influence effort, task processing and learning outcomes (Bandura, 1977; Hidi & Renninger, 2006; Nuutila et al., 2020). Socio-economic status seems to have an impact on students' academic self-efficacy in general. Several studies indicated that students from disadvantaged backgrounds (ie, with lower SES) report lower self-efficacy for academic tasks compared with students with higher SES backgrounds (Demanet & Van Houtte, 2019; Li et al., 2021; Wiederkehr et al., 2015). Research focusing on the influence of student's SES on interest is scarce. When looking into constructs related to interest, such as academic motivation and engagement, studies found that lower SES students tend to have higher levels of amotivation (indicating a lack of academic motivation) and lower levels of intrinsic motivation compared with higher SES students (Manganelli et al., 2021). Likewise, Engels et al. (2020) found that low SES students generally had lower levels of emotional classroom engagement compared with other students, suggesting that they have less interest towards learning activities compared with other students. McGeown et al. (2014), on the contrary, did not find a significant effect of SES on students' intrinsic motivation. Moreover, Steinmayr et al. (2012) found that intrinsic value and self-concept, two constructs which bear resemblance to interest and self-efficacy, mediated the relationship between SES and academic achievement in science subjects.

Overall, there seem to be indications from research on efficacy and interest-related constructs concerning traditional classroom tasks suggesting that students with a lower SES have lower self-efficacy and a lower level of interest in learning. Thus far, it is unclear whether this may also be the case in-game environments, and whether this may—in turn—affect students in-game performance.

The present study

Differences in students' SES are associated with inequality in learning opportunities (Mullis et al., 2020). As such, it is important to know whether students with different SES benefit equally from a game intervention or whether there might be differences in effectiveness. Thus far, only few studies examined whether the effects of games depend on students' background characteristics (Arztmann et al., 2022). Therefore, this study will investigate the effects of students' SES on their performance in a simulation game using AR concerning STEM education. More insights into potential SES differences in in-game performance may be helpful to know how to design games in a way that they benefit all students equally.

Moreover, both interest and self-efficacy have been shown to influence in-game behaviour (Nietfeld, 2020; Rodríguez-Aflecht et al., 2018; Wang et al., 2022), which could be of particular relevance for students with disadvantageous backgrounds who have been found to report lower self-efficacy (Demanet & Van Houtte, 2019; Li et al., 2021) and show less interest in academic tasks (Engels et al., 2020; Manganelli et al., 2021). Therefore, we aim to answer the following research question: *Does in-game performance differ for students with different SES and can these effects be explained by their interest and self-efficacy beliefs?* Based on preliminary evidence from a recent meta-analysis (Arztmann et al., 2022), we expect that in-game performance will be lower for students with lower socio-economic backgrounds, after taking into account students' ability levels based on their academic track. Moreover, based on prior research (Li et al., 2021; Manganelli et al., 2021; Steinmayr et al., 2012; Wang et al., 2022), we expect that both self-efficacy as well as situational interest to mediate the relation between SES and in-game performance.

METHOD

Design

This study followed a between-subject design where SES was a continuous between-subject variable.

Participants

The participants were recruited using a convenience sampling method (Daniel, 2011). In total, 276 year 1 and 2 students from Dutch secondary schools played the game in one of their science lessons ($M_{age}=12.9$, $SD=0.7$). The Dutch secondary educational system is differentiated into six different adjacent tracks. To increase heterogeneity of the SES distribution, multiple school tracks were included in the present study. The six tracks are as follows: (1) practical training, (2) basic pre-vocational secondary education, (3) middle pre-vocational secondary education, (4) theoretical pre-vocational education, (5) senior general secondary education and (6) pre-university education. The present sample included students of a combined track for theoretical pre-vocational education and senior general secondary education (18%), senior general secondary education (38%) and pre-university education (44%). For two of the outcome variables (ie, time-on-task and the number of mistakes), only the data of students who played through all game levels were considered since these variables could only be assessed after completion of the game. As such, the final sample for the analyses on these outcome variables consisted of $n=203$ students. For the other variable, dropout during the game, all 279 students were included.

Instruments

The game: Marie's ChemLab

Marie's ChemLab is a simulation game that is based on the TrainAR framework of Blattgerste et al. (2021). Marie's ChemLab uses mobile augmented reality (MAR) that provides a virtual environment to learn the basic concepts on acid–base. It is designed for early secondary school children and uses daily life chemistry to provide a relatable game experience. The game consists of three sequential levels that take place in different environments. To help the students proceed in the levels, they are guided by Marie, the intelligent agent of Marie's ChemLab, who provides hints and instructions throughout the game. In the present study, only data from the

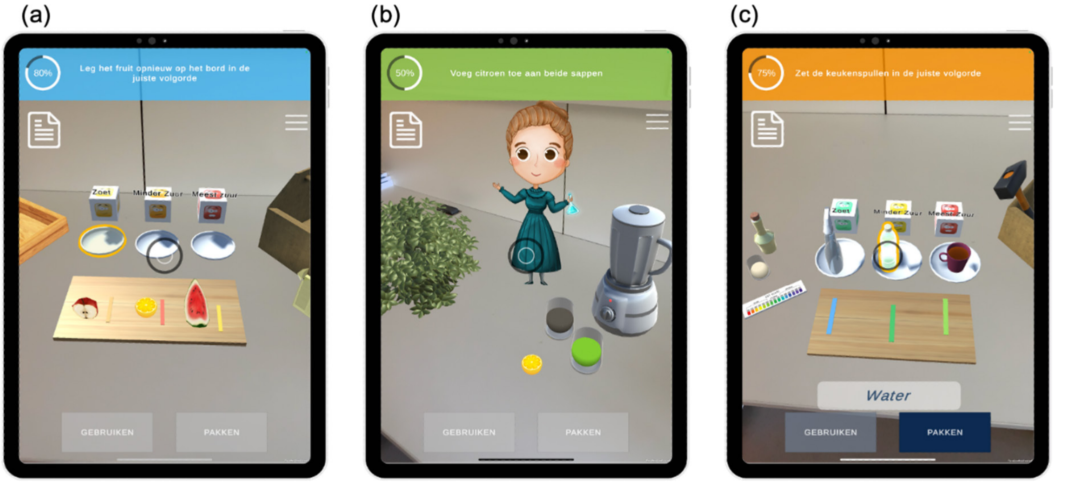

FIGURE 1 Three levels of Marie's ChemLab. (a) Fruit salad, (b) smoothie party, (c) kitchen detectives.

first and third level were included because they consisted of similar and therefore comparable interactions (see Figure 1), whereas level two was mainly designed as a short overlay with fun elements (eg, interacting with Marie). The flow of the game is procedural, which means that the player needs to follow certain steps to advance within a level or to the next level. The objects within the game need to be combined (eg, the fruits need to be smashed with the hammer) and in case of a wrong interaction, the player receives feedback in the form of a mistake sound. In this game, the students are supposed to rank objects based on their acidity, measure them and get introduced to different indicators (such as pH strips or blueberry juice).

Socio-economic status

To measure students' SES, the HBSC Family Affluence Scale (FAS III; Inchley et al., 2018) has been used. This scale has been widely used as a valid measure of SES that can be answered by students themselves (see Corell et al., 2021; Hobza et al., 2017). The FAS III consists of six items that measure material affluence (eg, *Does your family have a dishwasher at home?*). As such, it reflects a family's material resources, consumption pattern and purchase power. The scores on the items were summed and could range from 0 to 13, with a higher score reflecting a higher SES. Currie et al. (2008) originally suggested a summation of item scores to allow a categorization into three groups (low, medium and high). For this study, the SES was treated as a continuous variable and therefore no groups were created. The SES among the included students was normally distributed with a lower bound score of 4 and the upper bound score of 13 ($M = 9.25$, $SD = 1.74$).

In-game performance

Three indicators of in-game performance were distinguished: *time-on-task*, *number of mistakes* and *dropout*, which were calculated with the available log data of level 1 and level 3. *Time-on-task* was measured with the total time it took to complete one level. A longer time-on-task indicated that a student was less efficient in playing the game. *Mistakes* in both levels were measured with the number of wrong interactions; thus, the sum for each level was calculated. These two performance indicators were not correlated ($r = -0.01$; $p = 0.904$) for level 1, but correlated for level 3 ($r = 0.75$; $p < 0.001$). For *dropout*, the time-on-task of level 3 was used to determine whether the participant completed the game or not. In case, there was no time-on-task available for level 3, and the participant did not finish the game and was coded as dropout.

Situational interest and self-efficacy

Single-item questions reflecting situational interest and self-efficacy were embedded in the simulation game. For the present study, the questions that were asked after level 1 were used. The questions for situational interest (ie, *this game is interesting*) and self-efficacy (ie, I *think I am doing well in this game*) were based on the items used by Nuutila et al. (2020) with the term 'task' being exchanged with 'game' to fit the context. The items were embedded as a pop-up in the game environment and were ranked with smileys representing a Likert scale ranging from 1 to 5. Similar to Rodríguez-Aflecht et al. (2018), we used single items to measure situational interest and self-efficacy to avoid disrupting the gameplay too much. Findings of Gogol et al. (2014) suggest that single items measuring clear motivational constructs are a reliable alternative for longer scales.

Procedure

Prior to data collection, approval by the institutional ethics committee was obtained, and both parents and teachers were asked for consent. To ensure anonymity, the researchers assigned random ID numbers to the students, which were used to connect their questionnaire answers with the log data. The data collection took place during a regular science lesson of the students. The game was played on iOS tablets that were provided by the researchers including the matching headphones. Prior to playing the game, the students were instructed that they were to test a newly developed game about science, that they should try to play by themselves and to not talk to each other. In total, the students had 30 minutes to play the game, after which the game automatically moved them to the end. Students finishing early received riddles that they could solve until their classmates were done.

Data-analyses

First, the data distribution was checked for normality and potential outliers (Field, 2009). For easier interpretation, a z-score for the variable *time-on-task* was created. After that, correlations between all variables were calculated. Two independent parallel multiple mediation models were conducted using model 4 of the PROCESS tool (Hayes, 2022) in SPSS. For both models, the total, direct and indirect effects of the independent variable X (SES) on a dependent variable (Y: either time-on-task or mistakes) via multiple mediators (M: interest and self-efficacy) were estimated. In both models, we controlled for performance in level 1 and school track. Indirect effects were estimated using a 95% bias-corrected bootstrap intervals (95% BCI) with 5000 bootstrap samples (Preacher & Hayes, 2008). For the dichotomous outcome variable *dropout*, an ordinary least square regression (OLS) was conducted with the PROCESS tool (Hayes, 2022), using the same mediators and covariates as in the other mediation models. Based on the result of the Cook's distance, Mahalanobis and Levene's tests, six outliers for the outcome variable *time-on-task* and three outliers for the outcome variable *mistakes* were detected. After

TABLE 1 Descriptive statistics and correlation matrix of all included variables.

	n	*M*	*SD*	1.	2.	3.	4.	5.	6.	7.	8.
1. SES	275	9.25	1.74								
2. School track	–	–	–	−0.04							
After level 1											
3. Interest	202	3.74	1.06	0.01	−0.02						
4. Self-efficacy	202	3.51	1.09	0.06	−0.09	0.63***					
5. Time-on-task	202	0.01	1.02	−0.16*	−0.09	−0.07	−0.06				
6. Mistakes	202	26.50	21.32	0.11	−0.10	−0.27***	−0.24***	−0.01			
After level 3											
7. Time-on-task	202	0.38	0.80	0.05	−0.17*	0.01	0.01	−0.01	−0.07		
8. Mistakes	202	34.10	29.71	0.06	−0.07	0.03	0.02	0.03	−0.02	0.75***	
9. Dropout	251	–	–	0.03	−0.17**	−0.13	−0.10	−0.02	0.14*	−0.71***	−0.48***

Abbreviations: *M*, mean; *SD*, standard deviation.
*$p<0.05$ level (two-tailed); **$p<0.01$ level (two-tailed); ***$p<0.001$ level (two-tailed).

inspection of the data, one outlier was removed which clearly indicated wrong game behaviour (ie, the number of mistakes was very high in level one and no mistakes in level three, indicating that the student repeatedly clicked the same interaction several times by intention) resulting in a final $n=202$.

RESULTS

Descriptive statistics and correlations

The results of the descriptive statistics and correlations are displayed in Table 1. Looking at the correlations, the mediating variables interest and self-efficacy are highly positively correlated with each other. Moreover, there was a significant correlation between time-on-task and SES, as well as between mistakes, interest and self-efficacy at the beginning of the game.

SES differences in in-game performance

To examine the extent to which students' SES was associated with their in-game performance and the potential mediating role of students' self-efficacy and situational interest, two separate parallel multiple mediator models were performed for the two outcome variables *time-on-task* and *mistakes*. The findings in Table 2 show that, contrary to the hypotheses, there was no significant direct effect of SES on in-game performance. Furthermore, there was also no evidence that SES indirectly affected time-on-task or mistakes through its effect on interest and self-efficacy.

A similar mediation model, but based on OLS regression, was estimated for the outcome variable *dropout*. The findings are displayed in Table 3. It can be seen that students with lower self-efficacy ($B=-0.51$, $p=0.008$) and from a lower school track ($B=-0.76$, $p=0.001$) were more likely to not finish the game. Socio-economic status was not significantly related to the dropout rate, neither directly nor through interest and self-efficacy. Finally, as a robustness check, the same analyses were repeated with all outliers removed. The results of the models

TABLE 2 Total, direct and indirect effects of socio-economic status on in-game performance.

	Y_1 (time-on-task)			Y_2 (mistakes)		
	B	*SE*	95% CI	*B*	*SE*	95% CI
Total effect	−0.03	0.04	−0.05, 0.08	1.00	1.23	−1.41, 3.42
Direct effect	0.02	0.03	−0.05, 0.08	1.00	1.24	−1.44, 3.43
Indirect effect through						
Interest (M_1)	0.00	0.003	−0.01, 0.01	0.03	0.12	−0.20, 0.32
Self-efficacy (M_2)	−0.001	0.004	−0.01, 0.01	−0.02	0.15	−0.39, 0.27
Total indirect effect	−0.001	0.004	−0.01, 0.01	0.01	0.15	−0.31, 0.32

Note: 95% CI = confidence interval based on 5000 bootstrap samples.
Abbreviations: *B*, beta; *SE*, standard error.

TABLE 3 Results for the outcome variable *dropout*.

	B (*SE*)	*Z*	*p*
SES	−0.01 (0.10)	1.36	0.979
Interest	0.08 (0.20)	0.42	0.675
Self-efficacy	−0.51 (0.19)	−2.66	0.008**
School track	−0.76 (0.22)	−3.44	0.001***

Note: The results are expressed in a logs-odd metric and were calculated with $n = 251$.
Abbreviations: *B*, beta; *SE*, standard error; *Z*, *Z*-value.
*$p < 0.05$ level; **$p < 0.01$ level; ***$p < 0.001$ level.

including the outliers and the results of the models excluding the outliers did not differ from the results with the outliers included. Thus, including the outliers did not change the overall results.

DISCUSSION

The aim of the present study was to investigate whether students' SES was associated with their in-game performance and whether differences in performance could be explained by self-efficacy and situational interest. The findings showed no differences in in-game performance, nor self-efficacy or interest, for students with different SES backgrounds. Hence, contrary to our expectations, these findings suggest that students with different socio-economic backgrounds do not differ with regard to their performance in games. Additionally, our findings indicated that students in lower tracks or with lower self-efficacy during the game were more likely to drop out of the game early, suggesting that these factors may need to be taken into account when designing game-based learning environments. Below, the findings are discussed in more detail.

Based on previous research in traditional learning environments (Leest et al., 2020; Wiederkehr et al., 2015) and the preliminary findings of the meta-analysis by Arztmann et al. (2022), we expected that students with lower SES would be less successful in terms of their game performance. However, contrary to our expectations, we found no significant SES differences in students' in-game performance, suggesting that students with different SES are equally proficient in this game. It could be that the affordances of the game environment, where failure is expected and therefore allowing for graceful failure (Plass et al., 2020) may help mitigate possible differences due to students' background. This would align with the Cognitive Affective Model of Immersive Learning (CAMIL; Makransky & Petersen, 2021). According to that model, the immersive game environment provides the students with a feeling of performance accomplishment and agency which can increase self-efficacy, but influences also other factors such as higher situational interest, intrinsic motivation, self-regulation or lower levels of cognitive load. Since the game in this study used AR, it could also be that the engaging characteristics of this immersive environment could have motivated students enough to reduce any differentiating factors based on their backgrounds. This would also explain why we did not find significant SES differences in self-efficacy or situational interest during the game. It would be worthwhile to investigate in future studies whether these results can be also found after repeated interventions with the same technology when the novelty effect is being reduced.

Additionally, the findings of the present study also indicated that low self-efficacy in students makes it more likely for students to drop out of the game early, whereas interest was not associated with the likelihood of dropping out. This contradicts the findings of Rodríguez-Aflecht et al. (2018) who reported that poor in-game performance was related to decreasing situational interest, but they did not measure self-efficacy in their study. On the contrary, our findings align with research on traditional learning tasks which usually indicates that self-efficacy is a stronger predictor of performance than interest (see Kriegbaum et al. (2018) for a meta-analysis). Since self-efficacy influences the competence beliefs of students, it is usually found to have a stronger influence on persistency than situational interest (Kriegbaum et al., 2018; Schunk & DiBenedetto, 2020). As such, it may be that students lower in self-efficacy do not continue to persist in the game, regardless of their level of interest. The relatively high level of interest and relatively low degree of variance in interest which was found among the participants of the present study may account for the non-significant effect of interest on performance as well. That is, because most students reported to be highly interested and very few who reported a low level of interest in the game, there was no significant relation with the performance indicators.

Interestingly, the likelihood of early dropout of the game was also predicted by the school track of the students, showing that students attending lower tracks (ie, pre-vocational education) were more likely to not finish the game than students in higher school tracks. Hence, this suggests that prior ability affects the in-game performance of students. It may be that the game is easier to navigate for those students with higher ability levels. In addition, it could also be that other factors are at play as well since school tracks also differ based on student composition, but also in instructional quality (Guill et al., 2017; Strello et al., 2021). Future research could investigate what factor is having the strongest influence on the difference in in-game performance of students.

Since this is the first study to our knowledge that is investigating the influence of SES through interest and self-efficacy, our results provide valuable insights for both researcher and practitioners for designing the intervention with games in schools. First, the results suggest there is no difference in self-efficacy, interest or in-game performance for students with different socio-economic backgrounds. This is particularly relevant since in-game performance is increasingly being used to assess learning outcomes of students. Although more studies are needed to replicate these results with other game environments, our results indicate that game interventions can be equally effective for students with different SES backgrounds and can therefore be utilized as learning tool that motivates all students and does not fortify possible performance differences based on their socio-economic background. Second, low self-efficacy but also lower school track were associated with the likelihood to drop out of the game which means that there are students who may not optimally benefit when games are implemented in education and who may need additional support to be able to successfully navigate the complexity of AR/game environments. Therefore, it would be interesting for future research to examine how to provide additional instruction or help for these students to reduce the likelihood of them not finishing the game.

CONCLUSION

The aim of this study was to gain insight into whether students with different SES perform differently while playing an AR game and whether these differences in performance are mediated by their interest and self-efficacy beliefs. There were no differences in the effectiveness for students with different socio-economic backgrounds. However, students with lower self-efficacy beliefs and those attending lower school tracks were more likely to dropout and not finish the game.

While the present study makes a unique contribution to the literature with assessing the influence of students' SES on game performance, the major limitation is that the findings may be specific to the game that was used within this study. It could be that the findings differ if another game utilizing a different technology (eg, virtual reality, 2D) or focusing on another topic is being used for data collection. Hence, more studies on SES differences on game performance are needed to see whether the results are generalizable to other games. Moreover, even though the participants attended a diverse range of school tracks, no students of the lowest track were included which might have influenced the results through potentially less variance in the assessed variables. However, the descriptives suggest that our sample was quite diverse in terms of their SES. Therefore the effects of including the lowest track students might not have made a substantial change. Additionally, testing alternative models such as moderation were beyond the scope of this study. This could be interesting for future studies to explore as it could potentially reveal additional moderating patterns of students' interest and self-efficacy on their game performance. Finally, this study did not assess the gender of the students; therefore, gender effects could not be assessed.

Since we found that there is still a group of students that benefits less of the game intervention, future research could investigate how to support students' self-efficacy already before starting the game intervention to reduce the dropout rate. Moreover, future studies could investigate which behaviour patterns occur before students drop out of the game to investigate how this could possibly be addressed by adaptive instruction. Additionally, the finding concerning students' school track suggests that more research is needed on how students' ability levels, but potentially also other factors related to students' school track, may affect students' game performance. This could help to find ways in which the design of a game can better support lower track students. Given the wide use of games in education, investigating these issues could improve the overall effectiveness of games in education and could provide valuable insight on how to instruct students in order for them to benefit the most from game interventions.

ACKNOWLEDGEMENTS

The authors would like to warmly thank Tim Gallagher for his advice, David van Alten for his support and Quincy Muskita for his help with the data collection and data cleaning.

FUNDING INFORMATION

This work was supported by the European Union's EU Framework Programme for Research and Innovation Horizon 2020 [grant no 812716].

CONFLICT OF INTEREST STATEMENT

None.

DATA AVAILABILITY STATEMENT

Research data are not shared due to privacy and ethical restrictions.

ETHICS STATEMENT

This research has received ethics approval by the Ethics Review Board of the Faculty of Behavioral and Social Sciences (FERB) of Utrecht University.

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How to cite this article: Arztmann, M., Domínguez Alfaro, J. L., Hornstra, L., Jeuring, J., & Kester, L. (2023). In-game performance: The role of students' socio-economic status, self-efficacy and situational interest in an augmented reality game. *British Journal of Educational Technology*, *00*, 1–15. https://doi.org/10.1111/bjet.13395