An Exploration of the Relationship Between Personality and Strategy Formation Using Market Farmer: Using a Bespoke Computer Game in Behavioural Research

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Abstract. A computer game was designed for use in a study examining the relationship between facets of the personality trait openness to experience and exploration of a dynamic environment where initial knowledge is limited. A total of 38 females and 56 males aged between 18 and 62 completed a measure of openness to experience and exploration-exploitation before playing *Market Farmer*: a game specifically designed to engage players and record strategy formation behaviour over time. As expected, exploration increased initially and then fell as players learned successful strategies. It was hypothesised that openness to experience would positively moderate the relationship between exploration and score in the latter part of the game, through adventurousness and intellect. As expected adventurousness did positively moderate the relationship between exploration and score, however intellect did not, and liberalism did. These results may reflect differences in ambiguity tolerance and flexibility in expectations when establishing strategies and indicate that *Market Farmer* offers a promising tool for the examination of personality and strategy formation.

Keywords: Serious Games, Personality, Openness to Experience, Exploration, Strategy, Research

1 Introduction

1.1 Games as Tools for Research

Over the last decade there have been a number of calls for the use of games in psychological research [1] [2] [3] as a means of placing participants in semi-controlled situations where changes in behaviour can be recorded over time [2]. In the broader context of methodology, they complement existing approaches by offering a trade-off between the kind of mundane realism of observational studies and the high levels of experimental control available in laboratory experiments [4]. Furthermore, where studies require participants to be motivated to complete a given task, games engage participants in a way that can produce more authentic behaviour [5]. By deliberately

incorporating elements that motivate players' needs for competence, autonomy and relatedness [6], players experience a desire to continue playing the game.

However, as with any approach, games have their drawbacks as research tools. Developing a game is a resource-intensive process and the focus on engagement often comes at the cost of external validity, particularly when mechanisms unrelated to the target phenomena are introduced [5]. For example, a number of approaches have used commercially available games, but validity and cross-platform reliability are limited by the existing constraints of the selected game [7]. One way of resolving this is to select or produce games that can easily be modified according to the demands of individual studies [8]. This leads to a design sciences approach, where a platform is created that is capable of producing a wide variety of games with a common theme or genre relevant to a broad field of research, thus reducing the need to "reinvent the wheel" every time a game is produced [9]. The aim of this pilot study is to develop an online game that is sufficiently open-ended to offer the potential for further development into such a platform, while also displaying sufficient utility as a research tool. In order to demonstrate this utility, the game is used to examine the relationship between personality and strategic cognition.

1.2 Individual Differences in Strategic Cognition

Studies in strategic cognition examine the role of cognitive structures and processes in the formation of strategies that can occur, for example, in a business environment [10]. In this context, the conclusions drawn can differ according to the type of environment that managers work in, and recent years have seen a particular focus on the use of the *doing first* approach to strategy formation as a result of disruptive change in the technology sector [11]. In an environment where there is little understanding of an optimal strategy, this approach advocates action as a means of generating responses from the environment that are then evaluated. Actions that produce positive results are retained and others are discarded, and strategies are thus derived through a process of trial and error [12].

The trade-off between exploration and exploitation is fundamental to strategic cognition, as the exploitation of existing information or resources may be compromised by exploration that results in new sources [13]. An optimal model of an exploration-exploitation strategy produced by Berger-Tal, Nathan, Meron, and Saltz [14], suggests that in environments where there is little or no existing knowledge, individuals acquire strategies by initially exploring the environment and gradually acquiring information through feedback. Over time, however, the costs of exploration outweigh the returns from exploiting information gained in the past, and individuals gradually transition to an approach dominated by exploitation.

Considerable interest has been shown in understanding the antecedents of exploration and exploitation related to individual differences. In particular, the Five Factor Model (FFM) personality trait of openness to experience, which reflects a willingness to change and try new approaches [15], appears to naturally align with behaviours associated with exploration. Although studies have found small but positive correlations between openness to experience and exploration [16][17], these focus on establishing

relationships between dispositional variables measured through self-report scales rather than on behavioural observation. Furthermore, openness to experience is composed of a number of subfactors, or facets [15], each of which may contribute to differences in the way individuals use exploration. Therefore, studies examining relationships between exploration and openness to experience may result in weak or non-existent correlations because different facets of openness to experience may impact on exploration and exploitation at different points in time.

Conventional approaches to examining exploration have been valuable in developing an understanding of individual differences in strategic cognition. However, these approaches have not been able to give us much insight into how individual differences in personality affect the strategic use of exploration over time. As argued at the start, the use of computer games as research tools to gather behavioural data in real time can address this, as they are ideal for capturing data on the dynamic employment of exploration in strategy formation. A combination of approaches, where personality traits are measured before gathering behavioural data, could yield insights into the relationship between personality and the transition from exploration to exploitation. The use of a bespoke game would also allow for the development of a game specifically designed to capture this behaviour, while ensuring that participants begin with little or no knowledge of optimal strategies, thus simulating an environment where these are unknown.

2 Examining Strategic Cognition with *Market Farmer*

2.1 Development of *Market Farmer*

Strategic cognition is a process that includes exploration of the environment and the exploitation of information gathered through feedback [18]. Activities designed to capture this behaviour over time must provide participants with the opportunity to make decisions regarding the acquisition and use of this information. As our focus is not on decision-making behaviour under time pressure [19], the game is structured in a way that allows participants to control the advancement of the game. Game time was divided into 1200 ticks, with each tick activated by a button or the space bar that triggered game events related to that tick. This allowed players time to deliberate over decisions, though players were limited to a maximum of two hours to complete the game.

Games that succeed in engaging players draw on fundamental motivations of competence and autonomy [6]. Players enjoy facing and overcoming challenges that fit their skill level, as well as the sense of control in setting and meeting game goals [20]. This can be achieved by creating a system of rewards and punishments within the game that motivates players to form and improve on strategies. These considerations resulted in the game *Market Farmer*, based on a simple mechanic where players plant crops in fields when the price of the crop is low and then wait for the crops to grow while the price changes. When the crops mature, they are automatically sold at the current price, and thus the only control players have over their ability to make a profit is to gauge the

best time at which to plant the crops. This provides players with an opportunity to observe changes in crop prices and learn from past mistakes in selecting the right time to plant crops through a system of rewards and punishments that occur when players make a profit or loss. For example, when players plant at the wrong time, the crop will sell at a low price and the return will be less than the cost of planting the crop, thus incurring a loss.

This simple mechanic provides a low-level decision-making process. However, meaningful gameplay that sustains interest over longer periods requires a macro-level decision-making context that interacts with these micro-level decisions in a way that increases the tension experienced by the player [21]. Therefore, the concept of improvements was created to allow players the ability to increase profits and prevent losses. In order to incur more dramatic potential losses, floods that destroy crops and birds that eat them were introduced. This provided the player with the opportunity to install improvements to prevent losses incurred from floods and birds, and increase profits from fields, while constraining the number of improvements in each field forced the player to make decisions regarding which fields improvements should be installed in.

To create further tension in making these decisions, crop varieties were given different qualities according to predictability of price volatility and levels of investment and return, such that varieties with more unpredictable volatility required a larger investment, thus increasing the potential loss, but offering an equally large potential for profit. Thus, players were able to offset the risk of more volatile higher value varieties using improvements, while small differences in volatility between varieties offered players the opportunity to experiment with varying levels of risk. The combination of crop varieties with varying levels of risk and return, floods, birds, and improvements offered players many ways to achieve a high score, with the values, timing, and offsets of each game element carefully balanced to ensure that on average, preferences for a particular improvement type, for example, would not result in a difference in overall score.

Finally, to distract players from the use of the game as a research tool and create an enjoyable experience that would hold their interest for the duration of the game, common game elements such as bright, colourful graphics and lively animations were used to create a sense of action and movement in the game, along with cartoon-like auditory cues to provide feedback to the player. To control for differences in ability, a tutorial was included at the beginning of the game using a narrative to engage the player in a purposeful understanding of what was required, and to show examples of the game mechanics. To maintain motivation, the ability to acquire new crop varieties, fields, and improvements as rewards was staggered throughout the game to encourage goal-setting. Pop-up alerts and hints were also used throughout the game to ensure that players were aware of their options, particularly as new elements were being introduced, or rewards provided.

2.2 Playing *Market Farmer*

On loading the game, the player is presented with an introduction screen showing two farmers of the same gender as the player, who provide instructions on how to play the

game in the tutorial that follows. The farmers state the broad aim of the game in terms of maximising the amount of money made, and the player clicks through further screens with each farmer presenting aspects of gameplay from positive and negative perspectives: one stating a problem and the other offering a suggestion for solving it. For example, players are told that they can plant new crops and make improvements, but that some crops are expensive and risky. Players are then given an opportunity to sow and harvest a crop of potatoes, which provides very little profit, but is also very low risk. After this, the option to sow potatoes is removed and replaced with broccoli, thus signalling the beginning of the game. The player begins with $1000, and if this amount falls below $20, it is automatically topped up to $20, thus allowing the player to sow broccoli crops and continue playing the game. Features of the game such as floods and improvements are explained to the player as they appear in the game in a similar manner to the tutorial. Figure 1 shows a screenshot from the game with a farmer explaining how to access improvements.

Fig. 1. A farmer explains how to access improvements in the *Market Farmer* tutorial.

Over time, the player receives more fields at predetermined points unknown to the them, until they have a maximum of eight fields. Players also receive access to more crop varieties based on the cumulative total of crops sown, i.e. the more crops the player sows, the faster they gain access to new varieties. Players also purchase improvements using farmhands that accrue over time, with a total of 32 farmhands available throughout the game. Information relating to these and other aspects of gameplay is available at the top left of the screen, where the number of ticks remaining, the number of crops that need to be sown in order to gain the displayed variety, the number of farmhands accrued, and a button that advances the game to the next tick are displayed. The amount of money available to the player (score) is displayed at the top centre of the screen. When clicking on the farmhands icon, the screen shown in Figure 2 is displayed, allowing the player to select an improvement when there are farmhands available to pay for it.

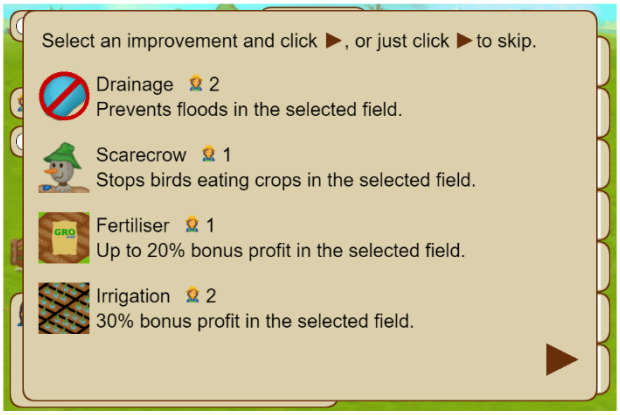

Fig. 2. A screen in *Market Farmer* showing the selection of improvements available to the player, the advantages they confer, and the cost in farmhands.

Once installed in a field, improvements produce a given benefit in that field for the remainder of the game and cannot be removed. The following improvements are available for purchase:

Drainage prevents floods from occurring in a field and costs two farmhands. A total of 27 floods are scheduled to occur at regular intervals throughout the game, and the more often a player sows a crop in a given field, the more likely it is that a flood will occur in that field. When a flood occurs in a field with a crop, the crop is removed from the field and the player loses their entire investment for that crop.

Scarecrow prevents birds from landing in a field and costs one farmhand. Birds land on crops at regular intervals and reduce the profit of the crop by a random amount of up to 20%.

Fertiliser adds a random amount of up to 20% of the profit from a crop when it is sold, but has no effect on crops that are sold at a loss. Fertiliser costs one farmhand.

Irrigation adds 30% of the profit from a crop when it is sold but has no effect on crops that are sold at a loss. Irrigation costs two farmhands.

These improvements are balanced so that the use of drainage and scarecrows, for example, will have the same mean effect on overall profits as irrigation and fertiliser, respectively.

Figure 3 shows the screen in the second half of a game where all of the seven crop varieties are available. Players sow each crop by dragging the relevant icon into a field. The fixed cost of sowing each crop is displayed above the respective icon, while the figure to the right of this shows the amount of money the player would gain if the crop were harvested in this tick. The recent history of these values is displayed in the accompanying chart, which illustrates the increasing volatility of each variety.

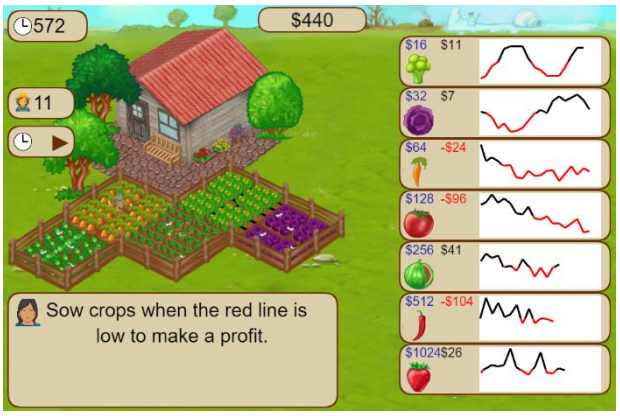

Fig. 3. The screen in Market Farmer showing all of the crop varieties available to the player by the end of the game and their price volatility.

The combination of increasing volatility and profitability with each crop and the advantages offered by the improvements affords players a number of different strategies for success when defined as the amount of money made at the end of the game. As players are limited to two improvements per field, choices must be made regarding the potential losses and gains provided by a combination of improvements, and the effect this has on mitigating the risk inherent in planting more volatile crops. Initially, there is a strong incentive for players to explore by experimenting with different combinations, and once a successful strategy has been established, players may then continue to exploit that strategy, or explore other strategies. However, players are not forced to choose between these approaches, and it is possible for players to pursue a given strategy in some fields while exploring alternatives in others, or to adopt a broad strategy within which there may be some room for exploration.

3 The Current Study

3.1 Introduction

We now demonstrate how Market Farmer can be used to understand the relationship between openness to experience and behavioural patterns of exploration performed in the game, and game performance. These patterns of behaviour are identified according to the extent to which players repeat strategies by trying new crop varieties and improvements, and varying the combination of these (behavioural exploration), or by planting the same crop varieties in fields with the same combination of improvements (behavioural exploitation).

The game consists of 1200 ticks, during which the game pauses so that players can perform actions, but there are a number of phases that occur during the course of the game. Initially, players learn about how to play the game, during which separate elements are introduced in a staggered fashion to prevent overwhelming the player with information. Furthermore, as the player begins with only one crop and one field, the

ability to extract meaningful information regarding strategies undertaken is limited until the player receives more crops and fields. As the crop growing times increasingly exceed the remaining game time in the last 100 ticks of the game, players' choices become more limited in regard to the crops that can be sown. For this reason, this period is not included in the analysis. Given that players begin the game with very little knowledge of what an optimal strategy might be, a period of behavioural exploration is expected, during which behavioural exploitation should be quite low. However, as the game progresses and players begin to acquire successful strategies, the situation is expected to reverse in line with the model offered by Berger-Tal et al. [14]. This suggests that performance may be associated with an understanding of the optimal time at which exploitation should take precedence over exploration. Therefore, once participants have had enough time to acquaint themselves with potential strategies, and mean levels of behavioural exploration have peaked, participants who decrease their levels of behavioural exploration while increasing behavioural exploitation should experience a concurrent increase in score (in-game money).

Facets of openness to experience likely to moderate the negative relationship between behavioural exploration and score in the latter part of the game include: intellect, as participants scoring higher on this measure may be more likely to recognise and select successful strategies rather than needlessly continuing to explore; and adventurousness, as participants scoring higher on this may be more likely to continue exploring increasingly successful strategies. Also, the lack of a moderating effect of imagination, artistic interests, emotionality, and liberalism on the relationship between behavioural exploration and score means that the overall relationship between openness to experience and behavioural exploration remains low. On the basis of this, it is hypothesised that once mean levels of behavioural exploration have peaked, higher levels of openness to experience facets intellect and adventurousness will positively moderate the negative relationship between behavioural exploration and score, while imagination, artistic interests, emotionality, and liberalism will not moderate the relationship between behavioural exploration and score.

3.2 Method

Participants Participants were recruited through an online recruitment service and remunerated for their time. Only participants aged at least 18 and using devices with screen dimensions of at least 640 pixels were able to take part in the study. Due to compatibility issues, participants were not able to complete the study using the Firefox browser. A total of 94 participants completed the study, including 38 females and 56 males with ages ranging from 18 to 62 (M = 31, SD = 9.93).

Procedure After providing demographic information, participants completed a number of surveys as part of a wider study before playing the game, with the time taken to play the game ranging from 21 to 129 minutes (M = 51, SD = 20.81). At the end of the game, participants were shown their score and asked a series of questions on how much they enjoyed playing the game.

Participants completed the IPIP-NEO-120, a short-form adaptation of a longer scale developed as a measure of factors and facets of the FFM. Participants were asked to

indicate the extent to which statements accurately described their personality on a 5-point Likert scale from 1 (strongly disagree) to 5 (strongly agree). Statements related to facets of openness to experience include "I have a vivid imagination" (imagination), "I love to read challenging material" (intellect) and "I believe that there is no absolute right or wrong" (liberalism). Chronbach's alpha for openness to experience is .83, with alphas for facets ranging from .64 (liberalism) to .76 (imagination and artistic interests).

While dispositional measures use conventional self-report approaches, behavioural exploration-exploitation is measured using participants' activity in playing the game. For each tick, there exists a matrix representing the player's strategy in terms of the number of improvement-crop combinations in use at that point. These strategic instances are then compared to determine the extent to which a player is repeating a previous strategy (exploitation) or creating a new strategy (exploration) that can include combinations of previous strategies or alterations to them. A simplified example of how exploration is calculated in a game with five fields; crop varieties, *a*, *b* and *c*; and improvements, *x* and *y*, is shown in the matrix below.

$$\boldsymbol{M}_t = \begin{array}{c|cccc} & - & x & y & xy \\ a & 1 & 0 & 0 & 0 \\ b & 0 & 0 & 2 & 0 \\ c & 0 & 0 & 0 & 1 \end{array}$$

This indicates that at *t*, there was a field with no improvements containing variety *a*, two fields with improvement *y* containing *b*, and one field with both improvements *x* and *y* containing *c*. This matrix $\mathbf{M}_t$ is then compared to all previous matrices by subtracting it from each matrix and summing the absolute values of the differences to derive a single value, *d*, representing the difference between both matrices. For example, the matrix at *t* - 1:

$$\boldsymbol{M}_{t-1} = \begin{array}{c|cccc} & - & x & y & xy \\ a & 1 & 0 & 0 & 0 \\ b & 0 & 0 & 1 & 0 \\ c & 0 & 1 & 0 & 0 \end{array}$$

indicates that, at *t*, the player has added a *b* crop to a field with improvement *y*, along with the *c* crop in a field with improvements *x* and *y*. Meanwhile, a crop of *c* in a field with improvement *x* has harvested. Subtracting $\mathbf{M}_t$ from $\mathbf{M}_{t-1}$ yields:

$$\begin{array}{c|cccc} & - & x & y & xy \\ a & 0 & 0 & 0 & 0 \\ b & 0 & 0 & -1 & 0 \\ c & 0 & 1 & 0 & -1 \end{array}$$

the summed absolute values of which is $d = 3$. The exploration value for $\mathbf{M}_t$ is the lowest value of *d* obtained after iterating over all previous matrices, multiplied by 1 divided by the number of fields in the game at *t* to control for the expansion of fields as the game progresses. Therefore, in a game with 5 fields:

$$exploration = d_{min}\frac{1}{n} = 3 \times .2 = .6$$

This value, calculated once at the end of each tick, provides an indication of the players' level of behavioural exploration at that point in the game. Taken together, these values provide a record of changes to the players' use of exploration as a strategy over time, with higher values at the beginning of the game suggesting a stronger preference for a *doing first* strategy.

Results Table 1 shows descriptive statistics and correlations for dispositional variables included in the analysis. Note that values of score are calculated as the square root of the in-game value to resolve issues related to differences in magnitude and normality that occurred during analysis.

Table 1. Descriptive statistics and correlations for dispositional variables.

	SC	OP	IM	AI	EM	AD	IN	LB
SC								
OP	-.05							
IM	-.00	.70**						
AI	-.16	.68**	.39**					
EM	-.18	.61**	.46**	.26*				
AD	.06	.60**	.29**	.28**	.18			
IN	-.13	.63**	.27**	.39**	.25*	.25*		
LB	.25*	.47**	.15	.16	.02	.30**	.19	
M	85.23	3.42	3.57	3.54	3.68	2.94	3.54	3.26
SD	35.21	0.49	0.82	0.86	0.85	0.76	0.77	0.73

*p < .05, **p < .01
SC = Score; OP = Openness to Experience; IM = Imagination; AI = Artistic Interests; EM = Emotionality; AD = Adventurousness; IN = Intellect; LB = Liberalism; M = Mean; SD = Standard Deviation

As expected, there were two broad phases in the game. The first of these occurs from tick 250 and extends to 550, when behavioural exploration increases while behavioural exploitation decreases as players extend their strategies to include more crops and improvements as they become available. Once behavioural exploration peaks at around 550, it then declines as successful strategies have been identified, and behavioural exploitation increases as these selected strategies are increasingly exploited.

Table 2 shows results from multilevel regression models, with score as the dependent variable, behavioural exploration as a level 1 predictor, and both openness to experience and its facets as level 2 predictors. As the study focuses on the influence of dispositional variables (level 2) on the slope between behavioural exploration (level 1) and

score over time (γ_{10}), slope values are presented for level 2 on score controlling for level 1 (γ_{01}), and the moderation of level 2 on the slope between level 1 and score (γ_{11}).

Table 2. Multilevel regression models with personality traits and facets at level 2, behavioural exploration as a level 1 independent variable, and score as the level 1 dependent variable.

Level 1	γ_{10}	Error		
Exploration	-5.10***	1.05		
Level 2	γ_{01}	Error	γ_{11}	Error
Openness	-0.45	3.59	-4.30*	2.06
Imagination	0.72	2.15	-1.32	1.28
Artistic Interests	-1.93	2.06	-0.93	1.23
Emotionality	-4.58*	2.02	-0.39	1.21
Adventurousness	1.47	2.33	-3.83**	1.37
Intellect	-1.19	2.29	-1.29	1.29
Liberalism	6.42**	2.34	-2.90*	1.39

*p < .05, **p < .01, ***p < .001

Multilevel regression analysis shows that on average, there was a significant negative slope between behavioural exploration and score (γ_{10} = -5.10, p < .001) following the peak in exploration at 550 ticks. Openness to experience reduced the negative slope between behavioural exploration and score (γ_{11} = -4.63, p < .05) through the facets of adventurousness (γ_{11} = -3.83, p < .01) and liberalism (γ_{11} = -2.90, p < .05). However, when controlling for behavioural exploration, Emotionality was negatively related to score (γ_{01} = -4.58, p < .05), while Liberalism was positively related to score (γ_{01} = -6.42, p < .01).

3.3 Discussion

The aim of this study was to assess whether or not theoretical relationships between personality dispositions and behaviours associated with strategy formation could be examined using a game that simulates this in a dynamic environment, where initial knowledge is limited. However, results were mixed. We were expecting that higher levels of openness to experience facets intellect and adventurousness would positively moderate the negative relationship between behavioural exploration and score, while imagination, artistic interests, emotionality, and liberalism would not moderate the relationship between behavioural exploration and score. Although adventurousness moderated the negative relationship between behavioural exploration and score as expected, intellect did not, but liberalism did. This suggests that the ability to recognise successful strategies and curtail further exploration is not related to intellect, and thus the task is not as cognitively demanding as it might be in real-word contexts. However, intellect focuses on reading challenging material, philosophical discussions, and abstract ideas, and may not reflect the kind of pragmatic application of cognition required by this task.

For example, entrepreneurs, who tend to operate in environments with initial levels of low information, are more likely to exhibit lower levels of cognitive motivation and rely more on heuristics and advice from others when solving cognitive tasks [22]. This ability to make decisions in the absence of information is also related to entrepreneurs' higher levels of ambiguity tolerance, which may account for the role of liberalism in reducing the negative relationship between behavioural exploration and score.

One surprising result was the significant relationship between liberalism and score after controlling for behavioural exploration, as expectations were that traits related to openness to experience would maintain higher levels of exploration at a time in the game when the focus should be shifting to exploitation in order to achieve a high score. However, this result suggests that liberalism is one of the more significant aspects of personality that contributes to success during this period of the game. Liberalism focuses on the rejection of moral absolutes and greater latitude in the use of punishment for crimes. Therefore, it may be that participants with a preference for ambiguity accurately sense that there is no right or wrong strategy to pursue, and are happy to assume this in exploring new strategies.

3.4 Conclusion

The current study demonstrates the advantages of using a game to examine behaviours associated with dispositional constructs over time in combination with multilevel modelling. However, it is often difficult to predict how players will respond to different, interacting features of a game, such that any data generated should inevitably lead to the further development and improvement of the game. This blurs the line between development and research, as an iterated development process, where successive versions of the game are produced based on feedback generated by the previous version [23], lends itself well to the successive gathering and analysis of data needed to establish validity. From this perspective, a game may never be truly finished, as further development can occur to improve validity, or to branch off into a different study. In order to engage players and examine more complex interactions between individuals and behaviours, games could incorporate greater functionality, which requires iterative testing for validity. Although the use of games in research is still in its early stages, these possibilities highlight their huge potential.

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