Bridging the Blank: A Defining from Property Uncertainty to Felt Uncertainty in Games

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Abstract

Recent years have seen a fast growth of design methods for enhancing the attractiveness of video games, such as the use of random number generators or intendedly hidden information. These design methods may result in an engaging play experience for the player, one that they can describe as being intrigued by the unknown. Generally referred to as "uncertainty in games," this builds on a substantial corpus of current ideas and research in human-computer interaction and game studies. Certain studies have proven that the use of uncertainty design elements can contribute to the play experience on the feeling of uncertainty. However, it is not clear in understanding how regulating rule-related uncertainty (the "property" uncertainty) results in dissimilar player experiences with uncertainty (the "felt" uncertainty), and how to define them. This gap is analogous to untouched black box about uncertainty in games existing between mechanics and dynamics to aesthetics that we are attempting to uncover in order to improve the transmission of goal experiences. Thus, the purpose of this study is to formalize and examine an ontological difference between property uncertainty and felt uncertainty, and how they correlated to each other. We further categorize four types of property uncertainty based on several widely read academic publications addressing sources of uncertainty in games: analytical complexity uncertainty (ACU), procedural randomness uncertainty (PRU), information uncertainty (IU), and player uncertainty (PU). We validated the study by using the strategy game, connect-4, with readily modifiable rules to create child games with varied categorized property uncertainties, and comparing the playthrough data gained via recruitment to the feedback received through interviews. Based on our research, we propose that the four categorized property uncertainties are born from the game system, affecting players' learning and mastering progress and ultimately leading to the felt uncertainty of players.

Keywords:

Uncertainty; Game Research; Game Mechanics; Game Design; Player Experience.

Contents

1. Introduction

The games, as a microcosm of the real world we created, are fascinating by reason of uncertainty, which should come as no wonder because the real-life we populate exhibits these properties. Human beings have an innate desire to discover new things, detect patterns, and create order (Loewenstein, 1994). This innate appetite for uncertainty makes them also have the same interest in the games they create. For millennia, procedures such as dice rolling and card shuffling have been utilized in games to emulate the arbitrary nature of reality (Averbakh, 2012), producing a variety of explorable content to maintain players' interest. In games, players have chances to engage in an unfamiliar experience, learn a new skill, pruning uncertainty and ambiguity to test and enhance their abilities without fear of the consequences that might occur in real life (Juul, 2011).

Uncertainty and the mastering of uncertainty are pivotal to the attractiveness of games. Caillois (Caillois & Barash, 1961) discusses that the outcome of every type of game has to be uncertain to be enjoyable, otherwise it would collapse into a pointless established fact. Similarly, Salen and Zimmerman (Salen, Tekinbaş, & Zimmerman, 2004) suggest that games are systems of uncertainty where players are engaged in rules, enjoyed the dynamics caused by feedback loops and chaotic emergence arose from the disordered systems, and brought order from the chaos. The trick is that the game designer should leave room aside uncertainty where players' movements and decision makings are valuable, as the player explores the outcomes brought by different choices and gradually masters uncertainty appearing is pivotal in the appeal of games (Power, Cairns, Denisova, Papaioannou, & Gultom, 2019), or even is the meaning of playing.

It is important for the game designer to be able to measure how property uncertainty results in dissimilar felt uncertainty in order to strike a balance of uncertainty participation. Uncertainty is a fundamental characteristic of all sorts of play and games, acting out the vagaries of fortune and stimulating desire for exploration (Costikyan, 2013). However, when the game or play has too high uncertainty, this could induce negative experiences and a sense of losing control to players. Players feel a sense of control during the process of continuous learning and pruning uncertainty, and this sense of control is one of the crucial incentives required for them to enter the flow state (Csikszentmihalyi, 2009). When the game has tipped the balance too strongly towards uncertainty at the expense of strategic intentionality, having no basis for accurate strategic foresight based on information, players could feel lost at the play, unable to recognize the interaction and correlation between decisions and results, then fed up with reduced enjoyment (Klimmt, Hartmann, & Frey, 2007). Thus, well-balanced property uncertainty is highly relevant to the play value of games and forge different felt uncertainty for players. But it requires a different formalization of the ontological distinction between property uncertainty and felt uncertainty for a better understanding of the transmission of goal experiences.

In this thesis, we categorized four types of property uncertainty based on academic publications on the discussions of uncertainty in games. Based on the categorization of property uncertainty, we developed child games with varying defined types of property uncertainty by regulating the rules of the parent game. We further compared the playthrough data about players' mastery progress collected from playtesting to the feedback about felt uncertainty received through interviews. Validation and data analysis of the experiment suggest that property uncertainty in games has four types that have the ability to affect the overall playing experience by influencing the player's learning process, contributing to the felt uncertainty. Game designers can evaluate and adjust game mechanics and rules to control the property uncertainty and lead to the felt uncertainty.

2. Precursors and Parallels on the Definition

Scholars have studied existing types of interpretation uncertainty correlated to the player experience, but little research has been undertaken to formalize an ontological distinction between property and felt uncertainty. Power and his teammates (Power, Denisova, Papaioannou, & Cairns, 2017) present a questionnaire to measure “players' feelings of uncertainty” during playing digital games. They discovered four factors, Disorientation, Exploration, Prospect, and Randomness, that emerged as contributing to the “feeling of uncertainty”. In his following article (Power et al., 2019), Power further verified his idea with experiments and took the notion of 5 types of “feelings of uncertainty” (they are: uncertainty in decision-making, uncertainty in taking action, uncertainty in problem-solving, exploration, and random elements as external uncertainty) as the foundational experience of play games. Májek and Iida (Májek & Iida, 2004) passed a series of experimental data and measured $\overline{U}$ to suggest a strong correlation between the “uncertain outcome” of a game and its enjoyment. Analyzing the conceptualization of uncertainty with measuring player experience paved the way for subsequent discussion on the quantitative level, contributing to an ontology of formalizing uncertainty. However, this is one way to conceptualize uncertainty in relation to the player experiences. Considering many investigations of recognizing uncertainty as two different dimensions (e.g., the difference between “epistemic uncertainty” and “aleatory uncertainty” (Fox & Ülkümen, 2011), and the difference between “external uncertainty” and “internal uncertainty” (Power et al., 2019)), a clear notion of classified designation and correlation between the “property uncertainty” and the “felt uncertainty” is still in urgent need of discussion.

2.1 Distinguish Property Uncertainty

Several investigations have hinted that property uncertainty is existing independently outside of the concept of felt uncertainty. As Kahneman and Tversky (Kahneman & Tversky, 1982) suggest, "external attributions of uncertainty" produced by the system itself are distinguished from the "internal attributions of uncertainty." The internal attributions of uncertainty are caused by people's ignorance and vary depending on different individuals. Power (Power et al., 2019) has cited examples to try to interpret the existence of two ontological different uncertainties with the terms of "external uncertainty (EXU)" and "internal uncertainty." He mentions that guessing the result of tossing a coin is in principle unknowable as an "existing objective uncertainty", but asking someone to guess whether the Nile is longer than the Amazon is an "internal uncertainty" to the person. However, the river question itself requires the answerer to carry related background knowledge, so there is a certain degree of "property uncertainty" in the question itself, while the degree of "felt uncertainty" of the respondent depends on his or her mastery of the knowledge. Therefore, the property uncertainty that exists in the game system itself is distinguished from the "feeling of uncertainty." The property uncertainty of a game system consists of various sources (Costikyan, 2013), such as analytic complexity, pure randomness, player unpredictability, hidden information (LeBlanc, 2006), etc., characterizing a situation that is in principle unknowable but partly learnable.

In the sense of the quantitative level to divide the difference, the property uncertainty is a fixed value once the game has been designed, whereas the felt uncertainty is a variable about the play experience. Koster (Koster, 2013) argues in his work that the fundamental of playing is the mastery that the player keeps learning for as long as possible before the player stops playing. The existence of property uncertainty is to provide play value for players, creating obstacles, bringing challenges, and preventing the game from being cracked in an instant due to the optimal strategy found by players. This fits with the discussion of Malone (Malone, 1982) about the correlation between uncertainty and challenge brought that a game must have challenges to be enjoyable while the uncertainty brings challenges. For instance, a game with limited amount of permutations and easy to master like Tic-tac-toe can be depleted in after a relatively low number of playthroughs, compared with chess which requires players have higher strategic intentionality and fall in a spectrum of complexity to create more possibility space, more branching factors, more analytic complexity, and lead to more uncertainty for the player (Lantz, Isaksen, Jaffe, Nealen, & Togelius, 2017). The uncertainty forged by the high degree of analytic complexity in chess itself is inherent, as a property of the system itself, while the uncertainty felt by the player varies with the level of knowledge of the different individuals. The felt uncertainty by the player can be reduced and resolved by learning chess conventions or with the help of a database of stored patterns.

2.2 The Felt Uncertainty

The property uncertainty plays a decisive role in the overall play value produced, whereas the felt uncertainty varies along with the players’ learning progress at different times. A seemingly unpredictable outcome portends the felt uncertainty to novice players but experienced players can understand it; even within the same length of time, the felt uncertainty would be very different depending on players' cognitive competence, decision-making capacity, and performance skill (Power et al., 2019). In the field of communication theory, Adams (Adams & Dormans, 2012) mentions a well-developed model of communication where a sender sends a message along a channel to a receiver, to be a metaphor of how game designers bring goal experiences to players by control over mechanics and dynamics (Hunicke, LeBlanc, & Zubek, 2004). However, the message does not always maintain its integrity completely during transmission, while the total property uncertainty produced by rules and systems set by designers is not equal to the felt uncertainty of players.

When the degree of property uncertainty is excessive, the high degree of felt uncertainty brought will generate negative experiences for players. Klimmt and his teammates (Klimmt et al., 2007) propose the word “effectance” to describe the feeling of influence on the game world, while they verify the idea that the perceived effectance is an important factor for providing enjoyment to players. Excessive felt uncertainty leads to a feeling of non-interaction with the game system, impeding from the experiences of effectance, fuzzing up the outcomes and feedback from the system, hampering the learning progress, ultimately bringing negative experiences to players.

Thus, it is important to balance between felt uncertainty and the feeling of control for creating a better experience for players. However, without defining an explicit intermediate agent to connect the designed property uncertainty and the felt uncertainty, it is only possible to measure empirically how property uncertainty in the game leads to the goal experiences of felt uncertainty. There seems to be a black box existing between mechanics and dynamics to aesthetics that game designers are trying to uncover for better controlling the transmission of goal experiences, exhaustively bridging the gap between game design and playing experience. With our work, we are proposing that the degree of property uncertainty has strong correlations with players' learning process, the time players spent in finding optimal strategies, and the felt uncertainty eventually.

3. Modeling and Situating Uncertainty

The progress of learning and mastery of a game is the intermediate agent to connect the designed property uncertainty and the felt uncertainty. Cook proposes the concept of gameplay Arcs & Loops (Cook, 2012) that players hold mental models of the game as their skills, taking actions evaluated by rules of the game, resulting in feedback, which is a closed arc to depict the gameplay loop while highlights the nature of any gameplay process is all about learning and gaining competence (Gee, 2007), eating the felt uncertainty, filling the vacancy of information, and satisfying curiosity as a natural desire (Marvin & Shohamy, 2016). Once players fully optimized their mental model of the game, the end of any arc is already known and foreseeable while there is no felt uncertainty anymore, and the next playthrough becomes monotonous and tedious (Cook, 2012), as solving the puzzle with known the solution that no more gameplay value yielded.

From the designer's view, adding or deleting uncertainty-related constitutive rules and lusory means (Suits, 1978) of the game can be a way to control the overall aesthetic of the game and to make the appeal (Rautzenberg, 2015). Famous MDA framework theory, developed by Hunicke, LeBlanc, and Zubek (Hunicke et al., 2004), states that the process of game designer transporting gameplay could be breaking into three components: mechanics create dynamic behavior, then the dynamic behavior produce aesthetic feeling for players; in reverse, from the player's perspective, aesthetics set the tone, then they see through the perceptible dynamics, and finally the mechanics. The property uncertainty is born out in the mechanics of the system, partially rest in the dynamics, bring the effect of felt uncertainty to players. Kumari has already demonstrated in his work (Kumari, Power, & Cairns, 2017) that the felt uncertainty by players can be measured by manipulating game visibility.

It can be sure that the game rules related to different sorts of uncertainty tightly correlates to the player's learning process by influencing the time spent in finding an optimal strategy or a dominant solution and reaching the mastery of the game. Power and his teammates (Power et al., 2019) break the felt uncertainty down into five constituent factors based on the feedbacks of the questionnaire that three of these are strongly related to internal uncertainty and the other two are exploration and external uncertainty, whereas we believe that the exploration and external uncertainty he mentioned could be an ambiguous but symbolic and integrated interpretation of, what we are proposing, the property uncertainty of the system. Based on all of the above discussions on how uncertainty brings experience to the player, and the 11 sources of uncertainty developed by Costikyan (Costikyan, 2013), we are proposing 4 sorts of the property uncertainty of a game:

(1) Analytic Complexity Uncertainty (ACU), corresponding to a measurable property of a game formal system Depth (Lantz et al., 2017) that the capacity of a game to absorb dedicated problem-solving attention and allow for long-term learning.

(2) Procedural Randomness Uncertainty (PRU), including from the pure random by rolling dice, using of random number generators, to procedural content generation by regulated (Smith, Gan, Othenin-Girard, & Whitehead, 2011), could be considered as the randomness elements of games, while the degree of this type of uncertainty depends on the designer’s interference with pure randomness.

(3) Information Uncertainty (IU), referring to the total amount of deliberately obscuring information from the player or the difference between the total amount of information in the game system and the information that the player had at the beginning. For instance, the fog of war (LeBlanc, 2006) in real-time strategy games often adds the uncertainty of hidden information to the game system itself, making collecting information an ingredient of the dynamics of play. The proportion of the area that was initially hidden could be regarded as a fixed value related to the information uncertainty in this case. As the player gradually explores and reduces the scope of the fog of war, the felt uncertainty will gradually decrease (Kumari et al., 2017).

(4) Player Uncertainty (PU), presenting as a situation where you are unable to predict what your opponent will do, which exists in every multiplayer game or a game with adequately capable artificial intelligence. When a game has all other sorts of uncertainty properties eliminated

in an inconceivable way, leaving only the player uncertainty, the overall uncertainty itself is only about trying to read your opponent's mind, which is so-called "Yomi" (Sirlin, Learning, & Age, 2012), making the game have virtually infinite depth and play value. Trying to read the opponent's mind is a kind of learning as well, but the learning is almost interminable. As long as the opponent's movement or action is uncertain to the player, the player can always be attracted by the experience of player uncertainty (Yu & Sturtevant, 2019).

On the basis of the foregoing sorts of the uncertainty of property of a game, it is possible to estimate an objective theoretical measure of the Property Uncertainty U_p we proposed here for games' analysis:

$$U_p = f_p \times f_i \times n_p \times d_a$$

where the f_p, f_i, n_p, d_a are respectively corresponding to the Procedural Randomness Uncertainty, the Information Uncertainty, the Player Uncertainty, and the Analytic Complexity Uncertainty; the f_p is the fraction of procedural randomness in the game system relative to the entire game system portion; the f_i is the fraction of hidden information relative to the integral information in the entire game system; the n_p is the number of players participating in the game with which interaction might be possible; the d_a is the measurable property of a game's system "*depth*" (Lantz et al., 2017) to the analytic complexity uncertainty. The equation summarizes the main concepts of objective measures of uncertainty theoretically, which is an attempt to make the approximation of the index of uncertainty than to determine a precise number seriously, for analyzing uncertainty as a property of games more profoundly in future research and creates the path to test how uncertainty-related game mechanics motivate players' feeling of uncertainty.

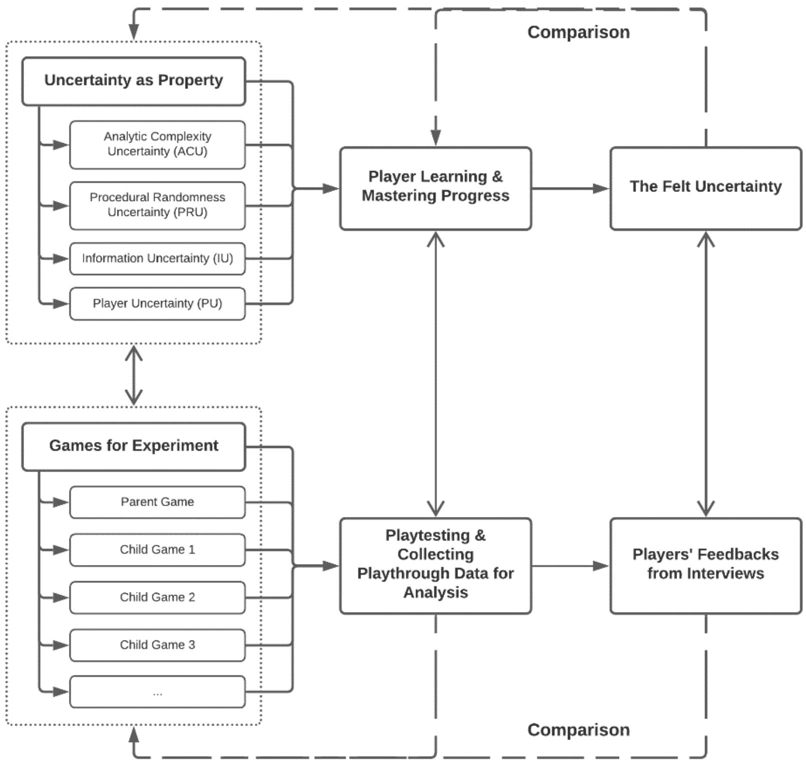


Figure 1. *The overview flow chart of experiment and methodology.*

4. Experiment and Methodology

To further substantiate the notion advanced above, we designed the following experiment, as shown in Figure 1. Inspire by Browne's work (C. Browne & Maire, 2010) and Kumari's work (Kumari et al., 2017), we pick *Connect-4* as the parent game which has rules that are easily changed to produce several child games with varying property uncertainty. We utilize these produced child games to collect data on players' playthroughs by enlisting participants. After the participants completed the playtesting, we took the interview to each player and gave them a survey designed based on Power's questionnaire (Power et al., 2019) to elicit their perceived felt uncertainty. The collected playthrough data is aiming to examine players' progress in learning and mastering various child games with varying uncertainty-related rules, using Osborn's play trace dissimilarity approaches (Osborn & Mateas, 2014). Comparing the analytical results of the playthrough data to the feedback obtained by the interviews confirmed our theory.

4.1 Development of the Games for Experiment

We created various child games for comparing purposes by changing aspects of the game's rules based on *Connect-4*, the parent game chosen. The alteration of rules is intended to hypothetically increase or decrease the property uncertainties previously categorized within different child games. To assist data collecting, we converted the experiment's games into video games. This study will primarily focus on the scenario where *analytic complexity uncertainty* (ACU), *procedural randomness uncertainty* (PRU), *information uncertainty* (IU), and *player uncertainty* (RU) are employed as independent variables. The dependent variable for property uncertainties is the player's progress in learning and mastering the game system, whereas the player's perceived uncertainty is another dependent variable for player progress in mastering the game system.

The games designed for the experiment are listed here in the order in which they were played:

(1) *FairGame7x6*: The standard parent game of Connect-4, with artificial intelligence acting randomly as an opponent, serving as a basic control group.

(2) *FairGame5x6*: Connect-4 on a smaller chessboard (5x6), as an experimental group with theoretically fewer branching factors and analytic complexity, using artificial intelligence that takes actions randomly as an opponent.

(3) *FairGame9x6*: Connect-4 on a larger chessboard (9x6), as an experimental group with more branching factors and analytic complexity, with artificial intelligence that takes actions randomly as an opponent.

(4) *Mirror*: Integrate Connect-4 with the rule that the opponent imitates the player's movement by placing the piece in the symmetry column to simulate a condition in which player uncertainty and even other conceivable uncertainties are minimized. The board is 7x6.

(5) *RandomSelectionGame*: Connect-4 with the rule that the player will be asked to select three columns and the player's next movement will be selected randomly from these three, as an experimental group with a high procedural randomness uncertainty. The board is 7x6.

(6) *FairGameWithMTCS*: The standard Connect-4 game, but with artificial intelligence taking actions based on selecting the column with the highest winning percentage calculated by Monte Carlo tree search (MCTS), as an experimental group with a high player uncertainty. The board is 7x6.

(7) *FairGameWithMTCSResultTold*: As with the FairGameWithMTCS, but the player will be presented with the winning percentages for each column calculated by the Monte Carlo tree search results at their turn, as an experimental group with less information uncertainty. The board is 7x6.

Each participant was required to finish a total of seven games in sequence, and each game variant must be played seven times for recording. The duration of each playtesting session in the plan was less than 30 minutes in order to guarantee that as much play data as possible was obtained while the players were engaged and focused.

4.2 Participants

All participants were recruited from Worcester Polytechnic Institute's undergraduate and graduate students by convenience sampling. To guarantee that the participants' gender does not become a variable that affects the experiment, we made every effort to screen an equal number of volunteers of various genders. There were 11 men, 9 females, and one non-binary gender participant among the 21 participants. The majority of participants were aged 18 to 24.

4.3 Materials

We chose a distraction-free environment on the Worcester Polytechnic Institute's Fuller Labs' Interaction Lab to hold all experiments. The research was entirely voluntary and without risk, and has been authorized by WPI's Institutional Review Board (IRB). Additionally, we used COVID-19 safeguards such as social isolation and sanitization to guarantee the safety of all participants. The players are asked to play the digital games for the experiment on 17-inch and 13-inch Windows laptops with desktop mice. We provided paper-based demographic questionnaires for participants to complete.

4.4 Procedure

Participants were escorted into the room and educated on the nature of the experiment and the tasks they would be doing. Participants were given an information sheet to peruse and were asked to sign a form of informed consent. Following that, participants were given the option to review the information sheet that detailed the game's interface and controls. Following the lecture, participants were instructed to begin the playtesting. Each participant was allocated randomly to one of two computers for gaming. Participants were instructed to try to win the games. Participants were not told of the game's rules before playing in order to better document their own investigation of the altered game rules. After the playtesting was done, participants were requested to participate in a ten-minute interview regarding their experience during the game. In appreciation for their time during the playtesting, participants were compensated with a token gift.

4.5 Playthrough Data Collection

Throughout the participant's playtesting procedure, all playthrough data was captured in the form of digitalized archives and utilized for further data analysis. The participant's every action regarding column selection as their play trace and the time spent making the decision were being recorded; the play trace data pertaining to the participant's actions was a time series input with determinants and values, where the determinant was the total number of columns and the value was the column selected by the participant for each turn. Given that the first-move advantage was a variable, the eventual victory condition and whether the player took the first action were also tracked during the game. In addition to the data above, and in light of the *RandomSelectionGame*'s peculiarities, we logged the participant's selection of all three columns and their sequence of selection.

4.6 Data Analysis

We compared the participants' play trace data to the Monte Carlo tree search (MCTS) simulated playthrough data in each game. Monte Carlo tree search is a method for discovering optimum options in a given domain by taking random samples in the decision space and constructing a search tree based on the findings (C. B. Browne et al., 2012). Considering its precision of tree search is combined with the generality of random sampling, a series of optimal choices made by the Monte Carlo tree search can be regarded as not only the actions closest to the optimal strategy in a single playthrough under a simple system but also the playthrough made by the most experienced player. The comparison can provide us with the rate at which players acquire knowledge of the game and their progress toward mastery across various versions of the game.

Following the methods described by Joseph Osborn (Osborn & Mateas, 2014), by computing the difference between the player's playthrough data and Monte Carlo tree search playthrough data, the sequence of actions taken in the columns picked by the player can be converted to a performance score of the playthrough. We calculated the difference of the winning chance of the participant's choice and the optimal choice made by MCTS in each movement and added them up to find the overall difference between the participant's playthrough and the optimal strategy. Given that the player's thinking time before each move is likewise a reflection of the player's learning obstacle caused by the emerging property uncertainties, we included a sequence of the time the participant takes for each action as a variable in the computation for the playthrough score. As seen in the following formula, a lower playthrough score indicates that the player's action-taking is more akin to the optimal strategy.

$$Playthrough\ Score\ (PS) = \sum_{i=1}^{n}((C_{MTCS} - C_{Player}) + T \times factor)$$

$$i - player\ movements$$

$$C_{MTCS} - \ MTCS\ calculated\ optimal\ winning\ chance$$

$$C_{Player} - Player\ winning\ chance$$

$$T - The\ amount\ of\ time\ the\ player\ takes\ for\ each\ action$$

In each type of game, we recorded 7 times playthrough data from each participant. For each round of the game, we averaged the playthrough scores of all 21 participants to get a round score.

$$Round\ Score = \sum_{j=1}^{n}(PS)$$

$$j - number\ of\ player \quad ,$$

By plotting round scores of each type of game, we can get visualized data graphs as the final results for discussion and make conclusions.

4.7 Results and Discussion

By comparing the data graphs generated by calculations based on the visualized average data of all participants in six out of seven games, it is possible to examine the distinct impacts of modifying the game rules on the participants' learning progress. As seen in Figure 2, the horizontal axes represent the number of times a certain version of the game was played, while the vertical axes represent the round score calculated using the aforementioned algorithm. A lower round score means that the participants' performance is closer to the optimal strategy, while the decreasing curve indicates progressive learning of participants. For instance, as the number of games played increases, it is obvious that in the version of the game *Mirror* with the theoretically least property uncertainties, the participants' mastery of the game gradually approaches the optimum strategies estimated by MCTS.

Correspondingly, the steady rising curve implies that the player's learning process is deteriorating, as seen in the graph for *FairGameWithMTCS*. Under most circumstances, a basic strategy game does not get increasingly difficult to master as the player explores more. This is often the result of an existence that cannot be learned in a short amount of time or perhaps at all. In our cases, this unintelligible existence is an MTCS artificial intelligence. Participants' learning progress is significantly hampered since they cannot even erase this player uncertainty by understanding their opponent's routines, facial expressions, and emotions. As participants spend increasing amounts of time thinking prior to each action, the graph's curve growth trend gets quicker and faster.

What should be noted is that at the conclusion of certain several games (the seventh playing), participants had lower round scores and the curve in the graph had shifted upward. Confirmed by our observations and interviews with participants, this is because the majority of the participants grew impatient and behaved arbitrarily at the end of the game after numerous rounds of play.

A fluctuating curve on a graph suggests that the participants' process of learning a particular version of the game was obstructed by the property uncertainties, resulting in an unstable performance of the playing. *FairGame9x6* presents an obvious sharply fluctuating curve. This is because the game's larger board provides more actionable areas and increases the analytic complexity for players; however, the difference between the maximum and minimum values of the game's round score is obviously smaller than the difference between the maximum and minimum values of the games *FairGame7x6* and *FairGame5x6*. This is because the three versions

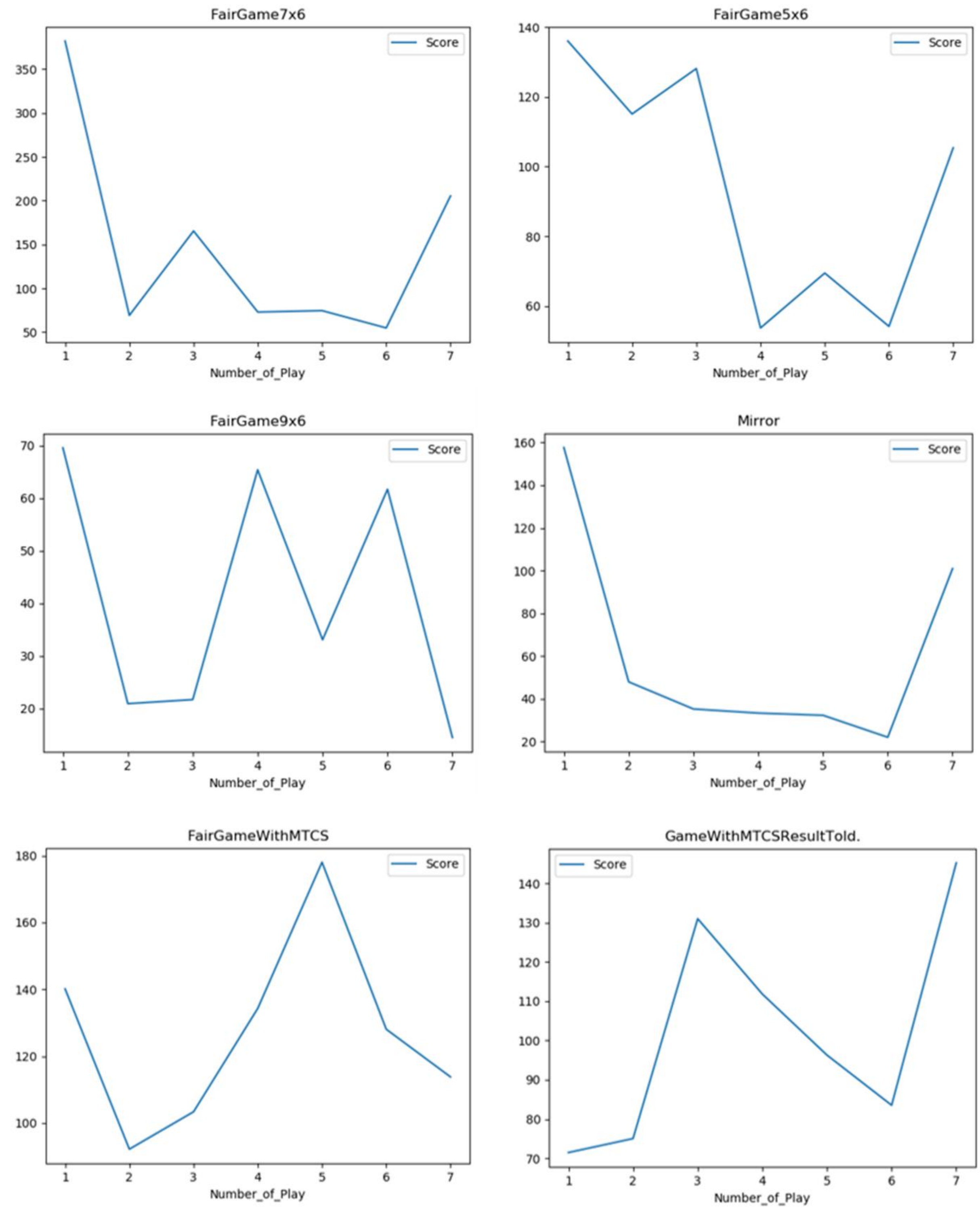


Figure 2. *Visualized average data graphs of all participants in 6 out of 7.*

of the game have identical rules except for the board size difference, and participants progressively learn and master the systems of these three games by following the sequential gameplay from *FairGame7x6* to *FairGame9x6*, and finally to *FairGame9x6*. This is also why, as the first-to-play parent game, *FairGame7x6* has the greatest beginning maximum value of all the game's variations. This progressive mastery of the three games' system by the players is clearly illustrated in Figure 3.

As seen in Figure 4, under the same condition of the existence of the player uncertainty, reducing the information uncertainty reduces the learning obstacles experienced by the participants. A portion of the participants in *GameWithMTCSResultTold* initially expressed doubt about the

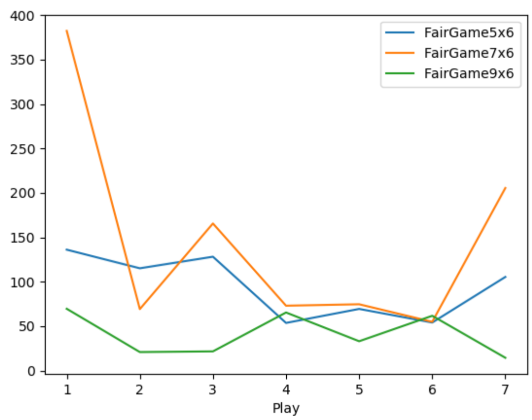


Figure 3. *Comparison between FairGame7x6, FairGame5x6, and FairGame9x6.*

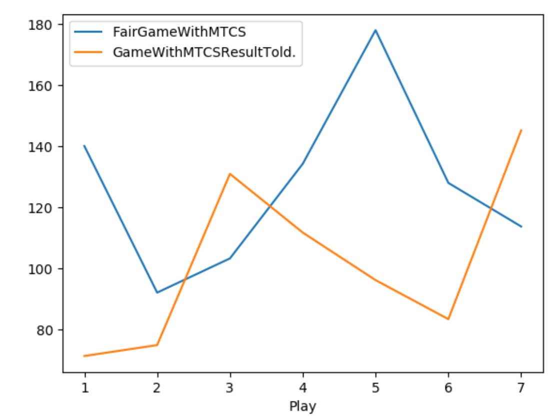
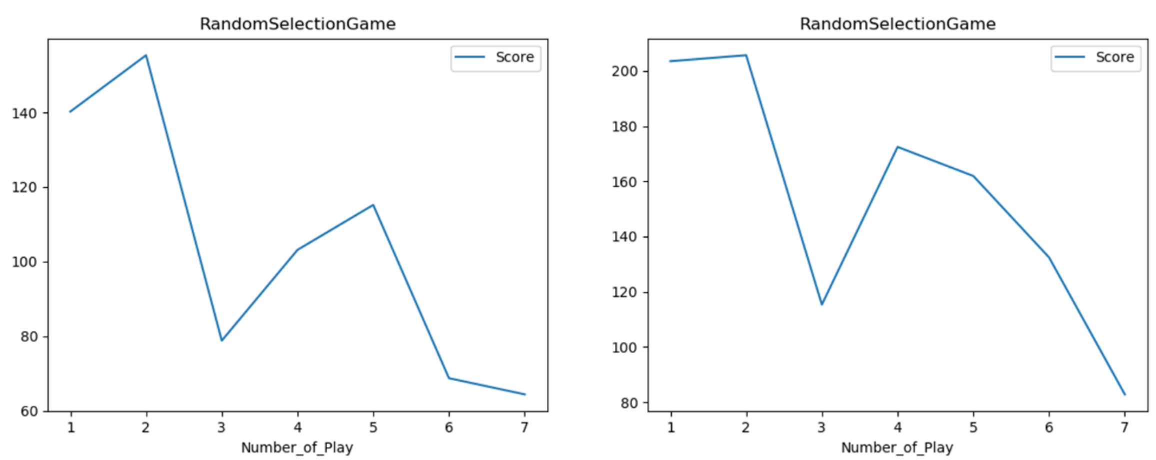


Figure 4. *Comparison between FairGameWithMTCS and GameWithMTCSResultTold.*



RandomSelectionGame, with only considering the first choice.

RandomSelectionGame, with considering all three choice made by participants to get a average score.

Figure 3. *Visualized average data graphs of all participants in RandomSelectionGame.*

winning probability of each column to take that was revealed, which explains why the curve in the graph shows a short rise. As participants became aware that the information about the winning probability was accurate, the graph's curve showed a steady decline.

Due to the procedural randomness uncertainty, we can see fluctuations in the curves of the players' learning processes in *RandomSelectionGame* through the graphs in Figure 5, although the general trend remains downward. Interestingly, there is no rising curve at the last playing of this game (the seventh playing) that reflects the players' ennui. Almost all participants said in the interviews that this version of the game was quite enjoyable, and they appreciated the process of gaming with randomness, despite their feeling the frustration caused by the property uncertainties. The left graph in Figure 5 considers just the first of the three columns picked by participants for computing the round score, which best depicts their desired choice, while the right graph displays the average score for the three columns selected by participants. The comparison demonstrates that under the effect of procedural randomization uncertainty, the participants' real learning process is hindered.

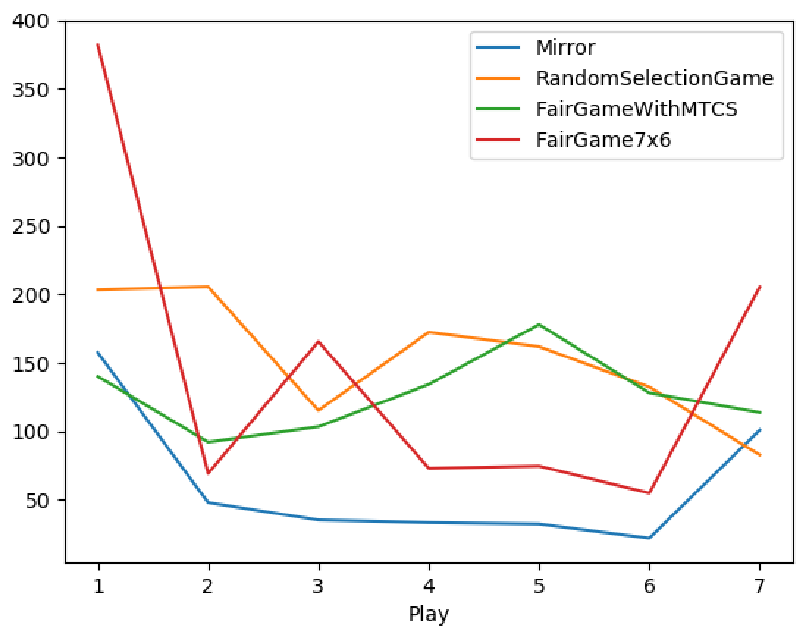


Figure 4. *Comparison between FairGame7x6, Mirror, RandomSelectionGame, and FairGameWithMTCS.*

We gathered participants' perceived felt uncertainty about various versions of the game via their interviews after the playtesting. Through a series of questions and a simplified questionnaire based on Christopher Power (Power et al., 2019), participants were asked to rate the uncertainty they felt about the games. We rated these experimental games based on participant comments and scores. The games ranked from highest to lowest in terms of uncertainty felt by the participants are *RandomSelectionGame*, *FairGameWithMTCS*, *FairGame7x6* as the parent game, and the

Mirror. This rating is entirely consistent with the data analysis findings given in Figure 6. This demonstrates the plausibility of our theoretical assumption.

5. Conclusions and Further Work

The study on the uncertainty of digital games in this field has been focused on the player experience. This might be because the intuition of uncertainty seems to be a universally recognized player experience and easily recognizable. While some of the literature mentions uncertainty as a game mechanism, the connection between game attributes and player experience with uncertainty is seldom examined.

We believe that uncertainty should be classified into two categories: property uncertainty and felt uncertainty. The objective of this article is to investigate how uncertainty as an attribute may affect a player's performance and learning progress, hence causing the player's captured felt uncertainty. We confirmed this hypothesis through a series of experiments and interviews and concluded that uncertainty is an essential property of the game system, providing an ontologically analytical concept for categorizing property uncertainties into four categories: Analytic Complexity Uncertainty, Procedural Randomness Uncertainty, Information Uncertainty, and Player Uncertainty. These property uncertainties have an effect on the player's overall learning and mastering process of the game system, resulting in the player's felt uncertainty. Game designers may investigate and adjust game mechanics and rules that pertain to uncertainty in order to control the player's perceived uncertainty.

This research can in fact be regarded as the following analytical research and a continuation on the external uncertainty (EXU) raised by Christopher Power (Power et al., 2019), the uncharted concepts that he mentioned in the PUGS work but did not further examine. We discovered this coincidence throughout the course of our study when Power and his colleagues mentioned a potential future work in which they would think about evaluating the three internal variables of uncertainty perceived by the player by changing the external uncertainty. According to the work by Costikyan (Costikyan, 2013), Power assumptively maps the external uncertainty to the randomness, complexity, hidden information, and unpredictability of co-players, which are documented in our initial research and verified by our experiments.

With the more trials we perform with increasing numbers of participants, the more we believe we should explore adding more versions of the game to the experiment or trying games with more complex systems. In our future work, the number of recruited participants and the number of rounds of game playtesting should be raised to acquire more accurate data, but more game rounds also mean that players will easily become bored and will stop taking the game seriously.

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