Hearth: A Game Supporting Non-Intrusive and Concurrent Tracking of Player Emotion and Mouse Usage

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Abstract

Empirical evidence has supported the idea that eSports players' emotions could be reflected in their mouse usage. Still, findings from IS literature on the exact relationships between users' mouse usage patterns and their emotional states have been mixed. Possible causes include adjustment effects and offsetting effects. To address these problems, this study proposes a self-developed game named Hearth, which supports non-intrusive and concurrent tracking of players' emotions and mouse usage. The game design supports the examination of the two possible effects. Results show that negative emotion was positively associated with the total mouse movement distance in a game turn, average task-level distance, and average task-level speed. *Moreover, the open-source game proposed in this study facilitates further data collection from natural experiments due to its triadic design that addresses reality, meaning, and play.*

Keywords: eSports, mouse tracking, affective gaming, natural experiment, Hearthstone

Introduction

Affective gaming is an emerging research area that uses players' affective states to enhance their gameplay experience and performance (Yang et al., 2018). The computer mouse is one of the most commonly used gaming controllers in personal computer (PC) games, including those played in the eSports world championships (Kou & Gui, 2020). It has been reported that players' emotions such as rage and anger are often reflected in their use of game devices such as keyboards and computer mice (Kahila et al., 2021). Hence capturing players' emotions based on their in-game mouse usage has been a promising direction in affective gaming (Samonte et al., 2018). Nevertheless, research on the correlations between mouse usage and players' emotion is still scarce, partly due to the limited number of features capturable by computer mice compared to other advanced devices such as biometric sensors. However, among various equipment and devices supporting players' emotion capturing, computer mice have been the most ubiquitous, unobtrusive, and cheap accessories that are accessible to not only professional eSports players but also casual gamers. As such, whether we can capture players' emotions based only on computer mice has been a vital but unsolved question.

Overall, empirical evidence has supported the idea that players' emotions could be reflected in their mouse usage. Still, findings from IS literature on the exact relationships between users' mouse usage patterns and their emotional states have been mixed (Freihaut & Göritz, 2021; Grimes & Valacich, 2015; Hibbeln et al., 2017; Yamauchi & Xiao, 2018). Part of the inconsistent findings might be attributed to individuals' emotion adjustment effect. In controlled experiments, researchers have manipulated participants' emotional states with various stimuli, such as pictures and additional mental workload (Freihaut et al., 2021; Hibbeln et al., 2017; Yamauchi & Xiao, 2018). If the stimuli have little relevance to the subsequent mouse-based tasks users are asked to perform, the users may adjust their emotional states by focusing on the task itself. In other words, the mouse usage and users' emotions are not simultaneously captured, potentially resulting in type II errors (i.e., the effect of emotion on mouse usage was not detected because it already diminished when mouse usage was tracked). Another possible cause of inconsistencies in the findings is the offsetting mouse usage patterns. For example, a player in rage could move the mouse rapidly to attack an opponent but also keep the mouse unmoved for a longer time between attacks. If the mouse speed is evaluated over the whole attacking action, the two patterns caused by the player's rage could offset each other, resulting in an average mouse speed that does not differ much from that when the player is in a calm state.

To address the emotion adjustment effect and offset effect, this study proposes a self-developed game named *Hearth*, which supports non-intrusive and concurrent tracking of players' emotions and mouse usage. To minimize the emotion adjustment effect, mouse tracking and players' emotion reports are seamlessly embedded as part of the gaming procedures without interrupting players' immersive gaming experiences. To minimize the offset effect, players' mouse usage is tracked in multiple fine-grained game phases. Moreover, the game is designed to be fun and playable in non-research settings, facilitating data collection from natural experiments. A preliminary empirical test in this study suggested that players' emotions can indeed be reflected in their mouse usage. The findings in this study provide insights into computer mouse-based player emotion detection.

The remainder of this paper is organized as follows: we first provide the background of this study by reviewing the literature on the role of player emotion in eSports and mouse tracking-based affective state detection. We then present our game system and its unique features that support the non-intrusive and concurrent tracking of players' emotions and mouse usage. Next, empirical tests based on a natural experiment and regression analyses are described, followed by results and discussions. Finally, we conclude this study by summarizing its research and practical implications and discussing limitations and future directions.

Related Works

Role of Player Emotion in eSports

Affective gaming is an emerging research area that utilizes players' affective states to enhance the gameplay experience and performance. In the eSports context, prior work has shown that positive emotions often lead to higher levels of player performance, whereas negative emotions such as anger, frustration, and irritation are often associated with decreased performance (Behnke et al., 2020; Himmelstein et al., 2017; Kou et al., 2018). Among various emotional experiences such as arousal, attention, certainty, commitment, etc. (see (Cowen & Keltner, 2017) for a complete list of emotional experience types), emotional valence (i.e., positive or negative emotional state) has been the fundamental and most well-studied factor of eSports players (Behnke et al., 2020). Understanding and capturing players' emotions during their gameplays could help evaluate the emotional benefits of games to players (G. Freeman & Wohn, 2017) and assist professional players with emotion regulation (Gross & Thompson, 2007; Kou & Gui, 2020).

Various types of equipment have been used to capture players' biometrics data suggestive of their emotional states, such as computer mice, gaming chairs, gaming glasses and VR goggles, body sensors with 3-axis accelerometers, facial recorders, eye-tracking devices, and respiration sensors (Seo et al., 2018; Yang et al., 2018). The major advantage of the computer mouse in affective gaming research is that it is a ubiquitous device that is accessible not only to professional eSports players but also to casual players who play games in their everyday life. It also allows for continuous data collection without requiring sophisticated equipment that may change the gamers' habitual behaviors during gameplay.

Affective State and Mouse Tracking

Mouse tracking is a popular research method in a wide range of applications (Freeman, 2018; Stillman et al., 2018; Jenkins et al., 2019). The idea of using computer mice to assess users' affective states was first introduced in an early study (Zimmermann et al., 2003). Since then, various studies have examined the relationship between users' affective states and mouse usage features. The mouse usage features can be generally categorized as spatial features, temporal features, and task-specific features (Freihaut et al., 2021). The spatial features focus on the distance and directions of mouse movement, such as total mouse movement distance and the frequency of changes in x-direction and y-direction. The temporal features include speed and acceleration of mouse movement. Duration of mouse usage and dwell time (i.e., the duration of time when the mouse is unmoved) can also be considered temporal features. The task-specific features account for other characteristics of mouse usage, such as the frequencies of using various mouse buttons (e.g., left-click vs. right-click) and whether the mouse is moved within a particular area of the screen. Several studies have examined how these mouse usage features can be used to predict users' emotional valence and arousal. Some studies examined the correlations between mouse usage features and specific psychological processes such as anxiety (Yamauchi & Xiao, 2018), stress (Freihaut et al., 2021; Freihaut & Göritz, 2021), fatigue (Pimenta et al., 2016), and arousal and valence of affective states (Grimes et al. 2013).

Although providing various insights into the relationship between mouse usage and users' affective states, findings on whether mouse usage can be used to predict users' affective states are mixed. Several IS studies found that when an individual was in a negative emotional state, the mouse tended to travel a longer distance at a slower speed in goal-oriented tasks (Grimes & Valacich, 2015; Hibbeln et al., 2017). Yamauchi and Xiao (2018) conducted four studies examining the relationships between mouse trajectory features and users' emotional states (Yamauchi & Xiao, 2018). Although they found a significant correlation between users' anxiety level and mouse trajectory patterns in one experiment, they did not observe significant correlations between users' negative emotional states and mouse usage in the remaining experiments. Studies have also examined whether users' stress can be predicted by their mouse usage, but no significant correlations were found (Freihaut et al., 2021; Freihaut & Göritz, 2021).

Among various discussions regarding the mixed findings, one possible explanation is the changes in participants' affective states. The majority of the studies presented above have used controlled experiments to manipulate participants' affective states. Typically, some stimuli (e.g., pictures, movie clips, music, etc.) were used to affect users' emotions before they were asked to perform mouse-based tasks. The stimuli could effectively induce certain emotional states, as evidenced in users' self-reported emotion metrics (Yamauchi & Xiao, 2018), but whether the users maintain the same emotional valence and arousal when performing the subsequent mouse-based tasks is unclear. First, the time lag between when users receive emotional stimuli and when the users' affective states are evaluated could matter (Gross & Thompson, 2007). Second, if the stimuli are not directly related to the goal-oriented tasks based on which mouse usage was tracked, participants may switch their attention to the tasks themselves (Lépine et al., 2005), reducing the impact of emotional stimuli introduced a while ago. As a result, they might use the mouse devices normally as usual during the tasks, seemingly unaffected by their emotional states. This conjecture can be partially supported by a study in an online shopping experiment (Hibbeln et al., 2017). In this experiment, participants' negative emotion was induced by intentional network delay and slow internet speed. The participants used their mice while experiencing the delay (even after controlling the mouse usage during the delay period), which possibly helped the study to capture users' abnormal mouse usage patterns.

Overall, empirical evidence supports the idea that players' mouse usage could somewhat correlate to their emotional states. However, the findings have been mixed, and there is limited research specifically examining players' emotions and mouse usage in gaming.

Methods

Development of the Game System

To investigate the possible association between players' emotions and mouse usage during gameplays, a game named *Hearth* was developed. The game was designed and developed with a "triadic game design" philosophy and addresses reality, meaning, and play in mind (Harteveld, 2011). The game addresses reality by imitating *Hearthstone: Heroes of Warcraft*, a real digital trading card game (TCG) initially released in 2014 by *Blizzard Entertainment*. We chose this game as the foundation of our self-developed game because of its popularity and the potential to collect non-intrusive gameplay data from participants. The number of players in *Hearthstone* surpassed 100 million in 2018, making it one of the most popular online TCGs nowadays. Based on the demographic data of representative professional gamers who stream Hearthstone gameplay, the game is most popular among players between 20 and 30. Therefore, our game has a high potential to attract gameplays from users who are young college students. The game was developed in Python. It can be downloaded on players' personal computers and played anytime, which supports non-intrusive data collection.

The Hearth is a turn-based game where each player starts with 30 cards in their deck and strategically uses these cards to their advantage to defeat the opponent. In each turn, players draw and add new cards to their hands. Given the current status, players need to decide what cards to play and what targets to attack. Figure 1 illustrates key elements of the game.

Figure 1. Key Game Elements

In a game turn, a player can play one or more cards from the player's Hand. Each card has its unique ability to influence the board, such as damaging opponents or even destroying them. Major types of cards include (but are not limited to) Minions, Spells, and Weapons. A Minion card can be summoned onto the board, and it can be used to attack opponents' minions or the opponent player directly. For example, in Figure 1, the main player (positioned at the lower half of the screen) has summoned a minion onto the battlefield, with three other cards remaining at Hand. The opponent on the upper half of the screen has summoned another minion. Whenever a minion or a player is attacked, its health points will decrease by a certain amount. When its health point reaches zero, the minion or player will be destroyed. Spell cards can be cast to invoke various effects on the gameplay, such as damaging opponents, restoring health, drawing new cards, and summoning unique minions. Some Spells need to specifically target another object in the game, such as an opponent character or a friendly minion. A player can equip a Weapon card to attack opponents directly without minions. A 30-second time limit is given to a player each turn to make all these decisions and perform mouse-based tasks. At the 20th second, an animation of exploding bomb is played to remind players about the time limit.

Game Features

Compared to the original game, our version of the game has the following unique features to address the *meaning* and *play* aspects of the triadic game design philosophy (Harteveld, 2011).

Custom cards

The game houses 3,812 original cards from Hearthstone (covering card set expansions up to "*Forged in the Barrens*") and more than 100 custom cards developed by the research team as of writing. Custom cards play a key role in making the game fun and playable, attracting gameplays from participants.

Mouse Tracking

The game tracks mouse usage on its backend. In each turn, a player performs one or more tasks such as playing a card, attacking opponents, or moving the mouse without a specific purpose. Each task generates a detailed mouse tracking record in our server database. Table 1 shows a list of turn-level tasks and their corresponding mouse usage tracked by our game system. We detail several design concerns next.

No	Task	Mouse Actions	Data Records
1	(Idle state) Move the mouse without performing a specific task	Move mouse →stop	Trajectory curve length
2	(Ineffective click) Click anywhere on the screen that does not do anything	Click	(x, y) coordinates of the mouse click
3	Play a Minion card from Hand	Click the Minion card → drag to the player's side of the board →release mouse	(x, y) coordinates of the mouse click; (x, y) coordinates of the mouse release; Total trajectory curve length; Time spent on the task in seconds
4	Play a non-targeting Spell or Weapon card from the Hand	Click the Spell or Weapon card → drag to anywhere on the screen → release mouse	
5	Play a targeting Spell or Weapon card from the Hand	Click the Spell or Weapon card→ drag to a Minion or a Hero specified in the card text → release mouse	
6	Attack an opponent	Click a Minion card or Hero on the player's side → drag to a Minion or a Hero on the opponent's side → release the mouse	

Table 1. Turn-level Tasks, Corresponding Mouse Actions, and Data Records

First, differing from goal-oriented tasks in prior literature (e.g., to navigate a website and choose a product in Hibbeln et al .2017), which typically takes several minutes, the tasks defined in our study are micro-level mouse tasks that can be completed in seconds. This design enables a fine-grained decomposition of mouse usage and helps minimize the potential offsetting effects between multiple small tasks. Second, our tasks include both tasks with specific purposes or without. Some tasks do not trigger any in-game changes, which we labeled as "Idle state" and "Ineffective click" in Table 1. Research has reported that negative emotional states such as anger induce irrational behaviors (Kahila et al., 2021). For this reason, meaningless mouse operations are purposefully captured in our game system. Third, when a mouse is moved, the trajectory length is captured instead of the Euclidean distance between the mouse start/end positions. The trajectory length is more effective in capturing the efficiencies of performing in-game tasks, which potentially relate to players' emotional states.

Emotion Capturing

Another unique feature we designed in our game system is emotion capturing based on a custom button. In the original game *Hearthstone*, a player can end a turn by clicking an "end turn" button located on the periphery of the game board. In our design, we replaced the original "end turn" button with a color bar button representing the different emotional states of players. Figure 2 shows a comparison of the original "end turn" button and our custom "end turn" button.

Figure 2. A Comparison of Original End Turn Button and Our Custom Button

A player must click somewhere on the color bar to end a turn. When the button is clicked, the player's Hero will send a corresponding emotional message to the opponent player. The message will also be printed on both players' screens. For example, when a player clicks on the red zone of the button, messages like "I will tear you apart!" (the actual message varies by selected heroes) will be displayed. This design encourages players to click an area that represents their actual emotional state at the end of each turn. Note that the emotional state captured by this button mainly reflects players' interpersonal emotion expressions rather than their experienced emotions. Interpersonal emotion expressions are used by players to interact with teammates or opponents. Players use interpersonal emotion expressions not only to express their true feelings (i.e., experienced emotion) but also to strategically influence gameplays (Kou and Gui 2020). For example, players can bluff their opponents by showing highly positive emotions. Alternatively, they can pretend to be losing and feeling anxious to deceive the opponents. However, due to the nature of the game used in this study, the interpersonal emotion expressions from players are very close to their actual experienced emotions. Compared to games requiring more complex decisions and operations (e.g., ganking in *League of Legends*), the proposed game has relatively limited decision space for players to respond to opponents' deceiving emotional expressions. As a result, the potential benefit of emotionally deceiving opponents is low. Therefore, the benefit of the button design outweighs its negative effect on capturing players' experienced emotions.

The button is located at the bottom right corner of the game screen in our current version of the game. To minimize the impact of button locations on users' mouse usage, we excluded the mouse trajectories involving the use of this button (i.e., moving the mouse to the button at the end of a turn and moving the mouse from the button at the start of a turn) from subsequent regression analyses.

At the end of each turn, all the task-level mouse usage features are aggregated to generate turn-level statistics, as illustrated in Figure 3. The total mouse movement distance, the total number of clicks, and overall mouse speed in a turn are calculated based on all tasks listed in Table 1. Additionally, average mouse movement distance, clicks, and speed for completing meaningful tasks are calculated based on tasks 3, 4, 5, and 6. Although tasks 7 and 8 are also meaningful mouse clicks, they are excluded from computing task-level measures in this study because they represent distinct mouse movement actions. Tasks 3, 4, 5, and 6 require generally similar mouse movement and clicks, and restricting statistical analyses on these tasks help reduce variances introduced by task differences.

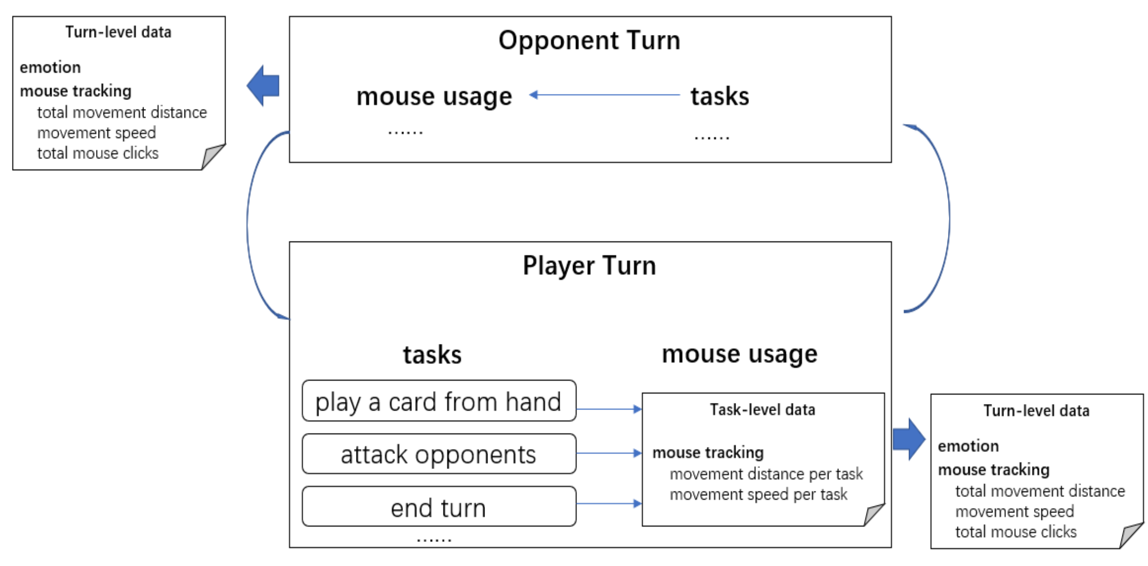

Figure 3. Illustration of Game Turns and Aggregation of Mouse Tracking Measures Comparison of Original End Turn Button and Our Custom Button

Natural Experiment

To examine possible associations between players' emotions and mouse usage, the game was introduced in two graduate-level Python programming courses offered during the 2020 Fall and 2021 Spring semesters. Student participants in these courses could voluntarily play the game outside classes, with opportunities to earn extra credits. The age of the participants ranged from 20 to 35, with approximately 37% female students and 63% male students.

Instructions were given to the participants regarding how to download and install the game on their own computers. Before playing the game, consent for collecting their gameplay data was obtained. During gameplay, the participants were asked to create usernames that replace their real names for privacy protection. The participants were also asked to click on the appropriate position of the emotion bar button to accurately represent their emotional states. They were told that the data would be used for research purposes, and accurately reporting their emotional states would increase their chances of obtaining extra credits. With voluntary participation, 13,969 tasks related to mouse usage were collected from 55 participants in 524 game matches. Some game matches ended in less than three turns, which likely resulted from test plays. Mouse operations during the last 10 seconds of each turn were also discarded because players are expected to move the mouse faster to complete tasks before the time limit. As a result, 104 game matches consisting of 677 game turns and 4,825 in-game tasks were used for the subsequent statistical analysis.

Regression Analysis

To test possible correlations between players' emotions and mouse usage, regression analyses were performed. The response variables included both turn-level and task-level mouse usage features. The explanatory variables included turn-level emotions reported by players and game turn numbers. Of the 677 game turns, 252 turns were labeled as negative emotion turns, 102 turns were labeled as positive emotion turns, and 323 turns ended without clear emotional valence. Table 2 lists these variables and their explanations. The game turn number was included as a control variable because players are expected to perform more tasks in the late stages (high turn numbers) of game matches, which are expected to significantly affect mouse usage features. It also helps control the effect of repetition of similar tasks (e.g., ending a turn) on mouse usage patterns over the game.

Variables	**Explanation**
Response Variables	
total distance	Total mouse trajectory length in a turn
speed	Overall mouse movement speed in a turn
clicks	Total number of mouse (left) clicks in a turn
distance per task	Average mouse trajectory length when performing meaningful tasks during a turn
speed per task	Average mouse movement speed when performing meaningful tasks during a turn
clicks per task	Average number of mouse (left) clicks when performing meaningful tasks during a turn
Explanatory Variables	
positive emotion	Dummy coding representing that the player ended a turn by clicking the first 1/3 of the bar
negative emotion	Dummy coding representing that the player ended a turn by clicking the last 1/3 of the bar
turn	The game turn number

Table 2. Variables Used in Regression Analysis

In this study, the screen size of the game was fixed to 1720 (WIDTH) × 960 (HEIGHT) pixels. The distance measures in Table 2 refer to pixel units, as illustrated in Figure 4. To further accommodate possible individual differences in screen size, screen resolution, mouse speed, and participants' familiarity with the game and personal habits in using the computer mouse, mouse speed measures were normalized by dividing the actual pixel speed by players' average mouse speed before performing regression analyses. In other words, the relative change in mouse speed (measured as a ratio to the player's average mouse speed) was used to control the individual differences in hardware.

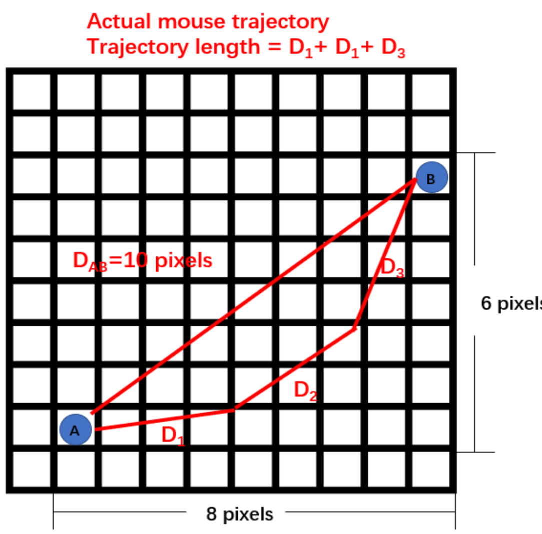

Figure 4. Illustration of Mouse Trajectory Length in Pixels

Results

We did not find statistically significant correlations between players' positive emotions and mouse usage features. However, some interesting findings were observed for negative emotions. Table 3 shows selected regression results regarding the effect of negative emotion on mouse usage in TCG gameplay. The estimated coefficient values are presented, and their p-values are shown in parentheses. The negative emotion variable was dummy coded as 1 when a turn was ended by users clicking the first one-third of the emotion bar button and 0 otherwise. Overall, both the negative emotion and game turns had significant correlations with several mouse usage features.

	Turn-level			Task-level (avg.)		
Explanatory Variables	**total distance**	**speed**	**clicks**	**distance per task**	**speed per task**	**clicks per task**
constant	3,747.41*** (.000)	1.24*** (.000)	1.85*** (.000)	2,037.41*** (.000)	1.50*** (.000)	1.17*** (.000)
negative emotion	1382.02*** (.000)	0.41 (.190)	2.51 (.142)	315.12*** (.000)	0.34* (.043)	1.41 (.521)
game turn	836.32** (.004)	-0.22** (.006)	1.20*** (.000)	272.23*** (.001)	-0.07** (.005)	-0.12 (.235)
# of obs.	677	677	677	677	677	677
Adjusted R^2	.162	.214	.137	.290	.153	.103
Significance coding: *** 0.001 ** 0.01 * 0.05						

Table 3. Effect of Negative Emotion on Mouse Usage in TCG Gameplay

The positive correlations between game turn and the distance of mouse movement match our expectations. As the game progresses, players have more resources (i.e., mana) to spend, which are usually associated with more cards being played. Consequently, the more complex gameplays resulted in longer distances of total mouse movement. The distance of mouse movement per task also significantly increased with game turns. It could be due to two reasons. First, when a more complex situation is present in the later stage of a game, players might hover their mice in different positions on the game board to evaluate the trade-offs between multiple options, resulting in a long distance of mouse movement. Second, players might fail a task (e.g., dropping a card onto a wrong area) and have to redo it, increasing the mouse movement associated with completing the task. These conjectures are further supported by the negative correlation between game turns and the speed of mouse movement. Players might need to spend more time making decisions in later game stages, both during waiting time between tasks and during each task when hovering their mice without movement. The increased waiting time led to the overall longer duration of a turn and the decreased average speed of mouse movement in the turn. The increased mouse hovering time could have contributed to the slower speed per task. Finally, the number of left clicks also increased along with game turns, likely due to the requirement for more complex gameplays in late-game.

Notably, the presence of negative emotion during gameplays was positively associated with the total mouse movement distance in a turn, average task-level distance, and average task-level speed. When players were irritated, they might increase the frequencies of meaningless mouse movements, resulting in a longer total distance of mouse movement. In turn-level analysis, we did not observe an increased number of mouse clicks or faster mouse movement speed when players were in negative emotional states. However, when performing task-level analyses, a positive correlation between the negative emotion and the distance per task was observed. It suggests that to complete each task, such as playing a card or attacking an opponent, players tended to move the mouse over longer distances when irritated. Figure 5 illustrates a comparison between Idealized Response Trajectory (IRT) (Freeman and Ambady 2010) and a possible longer mouse trajectory by an irritated player. A positive correlation between the negative emotion and the speed per task was also observed, indicating that players tended to move the mouse 34% faster when performing a task with specific goals.

Figure 5. Possible Mouse Trajectories from Players under Different Emotional States

In addition to the total distance, speed, and total clicks measures, we have also examined the correlation between players' reported emotions and several other mouse metrics, including mouse movement and speed during idle state, mouse movement and speed while mouse buttons were pressed down, mouse movement and speed while mouse buttons were released, and the number of meaningless (ineffective) mouse clicks. However, we did not observe any statistically significant correlations between these metrics and players' emotion.

Conclusion

In this study, we presented a self-developed TCG game system that supports non-intrusive and concurrent tracking of players' emotions and mouse usage. We reported a preliminary empirical test that examined the correlation between players' emotions and mouse usage. Based on the data collected from a natural experiment, our results showed that players' negative emotion was significantly associated with longer mouse movement distances. Negative emotion also led to faster mouse movement when players performed specific game tasks such as summoning a minion or targeting a Spell card onto an opponent. When performing these tasks, the task-level mouse movement distances also increased under negative emotion, possibly due to the increased likelihood of failures in mouse-based actions.

This study adds to affective gaming and mouse tracking literature by providing several unique insights. First, most existing studies collected participants' self-reported emotions under controlled experiment settings where emotion stimuli were introduced before the participants performed mouse-based tasks (Freihaut et al., 2021; Freihaut & Göritz, 2021; Grimes & Valacich, 2015; Hibbeln et al., 2017; Yamauchi & Xiao, 2018; Zimmermann et al., 2003). These experiments could effectively trigger changes in users' emotional stats with specific stimuli (e.g., displaying pictures associated with various arousal levels), but their findings regarding mouse usage could be affected by the players' emotion adjustment and mouse pattern offsetting effects. In this study, we examined data collected based on a game system that collected players' emotions and mouse usage in a non-intrusive and concurrent manner. During the gameplays, the participants could exhibit emotional state changes for various reasons. For example, players could feel irritated when their minions were destroyed, their health dropped to a low number, or they failed some tasks due to misoperation. By collecting these negative emotion events with the use of an "end turn" button, we minimized the possible emotion adjustment effect, and thus we were able to directly examine the relationship between players' emotions and mouse usage. Second, we performed a fine-grained mouse tracking analysis by decomposing emotion measurement events (i.e., a game turn) into multiple sub-events (i.e., in-game tasks). During gameplay, players could experience emotional state changes that last over a duration of time. Within the duration, players' emotions could be reflected in various mouse operations. When these subtasks are aggregated, however, the individual effects of emotion on mouse usage in the subtasks could potentially offset each other, resulting in an overall insignificant correlation between players' emotions and aggregated mouse-tracking measures, leading to Type II errors. In this study, we provided interesting empirical evidence for this offset effect by decomposing a game turn into multiple game tasks. We found that negative emotion did not correlate with the turn-level mouse speed but significantly correlated with the task-level mouse speed. These findings provide research implications for future studies in that the granularity of mouse tracking measures should be considered.

Practically, the proposed game system can be used by researchers to collect various gameplay data, including but not limited to mouse tracking measures. The source code of the game (over 40,000 lines of Python codes) is fully developed in an open-source environment and has great extensibility and customizability[1]. For example, the size and shape of the emotion button are fully customizable according to researchers' needs. For another example, gameplay statistics can be utilized as training data for developing smart computer AI. It is noteworthy that the proposed game can not only be used under controlled experiments in gaming research but also have the potential to collect a reasonably large amount of data from natural experiments because the game itself is fun and playable in leisure. A common issue in natural experiments is that the number of samples capturing emotional state changes could be limited compared to controlled experiments where such emotional state changes are carefully triggered with known stimuli. We addressed this issue by developing a serious game (i.e., a game designed with research purposes other than pure entertainment) that resembles a popular commercial game with a large number of players. The

[1] The Github repository of the game source code is available upon request.

game not only implemented 3,812 existing cards from the official Hearthstone but also enables custom card design and creation. At the time of writing, about 100 original cards have been designed and implemented in our version of the game, but more cards are being designed by some student participants and other fans of the game. These features also addressed the reality and play aspects of the triadic game design philosophy (Harteveld, 2011). At the time of writing, the game was only advertised to and test-played by a limited number of participants (N=55). If the game is made public (after replacing game assets using commercial licenses and trademarks with original assets), it has a great potential to collect much larger gameplay statistics based on real game experiences. For legal concerns and the notion of fair use, the game is now only distributed to individual scholars for scientific use. The source code (excluding licensed images and audio) of the game could be shared with scholars for research and education purposes.

This study has several limitations. First, among various mouse usage features, we focused only on the distance, speed, and click measures. Other common mouse usage features such as acceleration and direction change in axes were not included in our analysis, mainly due to the game performance concerns. Currently, all the mouse usage data were captured in-game using *pygame* libraries and automatically inserted into a database hosted on our game server. Increasing the mouse usage features would generate more database queries which could significantly slow down the game. We did not use an external mouse-tracking software (e.g., Mouse Recorder Pro) because we wanted the game installation process to be as simple as possible so more participants would voluntarily play the game. We are improving the game performance by tweaking algorithms and streamlining the database interactions so that more mouse usage features can be collected. Second, the current design of the emotion button mainly captures players' interpersonal emotion expressions rather than their experienced emotions. Although the difference is minimal in our preliminary experiments, a more carefully designed mechanism should be used in the future to capture players' experienced emotions more accurately. For example, presenting a second emotion button that does not display emotional messages to opponents so that players would not have any motivation to express deceiving interpersonal emotion. Third, the current study based on natural experiments lacks external criteria for evaluating players' true emotions during gameplays. A possible approach to address these problems would be studying the correlations between typical game events and players' experienced emotions in a separate survey, where participants rate various game events such as destroying an opponent's minion, losing a friendly minion, stealing the opponent's resources, involuntarily discarding cards, etc. A model can be trained based on the players' rating scores on various game events, which can then be used to estimate players' turn-level emotions in future plays. The estimated emotion scores can serve as external criteria in evaluating players' experienced emotions during natural experiments. Specifically, the estimated scores can be used to detect inconsistent emotion reporting between players' emotion button clicking and actual game situations.

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