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Time to decide: Diurnal variations on the speed and quality of human decisions

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ABSTRACT

Human behavior and physiology exhibit diurnal fluctuations. These rhythms are entrained by light and social cues, with vast individual differences in the phase of entrainment - referred as an individual's chronotype - ranging in a continuum between early larks and late owls. Understanding whether decision-making in real-life situations depends on the relation between time of the day and an individual's diurnal preferences has both practical and theoretical implications. However, answering this question has remained elusive because of the difficulty of measuring precisely the quality of a decision in real-life scenarios. Here we investigate diurnal variations in decision-making as a function of an individual's chronotype capitalizing on a vast repository of human decisions: online chess servers. In a chess game, every player has to make around 40 decisions using a finite time budget and both the time and quality of each decision can be accurately determined. We found reliable diurnal rhythms in activity and decision-making policy. During the morning, players adopt a prevention focus policy (slower and more accurate decisions) which is later modified to a promotion focus (faster but less accurate decisions), without daily changes in performance.

1. Introduction

Living organisms exhibit diurnal fluctuations driven by internal circadian clocks, which persist (with a close to 24 h period) in the absence of external cues (Panda, Hogenesch, & Kay, 2002). As in other species, human circadian rhythms are synchronized by light cycles and social cues (Roenneberg, Kumar, & Merrow, 2007; Wittmann, Dinich, Merrow, & Roenneberg, 2006). Individual differences in entrainment phases (which are defined as the difference between the subject's internal phase and the external time cues), known as "chronotypes", determine the existence of late owls (subjects with Late preferences), early larks (subjects with Early preferences) and intermediate types. Chronotypes can be assessed using standard questionnaires regarding diurnal preferences (MEQ, Morningness–Eveningness Questionnaire (Horne & Ostberg, 1976)), or sleep habits on working and free days (MCTQ, Munich Chronotype Questionnaire (Roenneberg, Wirz-Justice, & Merrow, 2003)). Both scores are highly correlated and also correlate tightly with physiological phase markers (Baehr, Revelle, & Eastman, 2000; Horne & Ostberg, 1976; Kudielka, Federenko, Hellhammer, & Wust, 2006; Zavada, Gordijn, Beersma, Daan, & Roenneberg, 2005).

Circadian variations in physiological and cognitive functions have been demonstrated using constant routine or forced-desynchrony protocols (Schmidt, Collette, Cajochen, & Peigneux, 2007; Wyatt, Ritz-De Cecco, Czeisler, & Dijk, 1999). However, there is a paucity of data on how cognitive function in real life scenarios varies throughout the day and whether this varies according to chronotype. Theories of circadian function postulate that cognitive performance is modulated by both circadian and homeostatic processes (which also control the wake-sleep cycle) (Borbely, 1982; Daan, Beersma, & Borbely, 1984; Goel, Basner, Rao, & Dinges, 2013). One factor that has been postulated to influence cognitive function is sleep pressure. This homeostatic component accumulates sleep drive constantly throughout the wake periods. It then results in a monotonic degradation of cognitive function as a function of the progressive accumulation of time without sleep

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(Schmidt et al., 2007). However, empirical studies find that fluctuations in behavior do not simply change monotonically throughout the day. This is because sleep pressure interacts with the circadian drive; a periodical fluctuation of physiological variables which among other things regulate the threshold needed to trigger sleep, but also might be able to counteract the effects of sleep pressure in cognitive functioning (Goel et al., 2013; Schmidt et al., 2007). These variables interact in a complex way, in fact the phase of circadian performance (the moment of the day in which one achieves maximal performance) varies with the nature and complexity of cognitive tasks (Goel et al., 2013). In simple tasks, performance is normally associated with body temperature rhythms (better performance when temperature is high –during the day-, worse performance when temperature is low –during the night-) reflecting an effect of a daily rhythm in arousal. Instead, higher order cognitive processes exhibit daily modulations but do not systematically reflect arousal rhythms or changes in physiological parameters (Horne, 2012; Schmidt et al., 2007). There are several intrinsic difficulties in these studies. One is that these tasks tend to show more learning modulations than simple tasks. Hence, the non-stationary nature of the task repetitions (in different days and moments of the day) can become problematic. To overcome these difficulties, performance in complex cognitive tasks is normally evaluated using between-subject designs or is assessed only in two times of the day in each subject, usually testing at optimal and non-optimal time of the day (inferred by subjects' chronotypes), showing that participants perform better when tested at their preferred time (synchrony effect) (Hidalgo et al., 2004; May, 1999). In laboratory settings, the influence of sleep pressure and circadian rhythms can be controlled independently. Instead, when cognitive function is measured in real-life conditions, these factors are very difficult to parse out because circadian rhythms and sleep pressure tend to be correlated. For instance, late chronotypes tend to wake up later and hence at night there is a difference both in that it is their preferred time, but also that they have less sleep pressure. In addition, there are several variables such as meal times, the amount of physical activity which interact with the circadian clock and which vary widely and are hard to control in real life settings (Schmidt et al., 2007).

In summary, there is substantial evidence and theoretical support for daily variations in several aspects of human performance including very low-level tasks (such as psychomotor vigilance task), memory tasks, complex tasks, sports (Blatter, Opwis, Munch, Wirz-Justice, & Cajochen, 2005; Facer-Childs & Brandstaetter, 2015; Johnson et al., 1992; May & Hasher, 1998; Wright, Hull, & Czeisler, 2002). These changes result from a complex interaction between two governing factors: sleep pressure and circadian rhythms. However, one aspect which remains unknown is whether decision-making changes throughout the day. One exception is a study of judges showing that the percentage of favorable rulings abruptly change along the day in relation to food breaks (Danziger, Levav, & Avnaim-Pesso, 2011).

Here we set out to investigate diurnal fluctuations in human decision-making, capitalizing on online rapid chess servers. Indeed, these public repositories offer a huge amount of data of human decision-making in natural conditions and without the problems associated to the repeated testing (a main problem when evaluating diurnal profiles in higher order functioning).

Chess has been widely used in psychology and cognitive neuroscience as a model for studying complex human thinking and decision-making in a controlled but natural way (Charness, 1992; Connors, Burns, & Campitelli, 2011; de Groot, 1978; F. Gobet & H. A. Simon, 1996; Leone, Petroni, Fernandez Slezak, & Sigman, 2012; Sigman, Etchemendy, Slezak, & Cecchi, 2010; Slezak & Sigman, 2012). Chess is a voluntary activity, players choose when to play and when to stop, and they have to make around 40 moves or decisions by game on a finite time budget. One of the main advantages of chess, compared to other decision-making domains, is that the quality of a player can be accurately determined through a rating system (Elo, 1978). Finally, a fundamental advantage of this setup is that a measure of the outcome of each decision can be determined accurately (Sigman et al., 2010).

Hence, analyses of chess playing allow us to precisely determine diurnal fluctuations not only in activity but also in the speed and accuracy of the decision-making process and how these fluctuations interact with individual chronotypes.

Based on previous evidence about diurnal fluctuations which we described above, we expect that individual diurnal preferences or chronotypes determine the daily changes in chess playing, with individuals being more active and effective in their optimal time (when time of day is in synchrony with their preferred time). In particular, we hypothesized that players would exhibit circadian fluctuations in speed and accuracy of the decisions revealing diurnal variations which depend on specific chronotypes. These may lead to two alternative hypotheses which here we seek to investigate: (H1) the entire efficiency of the decision-making system, revealed in more accurate and faster decisions varies with time of day according to chronotypes, or (H2) alternatively, circadian fluctuations affect regulatory aspects of decision-making such as the speed/accuracy trade-off (SAT). Hypothesis 1 seems plausible from current knowledge of circadian modulations of behavior reviewed above, revealing changes in performance. Instead, from a neurophysiological perspective, it is more natural to postulate that circadian modulation should affect and govern the SAT. This is because changing the SAT simply requires to change baseline neural activity in decision-related areas, with higher baseline responses when speed is given precedence over accuracy (Forstmann et al., 2008; Ivanoff, Branning, & Marois, 2008; Shadlen & Newsome, 2001). Circadian rhythms regulate the concentration of several hormones, including steroids and other molecules which in turn control basal levels of neural activity. Specifically, the decision threshold is mainly set by a circuit in the basal ganglia (Lo & Wang, 2006) and the basal ganglia is a brain region whose activity is modulated by circadian rhythms (Bussi, Levin, Golombek, & Agostino, 2014; Mendoza & Challet, 2014). Moreover, the SAT is related to stress (Rastegary & Landy, 1993) and the concentration of cortisol (which is a hormone which indexes stress) varies with a circadian rhythm (Krieger, Allen, Rizzo, & Krieger, 1971).

In addition, as described above, homeostatic daily fluctuations interact with circadian rhythms which are idiosyncratic for each individual. Hence, we expect that daily fluctuations should interact with an individual's diurnal preference. As described above this interaction is highly complex but overall we expect (based on the studies reviewed here) that the efficacy of decision-making should increase during the preferred time. Last, reflecting the interaction between homeostatic sleep pressure and circadian rhythms, the differences in phase between chronotypes should be smaller when testing time is referred relative to the phase of individuals' wake-sleep cycle.

We tested these hypotheses with international open-access databases of chess players playing games of different time budgets, which allowed us to evaluate the robustness of diurnal variations in rapid and slow decision-making scenarios.

2. Methods

2.1. Data acquisition

All games were downloaded from FICS (*Free Internet Chess Server*, http://www.freechess.org/), a free ICS-compatible server for

playing Internet chess games, with more than 400.000 registered users. This constitutes a quite unique experimental setup providing data from thousands of millions of decisions. Registered users may be human or computers and all have a rating (Glicko rating, http://www.glicko.net/glicko.html) that indicates the chess skill strength of the player, represented by a number ranging typically between 1000 and 3000 points. User ratings are updated depending on the result of every game played: when users win a game, their rating increases accordingly to the ratio between their opponent's rating and their own rating (i.e., if a player wins a game against a player ranked higher, his/her rating will increase more as compared to beating a player with a similar or lower rating).

Chess games could be played using different time controls and long thinking times are generally associated with a higher quality of play (A. Gobet & H. A. Simon, 1996; Chabris & Hearst, 2003; Jeremic, Vukmirovic, & Radojicic, 2010). In this work, we used games from three different time budgets: 180 s, 300 s, 900 s. On each time budget, each player has a total time to be used in the whole game. We performed global analyses using games from 180 s, 300 s and 900 s time budgets. As in our previous work (Leone, Fernandez Slezak, Cecchi, & Sigman, 2014; Sigman et al., 2010), we focused our discussion in 180 s games because: 1-rapid processes (related with pattern recognition) are good indicators of chess expertise (Burns, 2004), and 2-the FICS database for 180 s games has more games than for longer time budgets.

One concern with rapid chess is that it can lead to situations of extreme time pressure where a player has to make many moves in a few seconds. To avoid this very particular situation, for all analyses, we only considered moves where the available time was higher than 60 s. We also excluded the first 30 s of the game, in the opening stage, where many players play from memory.

We contacted FICS players with more than 2000 games with a total time budget of 180 s per game, played from November 2008 to June 2015. We asked them their Time Zone and their age, and to fill the Morningness-Eveningness Questionnaire (MEQ) (Horne & Ostberg, 1976) using a website (http://chess-time-zone.dc.uba.ar/timezone/). We only asked for the FICS username, which hides the real name. Absolute confidentiality and anonymity were strictly ensured. For 180 s, our sample included 94 subjects (with more than 2500 games) (age: 19–66 yr, only one player did not share his/her age), who completed both their Time Zone information and their MEQ questionnaire. 30% of the players live/play within GMT +1 (Central European Time Zone). The Time Zone information was necessary to correct the FICS time-stamp (Pacific Time, GMT −8) to the real time of each subject. If the total number of games of a player was higher than 20,000, we randomly selected 20,000 games (this was the case for 40 of the players). We also obtained a sample of players of 300 s games (n = 55, where 50 were members of the 180 s sample) with more than 500 and a maximum of 10,000 games (if players had more than 10,000, we randomly selected 10,000) and sample of players of 900 s games (n = 35, where all were members of 300 s sample) with more than 300 games (and a maximum of 10,000). 24 players were members of the three samples (some players only play a single kind of total time budget games). The number of games per player for each time budget and the number of subjects reflected the fact that FICS users play many more games of short time budgets (180 s).

Computers were excluded from all analyses, with the only exception of a specific control where we analyzed the 180 s games of 14 computers who play regularly in FICS, since computers are not expected to have diurnal fluctuations in the decision process.

We asked players to complete a short questionnaire about diurnal routines, including questions about sleep and meal habits in both working and weekend days, including the wake up times. A subset of the player sample (n = 30) completed the questionnaire and using this information we obtained a Mean Wake up time for each player ((5 ∗ Wake up time in working days + 2 ∗ Wake up time in free days)/7). Then, we represented variations relative to Time since awakening, considering the time of day where each player wakes up (on average, as we explained in the previous paragraph) as time zero.

2.2. MEQ questionnaire distribution

The Morningness-Eveningness questionnaire (MEQ) is composed of 19 questions and results in a score (MEQ score) of 16–86 points: low scores indicate evening or late preferences, and high scores indicate morning or early preferences. According to Horne and Ostberg, late types are those subjects with a MEQ score lower than 42 and early types, those with MEQ score higher than 58 (Horne & Ostberg, 1976). Using these limits, our sample included 33.3% of late types, 9.1% of early types and 57.6% of intermediate chronotypes. However, these limits were established for a young American sample and there are evidences showing than the limits should be established depending on culture (Caci et al., 2005) and age range (Adan, Caci, & Prat, 2005). In order to avoid the effect of cultural differences and age range, and comparing three groups with a similar number of subjects on each subsample (180 s, 300 s, 900 s), we split the distribution of MEQ scores into tertiles. For our 180 s sample, the MEQ score limits of each tertile were 41 and 51.54: the late group has a mean MEQ score of 33.59 (n = 32), the intermediate 46.1 (n = 30) and the early group 58 (n = 32).

2.3. Activity daily patterns

Every human player voluntarily chooses when to play chess online. FICS database is public: everyone has access to all these time-stamped public games. All games were first associated to an hour (i.e., divided into 1 h bins) and to a day of the week. Then, we converted GMT −8 daytimes to each user real time, using individuals' Time Zones. For each subject, the daily activity fraction was calculated on each time bin (1 h) dividing the number of games within the window by the total number of games. The number of games played on every hour of the day (after Time Zone correction and referred to total number of games) defines the activity pattern of each subject. To compare activity levels in different Day shifts (8–13 h, 15–20 h and 22–3 h), we added the corresponding activity fractions.

2.4. Decision variables

The degree of proficiency of a FICS chess player is documented in the website and changes according to game results. Each registered user has an associated rating that indicates their chess level, represented by a number between 1000 and 3000 points (calculated using Glicko rating system (Glickman, 1999)). Individual rating is updated after each game and depends on the game result, the opponent's strength and the rating deviations of both competitors (which indicate how frequently each player competes, http://www.glicko.net/glicko/glicko.pdf). In our case, users play frequently (2500–20,000 games for 180 s time budget) and they should have a low and stable rating deviation. The rating of a player shows fluctuations and one of our main aims was to identify whether these fluctuations were locked to circadian rhythmicity. To this aim, the rating mean was calculated on each 1-h bin for each subject and then normalized to their daily mean.

Another possibility to investigate quality in single moves is to determine the change in the value (dValue) of the position (see (Sigman et al., 2010). Briefly, we analyzed the moves and calculated the score of each position using Stockfish, an open source chess engine with a predefined depth of 12 plies (each ply is a

movement from one player). Using these scores, we obtained a dValue for each movement (Sigman et al., 2010), which is calculated subtracting the values of successive position scores. In bad moves (errors or blunders), the score of the positions decreases substantially and hence the dValue is indicative of the magnitude of errors (when a player lose a Bishop, the dValue is smaller than it the player lose a Rook). dValue has in general negative values, but we multiplied the original values by −1 and then higher positive values indicate worse errors. Moreover, we replaced dValues higher than 10 by dValue = 10 (because when a player missed a check mate, dValue is 999, and 9 represented the lost of a Queen). However, this measure is extremely variable and shows very weak effect sizes even when integrated across the entire day activity (Slezak & Sigman, 2012). This broad variability is due to the fact that a very simple and naive error such as blundering a piece directly, or a very sophisticated error due maybe to missing a complex variation which ends in losing a piece after 6 movements, is equally weighted by this measure. Then, we defined errors or blunders as those moves with a dValue higher than 1 (which is equivalent to the loss of a pawn). This threshold (dValue = 1) could appear strict but after this type of error a chess engine and a Grand Master of chess will qualified the position as clear advantage for the opponent.

Each chess movement is associated with a Move Decision time, which is the time elapsed between the last opponent movement and the player's own move. We use the more succinct term "Decision Time" from now on to refer to "Move Decision Time". Base 10 logarithm of mean Decision time (log(Decision time)) was calculated on each game and then these values were averaged on 1-h bins for each subject and then normalized to the subject's daily mean. Decision time Variability (standard deviation of the decision times) was computed on each game; these values were averaged on 1-h bins for each subject and then normalized to the subject's daily mean.

Rating is a measure of performance which integrates the winning rate over a series of games; although it is affected by the use of the time (a player could lose a game not only because of playing bad, but also because of a bad time usage).

For all analyses, we only used the fraction of each game where players are not guided by opening theory and they are not highly affected by time pressure. For 180 s games, we averaged previously described decision-associated variables over the part of the game where players had more than 60 s and less than 150 s of remaining time (usually the middle game). For 300 s games, we did the same with those moves made with more than 90 s and less than 255 s. For 900 s games, we selected moves made between 120 s and 780 s.

2.5. Time and weekdays intervals

To calculate correlations between daytime/nighttime activity differences and MEQ score, we considered daytime, from 8 to 13 h and from 15 to 20 h, and nighttime from 22 to 8 h. For each player, we added the corresponding 1-h bin values on each Day shift, and then we calculated the difference (daytime – nighttime). To show daily variations in activity along the day, we used three time shifts: Morning (8–13 h), Afternoon (15–20 h) and Night (22–3 h).

Monday to Friday were considered "working days" and Saturday and Sunday, "weekend days". Working days/weekend days activity differences were calculated for three different shifts (see above). We normalized the data of each subject dividing each 1-h time bin activity on the average working or weekend day by the average total activity (i.e., total activity divided by 7), obtaining a fraction of activity which allowed us to compare activity levels between working and weekend days. To compare activity levels during daytime and nighttime, we added the activity fractions of the respective time bins.

For other variables, we used only two Day shifts: Morning (8–13 h) and evening (17–22 h), where there was no main effect of time in activity, and we averaged the corresponding 1-h bin values on each Day shift.

2.6. Statistics

We investigated changes in decision variables and activity as a function of MEQ score using two different procedures: (a) Group analysis where we divided our sample in three groups using MEQ score tertiles (see above). Since the MEQ score distribution did not show modes and was close to Gaussian, we followed this analysis with a continuous linear regression where we accounted for the full variability of MEQ score.

Global analyses were conducted using Repeated Measures ANOVAs with Age as a covariate; Time Budget (180 s, 300 s, 900 s) and MEQ score group (or Chronotype: Late, Intermediate and Early) as between subjects factors; and Day Shift (Morning, Afternoon and Night –for Activity- or 8–13 h–17–22 h, for other variables) as the within-subjects factor.

MEQ score and daily differences associations were tested using Pearson correlation analysis (for all variables). A 2×2 Repeated measures Two Way ANOVA was used to test the effect of the main factors "Working hours/Night" and "Working/Weekend days", for activity. All data is represented as mean ± SEM.

All analyses were made with normalized data (using the total activity of each subject to calculate activity fractions and the daily mean of each subject for the other variables). This is important to state because it eliminated main differences between Time budgets and possible Age differences. For example: Decision time is longer in 900 s games compared with 180 s games, but we eliminated these differences with our normalizations to study diurnal fluctuations and their interactions with other factors. Power analyses of Observed and simulated data are included in Supplementary Table 1.

3. Results

Here we studied diurnal changes in activity, performance and decision-making properties from online chess games. All participants stated their Time Zone and completed the Chronotype questionnaire (Horne & Ostberg, 1976), which allow us to obtain their Morningness-Eveningness Questionnaire (MEQ) score. Demographic data is presented in Supplementary Fig. 1. As it was previously reported, MEQ score increases significantly with age (Pearson correlation, $r(98) = 0.3294$, $p = 0.0009$) (Supplementary Fig. 1D) (Iwasaki et al., 2013; Paine, Gander, & Travier, 2006; Taillard, Philip, & Bioulac, 1999).

3.1. Activity daily pattern

First, we determined whether chess-playing activity oscillates along the day and if the distribution of activity depends on the players' diurnal preferences.

We analyzed the Activity levels changes as a function of Day shift (within factor, with three levels: 8–13 h, 15–20 h and 22–3 h), MEQ group (between factor, with three levels: Late, Intermediate, Early), Time budget (between factor, three levels: 180 s, 300 s and 900 s) and Age (covariate). We found a significant interaction of Day shift with MEQ score (Repeated Measures ANOVA, $F(4,346) = 18.50$, $p < 0.0001$). However, interactions of Day shift with Age and Time budget were not significant. Power analyses

for Activity and other variables are included in Supplementary Table 1.

These results indicate that the interaction between Day shift and MEQ group (chronotypes) modulates Activity changes. Then, we studied the nature of the interaction between Day shift and MEQ group in 180 s games[1].

The global pattern of Activity exhibited diurnal fluctuations, with high levels during the afternoon and low levels at night (Fig. 1A). However, some players experienced their peak of Activity at night and others during the morning hours. Day-night Activity difference significantly correlated with MEQ score ($r(94) = 0.54$, $p < 0.0001$). This indicates that Early types had more daytime Activity and, conversely, Late types more nocturnal Activity (Fig. 1B). In addition, Activity bursts start earlier according to the MEQ score: Late types exhibited a delayed onset as compared to the Early types (Fig. 1E). Daily patterns of Activity for different MEQ groups showed the same result (Fig. 1C). Post hoc Sidak's multiple comparisons test showed that all players are significantly more active in the afternoon than during the morning. However, Late players are significantly more active during the night than during the afternoon (significantly higher than night Activity of Early types (Fig. 1D)). We observed similar differences in Activity daily patterns in longer games (300 s and 900 s), showing that players do not choose their playing Time budget in a different way along the day (Supplementary Fig. 2).

3.2. Activity in working and weekend days

Previous studies have shown that most people sleep more hours and sleep later at the weekend (Roenneberg, Allebrandt, Merrow, & Vetter, 2012; Roenneberg et al., 2004). We reasoned that the amount of play may also show variations during the week, revealing that this spontaneous leisure activity is limited by work schedule. Specifically, we hypothesized that (1) people will distribute their activity differently along the week: they will play much more during the daytime (working hours) at the weekend than during the working days, and (2) the time of playing at the weekend will be more determined by an individual's chronotype than during the week.

Diurnal patterns of 180 s games Activity (Fig. 2A) revealed differences in the number of games: people play more games during daytime, independently of the day of week (Repeated Measures Two Way ANOVA with Working/Weekend days and Daytime/Nighttime as main factors yielded only a significant main effect of Day shift ($F(1,93) = 5.93$, $p = 0.017$) (Fig. 2A, inset)). These results indicate that people play more games during daytime, independently of the Day of the week. Then, and opposite to our first hypothesis, we found no differences on the levels of daytime Activity between weekend and working days.

To test hypothesis 2, we analyzed the association between the MEQ score (index of Eveningness or Morningness) and the difference between working-weekend day Activity in three day shifts: morning (from 8:00 to 13:00 h), afternoon (15:00–20:00 h) and night (22:00–03:00 h). We found a significant association between morning Activity (Fig. 2B) during the weekend and MEQ score: high morning Activity during the weekend is associated with high MEQ scores (Early type) ($r(94) = -0.28$, $p = 0.0066$). Weekend afternoon Activity was higher for low MEQ scores (Late type), but the correlation did not reach significance level ($r(94) = 0.18$, $p = 0.082$). At night, we found no association between working-weekend Activity differences and MEQ scores ($r(94) = -0.057$, $p = 0.59$). Taken together, these results indicate that players play more games during what would be normal working hours or daytime, independently of the day of the week. At the weekend, Early types are more active in the morning and Late types in the afternoon. The frequency of night playing was not affected, which could be expected since the majority of players can play during the evening even during the working days.

3.3. Diurnal oscillations in decision-making policies: Decision time

First, we investigated whether decision time changes during the day and according to chronotypes. Here we concentrate on two estimators of time usage: logarithm of Decision time (log(Decision time)) and Decision time Variability (standard deviation). The first one provides an estimate of the center which may be more adequate than the mean given the non-Gaussian and long right-tail distribution of the data (Fig. 3A and B). However, in chess games, some decisions are made very rapidly and others require long deliberation. Hence, Decision time Variability may provide an even more sensitive estimator of changes in time policy. As both variables were highly correlated (Fig. 3C), we continued the analyses for log(Decision time).

We globally tested the effect of Age (covariate), MEQ group (Late, Intermediate, Early) and Time budget (180 s, 300 s and 900 s) on the log(Decision time) daily changes (8–13 h and 17–22 h). This analysis yielded a main effect of Day shift (Repeated Measures ANOVA, $F(1,170) = 7.73$, $p = 0.006$) and a significant interaction between Day shift and MEQ group (Repeated Measures ANOVA, $F(2,170) = 4.91$, $p = 0.0085$). Neither Age or Time budget affected daily fluctuations on log(Decision time). These results show that Decision time changes with time of the day and that Chronotype modulates these diurnal fluctuations. Then, we studied the nature of the interaction between Day shift and MEQ group in 180 s games.

Decision time is longer during 8–13 h shift for all MEQ score groups (Fig. 3D) and MEQ score modulates differences between Day shifts (Fig. 3E). Fig. 3F shows that Decision time is longer during the morning for all chronotypes (compared to the evening), and Chronotype modulates the amplitude of daily differences. Similar results were observed for Decision time Variability (Supplementary Fig. 3) and in other Time budgets (Supplementary Fig. 4).

As we were specifically interested in diurnal changes (within subjects) and not in the magnitude of Decision time, our data was mean-normalized before the analyses. Hence, our analyses could inform whether Age had an effect on diurnal differences, but not whether Age affected the overall decision time. However, non-normalized data exhibited significant and negative correlations between Age and Decision time for the three Time budgets (180 s games: $r = -0.28$, $p = 0.0066$; 300 s: $r = -0.34$, $p = 0.012$; 900 s: $r = -0.30$, $p = 0.08$), i.e. older participants played faster.

As conclusion, we observed a consistent diurnal fluctuation in Decision time which is modulated by chronotypes. The pattern observed is that players use more time (with higher variability) during the morning, and less time (and lower variability) during the evening. This effect has higher amplitude in Early types than in Late types.

3.4. Diurnal oscillations in decision-making policies: Accuracy

Next, we investigated circadian variations in accuracy. To this aim, we concentrated on two variables: dValue and Error rate. The first one is a continuous measure (between 0 and 10) of the quality of decisions: higher dValue indicates lower accuracy. Error rate represents the blunder rate, with a threshold previously defined where a decision is considered to be an error if dValue is higher than 1 (which is equivalent to the lost of a pawn). Because

[1] We selected 180 s games to represent the global results and to study the interaction between Day shift and MEQ score. 180 s games were chosen because the number of subjects (and games per subject) is higher than in other Time budgets. This occurred for all variables.

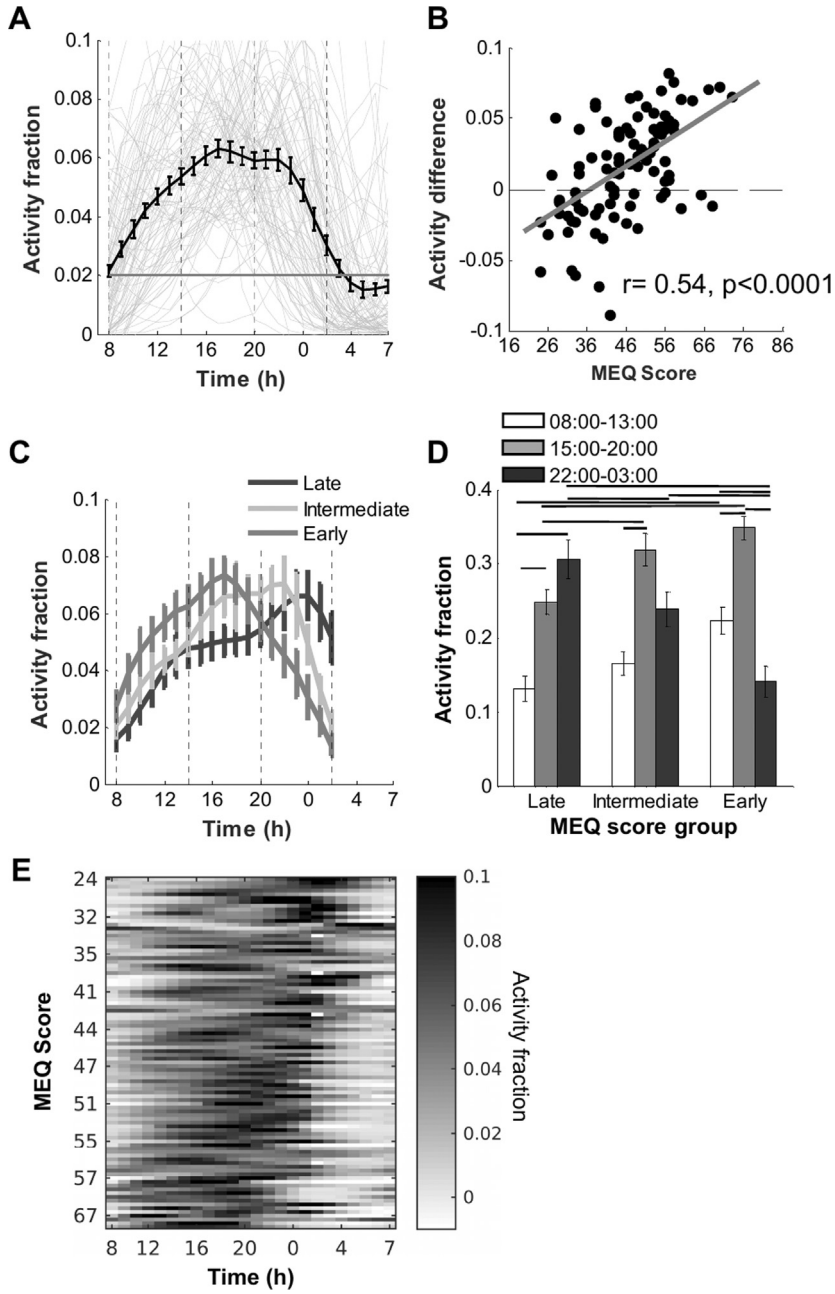

Fig. 1. Chess activity oscillates along the day. (A) Activity fluctuates with time. After Time Zone correction, Activity was normalized for each subject (total daily activity = 1). Between-subjects mean (±SEM) shows diurnal variations in the number of games played along the day (Time budget = 180 s, n = 94). Light gray lines show diurnal oscillations of individual subjects. The horizontal line indicates the 2% Activity threshold. (B) Day-night Activity differences significantly correlate with MEQ score: Late types (low MEQ score) show more negative values than Early types (i.e., daytime activity is lower than nighttime activity for Late types). (C) Daily patterns of Activity. Early types start to be active consistently earlier than Late types. (D) Activity depends on the interaction between Day shift and Chronotypes (MEQ score groups). Horizontal lines show significant ($p < 0.05$) differences between groups. (E) Grayscale-coded normalized Activity is plotted along the day for each subject (sorted by their MEQ scores, y-axis). Subjects with low MEQ scores (Late types) exhibited higher nocturnal Activity than subjects with high MEQ scores (Early types). Activity fractions were calculated on each subject based on the total number of games (M = 13300, SD = 6112, range 2500–20,000).

dValue and Error rate are highly correlated ($r = 0.8$, $p < 0.0001$), we analyzed only Error rate as our measure of accuracy[2].

We tested the effect of Age (covariate), MEQ group (Late, Intermediate, Early) and Time budget (180 s, 300 s and 900 s) on the Error rate daily changes (8–13 h and 17–22 h). This global analysis yielded a main effect of Day shift (Repeated Measures, ANOVA, $F(1,170) = 4.94$, $p = 0.028$), without significant interactions with any factor. These results showed that Accuracy was affected by Day shift without modulation of MEQ score groups, Age or Time budget. Fig. 4 shows the results for 180 s games.

Error rate is higher during 8–13 h shift, without MEQ score modulations (Fig. 4A–C). Similar results were obtained for other Time budgets (Supplementary Fig. 5).

As we were specifically interested in diurnal changes (within subjects) and not in the magnitude of Error rate, our data was mean-normalized before the analyses. Hence, our analyses indicate whether Age had an effect on diurnal differences, but not if Age

[2] We chose Error rate because dValue indexes the magnitude of errors and it has a long tail distribution (losing a small piece, a Rook or the Queen have very different dValues -approximately 3, 5 and 9, respectively-, but all these moves are errors that give decisive advantage to the opponent).

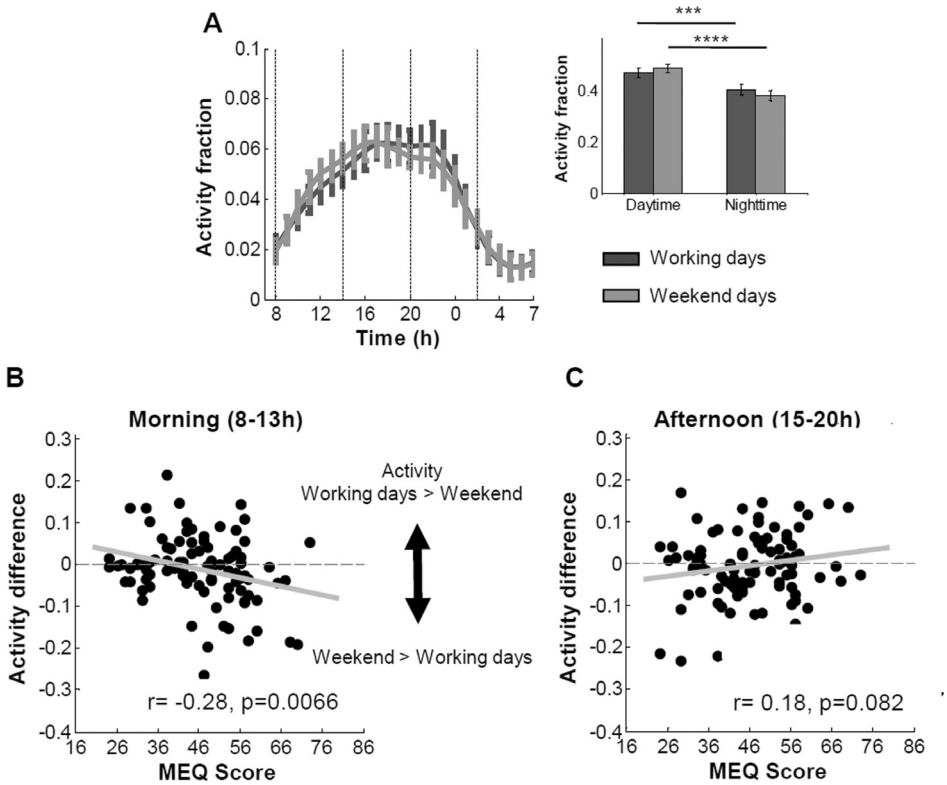

Fig. 2. Chess playing activity exhibits differences between working and weekend days. (A) Working days and weekend Activity patterns reveal similar average patterns with slight differences (Time budget = 180 s). Inset: daytime Activity is significantly higher for both working and weekend days, without differences between them. (B and C) During the weekend, subjects play more according to their chronotype. In the morning (8–13 h), we found an inverse correlation between Activity difference (working – weekend days) and MEQ score ($r(94) = -0.28$, $p = 0.0066$) (B), showing that the Activity for those player with high MEQ score (Early chronotypes) is higher in the 8–13 h shift of weekend than in working days. During the afternoon (15–20 h), we found a tendency towards a direct correlation between Activity difference and MEQ score ($r(94) = 0.18$, $p = 0.082$), with subjects with low MEQ score playing more games during this Day shift in weekend days than in working days (C). During the night (22–3 h), the correlation was non-significant ($r(94) = -0.057$, $p = 0.59$).

affected the overall Error rate. However, non-normalized data showed a significant correlation between Age and Error rate for the three Time budgets (180 s games: $r = 0.34$, $p = 0.0007$; 300 s: $r = 0.50$, $p = 0.0001$; 900 s: $r = 0.48$, $p = 0.0032$), i.e. older participant played less accurately.

Accuracy results showed that people make fewer errors during the morning, and they make more errors during the evening. Daily changes in accuracy did not depend on circadian preferences.

3.5. Diurnal oscillations in performance

To investigate if performance oscillates along the day, we analyzed fluctuations in players' rating.

We evaluated the effects of Age (covariate), MEQ group (Late, Intermediate, Early) and Time budget (180 s, 300 s and 900 s) on Performance daily changes (8–13 h and 17–22 h). This global analysis (Repeated Measures ANOVA) did not reveal any significant effect, suggesting that performance does not change with Day shift neither with its interaction with MEQ score.

In addition, we performed two controls to assure that the daily fluctuations we found in Accuracy and Decision time are indeed related to changes in individuals' decision-making properties and not in other factors. First, we evaluated whether the pool of players was the same at different hours, because it is possible that the ratings at different times of the day are not calibrated. To test this, we measured the daily fluctuations of rating in computers playing on the server. Computers play with a fixed algorithm and hence their rating is not supposed to show daily fluctuations, unless the average strength of (human) opponents systematically vary across the day. For instance, a computer would have a higher rating if there is a moment of the day in which the average quality of players is worse, because computers will win more often (on average). Our analysis showed no fluctuations in rating along the day on the computers group (One Way ANOVA yielded a non-significant main effect for Day shifts), thus discarding this possibility.

A second confound could be that players choose their opponents differently at different moments of the day, which could also explain daily differences in decision-making processes. However, MEQ score did not correlate with the Opponent Rating difference between 8–13 h and 17–22 h ($r(94) = -0.068$, $p = 0.52$) and a Repeated Measures Two Way ANOVA discarded this possibility. Thus, opponent rating is the same throughout the day and it is independent of the MEQ score (Repeated Measures Two Way ANOVA, non-significant main effects for Daytime, $F(1,88) = 0.64$, MEQ score group $F(2,88) = 0.08$; no significant interaction $F(2, 88) = 1.22$).

In summary, neither performance (as determined by rating) nor the choice/the distribution of opponents change along the day. A related but different concern could be diurnal preferences of opponents: if they are in their best time of day or if they are not. Our data does not allow us to study this possibility and then we could neither affirm nor discard that Early/Late types are playing only with Early/Late types, respectively (we did not have enough games played between two chronotyped users). However, since FICS users are not in the same Time Zone, opponents do not necessarily tend to have the same chronotype.

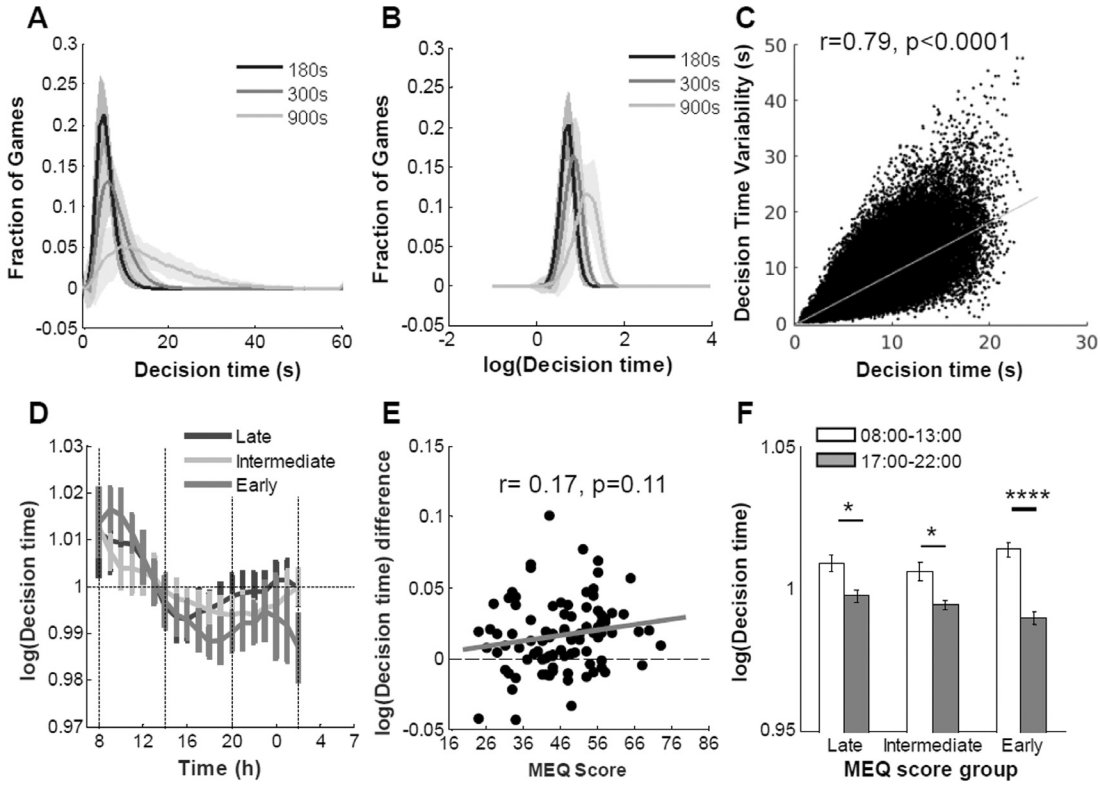

Fig. 3. Decision time exhibits daily fluctuations which are modulated by chronotypes. (A) The time used to make a movement (Decision time) on each Time budget (180 s, 300 s, 900 s) exhibits a non-Gaussian and long-right tail distribution. (B) Log(Decision time) transformation was calculated to obtain a better center-measure of Decision time. (C) Decision time and Decision time Variability highly correlated. (D) Log(Decision time) fluctuates along the day for all chronotypes in 180 s games. (E) Log(Decision time) differences between 8 and 13 h and 17–22 h shifts do not significantly correlate with MEQ score in 180 s games. (F) Log(Decision time) of 180 s games is significantly higher during the 8–13 h shift for all MEQ score groups and the amplitude of the difference is modulated by chronotypes. All data are mean-normalized.

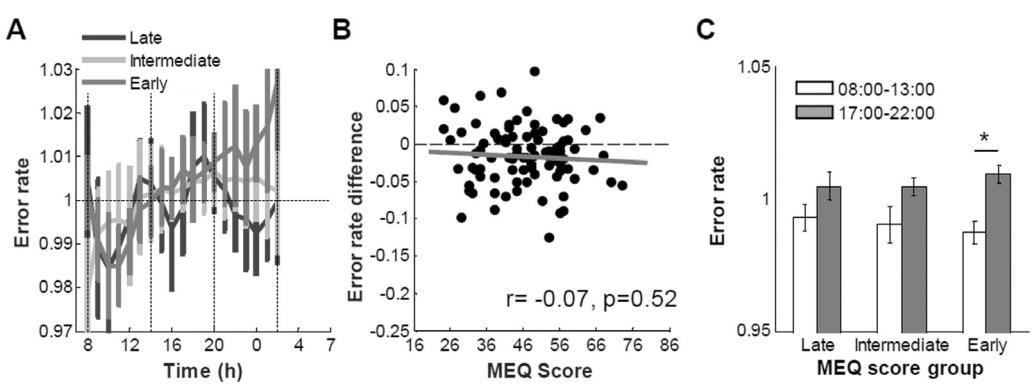

Fig. 4. Error rate oscillates along the day, without effect of chronotype. (A) Error rate fluctuates along the day for all chronotypes for 180 s games. (B) Error rate difference between 8–13 h and 17–22 h shifts does not correlate with MEQ score in 180 s games. (C) Error rate is lower during the 8–13 h shift, without a significant interaction with Chronotypes. The highest amplitude and significant difference in Error rate was obtained for Early types. All data are mean normalized (non-normalized Error rate: M = 0.2133, SD = 0.038).

3.6. Influences of sleep phase and/or Sleep pressure in our daily fluctuations

We previously evaluated Activity, Decision time, Accuracy and Performance as a function of time of the day. These diurnal fluctuations might be explained by the interaction between sleep pressure and circadian rhythms. In this case, our results are not compatible with an effect only determined by sleep pressure, since this should reflect a monotonically changing signal with different starting points for each chronotype (because they presumably have a different wake-up time). However, these results cannot factor out the effects of homeostatic sleep pressure and circadian rhythms and their interaction.

Circadian preferences and sleep pressure are naturally correlated since Late types wake up later and hence in the evening they are at their preferred time but also have accumulated less sleep pressure. The relation between these two variables is set by the wake-sleep cycle. Our observation that Activity and Decision time robustly depended on chronotype preferences may result as a consequence of circadian synchrony, sleep pressure, or both. It is difficult to disentangle these contributions in real-life measures because they are intrinsically correlated, in fact, in our sample wake-up time correlated with MEQ score (Supplementary Fig. 6A) and is significantly affected by MEQ score groups (Supplementary Fig. 6B). Nevertheless, we sought to determine which of these variables plays a greater role. To this aim, we measured

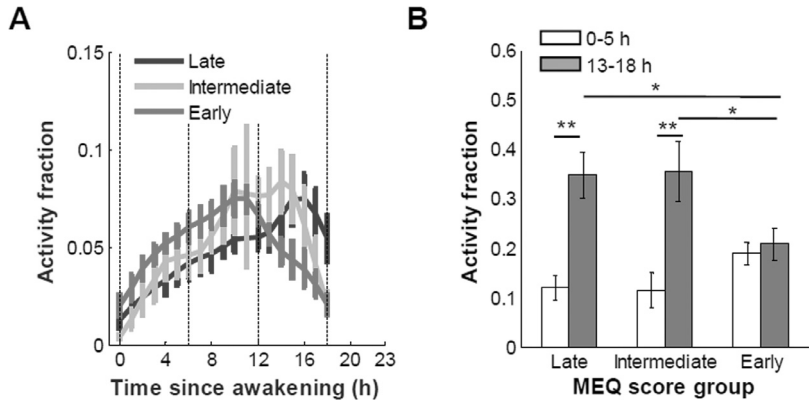

Fig. 5. Activity is modulated by both "Time since awakening" and its interaction with chronotype. (A) Activity changes with Time since awakening: all players increase their Activity according to the increase on Time since awakening, but chronotype modulates the amount of hours needed to reach the peak of Activity. (B) Activity levels significantly change according to "Time since awakening" and MEQ score group modulates the amplitude of the differences between 0–5 h and 13–18 h (Time since awakening) (Repeated Measures Two Way ANOVA, main effect of time $F(1,26) = 18.91$, $p = 0.0002$), interaction between Time and MEQ score group $F(2,26) = 4.39$, $p = 0.023$). All data is mean-normalized.

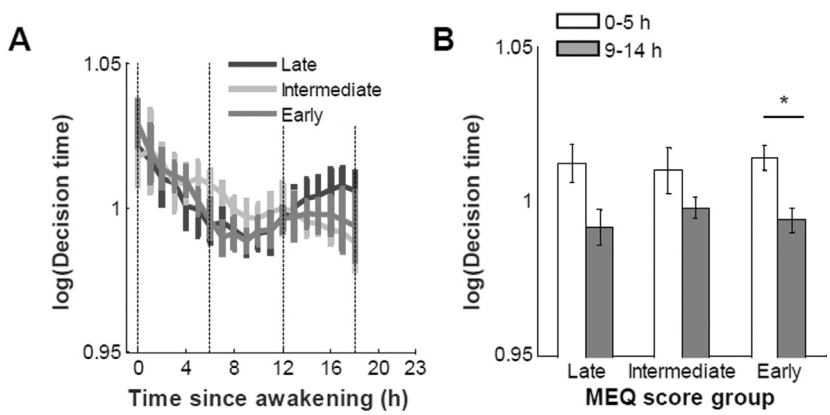

Fig. 6. Decision time is modulated by Time since awakening, without effects of chronotypes. (A) Log(Decision time) decreases with Time since awakening, without effects of chronotypes. (B) Decision time is longer during the first hours (Repeated Measures Two Way ANOVA, main effect of Time $F(1,26) = 16.28$, $p = 0.0005$). All data is mean-normalized.

Activity and Decision time as a function of "Time since awakening". If the MEQ score modulation we found previously on diurnal variations were due only to wake-up time differences between chronotypes, now we would find a main effect of Time since awakening, without MEQ score group modulation. However, if other intrinsic factors which characterized chronotypes were involved, chronotype modulation would be maintained.

Our results showed that Activity depended on Time since awakening, with Chronotypes modulating the phase of Activity changes (Fig. 5). Instead, modulations in Log(Decision time) (and also Decision time Variability) by chronotype preferences were fully accounted by wake-up time. Decision time is longer (Fig. 6) and more variable (Supplementary Fig. 7) during the first hours since time of waking up, and chronotypes do not affect these differences.

4. Discussion

Our results show that chess playing activity exhibited robust diurnal rhythms which interact with Chronotype (Early, Late) such that larks play more games in the morning and owls in the evening. There are mixed effects of diurnal rhythms on decision-making properties and there are not diurnal fluctuations in performance. Decision time varied robustly during the day, with subjects taking more time for each decision during the morning. In addition, there is an interaction with diurnal preference that accentuates this difference throughout the wake-sleep cycle: Early types have a greater difference in Decision time between day and night. Accuracy is high in the morning and decreases in the evening, without chronotype modulation. Performance did not show daily fluctuations or interactions with MEQ score. Then, our data discards the hypothesis that there is a time of the day when players play more efficiently, i.e. faster and more accurately. Our data reject this hypothesis showing instead that there is a change in decision-making policy: in the morning, players adopt a policy where decisions are slower and more accurate than in the evening, when decisions became faster but less accurate.

There are a handful of studies investigating temporal aspects of human behavior in natural conditions. School performance (grades) had been shown to depend on the interaction between time and chronotypes, but with testing times only in the morning and early afternoon (van der Vinne et al., 2015). Golder and Macy showed diurnal fluctuations on Twitter activity and mood (based on text analysis), which depended on the day of the week (Golder & Macy, 2011). Additionally, Yasseri and collaborators found diurnal variations in Wikipedia editorial activity across the world (Yasseri, Sumi, & Kertesz, 2012). Our study combined massive data analyses from a large corpus with a measure of circadian

preferences. This allowed us to demonstrate that participants are more active during their preferred moment of the day. This expected finding shows that each subject chooses when to be active consistently with his/her preferred time, indicating that the phase of diurnal cognitive activity is not only controlled by external and fixed everyday duties (family, work, etc.).

Above and beyond the capacity to combine a large corpus of activity data with preferred chronotypes, our main aim was to investigate how decision-making changes throughout the day. We found that players changed their decision-making policy throughout the day: players decide faster and less accurately as the day progresses, reaching a plateau early in the afternoon. This effect was observed for all players regardless of their chronotype, indicating that changes in Decision time are mainly determined by the time of the day. However, Decision time (and not Accuracy) is also modulated by the relative synchrony to the individual circadian phase: both Decision time and its Variability are higher during the evening for all chronotypes, but for Early types the morning-evening amplitude is higher. Higher Decision time Variability could be indexing a better use of time, as players might be recognizing the movements where they should use more time.

Hence, players change their decision-making policy during the day, and not simply a better or worst decision-making policy (which should be more accurate and faster moves, or less accurate and slower moves, respectively). More specifically, our results show that the increase in speed throughout the day has costs in accuracy, as it was observed in classical speed-accuracy tradeoffs in a broad class of problems in decision-making (Bogacz, Hu, Holmes, & Cohen, 2010; Gold & Shadlen, 2002; Wickelgren, 1977). These results could be related with the Regulatory focus theory (Higgins, 2002), which postulates that the decision frame is affected by the regulatory focus: the specific way in which someone approaches pleasure and avoids pain. Regulatory focus theory differentiates between two focuses: a prevention-focus based on safety (trying to avoid losing) and a promotion-focus based on hopes and accomplishments (seeking to win).

Our results show that players play more accurately and slower in the morning, which could be interpreted as a strategy based on safety (prevention focus), and they play faster and less accurately in the evening, which could be a more risky way of playing (promotion focus). This association was previously reported to be related with the level of the opponent: players adopted a prevention policy (slow and more accurate moves) when they play with opponents which are higher rated than him/her (Slezak & Sigman, 2012). However, our results show no daily differences in opponent levels. Indeed, during the morning players adopt a prevention policy, playing slower and more accurately (as if they were playing with higher level opponents) and, during the evening, they adopt a more risky (promotion) policy where decisions are faster but less accurate.

The data is not powerful enough to assess second degree interactions of these variables in order to reach conclusions on how they interact to yield changes in performance (i.e. whether the improvement in quality compensates the excess in time used). However, our analysis of performance suggests that all these effects are close to compensate each other, i.e. there is not a main effect of day time on rating.

Previous results suggested that "time since entrained awakening" is a better predictor than time of the day for sport performance, which could reflect the influence of both sleep pressure and chronotype (Facer-Childs & Brandstaetter, 2015). In-line with this general conclusion, when we evaluated our data as a function of "Time since awakening" we found that chronotype modulation of Decision time was fully accounted by Time since awakening. However, Activity was still modulated by chronotypes, with Late subjects being more active many hours later than Early types. These results suggest that either Sleep pressure is an important factor determining performance levels and/or that daily changes in decision-making policies depend on the phase of wake-sleep cycles, without intrinsic differences between chronotypes.

As it was previously stated, decision-making policies could be changing as the day progresses because the accumulation of sleep pressure makes it difficult to make the right decisions at night. However, this could also favor fast decisions, which of course gives an advantage when playing with a finite time budget. Alternatively, a circadian component, which is slightly out of phase between chronotypes, could be compensating the effect of sleep pressure. This effect could be based upon different mechanisms depending on chronotypes, and could improve the decision time-accuracy trade-off through a better use of time or by increasing accuracy when time of the day is in synchrony with diurnal preferences. For Early types the improvement should be in the morning and could occur throughout the modulation of Decision time (because Accuracy is high and Decision time is slow in the morning). In Late types, the advantage should be in the evening and could depend on modulation of Accuracy (since Accuracy is slow and Decision time is fast in the evening).

We also explored the effects of Age in activity, decision-making policies and performance. Age is a factor that correlates with circadian preferences and the amplitude of circadian rhythms is reduced with aging (May, Hasher, & Foong, 2005; Monk, 2005). Moreover, chess performance also decreases with Age (Jastrzembski, Charness, & Vasyukova, 2006; Moxley & Charness, 2013). We found that Age directly correlates with Rating and Error rate (younger players are higher rated and make less errors than older ones), and negatively correlated with Decision time (older players used less time than younger ones). This last result is opposite to previous findings where chess decisions were made faster by younger participants or where no significant age-differences were found (Charness, 1981; Jastrzembski et al., 2006). However, our result could be a consequence of players adopting a strategy of time usage with a finite time budget, as we measured Decision time only in the middle of the game where it had been reported that higher rated players allocated more time, compared to lower rated players (Sigman et al., 2010). Thus, the magnitude of the time allocated to a decision could be a consequence of players' level: older players both have lower ratings and play faster during the middle game. Indeed, how exactly Age affects decision times may vary widely depending on task constraints. However, all these main effects of Age were deleted with our normalizations and our results showed that Age has no effect on diurnal variations of Activity, Decision time or Accuracy.

Future experiments will be necessary to uncover the underlying mechanisms of temporal modulation and, specifically, sleep pressure effects on chess decision-making according to chronotype.

Our results provide an innovative approach to explore diurnal variations in natural conditions, combining a quantitative control of decision variables typical of laboratory experiments and a more realistic setting to study and apply circadian variation in behavior and performance.

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Appendix A. Supplementary material

Supplementary data associated with this article can be found, in the online version, at http://dx.doi.org/10.1016/j.cognition.2016.10.007.

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