Blink To Win

Blink Patterns of Video Game Players Are Connected to Expertise

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ABSTRACT

In this study, we analyzed the blinking behavior of players in a video game tournament. We aimed to test whether spontaneous blink patterns differ across levels of expertise. We used blink rate (blinks/m), blink duration, and general eyelid movements represented by features extracted from the Eye Aspect Ratio (EAR) to train a machine learning classifier to discriminate between different levels of expertise. Classifier performance was highly influenced by features such as the mean, standard deviation, and median EAR. Moreover, further analysis suggests that the blink rate is likely to increase with the level of expertise. We speculate this may be indicative of a reduction in cognitive load and lowered stress of expert players. In general, our results suggest that EAR and blink patterns can be used to identify different levels of expertise of video game players.

CCS CONCEPTS

• **Applied computing** → **Psychology**; • **Human-centered computing** → *Empirical studies in HCI*; Laboratory experiments.

KEYWORDS

blink patterns, video games, expertise, pattern stability

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1 INTRODUCTION

Video games can be used to communicate [4], train [30], and as research tools in the study of group differences [11], cultural differences [28], crisis management [24], and decision-making [14, 15]. One advantage of video games when it comes to studying these aspects is that they have the benefit of allowing the integration of unobtrusive, automatic personal measurements such as emotions and behaviors through e.g. a webcam camera.

Nowadays, competitive video game competitions are a large and growing industry [8]. Video game competitions often take place in tournaments, which organize players according to levels of skill and past performance. Such events are an opportunity to study highly skilled video game players using the aforementioned automatic measurement techniques, especially if they are video-based, such an approach has the advantage of not burdening the players with wearable sensors. However, this also poses several challenges when used during video game tournaments, such as unstable lighting conditions, natural movements, noise, and audience interaction.

Previous research showed that cognitive workload and states such as drowsiness can be measured through eye blink frequency and duration [3, 29]. We expect that expert video game players have lower cognitive loads during play than players with less in-game experience and that this would be visible in their blinking behavior. Therefore, in this study, we expect to be able to categorize players with respect to their in-game experience through the automatic analysis of their blinking frequency and duration. For this study, an esports Hearthstone tournament was organized, during which eye blink data was collected unobtrusively using a camera. Hearthstone often requires players to make complex in-game decisions in a restricted amount of time; the effect of such decisions and how they impact players with different levels of expertise might be captured using methods such as the one we are proposing in this work.

2 RELATED WORK

2.1 Video Games and Expertise

High levels of performance generally come about on account of practice [10]. Typical behavioral differences between novice and expert video game players are reflected in perceptuo-motor attenuation, including faster reaction times, better use of working memory, and faster perceptual processing. These changes typically do not generalize outside of video games and sometimes not even across video games [25]. Gray and colleagues [13] used Tetris to identify qualities of video game expertise that go beyond reaction time and manual dexterity, such as game-specific techniques and strategies for overcoming performance plateaus. Relevant to this study are the identified three classes of expertise, each connected to mastery over these techniques: novices, intermediates, and experts [12]. We

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connect these to differences in blink patterns, but further work with Hearthstone could also help identify specific techniques that expert players use to overcome performance plateaus.

2.2 Blinks and Brains

On average, a human being performs 17 blinks/m at rest [2], whereas a blink can last between 50 *ms* and 500 *ms* [32]. Average blink rate increases during tasks that require performance, such as a conversation, and decreases in tasks that require engagement and attention, such as reading [2]. Given such evidence, we can speculate that blink rate is likely the effect of the type of information processing done in the brain. Similarly, we know that spontaneous blink rate (SBR) is directly connected to activity in the striatum and in the prefrontal cortex [18], two relevant areas for cognitive functions and cognitive performance. It is worth mentioning that the striatum is connected to the ventral tegmental area (VTA) which plays a key role in motivation, volition, and cognitive performance [21], i.e the sort of psychological processes that performance in video games depends on.

These brain areas are important to mention in the context of this study for two reasons. First, neural activity in the striatum and SBR is mediated by dopamine and more specifically by D2 receptors, directly involved in attention, memory, and learning [26], which can be found in the aforementioned brain areas. Alteration in dopamine transmission connected to the D2 receptors can directly alter SBR in both human and animal models. Dopamine controlled by D2 receptors helps to update cognitive representations, semantic representations of action and the external world [7], and maintain focus on a specific task [33]. Given the connection between SBR and dopaminergic activity, previous studies suggested that SBR may be an indicator of goal-oriented behavior and cognitive performance [18]. Second, high SBR has been associated with higher accuracy on go/no-go tasks, where participants have to respond to specific stimuli and ignore others [33], and the Iowa Gambling Task, a task in which players win money when detecting the decks with the most rewarding cards [5]. Interestingly, SBR also has an inverse relationship with cognitive workload [18] and task difficulty [29]. However, other information related to blinking patterns may be relevant to detecting workload and performance.

Blink duration, on the other hand, has been consistently associated with mental and visual processing demands where the duration decreases as the processing demand increases. This may occur, for example, during extended driving [1]. In conclusion, differences in blinking patterns (as measured by blink frequency, SBR, and blink duration) can reflect cognitive as well as low-level neural processes that are engaged during task performance. It is for this reason that they may be an important window into the cognitive and neural differences between novice and expert video game players.

3 METHODS

3.1 Hearthstone Tournament

Hearthstone is an online card game typically played by two players as opponents. Prior to the match, players select 30 cards to be a part of their deck. Cards represent creatures or spells that interact with cards on the game board and the players' "health" points in a variety of ways. At each turn of the game, a player draws a card from their deck and uses a limited resource called "mana" to place it onto the game board. Players win when they reduce their opponent's health points to zero. Some cards are available to be selected to be a part of a deck for all players, but some are available only to a particular player "class", which has to be declared by the player. Given all this, player skill is a combination of an ability to place appropriate cards on the table during one's turn and the ability to create a deck of cards that performs well against a variety of opponent decks.

The tournament used in this research was a best-of-three matches double-elimination bracket, so a player had to win two games against their opponent in order to win a match. Players who lost a match were placed in the tournament's lower bracket and if they lost a match while there, they were eliminated from the tournament. The semi-finals and finals of the tournament were played in a best-of-five format (three-game wins required to win a match). Each player declared three (in best-of-three matches) or four (in best-of-five matches) decks of unique classes. Each deck that won a game within a match was not allowed to be used for the remainder of that match but could be used again in a different match. To increase player motivation, the top three finishing players could win tangible prizes. The tournament champion received a gaming mouse and a handmade Hearthstone souvenir card, while the runner-up and third-place winners received Blizzard gift cards. [1]

3.2 Participants and Data Collection

The participants involved in this study were recruited through the Esport association at the University of Tilburg, using posters placed in local game stores, and publishing the event as an official Blizzard Fireside Gathering. All participants signed an informed consent form and filled in a short demographic questionnaire before starting the tournament. This questionnaire collected the players' age, gender, the number of hours per week spent playing Hearthstone, and the self-assessed Hearthstone experience (on a Likert scale from 1 to 5). Seventeen players (all male, age M = 22.7 (SD = 3.6 years) voluntarily signed up and participated in the competition. The average self-assessed experience of players was 3.4 (SD = 1.2) and the average hours per week (hr/w) reported was 9.4 (SD = 6.8). A unique anonymizing identifier was assigned to each player. Players of a match faced each other (see Figure 1) and their monitors were set to minimum height to facilitate eye contact.

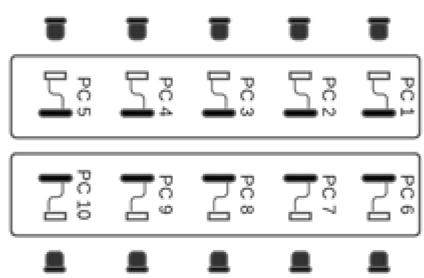

Figure 1: Tournament Space.

[1]Blizzard Entertainment is the developer of Hearthstone.

Each players' webcam feeds and game screens were recorded at 30 frames per second. Each recorded file contained both feeds (see Figure 2).

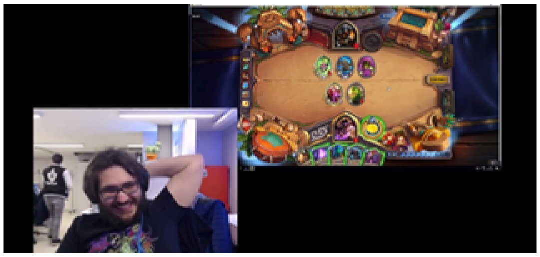

Figure 2: Webcam and game board recording.

Recording started on each computer 15 minutes prior to the start of the tournament and ended after the final game. Each recorded file includes timestamps for the start and end of a game and the participating players' unique identifiers for that interval. The start of each game was defined as the moment when player classes were announced on the screen; the end of a game was defined as the moment when a winner was announced on the screen. Gameplay events and results were manually annotated by inspection of recorded files. In sum, 156 separate gameplay videos (78 games x 2 players) were obtained with a total duration of 26.5 hours, with an average per-game duration of 10.4 minutes (SD = 5.4 minutes). Participants played 9.1 games on average (SD = 5.1 games).

3.3 Definition of Expertise

A k-means algorithm was used to cluster participants groups of similar self-assessed expertise and reported average hours of playing per week (hr/w). These two measures used for clustering purposes were significantly correlated (r = 0.77, p < 0.001). Three clusters, named "Novices" (n = 4), "Intermediates" (n = 9), and "Experts" (n = 4), were identified using the elbow method and silhouette score (0.58). See figure 3.

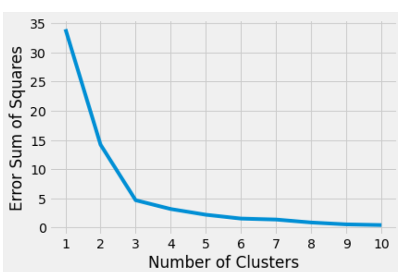

Figure 3: Results of the elbow method.

The "Novices" cluster had 4 players who played the game for 1.75 hr/w (SD = 1.30) and with a mean self-assessed experience score of 1.5 (SD = 0.5). The "Intermediates" cluster had 9 players with a mean of 8.28 hr/w (SD = 2.37) and mean experience equal to 3.78 (SD = 0.41). The "Experts" cluster had 4 players with a mean of 19.75 hr/w (SD = 3.90) and a mean experience equal to 4.75 (SD = 0.43).

Table 1: The landmarks used in FaceMeshDetector.

Point	Left Eye	Right Eye
P1	243	385
P2	22	252
P3	24	254
P4	130	463
P5	160	387
P6	158	359

3.4 Eye Aspect Ratio Extraction

In order to extract patterns associated with SBR, the videos were cropped to fit just the players' faces while playing the game. A Python code was implemented using the cv2 library (version = 4.5.5) and cvzone (version = 1.5.6) libraries. The FaceMeshDetector, from the cvzone library, was used for face detection while the cv2 library was used to plot the landmarks[2] used to calculate the eye aspect ratio (EAR). The EAR is a scalar distance that indicates if the eyes are closed or open [27] and it was calculated using the following formula:

$$\mathbf{EAR} = \frac{||P2 - P6|| + ||P3 - P5||}{2||P1 - P4||} \tag{1}$$

The points needed to calculate the EAR P1, P2, P3, P4, P5, P6 are visualized in Figure 4.

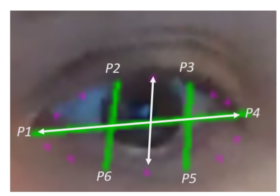

Figure 4: FaceMeshDetector landmarks and EAR points.

Such points correspond to specific landmarks related to both of the eyes in the FaceMeshDetector that are visualized in Table 1.

These points were used to calculate the average EAR between the two eyes since a blink occurs when both eyes are closed. For every single frame, the EAR provides information on the extent to which the eyes are open. The EAR generally provides a number ranging from 0.20 to 0.45. To improve the visualization plot, the EAR for each frame was multiplied by 100. As a consequence, the EAR values extracted from each participant were ranging between 20 and 45. A previous study suggests that whenever the EAR goes below 30, a blink occurs (figure 5) [27]. The EARs for each of the 156 videos were subsequently extracted and saved as .csv files.

[2] An implementation of a code to track blinks with the FaceMeshDetector can be found at the following link: https://www.youtube.com/watch?v=-TVUwH1PgBs

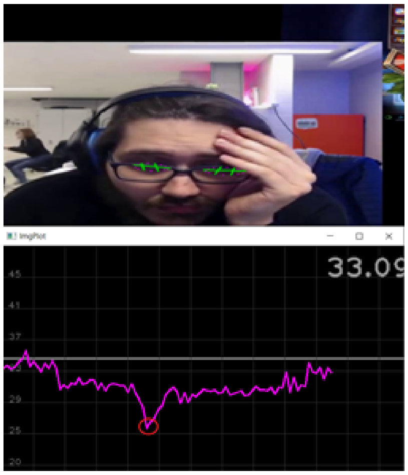

Figure 5: EAR during a gameplay and corresponding peak below 30 (circled in red).

3.5 Blink Information Extraction

In previous work [27], the number of blinks was directly extracted while plotting the online EAR visualization. However, to extract further information and clean the noise that may occur in a real video game tournament, the data were further preprocessed. During this preprocessing phase, the parameters for the minimum number of frames needed to detect a blink, the maximum blink duration, and the minimum interval between two blinks were implemented to reduce the presence of artifacts. Considering that a blink has a minimum duration of 50 *ms* and a maximum duration of 500 *ms* [32] we used 2 frames (approximately corresponding to 66 ms) and 15 frames (approximately corresponding to 500 *ms*) as the lower and upper thresholds to detect a blink. Such a process resulted in an improvement of the method provided in [27] making the blink patterns extraction procedure more robust to noise.

Generally, the blink interval ranges from 2 seconds up to 10 seconds [20]. However, blinks can have an interval as short as 300 *ms* [9]. Therefore, we set 9 frames (approximately corresponding to 300 *ms*) as the minimum distance required between two blinks. These values adopted resulted to be effective in detecting blinks in a few videos analyzed for test purposes. The EAR threshold used to detect peaks representing blinks is set to 30 as suggested in previous studies [27]. However, after having inspected a video for each participant we noticed that two participants required a threshold equal to 25, and three participants required a threshold of 35; the rest of the participants had their blinks effectively detected using a threshold of 30. This difference in thresholds was mostly due to the distance participants decided to keep from the screen and head's position; considering it was a tournament we did not establish a standard distance for all the participants, furthermore, this difference in threshold was also due to the eyes' size and shape. The peaks representing the blinks were detected using the Scipy library (version = 1.7.1) in Python.

The number of blinks extracted was divided by the total time of gameplay providing the blinks/m for each video. This information was used to detect abnormal values in the number of blinks due to excessive distraction, the presence of artifacts, or by excessive time spent keeping the face away from the computer screen. During this phase, the videos having a blink rate =< 3 or => 48 were further inspected [2, 9]. Eventually, 10 videos were excluded by further analysis due to excessive distractions or faces kept away from the screen for a prolonged time. One participant, belonging to the Intermediates group, was completely excluded from the analysis as all 4 videos containing his recording were excluded; this was mostly because he played in the dark with a low-head facing making it hard to detect blinks with the EAR. Another 6 videos, one belonging to the Expert group, two to the Novices group, and three to the Intermediates group, were discarded given movements that made it impossible to define a stable EAR or because of poor lighting conditions. This process left 146 videos to be used for further analysis out of the 156 original ones.

Once the blinks/m values were obtained, further information about the distance between two blinks and the blink duration were extracted from the .csv files containing the EARs. The mean, median, and standard deviation for the blink duration were extracted from all the videos; similarly, the same information was extracted from the intervals between blinks.

Furthermore, the mean, median, and standard deviation from the EARs were extracted to obtain insights into the general eyelid movements occurring during the game. Since different EAR thresholds were used for different groups of participants, the values were normalized to avoid that the different thresholds used may be connected to a different magnitude in the data.

At the end of the preprocessing phase, the labels were assigned to the information extracted from the 146 videos. The final dataset contained 146 instances (rows) and 10 features plus a label column, where 22 instances represented "Novices", 94 "Intermediates", and 30 "Experts". A visualization of the features used and their relevance is presented in the next section (see Figure 6).

4 RESULTS

Considering the data used for the final analysis, on average, the participants played 9.13 games (*SD* = 5.09 games). The mean blinks/m across all the videos was equal to 18.2 (*SD* = 9.92) and the data had a positive skew distribution similar to what was found in other studies conveying the nature of blinks distributions [15, 26]. The mean blink duration across all the videos was equal to 206.94 ms (*SD* = 43.18), while the mean distance between blinks was 4.63 seconds (*SD* = 3.26). Table 2 provides an overview of the mean descriptive information of the 3 levels of expertise.

Considering that the 146 videos used for analysis belonged to 16 participants (videos nested in participants), in order to explore whether there is a significant difference between the three levels of expertise in the blink/s and blink duration, a mixed linear model (MLM) implemented in R (lme4 package version = 1.1-29) was run to predict blink/s and blink duration. In this model, the 146 videos were used as fixed factors while the participants were added to the model as random intercept (grouping variable). The results show that the model has a total explanatory power of 0.68 (conditional R2) where the marginal R2, accounting for the fixed effects, was equal to 0.21. The model was implemented using Experts as reference category with the model's intercept being at 26.51 (*95% CI [18.56,*

Table 2: Descriptive statistics of the 3 groups.

	Novices n=4	Intermediates n=8	Experts n=4
Hours p/wk gaming	1.75 (SD : 1.30)	8.31 (SD : 2.51)	19.75 (SD : 3.90)
Experience (Self-assess)	1.5 (SD : 0.5)	3.75 (SD : 0.44)	4.75 (SD : 0.43)
Avg. of games	5.5 (SD : 2.69)	11.75 (SD : 5.40)	7.5 (SD : 2.87)
Avg. game duration	5.04 min (SD : 1.84)	7.17 min (SD : 3.51)	7.34 min (SD : 4.17)
Blinks/m	13.55 (SD : 7.70)	16.18 (SD : 8.44)	27.77 (SD : 11.01)
Avg. blink duration	221.12 ms (SD : 50.24)	199.19 ms (SD : 43.29)	228.16 ms (SD : 26.45)

34.47], t = 6.59, p < .001) and the level of expertise having an negative effect for both Novices (*B = -15.67, 95% CI [-27.07, -4.26], t = -2.72, p = 0.017; β = -1.57*) and Intermediates (*B = -11.11, 95% CI [-20.81, -1.41], t = -2.26, p = 0.042; β = -1.12*) showing that groups with lower levels of expertise have an overall lower blinks/m. After having fit the model, a Tukey-Kramer test was run for post-hoc correction between the 3 groups to detect significant differences. The results, listed in Table 3, show a significant difference between Novices and Experts ($B < .05$)

Table 3: Results of the Tukey-Kramer post-hoc test to evaluate the difference in blinks/m across the 3 groups.

	B	SD	*t*	*p*
Experts-Intermediates	11.11	4.91	2.66	.10
Experts-Novices	15.67	5.77	2.71	.04
Intermediates-Novices	4.55	5.00	0.91	.64

The same MLM was fit to predict blink duration in 3 levels of expertise obtaining a conditional R2 equal to 0.52 and a marginal R2 of 0.02. The results show that blink duration intercept seems to decrease as the level of expertise decreases. However, no significance was found when comparing the reference category Expert, with the model intercept being at 225.94 (*95% CI [195.01, 256.86], t = 14.44, p<.001*) with Intermediates, (*B = -20.09, 95% CI [-57.72, 17.55], t = -1.06, p = 0.31, β = -0.46*) and Novices (*B = -23.43, 95% CI [-67.96, 21.10], t = -1.04, p = 0.32, β = -0.54*). Given the lack of significance in the MLM, no post-hoc correction analysis was run.

To further explore the effectiveness of using blink-related information to discriminate the level of expertise across three groups, we train a Random Forest Classifier solving the class imbalance by balancing the weights (RFC-BW) and a Random Forest Classifier solving the class imbalance using the SMOTE function (RFC-SM) [6]. The difference between RFC-BW and RFC-SM is that the former classifier sets different weights to the classes so that the underrepresented classes will have higher weight while the RFC-SM upsamples the number of instances in the represented classes; both methods are used to balance imbalanced datasets. The results were compared to a baseline classifier, a Dummy Classifier (DC), that always returns the most frequent label. The metrics adopted for the evaluations and the results of the comparison, obtained using a 5-fold cross-validation, are listed in Table 4

Table 4: Classifier performance

	Acc.	ROC-AUC	Prec.	Recall	F1
DC	0.64 (SD: .01)	0.50 (SD: .00)	0.41 (SD: .02)	0.64 (SD: .01)	0.50 (SD: .02)
RFC -BW	0.81 (SD: .06)	0.90 (SD: .07)	0.83 (SD: .06)	0.81 (SD: .06)	0.81 (SD: .06)
RFC -SM	0.89 (SD: .03)	0.98 (SD: .01)	0.90 (SD: .03)	0.89 (SD: .03)	0.89 (SD: .03)

The results obtained by both the RFC-BW and RFC-SM show performance above chance with a respective accuracy of 0.81 and 0.89 and a ROC-AUC score of 0.90 and 0.98. After having performed the classification task, an Extra Trees method was run to detect the level of contribution for each single feature (figure 6).

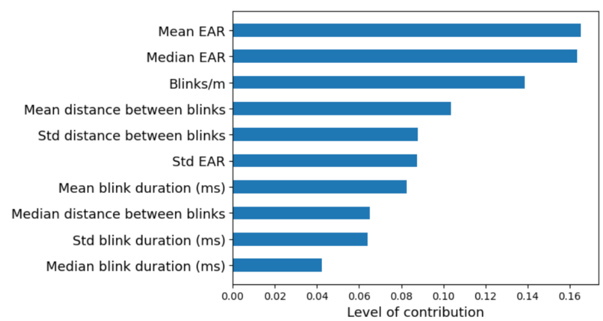

Figure 6: Features extracted and their level of contribution.

Interestingly, the results show that the two top features are extracted from the EAR. This might be the case since EAR information may be a proxy for general eye behavior and not only for blinks-related information. In our data, Expert and Intermediates have higher values of eyelid ratio (both with a M = 0.083 and a SD = 0.005) than Novices (M = 0.079, SD =0.012).

5 DISCUSSION

This study aimed to assess whether blink patterns can be used to discriminate between players with different levels of expertise during a Hearthstone tournament. We found Novice players and Experts to have a significant difference in blinks/m but no other significant difference was found when comparing the other groups. However, the increasing values in blinks/m across the 3 groups seem to suggest that blinks/m increases gradually with the gaining of expertise. Blink duration was not found significant when comparing the 3 groups. Nevertheless, the Random Forest Classifier provided satisfying results in discriminating players with different levels of expertise.

The results obtained in the classification task provide evidence that blink behavior, or more generally EAR- features, may be used effectively to discriminate between levels of expertise in video game players. Previous research has shown that blinks-related measures may reflect cognitive performance and cognitive flexibility [18, 33], and perceived stress [3, 7]. In line with these studies, we observed that experts blinked more during our Hearthstone tournament. The mean EAR during feature selection was found to have higher values in both Intermediates and Experts compared to Novices, high values in the EAR might either represent lower tension in the eye or a proxy for eye-opening connected to the number of blinks. Overall, it may be possible that more experienced players experience less stress during the tournament, which in turn mitigates the effect of cognitive load on blink patterns and the tension in the eyelids represented by the mean EAR. Less experienced players may experience more stress, perhaps as a result of a higher cognitive load. That said, differences in stress levels may also be affected by one's opponent. For example, when facing an "Expert", other expert players might be likely to experience more stress than when they face a "Novice" and show a decrease in blinks/m and blink mean duration, even though the latter is not significant in the MLM model. To settle this issue and validate this interpretation, future studies should investigate the effect of the other opponent on the player by treating it as an experimental manipulation.

A limitation affecting this study is the limited sample size (only 16 participants). Such a limited sample size might have swayed our classifier results in learning specific players' behaviors. Future studies might repeat this work with a bigger sample size comparing variations in Blinks/s and blink duration obtained at baseline and during the task. Such an approach might confirm our interpretation of the EAR values and further support the idea that cognitive workload and stress are related to blinks/m variations when performing a task.

Another aspect that seems to support the idea that stress is responsible for the effect we see in our study, is that neuroscience has established a direct link between blink frequency and the striatum, which is an area of the brain with a relatively dense population of D2 dopamine receptors [18]. The striatum is connected to, among other things, the pre-frontal cortex (PFC) and the ventral tegmental area (VTA), which are important to managing stress. These areas are also involved with executive functioning, motivation, and reward [21]. So, the pattern we observe here is at least in part explained by experts being able to respond better to the dopamine release. Experts, having learned how to deal with the game, might have a better response to the dopamine activity caused by specific events. This hypothesis seems to be supported by evidence in neuroscience where mild and intermittent stressors enhance dopaminergic activity in the VTA while chronic stressors decrease such activity [18].

A related interpretation of our results is that blink patterns are directly related to task difficulty. While playing Tetris, for example, blink frequency decreased as the level of difficulty increased [3, 22]. However, experts may find even higher difficulties undemanding, which would explain their maintaining the same blinking pattern as for lower levels of difficulty. If this is also true of Hearthstone, levels of expertise might moderate the effect of cognitive load on blink patterns.

Independently of these interpretations and their implications on video game expertise, our results showcase a novel non-invasive method of identifying a player's level of game mastery. This means that our methods can be applied during live competitive Esports broadcasts (the majority of which contain player face cameras) to provide an estimate of players' cognitive load, stress, or expertise during gameplay. Such aspects may be generalized to other tasks not strictly related to the gaming world and where expertise can not be estimated upfront. Furthermore, the application of this method might be used to estimate the effect of training in preparation for Esports tournaments and to detect if players unintentionally provide information about their hands to their opponents. A previous study, for example, showed that blink-related patterns provide information that modulates speaker length's response [16] while another study suggested that reduced blink frequency may occur when an observed object is perceived as relevant [23, 31]. Given this evidence, our method might be potentially used to assess the relevance of the information only accessible directly to the players and their capability of hiding it by displaying a "Poker face". Finally, given the relevant connection between blink patterns and dopaminergic activity, this method might also be effective to track behavioral changes connected to dopaminergic activity such as neurological and psychiatric disorders, like Parkison's or depression, and tracking the development of fundamental social cognition, such as the theory of mind [17–19].

6 CONCLUSION

In sum, the methods used in this study proved to be effective in estimating expertise in video games, however, results should be confirmed by more fine-grained measures, such as an eye-tracking device. The results of this study seem to suggest that extracting blink patterns from videos can be effective in providing information about expertise and players' behavior. Future research might apply this method to study behavior in other videogames and to test its effectiveness when applied in other fields.

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