


**Using Kahoot! to teach statistics: how does gamification implementation impact coding attitudes in students?**

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### **Abstract**

This study investigates how gamification techniques implemented in education affect students' attitudes towards coding. To investigate this link, as well as the impact of a variety of interacting variables, we recruited students from the mandatory research methods module Analysing Data in the BSc Psychology degree at the University of Sussex to complete an online questionnaire which measured coding attitudes and general self-efficacy, as well as collecting demographic information. The resulting regression analysis revealed a significant relationship between active participation in gamified teaching and positive coding attitudes and a significant effect of general self-efficacy. Gender was analysed separately from the original regression analysis due to sampling constraints – a relationship was found between gender and coding attitudes. Reasons for these relationships are suggested, such as stereotype threat and self-determination theory. Further research may find it beneficial to collect academic data to explore these explanations further and expand sampling periods to reduce the limitations found with the sample.

## Introduction

Video games are played by a considerable number of people around the world and are widely agreed to have a relatively high level of motivational potential (Garris et al., 2002; Przybylski et al., 2010; Ryan et al., 2006; Yee, 2006). The motivational potential of video games can be harnessed in real-world contexts, particularly in non-gaming contexts, to improve outcomes in activities, tasks or advertisements. Game design implementation in this way is typically referred to as gamification (Sailer et al., 2017). Gamification is a relatively new research area only gaining traction and popularity in the last fifteen years, and is a concept which was initially met with significant pushback – from researchers disagreeing on what truly counted as gamification to some more extreme views that the use of game design in public settings, such as in education or marketing, is exploitation (Bogost, 2011). As it is now, gamification can be considered an evolution of what is known as “serious games” – games used for purposes other than entertainment (Susi et al., 2007). Examples of serious games include, for example, flight simulators used by the military (i.e. ‘*Prepar3D*’, Lockheed Martin, 2020) or healthcare-related games, such as those which include physical activity or mental tasks (i.e. ‘*Just Dance*’, Ubisoft Paris, 2024). Unlike “serious games”, gamification typically implements only some aspects of game design, rather than presenting the user with a fully designed video game. However, research suggests that gamification utilises the motivational potential of video games by invoking a similar psychological experience to playing a video game, such as improvements to prosocial behaviour and content-specific learning (Jordan & Romer, 2014). These effects are beneficial in the different areas that gamification is typically enacted in (Huotari & Hamari, 2012), and allows for gamification to be used, to varying success rates, in a huge variety of fields: from marketing (Hamari, 2013, 2017), to data collection (Guin et al., 2012), to health (Jones et al., 2014), and, in the circumstances of this experiment possibly most importantly, to education.

In the context of education, gamified elements may be included in teaching in a variety of ways, such as: the use of in class quizzes or tasks that have a competitive element, e.g. Kahoot! or Quizlet; leaderboard or advancement style structures implemented in teaching/course design; badges or sticker rewards given upon completion of particular tasks; the unlocking of content following completion of a task; or storytelling through educational content (Dicheva et al., 2015; Yildirim, 2017). Other examples of gamification used in

teaching, but outside of a classroom context, include programs such as Codecademy or Duolingo, which both implement progression techniques and badges in their applications (Damsa & Fromann, 2016). Research which investigates gamification and its uses in education typically implements these teaching techniques in STEM subjects, with a particular focus on Computer Science, or in non-traditional teaching facilities, such as hybrid learning systems or fully online classes (Nah et al., 2014), due to the higher rate of access to technology and services to host gamification software. Whilst this research gives valuable information on its uses in teaching and education, it also raises a fundamental question surrounding the effects that gamification may have across gender identities.

Computer science degrees are disproportionately taken up by men in the UK – just 18.9% (N = 2940) of first-year computer science students in the UK are women (The Chartered Institute for IT, 2024). Considering the number of Universities and the number of undergraduate courses in the UK (What Uni?, n.d.), it is highly likely that any research conducted on undergraduate computer science students will not have more than one woman, if any, in the sample. Even when a slightly larger sample has been found, previous research still notes this disproportionate divide in sample sizes between male and female participants, again at an approximately 80:20 ratio (Zahedi et al., 2021). Whilst this research found no quantitative difference in results between male and female participants, it has been particularly relevant to the design of this experiment due to its qualitative findings. Zahedi et al.'s research – particularly interviews they conducted with their female participants – suggests that female participants are significantly less likely to find gamification motivating, and in some cases may even find it demotivating, especially if it is in a subject they are not academically sound in. Demotivation as a result of gamification is particularly relevant for gamification techniques that use public leaderboards – such as the system employed in this study – as students who are further down the leaderboard may be demotivated by that position, especially if they do not have a way to move up it.

Some research into the effects of gender on gamification also investigates individual differences that may further affect how people interact with gamified content (Denden et al., 2021). Denden et al. identified five personality traits that may affect how a person interacts with a gamified platform: extraversion, agreeableness, conscientiousness, neuroticism, and openness. Research into gamification in areas other than education suggests that intrinsic

motivations, such as general self-efficacy, impact people's willingness to participate in gamified tasks (Feng et al., 2018).

Considering all previous research, this study will explore whether active participation in a gamified teaching activity will improve attitudes towards coding in a group of undergraduate psychology students. This hypothesis will be investigated using students enrolled on a mandatory methods module (Analysing Data (C8891), University of Sussex) as part of the BSc Psychology degree. This module teaches the statistical methods required for a BPS-accredited Psychology degree using programming, specifically the R programming language. The Analysing Data module utilises several different types of gamified teaching methods, including Kahoot! in teaching sessions, a leaderboard system linked to these Kahoot! quizzes; badges available to students for completing modules, attainment, or engagement in the module; and "ChallengRs" – extra credit coding tasks which also give points for the in-class leaderboard. This experiment operationalises the Kahoot! Quizzes played during teaching sessions – these quizzes make up the basis of the gamified content in this module.

Secondly, it will explore whether participant gender is associated with coding attitudes in students, and if this is true, how does this association affect the relationship between gamification participation and coding attitudes? As previously noted, gender proportions on programming courses are typically disproportionately swung in favour of male students (The Chartered Institute for IT, 2024). However, the gender balance of psychology students is swung in the opposite direction – 80% of students are female (Johnson et al., 2020). This alternative gender balance gives this experiment a unique participant demographic, which completely contrasts with typical research on programming gamification and could give genuinely unique insight into the impact of gender on gamification.

Finally, this research will explore whether general self-efficacy mediates the relationship between gamification, gender and coding attitudes. General self-efficacy is a wide-reaching scale measuring optimism, problem solving and the ability to cope with anxiety. It is negatively correlated with many mental health disorders such as anxiety and depression (Schwarzer et al., 1995). This wide-reaching nature means it catches many intrinsic motivations which could affect gamification (Feng et al., 2018). However, it is doubtful that it will catch every individual difference that could affect this relationship.

## Method

### Participants

Eighty-two participants completed the study. Fifteen participants were excluded from the dataset as they completed the study at a timepoint which is not being considered in this analysis, and a further 20 participants were excluded for failing to complete the post-questionnaire. This leaves the final sample at 47 participants. All participants were over the age of 18 (range: 18 to 51,  $M = 20.72$ ,  $SD = 5.73$ ), and were Psychology students at the University of Sussex. Demographic data, separated by gender, can be found in Table 1 below. As a condition of participation, all participants were enrolled in the first-year, second-term research methods module Analysing Data (C8891). The final sample ( $N = 47$ ) consisted of 5 males, 40 females and two individuals who selected another gender option. The module teaching staff primarily recruited participants through Canvas announcements, in teaching sessions, and through the official module Discord server. The study was also listed on SONA, a research management and reward system used by the University.

**Table 1**

*Demographic characteristics of the final sample of participants.*

Gender	$N$ ( $n = 47$ )	Min.	Max.	$M$	$SD$
Male	5	18.00	31.00	21.20	5.50
Female	40	18.00	51.00	20.50	5.84
Prefer to self-describe	2	20.00	28.00	24.00	5.66

This experiment uses the data of participants who completed the study at the first of three timepoints across the Spring semester – data was collected during week 1, week 5 and week 10. Within each time point, the study had three stages – a pre-questionnaire, the Skills Lab, which acts as the gamified intervention, and a post-questionnaire. Students completed the General Self-Efficacy Scale, the Elementary Student Coding Attitude Survey – minimally modified for university student use (ESCAS-U) – and the State-Trait Inventory for Cognitive

and Somatic Anxiety during the pre-questionnaire. During the post-questionnaire, students completed the ESCAS-U and a bespoke Kahoot! engagement scale, as well as several qualitative questions. Students were given one SONA credit for completing the pre-questionnaire and one SONA credit for completing the post-questionnaire, up to two at all time points. The full materials, procedures, and study designs are described below.

## Materials

**Demographics.** Participants were asked to provide their gender identity, age, socioeconomic status, and prior gaming experience. They were also asked to indicate if they had a disability, classified by eligibility for registration with the disability support unit at the University of Sussex. Participants who indicated they had a specific learning difference, social or communication difficulty, or mental health condition, were then asked to indicate if they had a formal or informal diagnosis.

**General Self-Efficacy Scale.** The General Self-Efficacy Scale (GSE; Schwarzer et al., 1995) measures the ability to cope with daily life and other stressful life events. Participants are presented with a statement (i.e. “I can solve most problems if I invest the necessary effort”) and asked to rate this statement on a Likert scale from Not at all true (1) to Exactly true (4). There are no reverse-coded items. This study uses the reduced 10-item version. Composite scores will be calculated for each participant as the mean of all responses, having a possible range of 1-4, in which higher scores indicate a higher level of general self-efficacy.

**Elementary Student Coding Attitude Survey.** The Elementary Student Coding Attitude Survey (ESCAS; Mason & Rich, 2020) assesses coding attitudes in various contexts, such as interest in coding, social value and perceptions towards coding. Participants are presented with a statement (i.e. “I am good at coding.”) and rate these statements on a Likert scale from Strongly disagree (1) to Strongly agree (6). There are no reverse-coded items. The original scale was intended to measure coding attitudes in elementary-school children. For this study, the ESCAS has been modified for university student use (ESCAS-U) through minor language changes (i.e. “kids” to “people” and “school” to “university”). This study uses 23 items, which were presented to participants in both the pre-questionnaire and the post-questionnaire. At each time point, a composite score will be calculated for each participant as the mean of all responses, having a possible range of 1-6, in which higher scores indicate a higher level of positive coding attitudes.



***State-Trait Inventory for Cognitive and Somatic Anxiety.*** The State-Trait Inventory for Cognitive and Somatic Anxiety (STICSA, Ree et al., 2000, 2008) measures the level of anxiety a person is feeling at any one time. Participants are presented with a scenario (i.e. “I keep busy to avoid uncomfortable thoughts.”) and rate how often this scenario occurs from Almost never (1) to Almost always (4). There are no reverse-coded items. This study will use only the 10 items determined to measure cognitive anxiety (Ree et al., 2008). Composite scores will be calculated for each participant as the mean of all responses, with a possible range of 1-4, in which higher scores indicate higher anxiety levels.

***Kahoot Engagement.*** Engagement in the Skills Lab and the Kahoot! quiz presented in those Skills Labs was assessed using three scales in the post-questionnaire. These scales were developed by Dr Mankin and the research team for use in this study. Firstly, participants were presented with statements about the Skills Lab and Kahoot! quiz (i.e. “To what extent did you find the Skills Lab... boring/difficult”) and rate these statements on a Likert scale from Not at all (1) to A great deal (5). These two scales had six items each. An engagement scale was also created, which included 9 items (i.e. “I felt engaged by the Kahoot quiz”), which were rated on a Likert scale from Strongly disagree (1) to Strongly agree (5). There were three reverse-coded items. Additionally, several qualitative answer questions were presented to the participants, such as “Why did you decide to participate in the Kahoot or not?”. The engagement scales are not included in this analysis.

## Design

The study used a 2x3x3 mixed design, including a continuous covariate variable. There were three independent variables. The first independent variable was time, a within-subjects variable with two levels: the pre- and post-questionnaire. The second independent variable was gender – a between-subjects variable with three levels: male, female and a third gender group. The third gender group was composed of all participants who selected either the “other/third gender” group or “prefer to self-describe” when asked in the pre-questionnaire. The final independent variable was participation in Kahoot! - This was a between-subjects variable with three levels: participated in the Kahoot!, stayed to watch but did not participate, or did not participate. Participants were not allocated to conditions in the Kahoot! variable, they remained free to participate or not as they wished. The model used also includes a continuous covariate variable: general self-efficacy. The dependent variable was coding attitudes, measured by the ESCAS-U, presented at both pre- and post-questionnaires.

## Procedure

The study consisted of three stages. Firstly, the participants completed an online pre-questionnaire, administered through Qualtrics (*Qualtrics*, 2005). All participants had the week leading up to the teaching session of interest to complete the pre-questionnaire. All participants completed a consent form and provided their candidate number so we could link their responses across time points and with their attendance records. Additionally, participants provided demographic information, such as gender identity, age, socioeconomic status, prior gaming experience, and disability. The pre-questionnaire contained three scales: GSE, ESCAS-U and STICSA. The scales were presented to the participants randomly, as were the items in each scale. Participants were debriefed after the first section of the experiment. All participants were then required to attend a Skills Lab session. Skills Labs are mandatory teaching sessions and, as a standard, end with a Kahoot! quiz that is focused on the content covered in that teaching. Therefore, they act as the gamification intervention between the pre- and post-questionnaires. Finally, participants completed the post-questionnaire, also administered through Qualtrics. The post-questionnaire was available for a week following the Skills Lab session of interest for each time point. All participants were again required to enter their candidate number to link their responses and attendance records.

The post-questionnaire consisted of the ESCAS-U and the Kahoot engagement scales. Full details of these scales, including qualitative questions, can be found in the appendix.

Participants completing the study at the first or second timepoint were given an interim debrief to enable participation at successive timepoints. All participants were given a full debrief form after the final timepoint.

## **Ethics**

This study has been approved individually by the School of Psychology at the University of Sussex (ER/AB2327/1) and as part of a larger group of staff and student studies under Dr Jennifer Mankin, of which ethical approval was also gained from the School of Psychology at the University of Sussex (ER/JM636/23). Two major ethical issues were identified. Firstly, participant data was linked with student candidate numbers to access attendance records. To protect participant anonymity, this linked data and minimally identifying information were only accessible to Dr Mankin. Candidate numbers were replaced with randomised alphanumeric codes before the data was shared with student researchers. Dr Mankin retained the key to withdraw participants if requested. In addition to the removal of candidate numbers, all qualitative responses were screened by Dr Mankin, and identifying data was removed before this data was shared with student researchers. Secondly, some questionnaires also contained content which participants may find distressing; however, it was not expected that this would cause any greater distress than everyday life.

## Results

All regression analysis, data screening and data visualisation was conducted using R on the online platform Posit Cloud (previously known as R-Studio, using R version 4.4.3). Data cleaning and visualisation were conducted using tidyverse (Wickham & RStudio, 2023). The final model was fitted using nlme (Pinheiro et al., 2025) and the robust model was fitted using robustlmm (Koller, 2025). The two questionnaires involved in this analysis were the GSE and the ESCAS-U, however previous studies have indicated high correlations between the GSE and the STICSA (Mur et al., 2022) – this means that descriptive statistics and statistical assumption tests have been created for all three scales, as it is likely that any issues with the STICSA would also occur in the GSE and vice versa. As expected, STICSA and GSE mean scores were very similar (STICSA  $M = 2.50$ ; GSE  $M = 2.81$ ). The mean score for the ESCAS-U was higher, but this was to be expected as it was measured on a wider scale of 1-6 rather than 1-4 ( $M = 3.82$ ). The Jarque-Bera test for normality indicates that all three questionnaire samples do not have a distribution which significantly deviates from a normal distribution. All the descriptive statistics for these scales, alongside the skewness and kurtosis values for the scales can be found in Table 2. The STICSA is not included in any analysis beyond this point.

**Table 2**

*Descriptive statistics and skewness and kurtosis values for the STICSA, GSE and ESCAS-U*

Variable	$M$	$SD$	IQR	Min	Max	Skewness	Kurtosis	$n$	95% CI
STICSA	2.50	0.65	0.70	1.00	3.90	0.18	0.06	94	[2.37, 2.64]
GSE	2.81	0.45	0.60	1.70	3.90	-0.09	0.36	94	[2.71, 2.90]
ESCAS-U	3.82	0.77	1.17	2.00	5.39	-0.16	-0.42	94	[3.66, 3.96]

*Note.* Each participant was recorded in the final dataset twice – with unique ESCAS-U scores for each datapoint. STICSA and GSE scores remained the same across timepoints.

Before fitting the model, a basic survey of the data was conducted to assess if the three independent variables mentioned in the hypotheses of this study were appropriate for inclusion. Time and Kahoot! participation showed no major issues, however the small sample size meant that when the participants were split by gender group, some Kahoot! conditions were no longer filled. The “Other” gender category contained just two participants – the personal circumstances of these participants allowed for the merging of these participants into another group – and the male gender category contained just five participants. Within this category, there were no male participants fulfilling the “I did not participate and did not pay attention/left early” condition. As a result of this, the decision was made to remove gender as an independent variable in the final analysis, as there was no way to compare across all groups. The distribution of participants across Kahoot! participation conditions, separated by gender can be found in Table 3.

**Table 3**

*Distribution of participants in Kahoot! participation conditions, split by gender*

Gender	Kahoot! Participation	<i>n</i>
Male	I did not participate but stayed to watch	1
	Yes, I participated in the Kahoot!	4
	I did not participate and did not pay attention/left early	7
Female	I did not participate but stayed to watch	15
	Yes, I participated in the Kahoot!	18
Prefer to self-describe	I did not participate and did not pay attention/left early	1
	I did not participate but stayed to watch	1

The aim of this study was to assess whether participating in a gamification intervention during teaching time – namely Kahoot! participation during Skills Lab sessions – would affect coding attitudes in students. As well as this, the experiment investigates whether gender and general self-efficacy affect coding attitudes – either in combination with gamification or individually. As previously discussed, gender has since been excluded from the final model, but descriptive statistics were produced to assess that specific hypothesis. These descriptive statistics can be found in Table 4. Students who participated in the Kahoot! had similar ESCAS-U scores across gender groups (male  $M = 3.98$ , female  $M = 4.10$ ), however there was a larger increase in ESCAS-U scores between students who didn't participate in the Kahoot! and students who did participate in the Male condition compared to the female condition. This suggests, in line with the secondary hypothesis, that gender is associated with gamification and coding attitudes in students – male students are more affected by gamification techniques than female students.

**Table 4**

*Descriptive statistics for the ESCAS-U, split by participant gender and the Kahoot! participation condition.*

Gender	Kahoot! Participation	<i>n</i>	<i>M</i>	<i>SD</i>	CI [95%]	
Male	I did not participate but stayed to watch	1	2.54	0.77	-4.36	9.45
Male	Yes, I participated in the Kahoot!	4	3.98	0.49	3.57	4.39
Female	I did not participate and did not pay attention/left early	7	4.08	0.65	3.71	4.46
Female	I did not participate but stayed to watch	15	3.44	0.83	3.13	3.75
Female	Yes, I participated in the Kahoot!	18	4.10	0.66	3.87	4.32

Gender	Kahoot! Participation	<i>n</i>	<i>M</i>	<i>SD</i>	CI [95%]	
Prefer to self-describe	I did not participate and did not pay attention/left early	1	3.13	0.06	2.58	3.68
Prefer to self-describe	I did not participate but stayed to watch	1	4.02	0.03	3.75	4.30

To assess the first and third hypotheses, a mixed multiple regression analysis conducted. This model included two independent variables. Time was included as a repeated measures variable. Each participant was registered in the dataset twice – once for their response to the pre-questionnaire and once for their response to the post-questionnaire. Due to the composition of the dataset, the model was conducted as a linear mixed-effects model which was then put through an ANOVA analysis for model fit statistics. A linear mixed-effects model gives significantly more control over the effect of time and allows for more complex modelling of individual differences in change over time – giving a more accurate model of the effects of an intervention. Kahoot! participation was included as a between-subjects variable and was measured only in the post-questionnaire. GSE was also included in the model as an additional covariate, centred around its grand mean and modelled as a mediating variable. Two contrasts were formed to break down the Kahoot! participation variable, and its interactions, one of which compares students who actively participate in the Kahoot! with those who did not (referred to as participated), and another which compared students who stayed in the teaching session with those who left, whether or not they participated in the Kahoot! (referred to as attended).

Linear mixed models follow four main statistical assumptions, which were checked as part of the analysis process: linearity, normality of residuals, independent of errors and constant variance. Diagnostic scatter plots indicated that the data was linear and that it met the assumption of homoscedasticity – the residuals had constant variance across all levels of the independent variables. The scatter plot lacking any clear pattern similarly indicated that the data was independent of errors. A Q-Q plot was also fitted – all points fell within the acceptable range of the  $x = y$  line, indicating that the residuals fell within a normal

distribution. Following the completion of these assumption tests, it can be assumed that a linear mixed effects model is an appropriate method for testing this hypothesis. However, as this experiment has a relatively small sample, a robust model was fitted. The robust model's intercept confidence interval was 0.38 to 3.09, compared to 3.55 to 4.00 for the non-robust model. All further confidence intervals of the robust model were similar to the non-robust model and can be found in Table 5. With this in mind and considering that no statistical assumptions were violated by the original model, the final model in this analysis is the non-robust model.

**Table 5**

*Confidence intervals and p-values for the original model and robust model*

Parameter	CI [LME model]		<i>p</i> [LME model]	CI [robust model]		<i>p</i> [robust model]
(Intercept)	3.55	4.00	0.00	0.38	3.09	0.01
time [post]	-0.07	0.17	0.38	-0.03	0.17	0.19
Kahoot! participation [participated]	0.02	0.32	0.03	-0.01	0.31	0.06
Kahoot! participation [attended]	-0.31	0.11	0.36	-0.29	0.15	0.51
GSE (centered)	0.25	1.15	0.00	0.26	1.20	0.00
time [post] × Kahoot! participation [participated]	-0.11	0.06	0.54	-0.10	0.04	0.46



Parameter	CI [LME model]		$p$ [LME model]	CI [robust model]		$p$ [robust model]
time [post] × Kahoot! participation [attended]	-0.11	0.11	0.98	-0.09	0.10	0.88

The final model showed no significant main effect for time:  $F(1, 45) = 0.52, p = 0.47$ . This indicates that there was no significant difference in ESCAS-U scores between the pre-questionnaire and the post-questionnaire without accounting for any other variable. This effect has very little impact on the main hypothesis – the inclusion of time as a variable accounts for any change in ESCAS-U scores that happens naturally as a result of the passing of time. The non-significant main effect indicates that this change over time has no significant impact on ESCAS-U scores, and any significant change is resulting from an intervention. There was a significant main effect of Kahoot! participation:  $F(2, 42) = 5.71, p = .006$ . This suggests that there was a significant difference in coding attitudes when students participated in the Kahoot! compared to when they either only stayed to watch or if they left early. This effect is consistent with the first hypothesis – participation in the Kahoot! significantly improves coding attitudes in students.

General self-efficacy was included as an additional covariate variable. Before being included in the analysis, GSE was centred around its grand mean to make the results interpretable. GSE showed a significant main effect:  $F(1, 42) = 11.55, p = .002$ . This indicates that general self-efficacy had a significant effect on coding attitudes – students with higher levels of GSE (i.e. students with the scores closest to 4) had significantly higher levels of positive coding attitudes (i.e. scores closest to 6) than students with low GSE scores, across all categories of students. There was a non-significant interaction effect:  $F(2, 45) = 0.22, p = .807$ . This indicates that the effect of Kahoot! participation was not significantly affected by the effect of time.

The relationship between Kahoot! participation and ESCAS-U scores showed significant variance in intercepts between participants,  $SD = 3.78$  (95% CI: 3.57, 3.99),  $\chi^2 =$

73.75,  $p < .0001$ . The slopes did not significantly vary between participants,  $\chi^2 = 1.75$ ,  $p = .417$ . ESCAS-U scores were not significantly predicted by which stage of the experiment the questionnaire was conducted in,  $b = 0.05$ ,  $SE = 0.06$ ,  $t(45) = 0.81$ ,  $p = .423$ .

Two contrasts were created to break down the effect of Kahoot! participation on ESCAS-U scores. The first contrast, denoted in the breakdown tables as participated, compared the two non-participatory Kahoot! groups (Did not participate and did not stay; and did not participate but did stay to watch) to the actively participated Kahoot! group. Active participation in the Kahoot! significantly predicted ESCAS-U scores:  $b = 0.17$ ,  $SE = 0.07$ ,  $t(42) = 2.32$ ,  $p = .025$ . This indicates that students who actively participated in the Kahoot! at the end of the Skills Lab had significantly higher ESCAS-U scores than participants who did not participate in the Kahoot!. The second contrast compared the students who remained in the Skills Lab session for the Kahoot!, whether or not they participated in the Kahoot!, which the participants who did not participate and did not stay. This contrast is denoted in the breakdown tables as attended, and did not significantly predict ESCAS-U scores:  $b = -0.09$ ,  $SE = 0.10$ ,  $t(42) = -0.94$ ,  $p = .354$ . This indicates that students who stayed in the Skills Lab did not have any higher ESCAS-U scores than students who left. The combination of these two contrasts suggests that active participation in the Kahoot! is the key variable in improving ESCAS-U scores rather than simply being present for the Kahoot!. The interaction effect for both contrasts with the effect of time was non-significant: [participated]:  $b = -0.02$ ,  $SE = 0.04$ ,  $t(45) = -0.61$ ,  $p = .544$ ; [attended]:  $b = 0.002$ ,  $SE = 0.06$ ,  $t(45) = 0.04$ ,  $p = .972$ .

General self-efficacy also significantly predicted ESCAS-U scores,  $b = 0.74$ ,  $SE = 0.22$ ,  $t(42) = 3.40$ ,  $p = .002$ . General self-efficacy was prepared as a mediating variable and was centred around its grand mean. This indicates that general self-efficacy has a significant effect on ESCAS-U scores across all groups of participants.

## Discussion

This study was intended to investigate the links between gamification, coding attitudes, gender and general self-efficacy. Research supporting gamification in this area is rocky at best, and this experiment provides support for the use of gamification in teaching. This study found that active participation in Kahoot! is associated with increased positive coding attitudes. Students who participated in Kahoot! during Skills Lab sessions produced higher scores on the ESCAS-U than students who only watched the Kahoot! or left the session. A possible explanation for this finding comes from self-determination theory (Khoshnoodifar et al., 2023). Self-determination theory posits that humans have an innate need to feel effective in the world (Deci et al., 2017) – in the context of this experiment, people have an innate desire to win each challenge. The results of this hypothesis support the findings of several other experiments (Åzer et al., 2018; Smith, 2017). However, this study is unique in its use of an uncommon in-person gamification technique, as well as the use of an alternate attitude measurement scale and a demographically unique sample due to the use of Psychology students.

Additionally, although this hypothesis could not be put through significance testing due to the small sample size, it was found that there was a link between gender, Kahoot! participation and coding attitudes. In particular, there was a larger difference in coding attitude scores between Kahoot! participation groups in the male condition than in the female condition – this suggests that males are more affected by gamification techniques in teaching than females are, which is shown by the increase in ESCAS-U scores. Other research into the effect of gender in gamification suggests several reasons for this result. Firstly, it is suggested that men are more receptive to gamification techniques because of their similarity to video games – men are significantly more likely to use the internet problematically, and to engage in addictive behaviours relating to the internet, such as excessive video game usage, than women (Bakhiet et al., 2023; Piquer Martínez et al., 2024). This characteristic means it is more likely that men will be more confident in using the gamified learning platform than women, which reduces the amount of content they need to learn, instead focusing on the teaching rather than familiarising themselves with the platform.

Secondly, it is suggested that gamification does not motivate women – in fact, they may be demotivated by it (Mellado et al., 2024). This is particularly relevant in programming courses, in which the gamification techniques include some form of social aspect, such as that

in the Analysing Data module. Duda et al. (2023) found that women typically favour gamification techniques that do not have this social aspect, such as learning activities – this may be translated as the Challengr activities in the Analysing Data module – whilst men prefer reward-based learning, such as the Kahoot! activity or collecting badges. Mellado et al. (2024) suggest this preference may arise due to stereotype threat. Stereotype threat is generally defined as a psychological threat that arises when a member of a marginalised group completes an activity that has an applicable negative stereotype for that marginalised group (Brooks, 2023). Whilst stereotype threat was initially tested on and defined through intelligence tests on Black communities (Steele & Aronson, 1995), it is generally accepted, and subsequent research has confirmed, that it occurs in a huge variety of marginalised communities and with a massive variety of negative stereotypes – from women (Hoyt & Murphy, 2016; Spencer et al., 1999) to the LGBTQ+ community (LeBlanc et al., 2024; Ojeda-Leitner & Lewis, 2021), a huge variety of people face stereotype threat in the day-to-day world, making this an incredibly relevant issue to everyday life. Women typically face educational stereotype threat in areas that include mathematics or computer science (Smith & Hung, 2008), exposing this as a particularly important mediating factor in the relationship between this study's gamification techniques, educational content and coding attitudes. It is hypothesised that introducing a social aspect into gamification techniques introduces a competitive element, essentially making the female participants believe that they are being put against each other, even if there is no outcome. This feeling then induces anxiety and can make female participants perform worse on the activity (Albuquerque et al., 2017; Christy & Fox, 2014). This will likely reduce motivation scores as students drop down the leaderboard. It is also important to note that this study did not collect the grades obtained for this module, mainly due to time constraints. This means that we do not actually know if there would be any academic difference between the gender groups, which is typically how stereotype threat is empirically measured in dedicated studies due to the stereotype in question affecting educational ability (Betz et al., 2013). While the collection of this data would certainly enhance future research in this area, the collection of the ESCAS-U still provides valuable data about how students, particularly female students, feel about the source of the stereotype.

The link to threat and attitudes also brings forward the third hypothesis of this study: a relationship was found between general self-efficacy and ESCAS-U scores across all conditions – this indicates that students with higher GSE scores also had higher ESCAS-U scores, whether or not they participated in the Kahoot! and across all gender conditions. This

finding was expected and confirms that GSE influences coding attitudes, acting as a mediating variable and explaining and influencing the relationship between coding attitudes, gender, and Kahoot! participation. Intrinsic motivations, such as GSE, have been previously explored as a possible mediating variable in gamification. However, this was only in the context of marketing engagement, not educational gamification (Feng et al., 2018).

Future research in this area could address two key limitations of this study. Firstly, a non-representative and relatively small sample was collected. This limitation occurred for two reasons. The first reason was because of the short sampling period. Whilst the overall study, conducted by Dr Mankin and the rest of the research team, collected data from three different time points across the second semester, this study only used data from the first time point. This time point was in the first week of term – students generally start completing academically required research participation much later in the term, unless it provides a substantial reward, which this study did not (Brewer & and Robinson, 2018). The second reason is the relatively skewed possible sample. This study only accepted Psychology first-year students enrolled on Analysing Data, as they were being taught using the Kahoot! gamification intervention. It can be argued that the use of Psychology students in research reduces the study's validity, due to the increased education on psychological research methods (Leentjens & Levenson, 2013). This issue is circumvented by this study's design – it is a test of pre-existing gamification strategies in place on a Psychology module. However, issues with the sample still arose. As previously mentioned, Psychology students have a skewed 20:80 male-to-female ratio (Johnson et al., 2020), resulting in a very small male final sample. Both of these issues can be solved in future research by increasing the sampling period across teaching sessions or possibly using a teaching session much later in the term, when students are more likely to complete required research participation (Brewer & and Robinson, 2018).

Secondly, future research could collect academic data as well as ESCAS-U scores. Academic data is very commonly collected to test the efficacy of gamification techniques and their uses in education (Huang et al., 2020; Kalogiannakis et al., 2021). Additionally, academic data may be helpful in enhancing analysis and interpretation of stereotype threat surrounding gender differences in gamification efficacy (Betz et al., 2013). The collection of academic data in future studies could provide valuable insight into the efficacy of this

gamification technique in actually improving educational outcomes and students' attitudes towards their education.

In conclusion, this research supports previous research into gamification and provides evidence for a link between gamification techniques used in education and improved coding attitudes. Additionally, it suggests that there is a gender difference in how gamification techniques affect students' motivations and that students' general self-efficacy levels have a significant impact on how their coding attitudes develop across all gamification conditions. Any future research would likely find it helpful to address issues found with the sampling methods by altering the sampling period to later in the academic year and to collect academic data and ESCAS-U scores.

### References

- Albuquerque, J., Bittencourt, I. I., Coelho, J. A. P. M., & Silva, A. P. (2017). Does gender stereotype threat in gamified educational environments cause anxiety? An experimental study. *Computers & Education*, *115*, 161–170.  
<https://doi.org/10.1016/j.compedu.2017.08.005>
- Ã–zer, H. H., Kanbul, S., & Ozdamli, F. (2018). Effects of the Gamification Supported Flipped Classroom Model on the Attitudes and Opinions Regarding Game-Coding Education. *International Journal of Emerging Technologies in Learning (iJET)*, *13*(01), Article 01. <https://doi.org/10.3991/ijet.v13i01.7634>
- Bakhiet, S. F., Ziada, K. E., Abdelrasheed, N. S. G., Dutton, E., Madison, G., Almalki, N. S., Ihsan, Z., Furnham, A., & Essa, Y. A. S. (2023). Sex and national differences in internet addiction in Egypt and Saudi Arabia. *Acta Psychologica*, *240*, 104043.  
<https://doi.org/10.1016/j.actpsy.2023.104043>
- Betz, D., Ramsey, L., & Sekaquaptewa, D. (2013). *Gender stereotype threat among women and girls* (pp. 428–449). <https://doi.org/10.4135/9781446269930.n26>
- Bogost, I. (2011, May 3). *Persuasive Games: Exploitationware* [Blog]. Game Developer.  
<https://www.gamedeveloper.com/design/persuasive-games-exploitationware>
- Brewer, G., & Robinson, S. (2018). ‘I like being a lab Rat’: Student experiences of research participation. *Journal of Further and Higher Education*, *42*(7), 986–997.  
<https://doi.org/10.1080/0309877X.2017.1332357>
- Brooks, J. T. (2023). Defining Stereotype Threat and Why It Matters. *Journal of the Pediatric Orthopaedic Society of North America*, *5*, 576.  
<https://doi.org/10.55275/JPOSNA-2023-576>

- Christy, K. R., & Fox, J. (2014). Leaderboards in a virtual classroom: A test of stereotype threat and social comparison explanations for women's math performance. *Computers & Education*, 78, 66–77. <https://doi.org/10.1016/j.compedu.2014.05.005>
- Damsa, A., & Fromann, R. (2016). Gamification and Gameful Approaches in Education, Business, and IT. *INFORMATIKA*, 18(1), 28–33.
- Deci, E. L., Olafsen, A. H., & Ryan, R. M. (2017). Self-Determination Theory in Work Organizations: The State of a Science. *Annual Review of Organizational Psychology and Organizational Behavior*, 4(Volume 4, 2017), 19–43. <https://doi.org/10.1146/annurev-orgpsych-032516-113108>
- Denden, M., Tlili, A., Essalmi, F., Jemni, M., Chen, N.-S., & Burgos, D. (2021). Effects of gender and personality differences on students' perception of game design elements in educational gamification. *International Journal of Human-Computer Studies*, 154, 102674. <https://doi.org/10.1016/j.ijhcs.2021.102674>
- Dicheva, D., Dichev, C., Agre, G., & Angelova, G. (2015). Gamification in Education: A Systematic Mapping Study. *Journal of Educational Technology & Society*, 18(3), 75–88.
- Duda, E., Anacka, H., Kowal, J., Nowakowska, I., Obracht-Prondzynska, H., Geirbo, H. C., Radziszewski, K., Romanowska, M., Wyciszkiewicz, A., & Zawieska, J. (2023). Encouraging Pro-environmental Behaviour Through an Educational Mobile Application: Preliminary Insights from Early Adopters. *International Journal of Pedagogy, Innovation and New Technologies*, 10, 64–78. <https://doi.org/10.5604/01.3001.0053.9400>
- Feng, Y., Jonathan Ye, H., Yu, Y., Yang, C., & Cui, T. (2018). Gamification artifacts and crowdsourcing participation: Examining the mediating role of intrinsic motivations.



*Computers in Human Behavior*, 81, 124–136.

<https://doi.org/10.1016/j.chb.2017.12.018>

Garris, R., Ahlers, R., & Driskell, J. E. (2002). Games, Motivation, and Learning: A Research and Practice Model. *Simulation & Gaming*, 33(4), 441–467.

<https://doi.org/10.1177/1046878102238607>

Guin, T. D.-L., Baker, R., Mechling, J., & Ruyle, E. (2012). Myths and Realities of Respondent Engagement in Online Surveys. *International Journal of Market Research*, 54(5), 613–633. <https://doi.org/10.2501/IJMR-54-5-613-633>

Hamari, J. (2013). Transforming homo economicus into homo ludens: A field experiment on gamification in a utilitarian peer-to-peer trading service. *Electronic Commerce Research and Applications*, 12(4), 236–245.

<https://doi.org/10.1016/j.elerap.2013.01.004>

Hamari, J. (2017). Do badges increase user activity? A field experiment on the effects of gamification. *Computers in Human Behavior*, 71, 469–478.

<https://doi.org/10.1016/j.chb.2015.03.036>

Hoyt, C. L., & Murphy, S. E. (2016). Managing to clear the air: Stereotype threat, women, and leadership. *The Leadership Quarterly*, 27(3), 387–399.

<https://doi.org/10.1016/j.leaqua.2015.11.002>

Huang, R., Ritzhaupt, A. D., Sommer, M., Zhu, J., Stephen, A., Valle, N., Hampton, J., & Li, J. (2020). The impact of gamification in educational settings on student learning outcomes: A meta-analysis. *Educational Technology Research and Development*, 68(4), 1875–1901. <https://doi.org/10.1007/s11423-020-09807-z>

- Huotari, K., & Hamari, J. (2012, October 3). *Defining Gamification—A Service Marketing Perspective*. ACM J. <https://doi.org/10.1145/2393132.2393137>
- Johnson, J., Madill, A., Koutsopoulou, G. Z., Brown, C., & Harris, R. (2020, July 24). *Tackling gender imbalance in psychology*. The British Psychological Society. <https://www.bps.org.uk/psychologist/tackling-gender-imbalance-psychology>
- Jones, B. A., Madden, G. J., & Wengreen, H. J. (2014). The FIT Game: Preliminary evaluation of a gamification approach to increasing fruit and vegetable consumption in school. *Preventive Medicine*, 68, 76–79. <https://doi.org/10.1016/j.ypmed.2014.04.015>
- Jordan, A. B., & Romer, D. (2014). *Media and the Well-being of Children and Adolescents*. Oxford University Press.
- Kalogiannakis, M., Papadakis, S., & Zourmpakis, A.-I. (2021). Gamification in Science Education. A Systematic Review of the Literature. *Education Sciences*, 11(1), Article 1. <https://doi.org/10.3390/educsci11010022>
- Khoshnoodifar, M., Ashouri, A., & Taheri, M. (2023). Effectiveness of Gamification in Enhancing Learning and Attitudes: A Study of Statistics Education for Health School Students. *Journal of Advances in Medical Education & Professionalism*, 11(4), 230–239. <https://doi.org/10.30476/JAMP.2023.98953.1817>
- Koller, M. (2025). *robustlmm: Robust Linear Mixed Effects Models* (Version 3.3-2) [Computer software]. <https://cran.r-project.org/web/packages/robustlmm/index.html>
- LeBlanc, M. E., Trinh, M.-H., Zubizarreta, D., & Reisner, S. L. (2024). Healthcare stereotype threat, healthcare access, and health outcomes in a probability sample of U.S.

transgender and gender diverse adults. *Preventive Medicine Reports*, 42, 102734.

<https://doi.org/10.1016/j.pmedr.2024.102734>

Leentjens, A. F. G., & Levenson, J. L. (2013). Ethical issues concerning the recruitment of university students as research subjects. *Journal of Psychosomatic Research*, 75(4), 394–398. <https://doi.org/10.1016/j.jpsychores.2013.03.007>

Lockheed Martin. (2020). *Prepar3D* (Version v5.4) [Microsoft Windows]. Lockheed Martin Corporation.

Mason, S. L., & Rich, P. J. (2020). Development and analysis of the Elementary Student Coding Attitudes Survey. *Computers & Education*, 153, 103898. <https://doi.org/10.1016/j.compedu.2020.103898>

Mellado, R., Cubillos, C., Vicari, R. M., & Gasca-Hurtado, G. (2024). Leveraging Gamification in ICT Education: Examining Gender Differences and Learning Outcomes in Programming Courses. *Applied Sciences*, 14(17), Article 17. <https://doi.org/10.3390/app14177933>

Mur, J. A., Rivas, A., Trueba, D. A., & Girardi, C. I. P. (2022). *The Relationship Between Self-Efficacy, State-Trait Anxiety and Cognitive Test Anxiety: A Study Among University Students in Argentina*. 75–94. <https://doi.org/10.37708/psyct.v15i2.664>

Nah, F. F.-H., Zeng, Q., Telaprolu, V. R., Ayyappa, A. P., & Eschenbrenner, B. (2014). Gamification of Education: A Review of Literature. In F. F.-H. Nah (Ed.), *HCI in Business* (pp. 401–409). Springer International Publishing. [https://doi.org/10.1007/978-3-319-07293-7\\_39](https://doi.org/10.1007/978-3-319-07293-7_39)

Ojeda-Leitner, D., & Lewis, R. K. (2021). Assessing health-related stereotype threats and mental healthcare experiences among a LGBT sample. *Journal of Prevention &*

*Intervention in the Community*, 49(3), 251–265.

<https://doi.org/10.1080/10852352.2019.1654262>

Pinheiro, J., Bates, D., DebRoy, S., Sarkar, D., EISPACk, Heisterkamp, S., Willigen, B. V.,

Ranke, J., & R Core Team. (2025). *nlme: Linear and Nonlinear Mixed Effects Models*

(Version 3.1-168) [Computer software]. [https://cran.r-](https://cran.r-project.org/web/packages/nlme/index.html)

[project.org/web/packages/nlme/index.html](https://cran.r-project.org/web/packages/nlme/index.html)

Piquer Martínez, C., Valverde Merino, M. I., Gómez Guzmán, M., & Zarzuelo Romero, M. J.

(2024). *Gender-based differences in gamification and mobile learning*.

<https://doi.org/10.1111/apha.14206>

Przybylski, A. K., Rigby, C. S., & Ryan, R. M. (2010). A Motivational Model of Video

Game Engagement. *Review of General Psychology*, 14(2), 154–166.

<https://doi.org/10.1037/a0019440>

*Qualtrics* (Version January 2025). (2005). [Computer software]. Qualtrics.

<https://www.qualtrics.com>

Ree, M. J., French, D., Macleod, C., & Locke, V. (2008). Distinguishing cognitive and

somatic dimensions of state and trait anxiety: Development and validation of the

state-trait inventory for cognitive and somatic anxiety (STICSA). *Behavioural and*

*Cognitive Psychotherapy*, 36, 313–332. <https://doi.org/10.1017/S1352465808004232>

Ree, M. J., Macleod, C., French, D., & Locke, V. (2000, November). *The state-trait inventory*

*for cognitive and somatic anxiety: Development and validation* [Poster session].

annual meeting of the Association for the Advancement of Behaviour Therapy, New

Orleans, LA.

- Ryan, R. M., Rigby, C. S., & Przybylski, A. (2006). The Motivational Pull of Video Games: A Self-Determination Theory Approach. *Motivation and Emotion*, 30(4), 344–360.  
<https://doi.org/10.1007/s11031-006-9051-8>
- Sailer, M., Hense, J. U., Mayr, S. K., & Mandl, H. (2017). How gamification motivates: An experimental study of the effects of specific game design elements on psychological need satisfaction. *Computers in Human Behavior*, 69, 371–380.  
<https://doi.org/10.1016/j.chb.2016.12.033>
- Schwarzer, R., Jerusalem, M., Weinman, J., Wright, S., & Johnston, M. (1995). Generalized Self-Efficacy Scale. *Measures in Health Psychology: A User's Portfolio. Causal and Control Beliefs Windsor*.
- Smith, C. S., & Hung, L.-C. (2008). Stereotype threat: Effects on education. *Social Psychology of Education*, 11(3), 243–257. <https://doi.org/10.1007/s11218-008-9053-3>
- Spencer, S. J., Steele, C. M., & Quinn, D. M. (1999). Stereotype Threat and Women's Math Performance. *Journal of Experimental Social Psychology*, 35(1), 4–28.  
<https://doi.org/10.1006/jesp.1998.1373>
- Steele, C. M., & Aronson, J. (1995). Stereotype threat and the intellectual test performance of African Americans. *Journal of Personality and Social Psychology*, 69(5), 797–811.  
<https://doi.org/10.1037//0022-3514.69.5.797>
- Susi, T., Johannesson, M., & Backlund, P. (2007). *Serious Games: An Overview* (Other Academic HS-IKI-TR-07-001; IKI Technical Reports, p. 28). Institutionen för kommunikation och information. <https://urn.kb.se/resolve?urn=urn:nbn:se:his:diva-1279>

The Chartered Institute for IT. (2024, August 15). *Number of women taking computer science degrees continues to grow*. Bcs.Org. <https://www.bcs.org/articles-opinion-and-research/number-of-women-taking-computer-science-degrees-continues-to-grow/>

Ubisoft Paris. (2024). *Just Dance* (Version 2025 Edition) [Unity]. Ubisoft Paris.

University of Sussex. (n.d.). *Analysing Data (C8891)*. University of Sussex.  
<https://www.sussex.ac.uk/study/modules/undergraduate/2024/90520-analysing-data>

What Uni? (n.d.). *Computer Science Undergraduate Degree Courses List*. Whatuni.Com.  
<https://www.whatuni.com/degree-courses/search?subject=computer-science&pageno=21>

Wickham, H., & RStudio. (2023). *tidyverse: Easily Install and Load the 'Tidyverse'* (Version 2.0.0) [Computer software]. <https://cran.r-project.org/web/packages/tidyverse/index.html>

Yee, N. (2006). Motivations for Play in Online Games. *CyberPsychology & Behavior*, 9(6), 772–775. <https://doi.org/10.1089/cpb.2006.9.772>

Yildirim, I. (2017). The effects of gamification-based teaching practices on student achievement and students' attitudes toward lessons. *The Internet and Higher Education*, 33, 86–92. <https://doi.org/10.1016/j.iheduc.2017.02.002>

Zahedi, L., Batten, J., Ross, M., Potvin, G., Damas, S., Clarke, P., & Davis, D. (2021). Gamification in education: A mixed-methods study of gender on computer science students' academic performance and identity development. *Journal of Computing in Higher Education*, 33(2), 441–474. <https://doi.org/10.1007/s12528-021-09271-5>