**Exploring The Effects of Different Data Science Tutorials, And Personality, On Learning**

Candidate number: 218063

Word count: 5,828

Date of submission: 8th May 2022

Supervisor: Dr Milan Valasek

School of Psychology

Logo, company name

Description automatically generated

**Acknowledgements**

Firstly, thank you to my supervisor, Dr Milan Valasek, for providing guidance and directions throughout my project, along with his patience for addressing my concerns and doubts. I’d also like to thank Milan for creating the final design of my proposal for a gamified tutorial using his expertise in HTML, JavaScript, and CSS, and for embedding the gamified tutorial into Qualtrics. Without his skills the tutorial would be non-existent.

I created the initial game mechanics design for the gamified R programming tutorials along with the coffee-shop-based story to teach R programming. The non-gamified R programming tutorial was created in collaboration with Angel White. I also designed the learning outcome quiz with Angel White’s help who assisted me by creating datasets presented in the quiz and collecting participants. Ideas for the visuals, audio stimuli, and datasets incorporated in the tutorials were done in collaboration with Milan Valasek and Angel White.

I’d also like to thank my family and friends for their continuous support throughout my project, and God for giving me the courage to pursue this dissertation.

Finally, I would also like to thank Sussex University for funding monetary incentives for participants in this study, as well as the participants themselves for partaking in this experiment.

**Abstract**

Due to the continuous growth of technology, demand for people with IT skills will persist. However, not many students are interested in pursuing this subject due to its complexity (Mezak & Papak, 2018). This posits potential issues in keeping the IT industry abundant with a skilled labour pool. Previous literatures have established the usefulness of employing game elements in learning materials for enhancing student’s motivation and engagement, especially when these game elements complement learner’s characteristics. However, little research has investigated its practicality on improving learning. Therefore, our study attempted to investigate whether a story-based gamified material positively impact learning outcome for R programming, and whether this relationship was strengthened by openness personality. Participants completed Goldberg’s (1992) 50-item personality questionnaire before being randomly allocated to complete either a story-based gamified tutorial or a tutorial without a story for learning R programming language. This was followed by a small quiz which measured learning outcome. Our results indicated the effects of a story-based gamified tutorial doesn’t significantly improve learning outcome and that openness personality had no impact on this relationship contrary to our predictions. Limitations, implications, and suggestions for future research have been suggested.

**Exploring The Effects of Different Data Science Tutorials, And Personality, On Learning**

Recently, the Information Technology (IT) sector has been experiencing skill shortages, leading to countries like the UK undergoing an increased demand for workers with IT skills (*Addressing the Computer Science Skills Gap*, 2019). Resultingly, high pressure has been placed upon the education institution to implement strategies encouraging students into programming. E.g., introducing a software called ‘Scratch’ in primary school allowing them to visualise the process of coding (CodeBeeDo, n.d.). Despite the increased availability of programming courses in secondary schools, only 11% of students took computer science (‘Government Urged to Act over Computer Science GCSEs’, 2017). Moreover, high drop-out rates and low learning attainment persists (Ortiz et al., 2017), one reason being that students find computing uninteresting or too complex (Mezak & Papak, 2018). For this reason, education institutions should create effective and exciting ways of teaching computing and programming to boost attainment and engagement. This is important to ensure there’s ample amount of skilled labour pool within the IT domain that are qualified for employers to recruit from in the long term, especially during the digital era we currently live in.

One way of increasing engagement in tasks is via gamification. Gamification is commonly defined as integrating game elements (i.e., leader boards, badges, points, and stories) in non-gaming tasks (Deterding et al., 2011). The concept of gamification has been increasingly applied in contexts other than for entertainment, namely in the education system. For example, Duolingo is an application incorporating points and reward incentives to keep people entertained while learning languages (Munday, 2017). The effectiveness of gamification for elevating task engagement has been empirically proven by Ortiz et al (2017). They demonstrated that awarding badges to undergraduates who completed tasks significantly encouraged them to pursue other mandatory, and optional activities, assigned to them. The mechanism of embedding game elements into activities to increase engagement can be explained by two theories. Firstly, Zichermann & Cunningham's (2011) theory of motivation which can be divided into two types: intrinsic motivation where one performs an activity because doing the activity itself is rewarding; and extrinsic motivation wherein one undertakes an activity only in exchange for external rewards regardless if they find the activity rewarding or otherwise. The second theory is self-determination theory (Deci & Ryan, 1980), suggesting that we find activities intrinsically motivating if it fulfils our three needs: attachment with others; sense of achievement; and autonomy (Christenson et al., 2012). In the experiment by Ortiz et al (2017), the positive effects of gamification on engagement can be explained by the self-determination theory; integrating game elements in learning via awarding badges for the completion of assignments would make student sense of competence and achievement more salient, thus motivating them to engage further by completing even the optional assignments. However, while the literature on gamification declares general positive effects on engagement, there are mixed findings (Majuri et al., 2018). In Ortiz et al (2017), findings depicted no impact of badges on intrinsic motivation despite increased engagement. This entails that to fully comprehend how gamification can be an effective learning strategy, the game elements incorporated should be customised to the learners (Hallifax et al., 2019; Hamari et al., 2014), especially since there are individual differences in learning techniques (Majuri et al., 2018) and the sense of gratification it gives (Botte et al., 2020). This is often the case when applying gamification within the learning environment consisting of a heterogenous population of students.

One way individual differences have been examined in the context of gamification is by exploring the role of personality traits. Personality traits are defined as a stable set of characteristics determining the common attributes, and differences, in one’s thoughts, feelings, and actions (Maddi, 1996). This influences their interpretations of their environment. A universal method of identifying one’s personality trait is using Goldberg's (1992) five-factor model which differentiates between five different personality traits (see Table 1).

**Table 1**

*Definitions of each five dimensions of personality traits in Goldberg’s (1992) five-factor model.*

|  |  |
| --- | --- |
| Five dimensions of personality trait | Definition |
| Extraversion | Describes the level of one’s liveliness and sociability. High scorers here are described as highly energetic and assertive. |
| Agreeableness | Describes the extent one holds a positive outlook of others. High scorers are deemed as cooperative, warm, and friendly. Low scorers are associated with selfishness and are emotionally distant to others. |
| Conscientiousness | Demonstrates one’s level of organisation and attentiveness to fulfil duties and favour order. High scorers tend to be organised and efficient in what they do. |
| Neuroticism | Extent to which one experiences instability in their emotions. High scorers are more prone to experience negative emotions such as anger and anxiousness while low scorers tend to be calmer and relaxed. |
| Openness | Describes one’s level of imagination, creativity, and extent to which they welcome new ideas. High scorers are more imaginative, creative, and open to new concepts. |

*Note.* Definitions were sourced from Topolewska-Siedzik et al (2014)

Ghaban & Hendley (2019) observed different personalities responded uniquely to different game elements. Specifically, extraverts reacted favourably to game elements such as leader boards (Jia et al, 2016) and points than low scorers on extroversion. This can be explained by the observation that extroverts seek stimulation external to their self (Buckley & Doyle, 2017). In other words, extrinsically rewarding game elements, i.e., badges in exchange for task completion (Mekler et al., 2013) are more likely to influence extroverts into engaging in activities in exchange for an external reward (Buckley & Doyle, 2017) regardless of how satisfying they found the activity. However, academics should be cautious in utilizing extrinsically rewarding game elements. Almeida et al (2021) observed undesirable outcomes, namely a decline in performance when badges and points were used. Toda et al (2018) claims the reason for this pattern is due to extrinsic reward undermining intrinsic motivation to pursue a task as it cripples one’s sense of autonomy (Lin et al., 2003). Extrinsic rewards may also reinforce the idea that doing such activities would consistently result in perks (often not the case in reality). This impairs intrinsic motivation as individuals would be reinforced to engage in an activity for the pursuit of rewards rather than for the sake or enjoyment of it, thus hindering the goal of education to motivate students for continuous learning (Lin et al., 2003).

Meanwhile, Buckley & Doyle (2017) observed negative reactions of conscientious individuals when gamification was assimilated in their learning. Here, they explained the relationship is due to the trait’s inclination with order; features of which are absent in a gamified educational setting as game elements often resemble play as opposed to a work-oriented environment.

With agreeableness, Codish & Ravid (2014) found low scorers exhibited preferences for game elements such as progress bars than high scorers which shows moderating effects of personality on fondness for certain game elements.

Regarding openness, Andrus (2018) found high scorers favoured story-based game elements as opposed to points (Denden et al., 2018). A general definition of a story (also known as narratives) describes sequences of events. In the context of gamification, story-based game elements enables individuals to become immersed into an activity (Aldemir et al., 2018). According to McNett (2016), stories feed our disposition to seeking patterns and meanings behind information for comprehension. With this, assimilating stories in teaching methods has the potential to facilitate a learner’s understanding of concepts ought to be taught. This is known as the narrative hypothesis (Landers et al., 2017) where information in the form of stories were better retained than information presented without a story. This can include, but isn’t limited to, employing characters and fiction (Aldemir et al., 2018). Studies like Graesser et al (1980) support the narrative hypothesis as their findings indicated better retention of information, as a measure of learning, when information was presented in a story. However, this was contradicted by Cunningham & Gall (1990), who found no difference in learning achievements between students who read a standard literature book compared to those who read a narrative version of the book. In relation to personality traits, preferences of openness traits for these story-based elements can be explained via the trait’s disposition to novelty, distinctive perspectives and imagination; features of which can be reflected using story elements (Alexiou & Schippers, 2018). This explanation was supported by Denden et al (2018) who observed the preferences of openness traits for feedback game elements, thus mirroring their acceptance to distinct perspectives.

Therefore, it’s plausible to assume that individuals with different characteristics responds uniquely to gamification, meaning we shouldn’t generalise the positive effects of one game element to everyone. This implies that tailoring gamified learning material, in line with the learner’s characteristics, is fundamental when accounting for individual needs rather than administrating “one-size-fits-all” learning methods. By doing so, motivations and engagement can be positively impacted which in turn can also increase learning achievements (Carini et al, 2006).

While the gamification literature is abundant with research on enhancing engagement and motivations, it’s not without limitations. Consequences of gamification on learning outcome is still currently neglected (Bai et al., 2020). While learning performance is accounted for by some research such as Hallifax et al (2019), it shouldn’t be confused with learning outcome as they’re two distinctive constructs (Smith, 2017); learning outcome is defined as the knowledge and abilities learners can demonstrate upon completing a task (Kennedy, 2006) whereas learning performance is often quantified as the percentage of submitted assignments such as in Smith's (2017) study. However, measuring learning performance based on the number of submitted assignments does not validly represent one’s ability to demonstrate their skills. Hence, Smith (2017) collected data on both learning performance and learning outcome (measured by grades). Consequently, the study found higher homework grade among students in the gamified module. Although we could consider this finding as evidence that gamification improves learning outcome, participants weren’t randomised between the gamified and non-gamified module. Essentially, this makes it difficult to compare the two modules due to a possible presence of selection bias. Moreover, there’s also a need for research to examine the effectiveness of each game elements in isolation with other elements (Faiella & Ricciardi, 2015) to further scrutinize the impact of each game element on individual traits. Finally, the narrative hypothesis still receives contradicting findings in the context of learning.

Therefore, with the literature observing various effects of gamification depending on the learner’s characteristics (Smiderle et al., 2020), this study aims to investigate how learners exhibiting openness personality traits can strengthen the relationship between a gamified tutorial and learning outcome, as well as address the aforementioned limitations of the literature. Specifically, the present study uses two types of tutorials: a gamified tutorial that incorporates a story-based game element, and a non-gamified tutorial (absence of the story element) for teaching R programming for the purpose of improving people’s knowledge in coding. R programming language involves cleaning and analysing data used by a variety of researchers (Yee, 2017). For this study, participant’s learning will be based on simple data cleaning steps (i.e., modifying and identifying relevant data). A story-based game element was chosen for this study as previous research has demonstrated how story-based game elements feed the dispositions of those scoring high in the openness personality domain.

In line with the claims of the current literature, I predicted that (1) participants exposed to the story-based gamified tutorial would score higher on the quiz than participants in the non-gamified group and (2) this relationship will be moderated by openness by strengthening the effect of the story-based gamified tutorial on learning outcome.

**Method**

**Participants**

Volunteer sampling was used by posting advertisements on social media platforms (Facebook, Instagram, and Reddit) which contained the link to access the experiment online. The advertisement explicitly targeted participants who were (1) fluent in English to comprehend instructions (2) have normal or corrected-to-normal vision as they were presented with stimuli (3) have no previous experience in R coding to maintain novelty and control for confounding effects of experience on participant’s learning outcome. Resultingly, an initialsample of 149 participants was obtained. However, data from 48 participants were removed due to incomplete responses, 30 due to unspecified age, and 2 for being under eighteen years old. Therefore, a final sample of 69 participants (36 male, 31 female, and 2 “other”) remained in our study between the ages 19 and 55 years (*M*age = 25.52, *SD*age = 8.56). Table 2 and 3 illustrates sample characteristics for each condition.

**Table 2**

*Sociodemographic characteristics of participants by experimental condition*

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| Sample characteristics | Non-gamified group | | Gamified group | |
|  | *n* | *%* | *n* | *%* |
| Gender |  |  |  |  |
| Male | 16 | 41.03 | 20 | 66.67 |
| Female | 22 | 56.41 | 9 | 30.00 |
| Other |  |  | 1 | 3.33 |
| Prefer not to say | 1 | 2.56 |  |  |
| Education |  |  |  |  |
| Highschool | 16 | 41.03 | 10 | 33.33 |
| Undergraduate degree | 17 | 43.59 | 15 | 50.00 |
| Master’s degree | 5 | 12.82 | 4 | 13.33 |
| Prefer not to say | 1 | 2.56 | 1 | 23.33 |
| Occupational status |  |  |  |  |
| Student | 20 | 51.28 | 15 | 50.00 |
| Full-time work | 11 | 28.21 | 10 | 33.33 |
| Other | 7 | 17.95 |  |  |
| Prefer not to say | 1 | 2.56 | 5 | 16.67 |
| Total | 39 | 56.52% | 30 | 43.48% |

*Note. N =* 69.

**Table 3**

Descriptive statistics of participant’s age (years) by Experimental condition

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| Experimental condition | *Mage* | *SDage* | Median | Range |
| Non-gamified group | 25.38 | 8.26 | 22 | 19 - 54 |
| Gamified group | 25.70 | 9.07 | 22 | 19 - 55 |

**Materials**

*Qualtrics***.** The study was conducted online through Qualtrics, version 2022 (URL: <https://www.qualtrics.com>) where questionnaires and stimuli were all embedded into. Participants only required a laptop/desktop computer and an internet connection to complete this study in their own time, ensuring their convenience.

*International Personality Item Pool (IPIP) Big-Five Factor Markers (Goldberg, 1992).*This is a public domain personality test consisting of fifty items, each employing a 5-point Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree). The scale was designed to measure five types of personality traits (illustrated in Table 1). In this study, the personality of interest was Openness. This test was chosen due to its established replicability across societies (Gurven et al, 2013). All fifty items were randomised to minimises response biases from survey fatigue.

*The situational Motivation Scale (Guay et al ,2000).* The scale measures the motivations behind why a respondent is completing a task. Data for this scale was collected for the purpose of another study unrelated to my research.

*Gamified R programming tutorial.*This web browser-based application tutorial (written in HTML, JavaScript, and CSS) was embedded into Qualtrics. The tutorial was centred around a story where participants play as a coffee shop trainee who learns how to code to charge customers the right prices according to the drink menu. The game begins with a female managerial figure who introduces participants to three datasets: hot chocolate; coffee; and bubble tea. Each dataset was presented in the form of menus to fit the coffee shop story. The menus outlined the ingredients, drink sizes (small, medium, and large) and prices which vary (see Appendix C1 for an example of the coffee menu). The manager then proceeded to introduce R code in a sequence of increasing complexity, followed by a few practice tasks of dragging and dropping elements of R commands to a virtual console to familiarise participants with the game mechanics (see Appendix C3 for an example). Verbal feedback from the manager was displayed following participant’s actions (see Appendix C5). After a few guided activities, participants were approached by eight customers ordering drinks (see Appendix C7 for an example of a customer’s order). Here, participants were tasked with identifying the price of the drink according to its menu by entering R code to filter and select the appropriate cell of the menu. Upon entering the correct order of command, a cash register audio would be played which indicated that the customers have been served successfully, followed by positive comments (see Appendix C9). Participants get three attempts to enter the right code per customer. After failing on the third attempt, an unhappy customer would be displayed accompanied by a “booing” audio and negative comments indicating that participants were unsuccessful (see Appendix C11). After serving eight customers, the manager provides them with a positive or negative verbal and facial feedback depending on their performance by scoring them on how many customers were correctly served out of eight (illustrated in Appendix C12 and C13). Some game elements from various literatures were assimilated in this tutorial to form the coffee shop story (outlined in Table 4). Although the study attempts to address the lack of game elements examined in isolation throughout the literature, it was necessary to incorporate these game elements in this study to form one coherent coffee shop story element in comparison to a tutorial without a story. The tutorial used the tidyverse dialect of R (Wickham et al., 2019).

**Table 4**

*Game elements used to form a coffee shop story in the gamified tutorial*

|  |  |  |
| --- | --- | --- |
| Game element | Definition | Examples |
| Fantasy | The made-up scenarios, characters, and the roles participants identified themselves with (Bedwell et al., 2012) | Participants played as a coffee shop trainee instructed by a female manager and a mixture of male and female customers. The fantasy game element contributed to our coffee shop story by attempting to replicate the tasks of working in a cafe. |
| Language and communication | The way in which the rules of the tutorial was delivered (Bedwell et al., 2012) | Communication between the manager and participants helped to explain the instructions and function of R code. Communication was used to reinforce the coffee shop story for replicating the way in which the rules and goals are communicated to trainees to progress and become successful. |
| Challenges | Level of difficulty one faces (Smith, 2017). | Participants began with easy guided tasks, i.e., which code to drag and drop first (Appendix C14). As participants progress, tasks become increasingly complex without the aid of the manager (see Appendix C7 as an example). Challenges helped to maintain the coffee shop story by attempting to replicate the learning curve of new recruits when training them on the job. |
| Assessment | Indicators of achievements in the game (Bedwell et al., 2012). | A “ding” sound was used to indicate when players drag the correct code in the right place. A buzzer sound was played when they failed to complete a task.  Manager and customers’ positive/negative facial and verbal expressions were also indicators of correct/incorrect code players inputted.  Assessment game element was incorporated as it reflected the type of feedback one would receive from customers or superiors at work. |
| Interaction | Extent to which the game responds according to player’s actions. (Bedwell et al., 2012) | Players can choose to: click on different drink menus they want displayed in their screen; change to typing mode versus drag and drop mode; and which boxes they can drag and drop. The interactive element of this tutorial maintained the coffee shop story as it attempts to reflect the various decisions one would make when operating a system that helps with preparing drinks and charging money such as cashiers. |

*Note.* Characters were sourced from Freepik (URL: <https://www.freepik.com>); audio stimuli were sourced from Freesound (URL: <https://freesound.org/>).

*Non-gamified R programming tutorial.* This version of the tutorial didn’t include the coffee shop story or any fantasy, communication, interaction elements, or audio stimuli to allow for a controlled comparison between the gamified and non-gamified R programming tutorials. The tutorial began with presenting participants with the same three datasets: hot chocolate; coffee; and bubble tea, which also contained ingredients and prices (see Appendix C2 for the coffee dataset). Next, tidyverse code functions were introduced and the order in which they go in, followed by multiple choice questions (MCQs) where participants chose, from a choice of seven, the missing code element (see Appendix C4). This was followed by verbal feedback which displays the correct answers (Appendix C6). After several guided tasks, participants undertook eight unguided exercises. Using the rank order question format from Qualtrics, participants were tasked to put R code elements in order according to which box they belong in (see Appendix C8). After each exercise, verbal feedback with the correct answers was also displayed to allow participants to compare their answers (Appendix C10).

*Learning outcome quiz* ***(****see Appendix B for the full quiz)****.*** This construct was quantified using multiple choice questions (MCQ), as opposed to other test formats due to its ability to measure learning outcome during a short period of time (Allen, 2003), thus appropriate for our 45-minute experiment. This was designed to test the knowledge from the R programming tutorials and their ability to administer this to new datasets, e.g., modifying new datasets (see Appendix B4 for an example). The MCQ test comprised ten questions with four choices per question (only one correct choice) which was ideal for minimising participants from experiencing choice overload (Chernev et al., 2015). Although questions weren’t randomised to maintain coherence, response options were randomised to control for order effects.

**Design**

A between-subject design was applied to this study. The independent variable had two levels: gamified tutorial (experimental group) and a non-gamified tutorial (comparison group) to assess the effect of employing a story game element on learning. Each score on the learning outcome MCQ (out of 10) was the dependent variable. To control for individual differences, our moderating variable was participants’ scores on Openness trait.

**Procedure**

Upon completing the consent forms, participants were asked for their age, gender, education, and employment status to determine sample representativeness of the study, followed by the IPIPBig-Five Factor Markers questionnaire to assess personality traits. Subsequently, participants were initially randomly assigned to complete the gamified or non-gamified tutorial for R programming. However, our sample was unequally distributed more to the non-gamified tutorial compared to the gamified tutorial as attrition rate was higher in the gamified tutorial. Possible explanations for this can be the result of an unsolvable bug in the gamified tutorial preventing participants from progressing, and therefore dropping out from our study (e.g., the gamified tutorial becoming frozen which prevented them from continuing with the rest of our questions from Qualtrics). Though this wasn’t an optimal solution, the non-gamified tutorial was disabled to gain a minimum of thirty participants for each condition. This was necessary as research shows a sample size of thirty per condition gives us sufficient power for detecting an effect size (VanVoorhis & Morgan, 2007).

After the tutorial, participants were informed that they’ll be undertaking a quiz to see how the tutorial was effective in teaching them R. Finally, participants were questioned on their experience of the tutorial using the SIMS, followed by their learning outcome quiz score, and were debriefed.

Following data collection, two random participants who completed the experiment were chosen for a chance to win a £25 Amazon voucher.

**Ethical issues**

Ethical approval was obtained from Sussex University’s Research Ethics committee prior data collection. All participants were given consent forms online (Appendix D) which they could download from Qualtrics. All participants indicated their consent in line with Sussex’s ethical procedure and were debriefed at the end of the experiment. They were also given a choice to view the other R programming tutorial they weren’t exposed to, or to skip to the reward prize draw where they were redirected to a different webpage. This was to ensure their anonymity by separating their contact details from the experimental data. Anonymity was further ensured by excluding IP addresses.

**Results**

Our analysis was done using RStudio Team (2020). Some packages employed throughout our analysis included: tidyverse (Wickham et al., 2019); psych (Revelle, 2022); GPArotation (Jennrich et al, 2022); parameters (Lüdecke et al., 2020); dplyr (Wickham et al., 2022); broom (Robinson et al., 2022); Hmisc (Harrell, 2022); here (Müller & Bryan, 2020); kableExtra (Zhu et al., 2020); cowplot (Wilke, 2020); and readr (Wickham et al., 2022).

**Examining the factor structure of Goldberg’s Big Five-factor Marker**

The factor structure was examined to see whether our exploratory factor analysis would yield the same factor structure concordant with that of Goldberg’s to determine how the personality questionnaire will be scored.

Firstly, sampling adequacy was checked via Kaiser–Meyer–Olkin to investigate whether exploratory factor analysis was appropriate for our sample. Our results found an unacceptable value (0.46) according to Kaiser & Rice (1974). Thus, our sampling is inadequate since the proportion of the number of participants to the number of items was lacking. However, Bartlett’s test of sphericity was calculated and was found to be significantly different from an identity matrix despite our sample of sixty-nine participants (χ2 (1225) = 2329.143, p < .001). According to BornGraeber (2010), this enables us to inspect the factor structure of Goldberg’s scale.

As a method of factor extraction, parallel analysis was implemented for its accuracy (Watkins, 2005). Resultingly, 6 factors from our actual dataset with eigenvalues higher than the random data generated was retained.

Regarding the method of factor rotation, Condon & Mroczek (2016) claimed that the Five-factor Marker was not based on orthogonality. Therefore, oblique factor rotation method was incorporated since several researchers, even Goldberg himself, supported this (Condon & Mroczek, 2016). TenBerge as a method of estimating factor scores was implemented. Consequently, 6 factors together explained 49% of the overall variance in our dataset. Moreover, Tucker Lewis Index as an indicator of how well our model fits our dataset was observed. With a value of 0.74, our model wasn’t a good fit. However, RMSEA fit indices was also viewed to check our model fit to which we found a value of 0.05 with a 90% confidence interval between 0.04 and 0.07. According to Whale et al (2019), these values imply our six-factor model was an acceptable fit.

Despite the Five-Factor Marker being an established scale, a small threshold of 0.2 was implemented to ensure factor loadings above 0.2 was visible due to our small sample size. Examining our factor loadings, a six-factor structure emerged since the items that were expected to measure agreeableness factor made up two factors. Therefore, to reduce this duplication a five-factor structure was chosen. Consequently, this reduced the amount of variance explained in our dataset from 49% to 44%. In addition to an increased RMSEA index from 0.05 to 0.06 with a new confidence interval of 0.05 to 0.08. According to Kim et al (2016) our model was still an acceptable fit. Regarding the item’s factor loadings, items 35 (I am quick to understand things) was removed as it cross-loaded onto agreeableness (0.33) and conscientiousness (0.22), both of which don’t make conceptual sense to be in. For the same reason, item 19 (I seldom feel blue) was also removed for cross-loading onto agreeableness (0.23) and conscientiousness (0.33) which also doesn’t make conceptually sense. Items that loaded onto one factor remained whilst items cross loading across other factors were kept based on which factor the item loaded the highest in. E.g., item 33 (I like order) had a loading of -0.21, 0.22, and 0.46 for extraversion, agreeableness, and conscientiousness respectively and was therefore considered to measure conscientiousness personality domain. However, although item 22 (I am not interested in other people's problems) had a higher loading on conscientiousness (0.51) than agreeableness (-0.43), it remained under agreeableness as it doesn’t make theoretically sense for the item to be measuring one’s level of organisation. With this logic, items 12, 9, 28, 38, 18, 13, and 48 (see Appendix A for the items) loaded onto different subscale than anticipated (see Appendix E for the final loadings). Regarding our personality of interest (openness), items 13 and 48 unexpectedly loaded the highest into openness.

Internal consistencies for items within our five factors was also established using Cronbach’s alpha. According to Cortina (1993), a subscale with alpha values of .7 as a minimum has sufficient internal consistency. Each factor except conscientiousness met this requirement (see Appendix E). However, a Cronbach alpha coefficient above .6 still indicates good reliability (Daud et al, 2018)

**The influence of the gamified and non-gamified R programming tutorial on learning outcome**

To investigate whether learning outcome was affected by the gamified tutorial, a two-sample t-test was conducted. The mean learning outcome score in the gamified group was *M* = 7.80 (*SD* = 2.28) while the non-gamified group had a mean learning outcome score of *M* = 7.44 (*SD* = 2.58). However, difference in score wasn’t significant, t (67) = -0.61, p = .544, with only minimal difference (*Mdiff* = -0.36, 95% CI [-1.55, 0.83]). Figure 1 outlines the mean learning outcome score for each condition.

**Figure 1**

Chart

Description automatically generated*Mean Learning Outcome Quiz Score by Experimental group*

**Moderation analysis**

In relation to whether the relationship between the effects of the gamified tutorial on learning outcome varied depending on the extent a person exhibits openness traits; a moderation analysis was implemented. Figure 2 displays the conceptual framework of the moderating effects of openness traits on the relationship between the type of R tutorial and learning outcome.

**Figure 2**

*Moderation model fitted to examine whether the tutorial, openness trait and their interaction effect influences learning outcome*

Diagram

Description automatically generated

Before performing moderation analysis, openness personality trait score for each participant was calculated by reversing negatively phrased openness items and obtaining the mean score of participants from items measuring openness according to Goldberg (see Appendix A). In this sense, the factors scores obtained in our factor analysis wasn’t incorporated as there were only minor differences between our factor loadings under the openness domain and the factor loading expected according to Goldberg.

Openness scoring was then centred to allow for more interpretable coefficients for low-order effects. Next, a linear model was fitted where the type of R programming tutorial, openness personality trait, and their interaction predicted learning outcome.

Firstly, the overall fit statistics for our linear model with an interaction effect was examined. While our three predictors (tutorial, openness trait and their interaction) only accounted 1.44% of our variance in learning outcome, this was also non-significant (*p* = .81).

Regarding the main effects of the gamified tutorial on participant’s learning outcome at the mean scores of their openness traits, its effect was non-significant (*b =* 0.33, 95% CI [-1.88, 1.13], *t =* 0.55, p = .58). Similarly, the main effects of openness trait on learning outcome also indicates a non-significant effect (*b =* 0.40, 95% CI [-0.65, 1.45], *t =* 0.76, p = .45). Meanwhile, the interaction between the type of R programming tutorial and openness trait on learning outcome also wasn’t significant (*b =* -0.376, 95% CI [-1.88, 1.13], *t =* -0.498, p = .62).

**Discussion**

This study aimed examine whether openness personality trait had moderating effects on the impact of our gamified tutorial on learning outcome. Specifically, a story-based gamified tutorial was compared against a tutorial without a story to determine which intervention improved participant’s knowledge in the tidyverse dialect of R. As previous findings demonstrated that gamification improves learning (Smith, 2017), I expected (1) participants who were exposed to the story-based gamified tutorial would score higher on the quiz than participants in the non-gamified group and (2) this relationship will be moderated by openness via strengthening the effect of the gamified tutorial on learning outcome. Following our first hypothesis, results showed some positive effect of our gamified tutorial on learning outcome. However, contrary to my predictions, this relationship wasn’t statistically significant. Similarly, our second hypothesis also wasn’t supported as openness trait had no significant moderating effect on the relationship between the type of R programming tutorial and learning outcome. In other words, openness traits didn’t strengthen the relationship between our gamified tutorial and learning outcome.

Despite our experiment incorporating story-based game elements (i.e., game fiction/fantasy) as Smith (2017) did, we still didn’t reach similar conclusions regarding their impact on learning. Moreover, using story-based elements also did not improve participant’s knowledge in R programming in this study contrary to McNett's (2016) argument that using stories would facilitate comprehension and knowledge. Subsequently, our research contradicts that of the narrative hypothesis by Landers et al (2017). However, our results appear to be in parallel with Cunningham & Gall (1990) who demonstrated no effects of story-based information on knowledge, abilities, and skills for a topic in History compared to information presented without a story. Meanwhile, findings from our second hypothesis cannot be compared against previous studies due to the lack of research investigating the moderating role of personality on gamification and learning, as well as the non-standardised designs and contexts in which gamification was implemented by past researchers (Hung, 2017).

The contradictions between our findings and that of the literature’s may be attributable to the differences in our methodological design compared to prior research. For example, our study didn’t concord with Graesser et al (1980) as their learning outcome was operationalised based on information retained (memory) whereas our concept of learning was measured according to one’s ability to recognise and apply knowledge in a novel context (i.e. recognising a correct sequence of R code needed to manipulate new datasets). Thus, it’s questionable whether gamification has similar impact on the amount of recalled information compared to ability to apply skills to new contexts. Regardless, the way we operationalised learning outcome may have been the reason we reached similar conclusions as Cunningham & Gall (1990), possibly due to both our studies measuring knowledge, skills and abilities as part of learning in contrast to the amount of retained information alone. For this reason, it would be interesting for future research to examine the effects of a story-based game element on the amount of information retained, information recognised, and ability to apply skills into novel contexts to validly capture all facets of learning outcome.

Additionally, despite our study using story-based game elements appealing to the preferences of openness traits as a way of increasing engagement (Andrus, 2018), and therefore potentially learning outcome, we didn’t explicitly confirm this relationship since it wasn’t a goal in our study. As a result, it’s possible our story-based gamified tutorial did not complement the traits of openness people, hence the absence of moderating effect of openness contrary to our prediction. Therefore, we couldn’t reach the same conclusions that engagement improves learning (Carini et al, 2006). We should therefore take precaution in assuming that the engagement of participants scoring high in openness were somewhat impacted by our gamified tutorial. Thus, further studies should validate if our gamified tutorial does positively impact the engagement of participants exhibiting openness traits before associating engagement with improved learning. As some literatures measured engagement via participant dropouts (Ghaban & Hendley, 2019) you could say that our gamified tutorial actually resulted in a decreased engagement due to higher dropout rates compared to our non-gamified tutorial, hence no significant differences in learning outcome between the two interventions. However, we should also be cautious with this interpretation as the high dropout rates in our gamified intervention were partially caused from the bugs in our gamified tutorial that prevented progression. Thus, future research should ensure that any errors within browser-based learning tutorials are detected before publishing the experiment.

Regardless of inconsistencies between our study and the literature’s, our research does demonstrate some strengths. Since much of the literatures on gamification and personality are too focused on how preferences and engagement are impacted, (Codish & Ravid's, 2014; Denden et al, 2018) our study, despite our non-significant results, could be one step towards developing more robust methods of examining each game elements in isolation; which is currently the gap in the literature (Faiella & Ricciardi, 2015), and to scrutinize to what extent individual characteristics strengthens the impact of gamification on learning outcome.

Moreover, our story-based elements included in our tutorial can be considered representative of what constitutes stories as it conforms to Thorndyke's (1977) rules of how narratives are created.

Furthermore, since our study was conducted in non-lab settings, our research can be deemed as more ecologically valid than previous literatures regarding the environment participants learned. This is especially the case since the development of more asynchronous online teaching being assimilated within educational institutions of all levels following the COVID-19 pandemic.

However, the lack of consensus between our study and previous literatures may also be the result of the limitations within our methodology. Namely, our non-significant differences in learning outcome between the two tutorials may be a result of our failure to filter out participants in our data analysis who were familiar with R coding or fluent in other programming language operating with similar syntax. Consequently, it’s possible there’s a degree of bias in our results. Future research should screen out participants with knowledge in programming by asking them of their level of knowledge and skills in coding beforehand to maintain a degree of novelty and reduce the confounding effects of experience on learning. Alternatively, pre-test post-test design can be incorporated to control for this bias. Moreover, sample from our research conducted online may be further biased as it involves those who have access to internet and technology, especially the educated and middle-class population (Hewson, 2003), thus limiting the generalisability of our findings to disadvantaged groups. Future studies should offer facilities with computers to enable unrestricted participation, therefore employing sample heterogeneity to increase generalisability. Additionally, the lack of statistical significance reached in our study can be attributable to our small sample size which is often the case in empirical research on gamification (Faiella & Ricciardi, 2015). Therefore, we recommend further research to extend our experiment with a larger sample size than our current experiment.

Finally, it’s also questionable whether both tutorials contained the same level of cognitive effort needed to complete them, or whether our non-gamified tutorial validly represents a standard tutorial for coding online as ours didn’t involve typing code as it does in typical self-guided tutorials. Particularly, the gamified tutorial may have required more mental effort than the non-gamified intervention as participants were instructed to drag and drop all relevant code in order until it’s correct, whereas participants in the non-gamified tutorial only needed to drag and rank a few pieces of code, with some of the correct code already in place. This could’ve confounded the relationship between effects of our gamified tutorial on learning. Future research should attempt to control for level of mental effort needed to complete these tutorials, i.e., changing the rank order question format in our non-gamified tutorial to having participants typing the sequence of code in an empty text box to reflect most self-guided coding tutorials.

The practical implications of our findings suggest tailoring gamified learning materials according to personality characteristics may not improve learning. While this opposes previous literature’s recommendations to adapt game elements to individuals’ traits, further research extending our study should also confirm this. If future experiments also concords with our results, the usefulness of gamification, specifically with story-based game elements, cannot extend beyond entertainment purposes. Nevertheless, research in the repercussions of gamification for learning must be continued to overcome non-reliable results in the literature arising from the non-standardised designs of gamification (Hung, 2017).

In sum, our study is first among the gamification literature to investigate whether openness traits would positively impact the effect of a story-based gamified tutorial on knowledge in basic data cleaning steps in R programming. Though our findings did not confirm this relationship, further studies should be done to corroborate this conclusion before assuming the usefulness of gamification in teaching coding. Meanwhile, the educational institution should continue introducing the concept of coding throughout primary school using a software like Scratch and emphasise the importance and benefits of being able to code to maintain the interests of students and keep the IT industry afloat. This is well needed to support the age of technology we currently occupy.

**References**

*Addressing the Computer Science skills gap*. (2019, March 24). University of York. https://online.york.ac.uk/addressing-the-computer-science-skills-gap/

Aldemir, T., Celik, B., & Kaplan, G. (2018). A qualitative investigation of student perceptions of game elements in a gamified course. *Computers in Human Behavior*, *78*, 235–254. https://doi.org/10.1016/j.chb.2017.10.001

Alexiou, A., & Schippers, M. C. (2018). Digital game elements, user experience and learning: A conceptual framework. *Education and Information Technologies*, *23*(6), 2545–2567. https://doi.org/10.1007/s10639-018-9730-6

Allen, M. J. (2003). *Assessing Academic Programs in Higher Education*. John Wiley & Sons.

Almeida, C., Kalinowski, M., & Feijó, B. (2021). A Systematic Mapping of Negative Effects of Gamification in Education/Learning Systems. *2021 47th Euromicro Conference on Software Engineering and Advanced Applications (SEAA)*, 17–24. https://doi.org/10.1109/SEAA53835.2021.00011

Andrus, K. H. K. (2018). *Personality & Game Design Preference: Towards Understanding Player Engagement and Behavior*. http://lup.lub.lu.se/student-papers/record/8952576

Bai, S., Hew, K. F., & Huang, B. (2020). Does gamification improve student learning outcome? Evidence from a meta-analysis and synthesis of qualitative data in educational contexts. *Educational Research Review*, *30*, 100322. https://doi.org/10.1016/j.edurev.2020.100322

Bedwell, W. L., Pavlas, D., Heyne, K., Lazzara, E. H., & Salas, E. (2012). Toward a Taxonomy Linking Game Attributes to Learning: An Empirical Study. *Simulation & Gaming*, *43*(6), 729–760. https://doi.org/10.1177/1046878112439444

BornGraeber, N. (2010). *An Investigation into the Factor Structure of a German Version of Goldberg’s Big-Five Factor Markers* [Other]. Manchester Metropolitan University. https://e-space.mmu.ac.uk/576463/

Botte, B., Bakkes, S., & Veltkamp, R. (2020). Motivation in Gamification: Constructing a Correlation Between Gamification Achievements and Self-determination Theory. In I. Marfisi-Schottman, F. Bellotti, L. Hamon, & R. Klemke (Eds.), *Games and Learning Alliance* (Vol. 12517, pp. 157–166). Springer International Publishing. https://doi.org/10.1007/978-3-030-63464-3\_15

Buckley, P., & Doyle, E. (2017). Individualising gamification: An investigation of the impact of learning styles and personality traits on the efficacy of gamification using a prediction market. *Computers & Education*, *106*, 43–55. https://doi.org/10.1016/j.compedu.2016.11.009

Carini, R. M., Kuh, G. D., & Klein, S. P. (2006). Student Engagement and Student Learning: Testing the Linkages\*. *Research in Higher Education*, *47*(1), 1–32. https://doi.org/10.1007/s11162-005-8150-9

Christenson, L., S., Reschly, L., A., WYLIE, CATHY, & Widiasani, A. (2012). *Handbook of Student Engagement*.

CodeBeeDo. (n.d.). Coding Games For Kids In Malaysia: Awesome Coding Class For Beginners. *CodeBeeDo Academy*. Retrieved 8 March 2022, from https://codebeedo.com/scratch/

Codish, D., & Ravid, G. (2014). Personality based gamification: How different personalities percive gamification. *ECIS 2014 Proceedings - 22nd European Conference on Information Systems*.

Condon, D. M., & Mroczek, D. K. (2016). Time to Move Beyond the Big Five? *European Journal of Personality*, *30*(4), 311–312.

Cortina Jose M. (1993). What is coefficient alpha? An examination of theory and applications. *Journal of Applied Psychology*, *78*. https://www.elibrary.ru/item.asp?id=8694091

Cunningham, L. J., & Gall, M. D. (1990). The Effects of Expository and Narrative Prose on Student Achievement and Attitudes Toward Textbooks. *The Journal of Experimental Education*, *58*(3), 165–175. https://doi.org/10.1080/00220973.1990.10806532

Daud, K. A. M., Khidzir, N. Z., Ismail, A. R., & Abdullah, F. A. (2018). *Validity and reliability of instrument to measure social media skills among small and medium entrepreneurs at Pengkalan Datu River*. *7*(3), 12.

Deci, E. L., & Ryan, R. M. (1980). Self-determination Theory: When Mind Mediates Behavior. *The Journal of Mind and Behavior*, *1*(1), 33–43.

Denden, M., Tlili, A., Essalmi, F., & Jemni, M. (2018). Does Personality Affect Students’ Perceived Preferences for Game Elements in Gamified Learning Environments? *2018 IEEE 18th International Conference on Advanced Learning Technologies (ICALT)*, 111–115. https://doi.org/10.1109/ICALT.2018.00033

Deterding, S., Dixon, D., Khaled, R., & Nacke, L. (2011). From game design elements to gamefulness: Defining" gamification". *Proceedings of the 15th International Academic MindTrek Conference: Envisioning Future Media Environments*, 9–15.

Faiella, F., & Ricciardi, M. (2015). Gamification and learning: A review of issues and research. *Journal of E-Learning and Knowledge Society*, *11*, 13–21. https://doi.org/10.20368/1971-8829/1072

Ghaban, W., & Hendley, R. (2019). How Different Personalities Benefit From Gamification. *Interacting with Computers*, *31*(2), 138–153. https://doi.org/10.1093/iwc/iwz009

Goldberg, L. R. (1992). The development of markers for the Big-Five factor structure. *Psychological Assessment*, *4*(1), 26–42. http://dx.doi.org/10.1037/1040-3590.4.1.26

Government urged to act over computer science GCSEs. (2017, November 10). *BBC News*. https://www.bbc.com/news/technology-41928847

Graesser, A. C., Hauft-Smith, K., Cohen, A. D., & Pyles, L. D. (1980). Advanced Outlines, Familiarity, and Text Genre on Retention of Prose. *The Journal of Experimental Education*, *48*(4), 281–290.

Guay, F., Vallerand, R. J., & Blanchard, C. (2000). On the Assessment of Situational Intrinsic and Extrinsic Motivation: The Situational Motivation Scale (SIMS). *Motivation and Emotion*, *24*(3), 175–213. https://doi.org/10.1023/A:1005614228250

Gurven, M., von Rueden, C., Massenkoff, M., Kaplan, H., & Lero Vie, M. (2013). How universal is the Big Five? Testing the five-factor model of personality variation among forager–farmers in the Bolivian Amazon. *Journal of Personality and Social Psychology*, *104*(2), 354–370. https://doi.org/10.1037/a0030841

HALLIFAX, S., Serna, A., Marty, J.-C., & Lavoué, E. (2019). Adaptive gamification in education: A literature review of current trends and developments. *European Conference on Technology Enhanced Learning (EC-℡)*, 294–307. https://hal.archives-ouvertes.fr/hal-02185634

Hewson, C. (2003). Conducting research on the internet. *PSYCHOLOGIST-LEICESTER-*, *16*(6), 290–293.

Hung, A. C. Y. (2017). A critique and defense of gamification. *Journal of Interactive Online Learning*, *15*(1).

Jennrich, C. B. and R. (2022). *GPArotation: GPA Factor Rotation* (2022.4-1) [Computer software]. https://CRAN.R-project.org/package=GPArotation

Jia, Y., Xu, B., Masterson, Y., & Voida, S. (2016). *Personality-targeted Gamification: A Survey Study on Personality Traits and Motivational Affordances*. 2001–2013. https://doi.org/10.1145/2858036.2858515

Jr, F. E. H., & functions), C. D. (contributed several functions and maintains latex. (2022). *Hmisc: Harrell Miscellaneous* (4.7-0) [Computer software]. https://CRAN.R-project.org/package=Hmisc

Kaiser, H. F., & Rice, J. (1974). Little Jiffy, Mark Iv. *Educational and Psychological Measurement*, *34*(1), 111–117. https://doi.org/10.1177/001316447403400115

Kennedy, D. (2006). *Writing and using learning outcomes: A practical guide*. University College Cork. https://cora.ucc.ie/handle/10468/1613

Kim, H., Ku, B., Kim, J. Y., Park, Y.-J., & Park, Y.-B. (2016). Confirmatory and Exploratory Factor Analysis for Validating the Phlegm Pattern Questionnaire for Healthy Subjects. *Evidence-Based Complementary and Alternative Medicine : ECAM*, *2016*, 2696019. https://doi.org/10.1155/2016/2696019

Landers, R. N., Armstrong, M. B., & Collmus, A. B. (2017). How to Use Game Elements to Enhance Learning: Applications of the Theory of Gamified Learning. In M. Ma & A. Oikonomou (Eds.), *Serious Games and Edutainment Applications: Volume II* (pp. 457–483). Springer International Publishing. https://doi.org/10.1007/978-3-319-51645-5\_21

Lin, Y.-G., McKeachie, W. J., & Kim, Y. C. (2003). College student intrinsic and/or extrinsic motivation and learning. *Learning and Individual Differences*, *13*(3), 251–258. https://doi.org/10.1016/S1041-6080(02)00092-4

Lüdecke, D., Ben-Shachar, M. S., Patil, I., & Makowski, D. (2020). Extracting, Computing and Exploring the Parameters of Statistical Models using R. *Journal of Open Source Software*, *5*(53), 2445. https://doi.org/10.21105/joss.02445

Maddi, S. R. (1996). *Personality theories: A comparative analysis, 6th ed* (pp. xiv, 586). Thomson Brooks/Cole Publishing Co.

Majuri, J., Koivisto, J., & Hamari, J. (2018). *Gamification of education and learning: A review of empirical literature*. 9.

McNett, G. (2016). Using Stories to Facilitate Learning. *College Teaching*, *64*(4), 184–193. https://doi.org/10.1080/87567555.2016.1189389

Mekler, E. D., Brühlmann, F., Opwis, K., & Tuch, A. N. (2013). Do points, levels and leaderboards harm intrinsic motivation? An empirical analysis of common gamification elements. *Proceedings of the First International Conference on Gameful Design, Research, and Applications*, 66–73. https://doi.org/10.1145/2583008.2583017

Mezak, J., & Papak, P. P. (2018). Learning scenarios and encouraging algorithmic thinking. *2018 41st International Convention on Information and Communication Technology, Electronics and Microelectronics (MIPRO)*, 0760–0765. https://doi.org/10.23919/MIPRO.2018.8400141

Müller, K., & Bryan, J. (2020). *here: A Simpler Way to Find Your Files* (1.0.1) [Computer software]. https://CRAN.R-project.org/package=here

Munday, P. (2017). Duolingo. Gamified learning through translation. *Journal of Spanish Language Teaching*, *4*(2), 194–198. https://doi.org/10.1080/23247797.2017.1396071

Ortiz, M., Chiluiza, K., & Valcke, M. (2017). *Gamification in Computer Programming: Effects on learning, engagement, self-efficacy and intrinsic motivation*.

Revelle, W. (2022). *psych: Procedures for Psychological, Psychometric, and Personality Research* (2.2.3) [Computer software]. https://CRAN.R-project.org/package=psych

Robinson, D., Hayes, A., Couch [aut, S., cre, RStudio, Patil, I., Chiu, D., Gomez, M., Demeshev, B., Menne, D., Nutter, B., Johnston, L., Bolker, B., Briatte, F., Arnold, J., Gabry, J., Selzer, L., Simpson, G., Preussner, J., … Sjoberg, D. D. (2022). *broom: Convert Statistical Objects into Tidy Tibbles* (0.8.0) [Computer software]. https://CRAN.R-project.org/package=broom

Smiderle, R., Rigo, S. J., Marques, L. B., Peçanha de Miranda Coelho, J. A., & Jaques, P. A. (2020). The impact of gamification on students’ learning, engagement and behavior based on their personality traits. *Smart Learning Environments*, *7*(1), 3. https://doi.org/10.1186/s40561-019-0098-x

Smith, T. (2017). Gamified Modules for an Introductory Statistics Course and Their Impact on Attitudes and Learning. *Simulation & Gaming*, *48*(6), 832–854. https://doi.org/10.1177/1046878117731888

Thorndyke, P. W. (1977). Cognitive structures in comprehension and memory of narrative discourse. *Cognitive Psychology*, *9*(1), 77–110. https://doi.org/10.1016/0010-0285(77)90005-6

Toda, A., Valle, P. H., & Isotani, S. (2018). *The Dark Side of Gamification: An Overview of Negative Effects of Gamification in Education*. https://doi.org/10.1007/978-3-319-97934-2\_9

Topolewska-Siedzik, E., Skimina, E., Strus, W., Cieciuch, J., & Rowiński, T. (2014). The short IPIP-BFM-20 questionnaire for measuring the big five. *Roczniki Psychologiczne // Annals of Psychology*, *17*, 385–402.

*Understanding Statistical Power and Significance Testing—An Interactive Visualization*. (n.d.). Retrieved 14 April 2022, from https://rpsychologist.com/d3/cohend/

Watkins, M. W. (2005). Determining Parallel Analysis Criteria. *Journal of Modern Applied Statistical Methods*, *5*(2), 344–346. https://doi.org/10.22237/jmasm/1162354020

Whale, R., Fialho, R., Field, A. P., Campbell, G., Tibble, J., Harrison, N. A., & Rolt, M. (2019). Factor analyses differentiate clinical phenotypes of idiopathic and interferon-alpha-induced depression. *Brain, Behavior, and Immunity*, *80*, 519–524. https://doi.org/10.1016/j.bbi.2019.04.035

Wickham, H., Averick, M., Bryan, J., Chang, W., McGowan, L., François, R., Grolemund, G., Hayes, A., Henry, L., Hester, J., Kuhn, M., Pedersen, T., Miller, E., Bache, S., Müller, K., Ooms, J., Robinson, D., Seidel, D., Spinu, V., … Yutani, H. (2019). Welcome to the Tidyverse. *Journal of Open Source Software*, *4*(43), 1686. https://doi.org/10.21105/joss.01686

Wickham, H., François, R., Henry, L., Müller, K., & RStudio. (2022). *dplyr: A Grammar of Data Manipulation* (1.0.9) [Computer software]. https://CRAN.R-project.org/package=dplyr

Wickham, H., Hester, J., Francois, R., Bryan, J., Bearrows, S., RStudio, library), https://github com/mandreyel/ (mio, implementation), J. J. (grisu3, & implementation), M. J. (grisu3. (2022). *readr: Read Rectangular Text Data* (2.1.2) [Computer software]. https://CRAN.R-project.org/package=readr

Wilke, C. O. (2020). *cowplot: Streamlined Plot Theme and Plot Annotations for ‘ggplot2’* (1.1.1) [Computer software]. https://CRAN.R-project.org/package=cowplot

Yee, S. J. W. and D. (2017). Why You Should Become a UseR: A Brief Introduction to R. *APS Observer*, *30*. https://www.psychologicalscience.org/observer/why-you-should-become-a-user-a-brief-introduction-to-r

Zhu [aut, H., cre, Travison, T., Tsai, T., Beasley, W., Xie, Y., Yu, G., Laurent, S., Shepherd, R., Sidi, Y., Salzer, B., Gui, G., Fan, Y., Murdoch, D., & Evans, B. (2020). *kableExtra: Construct Complex Table with ‘kable’ and Pipe Syntax* (1.3.1) [Computer software]. https://CRAN.R-project.org/package=kableExtra

Zichermann, G., & Cunningham, C. (2011). *Gamification by Design: Implementing Game Mechanics in Web and Mobile Apps*. O’Reilly Media, Inc.