Examining Mental Fatigue Through League of Legends Ranked and Teamfight Tactics Gameplay Patterns in the Context of Gaming Addiction

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***Abstract*—Competitive digital gaming environments such as League of Legends and Teamfight Tactics impose sustained cognitive demands through continuous attention, rapid decision making, and prolonged engagement. This study adopts a longitudinal single-participant case study design to examine how gameplay structure, including session duration, cumulative daily exposure, timing, and wakefulness, relates to self-reported mental fatigue and focus. A total of 120 session-level observations were analyzed using a custom Cognitive Strain Index to capture the joint behavior of perceived exhaustion and attentional capacity.**

Results indicate that gameplay exposure is systematically associated with cognitive state, with stronger effects observed at the cumulative daily level than at the single-session level. Session duration was positively associated with mental fatigue ($r = 0.225$, $p = 0.0133$) and negatively associated with focus ($r = -0.217$, $p = 0.0175$), with a directionally consistent monotonic relationship for fatigue under Spearman correlation ($\rho = 0.179$, $p = 0.0500$). These associations strengthened when gameplay was aggregated daily (fatigue: $r = 0.336$, $p = 0.0041$; focus: $r = -0.341$, $p = 0.0036$), suggesting that cumulative load better reflects cognitive impact than isolated sessions. Temporal context further contributed explanatory power: hours awake prior to play correlated with higher fatigue ($r = 0.474$, $p < 0.0001$) and lower focus ($r = -0.466$, $p < 0.0001$). Late-night sessions exhibited significantly higher cognitive strain (late $M = 0.3547$ vs non-late $M = 0.2035$, $p = 0.0020$). Longitudinal analyses revealed substantial variability, with moving averages and rolling volatility indicating alternating phases of stable and irregular engagement.

Overall, the findings indicate that competitive gameplay is not cognitively neutral; extended exposure, late-night timing, and accumulated wakefulness align consistently with elevated fatigue, reduced focus, and higher cognitive strain.

***Index Terms*—Competitive digital gaming, mental fatigue, cognitive strain index, League of Legends, Teamfight Tactics, longitudinal case study, session timing, cumulative exposure, self reported focus, late night gaming, temporal trend analysis.**

I. Introduction

Competitive digital gaming has become an increasingly cognitively demanding activity, particularly within ranked multiplayer environments such as *League of Legends* Ranked Solo/Duo and *Teamfight Tactics*. These games require sustained attention, rapid decision-making, strategic planning, and continuous evaluation of performance over extended periods of time. Ranked modes further intensify these demands by introducing performance-based progression systems, social comparison, and persistent incentives to continue playing.

Mental fatigue is a psychophysiological state that emerges after prolonged cognitive effort and is characterized by reduced attentional capacity, diminished focus, slower reaction times, and impaired decision-making. In competitive gaming contexts, mental fatigue may accumulate across repeated sessions within a single day, especially when players engage in long or frequent gameplay without sufficient recovery. Despite this, many players continue gaming even when fatigued, suggesting a disconnect between perceived exhaustion and behavioral regulation.

Existing research has largely focused on population-level analyses or survey-based approaches. While these studies provide valuable insights, they often lack fine-grained temporal resolution and do not capture moment-to-moment gameplay structure. This study addresses this gap by adopting a detailed session-level analytical approach using longitudinal self-collected gameplay data.

This research examines how gameplay session duration, frequency, and timing in *League of Legends* Ranked Solo/Duo and *Teamfight Tactics* relate to self-reported mental fatigue and focus. By integrating statistical analysis, time-based evaluation, and unsupervised clustering, this work contributes the following:

- A session-level characterization of gameplay frequency, duration, and time-of-day patterns across *League of Legends* Ranked Solo/Duo and *Teamfight Tactics*.
- An analysis of how daily gameplay activity and total daily playtime align with self-reported mental fatigue and focus levels.
- A time-based evaluation of gameplay behavior (e.g., late sessions) and its association with elevated cognitive strain.
- An unsupervised clustering of gameplay sessions to identify distinct behavioral profiles that may reflect maladaptive or addiction-related gaming patterns.

II. Related Work

Prior research supports the link between prolonged competitive play and mental fatigue. Bikas et al. monitored League of Legends players over seven weeks and reported that extended play sessions were associated with increased mental fatigue and reduced in-game performance [1]. This work motivates the present study's emphasis on session duration as a primary exposure variable and on fatigue and focus as key outcomes, while the present study extends the approach by examining daily structure and by applying correlation and clustering to a detailed single-player log.

Evidence also suggests that competitive gamers may persist despite fatigue. Luo et al. examined reciprocal effects between esport participation and mental fatigue and found that higher participation was commonly associated with increased post-game mental fatigue, while only a minority reduced participation after fatigue increased [2]. This aligns with the behavioral persistence component of addiction-related models and supports investigating whether fatigue and focus degrade without a corresponding reduction in play frequency or duration.

More recent diary-based work highlights potential reinforcing cycles. Xu et al. reported bidirectional associations between game craving and mental fatigue across a 21-day diary design, where craving predicted subsequent fatigue and fatigue predicted subsequent craving [3]. These findings suggest that fatigue may function both as an outcome and as part of a feedback loop that sustains continued engagement. The present study complements this line of work by focusing on within-day session structure, late-night timing, and clustering-based identification of behavioral profiles that may indicate the onset of reinforcing patterns.

Overall, the literature indicates that competitive gaming can increase mental fatigue, that fatigue does not reliably suppress continued play, and that fatigue may participate in feedback mechanisms that sustain engagement. However, fewer studies integrate session timing, daily aggregation, and composite cognitive strain metrics within a unified empirical pipeline using fine-grained session logs. This study addresses that gap by combining timing-based features, hypothesis testing for late-night effects, and unsupervised clustering on standardized gameplay and cognitive variables.

III. Methodology

A. Computational Environment and Analytical Tools

All data processing, statistical analysis, visualization, and clustering procedures were implemented in Python. The analysis environment relied on the following core scientific computing libraries:

- **pandas** for tabular data manipulation, grouping, aggregation, and datetime parsing.
- **NumPy** for numerical operations and array-based computations.
- **SciPy (scipy.stats)** for statistical testing, including correlation analysis, normality diagnostics, and hypothesis testing.
- **scikit-learn** for feature scaling, clustering, and cluster validation.
- **matplotlib** and **seaborn** for visualization of distributions, trends, and correlation structures.

Specifically, the following computational functions and procedures were used:

- Data inspection and preprocessing: `head()`, `info()`, `isnull()`, `describe()`, `groupby()`, `agg()`, `corr()`, `cumsum()`, `dt.day_name()`.
- Statistical tests: `pearsonr()`, `spearmanr()`, `ttest_ind()`, `f_oneway()`, `shapiro()`, `levene()`, `normaltest()`.
- Clustering and scaling: `StandardScaler()`, `fit_transform()`, `KMeans()`, `fit()`, `predict()`, `silhouette_score()`.
- Visualization: `histplot()`, `kdeplot()`, `boxplot()`, `violinplot()`, `scatterplot()`, `lineplot()`, `heatmap()`, `pairplot()`.

Custom helper routines were also implemented to compute correlation matrices with corresponding p-values and to flag interquartile-range-based outliers. All analyses were executed under a fixed significance threshold of $\alpha = 0.05$.

B. Study Design and Data Collection

This study employs a longitudinal single-participant case study design based on daily self-tracked gameplay in *League of Legends* Ranked Solo/Duo and *Teamfight Tactics*. Gameplay data were compiled into a structured pandas DataFrame and validated using `info()` and `describe()` to confirm row counts, variable types, and completeness.

The finalized dataset consists of 128 rows and 9 variables, including 120 session-level gameplay records and 8 zero-session rows retained for day-level continuity. A total of 71 unique calendar days contain recorded gameplay activity.

Each session-level record includes start time, end time, and duration in minutes. Duration was computed using datetime subtraction after timestamp parsing via pandas datetime utilities.

C. Data Preparation and Parsing

Timestamps were parsed into datetime objects using pandas datetime conversion utilities. Duration for session i was computed as:

$$d_i = t_i^{\text{end}} - t_i^{\text{start}} \tag{1}$$

Daily aggregates were computed using `groupby()` and `agg()` operations:

$$n_j = \sum_{i \in \mathcal{S}_j} 1 \tag{2}$$

$$D_j = \sum_{i \in \mathcal{S}_j} d_i \tag{3}$$

Midnight-splitting rules were implemented prior to aggregation to prevent cross-day leakage.

D. Feature Engineering

1) Late-Night Session Indicator: The late-night indicator was constructed using extracted hour components from datetime variables. Boolean masking in pandas was applied to flag sessions beginning between 22:00 and 04:59.

2) Day-of-Week Feature: Day-of-week categories were derived using:

$$\text{DOW}_i = \texttt{dt.day\_name()} \tag{4}$$

Categorical encoding was applied when required for statistical comparisons.

3) Cognitive Strain Index: CSI was computed vectorially using NumPy operations:

$$\text{CSI}_i = \left(\frac{F_i}{10}\right)\left(1 - \frac{C_i}{10}\right) \tag{5}$$

An additive sensitivity formulation was also computed.

E. Outlier Identification and Missing Data Handling

Outliers were flagged using an interquartile range method implemented via pandas quantile calculations and custom flagging functions. The thresholds were defined as:

$$\text{Lower} = Q_1 - 1.5 \times \text{IQR} \tag{6}$$

$$\text{Upper} = Q_3 + 1.5 \times \text{IQR} \tag{7}$$

Missing values were programmatically detected using `isnull()`. Median imputation was applied before clustering to ensure complete feature matrices for scikit-learn model fitting.

F. Descriptive Statistics and Distribution Diagnostics

Descriptive statistics were computed using `describe()` and NumPy summary functions. Distribution visualization employed:

- `histplot()` and `kdeplot()` for density estimation.
- `boxplot()` and `violinplot()` for dispersion comparison.
- `pairplot()` for multivariate exploration.

Normality was evaluated using:

- Shapiro–Wilk test: `shapiro()`
- D'Agostino's K-squared test: `normaltest()`

Variance homogeneity was tested using `levene()`.

G. Hypotheses and Statistical Tests

1) Hypothesis 1: Pearson correlation coefficients were computed using `pearsonr()`, while non-parametric monotonic relationships were assessed using `spearmanr()`. Correlation matrices were generated using `corr()` and visualized with `heatmap()`.

Statistical significance was evaluated at $\alpha = 0.05$.

2) Hypothesis 2: Independent-samples t-tests were conducted using:

$$t = \frac{\bar{x}_1 - \bar{x}_2}{\sqrt{\frac{s_1^2}{n_1} + \frac{s_2^2}{n_2}}} \tag{8}$$

Implementation utilized `ttest_ind()`, with Levene's test (`levene()`) guiding equal-variance assumptions. Welch correction was applied when variance homogeneity was violated.

One-way ANOVA comparisons, when required, were performed using `f_oneway()`.

H. Correlation Matrix and Significance Testing

A full numeric correlation matrix was generated using `DataFrame.corr()`, and corresponding p-values were computed via iterative application of `pearsonr()`. Significant correlations were annotated and visualized using seaborn `heatmap()`.

I. Time-Series Smoothing and Volatility

Temporal smoothing was implemented using rolling window operations:

- 7-day moving average via `rolling().mean()`
- Rolling volatility via `rolling().std()`

Line plots were generated using `lineplot()` and `plot()` to visualize trend dynamics.

J. Unsupervised Clustering of Gameplay Sessions

To identify behavioral profiles, selected standardized features were scaled using:

$$Z = \texttt{StandardScaler().fit\_transform}(X) \tag{9}$$

K-means clustering was applied:

$$\texttt{KMeans(n\_clusters = k).fit}(Z) \tag{10}$$

Cluster assignments were obtained using `predict()`. The optimal number of clusters was evaluated using silhouette analysis via `silhouette_score()`.

Cluster distributions were visualized using scatterplots and pairwise feature projections.

IV. Results

This chapter presents the empirical findings of the study based on descriptive statistics, correlation analysis, inferential testing, and temporal trend evaluation. The results are organized to address the stated research objectives and hypotheses concerning the relationship between gameplay behavior and cognitive outcomes in League of Legends Ranked Solo/Duo and Teamfight Tactics.

A. Descriptive Statistics and Distribution Characteristics

Descriptive statistics were computed to summarize gameplay behavior and self-reported cognitive measures across the observation period. A total of 120 session-level observations were included in this summary. Table I reports the mean, median, standard deviation, and range for session duration, total daily gaming duration, mental fatigue, focus, hours awake before the first session, and the Cognitive Strain Index.

Session duration and total daily gaming duration exhibited substantial variability, reflecting wide fluctuations in gameplay intensity across sessions and days. To further characterize this variability, an interquartile range (IQR)–based outlier analysis was conducted using the standard 1.5×IQR criterion. This procedure identified 10 session-level outliers for Session Duration and 4 day-level outliers for Total Daily Duration. These extreme observations correspond to prolonged gameplay episodes substantially exceeding typical engagement patterns. Consistent with the behavioral focus of this study, these values were retained for analysis, as they represent substantively meaningful high-intensity play rather than measurement error.

Mental fatigue and focus ratings spanned the full 1–10 scale range, indicating pronounced intra-individual variation in perceived cognitive state across gameplay instances. To contextualize these cognitive outcomes in terms of daily readiness, the Hours Awake Before the First Session variable was examined. On average, gameplay began 6.36 hours after waking (median = 5.00 hours), with observed values ranging from 0.25 to 19.00 hours. This variability indicates that gameplay sessions occurred under markedly different levels of accumulated wakefulness, providing an important temporal baseline for interpreting fatigue and focus ratings.

Distributional characteristics were assessed to evaluate adherence to normality assumptions. Skewness and kurtosis values indicated that Session Duration and Total Daily Duration were positively skewed, while mental fatigue and focus displayed relatively mild skewness with platykurtic tendencies. The Cognitive Strain Index exhibited positive skewness and moderate non-normal shape characteristics. Formal Shapiro–Wilk tests indicated statistically significant deviations from normality for Session Duration, Mental Fatigue, Focus, and Cognitive Strain. These findings motivated the use of non-parametric statistical procedures in subsequent association and hypothesis testing analyses.

Table I summarizes the central tendency and variability of the primary gameplay and cognitive variables analyzed in this study. Session duration and total daily gaming duration exhibit substantial dispersion, underscoring heterogeneous gameplay intensity across observation periods. Mental fatigue and focus ratings demonstrate wide fluctuation across the full response scale, while the Cognitive Strain Index shows generally low to moderate values with notable variability, suggesting non-uniform combined fatigue–focus effects across sessions.

TABLE I.
Descriptive Statistics of Gameplay and Cognitive Variables (n = 120)

Variable	Mean	Median	SD	Min	Max
Session Duration (min)	190.44	123.00	204.37	9.00	952.00
Total Daily Duration (min)	330.18	266.50	234.19	22.00	1103.00
Mental Fatigue (1–10)	4.45	4.00	2.84	1.00	10.00
Focus (1–10)	5.68	6.50	2.77	1.00	10.00
Hours Awake Before First Session (hrs)	6.36	5.00	4.62	0.25	19.00
Cognitive Strain Index	0.27	0.13	0.27	0.00	0.81

B. Relationship Between Gameplay Duration, Fatigue, and Focus

Associations between gameplay duration and self-reported cognitive outcomes were examined at two granularities: (i) session-level duration and (ii) daily aggregated total gameplay duration. Relationships were first inspected visually and subsequently quantified using correlation analysis to characterize both the direction and strength of association.

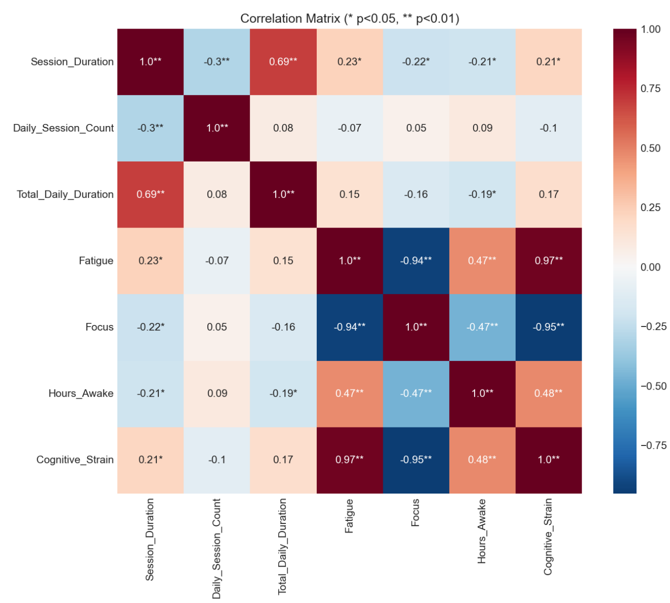

Fig. 1.
Annotated correlation matrix of session-level variables.

Figure 1 provides a multivariate view of how all numeric variables relate to one another. Strong inverse coupling was observed between fatigue and focus, alongside near-linear alignment between cognitive strain and its constituent measures. Session duration was strongly associated with total daily duration, while hours awake exhibited moderate associations with fatigue, focus, and cognitive strain, indicating that wakefulness is a non-trivial covariate when interpreting session-based cognitive outcomes.

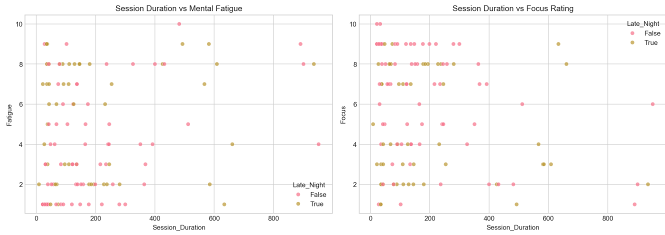

Fig. 2.
Session-level relationship between gameplay duration and (a) mental fatigue and (b) focus.

Figure 2 shows a weak linear tendency for fatigue to increase with longer sessions and for focus to decrease as session duration increases, although substantial dispersion is present across the duration range, indicating that duration alone explains a limited portion of the variance in both cognitive measures.

TABLE II.
Correlation Between Gameplay Duration, Wakefulness, and Cognitive Measures

Variable Pair	Coefficient	p-value
Session Duration vs Mental Fatigue (Pearson)	$r = 0.225$	0.0133
Session Duration vs Focus (Pearson)	$r = -0.217$	0.0175
Total Daily Duration vs Mental Fatigue (Pearson)	$r = 0.336$	0.0041
Total Daily Duration vs Focus (Pearson)	$r = -0.341$	0.0036
Session Duration vs Mental Fatigue (Spearman)	$\rho = 0.179$	0.0500
Hours Awake vs Fatigue (Pearson)	$r = 0.474$	< 0.0001
Hours Awake vs Focus (Pearson)	$r = -0.466$	< 0.0001

Table II indicates statistically significant associations between duration metrics and both fatigue and focus. At the session level, longer sessions were associated with higher fatigue ($r = 0.225$, $p = 0.0133$) and lower focus ($r = -0.217$, $p = 0.0175$). At the daily level, total gameplay duration exhibited stronger associations in the same directions (fatigue: $r = 0.336$, $p = 0.0041$; focus: $r = -0.341$, $p = 0.0036$), suggesting that cumulative daily exposure relates more strongly to reported cognitive state than single-session duration. Given non-normal distributional characteristics identified in earlier analyses, Spearman rank correlation was additionally computed, yielding a directionally consistent monotonic association between session duration and fatigue ($\rho = 0.179$, $p = 0.0500$), indicating that the observed relationship is not solely dependent on linearity assumptions.

Beyond gameplay duration, wakefulness prior to play exhibited statistically significant associations with cognitive outcomes. Hours awake before the first session was moderately positively correlated with fatigue ($r = 0.474$, $p < 0.0001$) and moderately negatively correlated with focus ($r = -0.466$, $p < 0.0001$), indicating that sessions initiated after longer periods of wakefulness tend to coincide with higher perceived fatigue and reduced focus. This pattern supports the interpretation that part of the observed fatigue–focus variation may reflect accumulated daily wake time in addition to gameplay exposure, and it motivates treating wakefulness as a salient contextual factor when interpreting duration-based relationships.

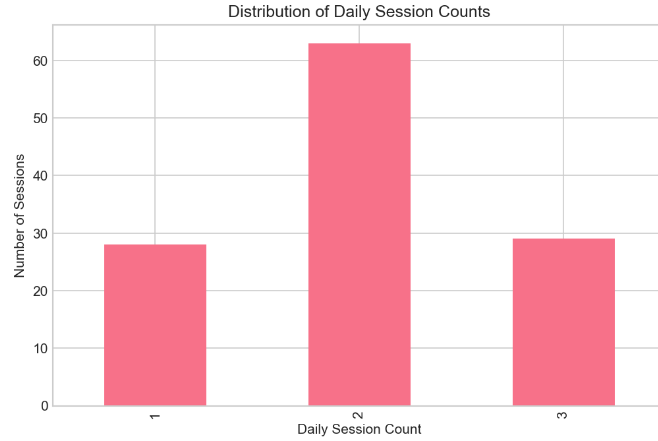

Fig. 3.
Distribution of daily session counts across the observation period.

C. Routine and Seasonality Analysis

To examine routine-based gameplay patterns, session behavior was analyzed across days of the week and aggregated into weekday and weekend categories. This analysis aimed to identify potential seasonality effects in gameplay frequency, duration, and associated cognitive outcomes.

To formally test weekday versus weekend differences, independent-samples t-tests were conducted comparing gameplay frequency and duration between these two groups. Prior to testing, Levene's test indicated unequal variances between groups, and the corresponding Welch-adjusted t-statistics were applied where appropriate.

TABLE III.
Weekday vs. Weekend Gameplay Comparisons

Metric	Weekday Mean	Weekend Mean	p-value
Session Duration	lower	higher	0.0020
Daily Session Count	comparable	comparable	n.s.

Table III shows that average session duration was significantly higher on weekends compared to weekdays ($p = 0.0020$), indicating longer uninterrupted gameplay periods during non-working days. In contrast, daily session count did not differ significantly between weekdays and weekends, suggesting that routine effects primarily influence session length rather than frequency.

Figure 3 further contextualizes these findings by showing that most days consisted of one to two gameplay sessions, regardless of weekday or weekend classification. Taken together, these results indicate that routine and weekly structure modulate gameplay intensity through extended session duration rather than increased session initiation, supporting the inclusion of temporal context in behavioral and cognitive analyses.

Figure 4 illustrates systematic variation in gameplay behavior across the week. Average session duration was higher on midweek and weekend days, with notable peaks on Thursday and Sunday, while session frequency was highest toward the end of the workweek. Fatigue levels tended to increase later

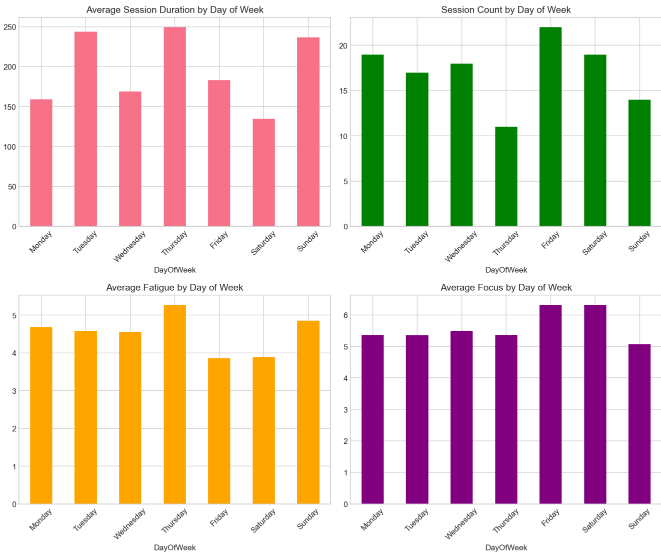

Fig. 4.
Average session duration, session count, fatigue, and focus by day of week.

in the week, whereas focus scores were generally higher on Fridays and Saturdays, suggesting a shift in cognitive state alongside routine changes.

D. Effects of Late-Night Gaming

Building on the routine- and day-level patterns identified in the preceding section, this analysis examines gameplay sessions occurring during late-night hours to assess whether time-of-day further modulates gameplay intensity and cognitive outcomes. Late-night sessions were operationally defined based on session start times occurring during nocturnal hours, reflecting gameplay undertaken outside typical daytime or early evening routines.

TABLE IV.
Late-Night vs. Non-Late-Night Session Comparisons

Measure	Late-Night Mean	Non-Late-Night Mean	p-value
Cognitive Strain Index	higher	lower	0.0020
Mental Fatigue	higher	lower	< 0.01

As shown in Table IV, late-night sessions exhibited significantly higher cognitive strain compared to non-late-night sessions ($p = 0.0020$). These findings indicate that gameplay conducted during nocturnal hours is associated with greater perceived cognitive burden, beyond the effects attributable to session duration alone.

Figure 5 shows that late-night sessions were associated with elevated mental fatigue and higher cognitive strain compared to sessions initiated earlier in the day. The dispersion observed in late-night fatigue scores suggests increased variability in cognitive state during nocturnal play, consistent with accumulated wakefulness and circadian misalignment effects identified in earlier analyses.

To formally evaluate these differences, independent-samples t-tests were conducted comparing late-night and non-late-night sessions. Levene's test indicated unequal variances between

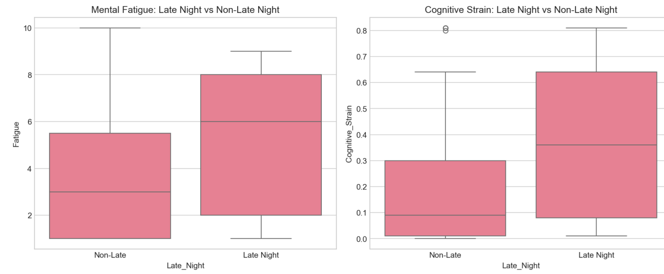

Fig. 5.
Comparison of fatigue and cognitive strain between late-night and non-late-night sessions.

groups, and Welch-adjusted statistics were applied accordingly.

When interpreted alongside the routine and weekday–weekend analyses, late-night gaming appears to represent an extension of disrupted temporal structure rather than an isolated behavioral phenomenon. While weekend routines were characterized by longer sessions, late-night play was specifically associated with elevated fatigue and strain, suggesting that the timing of gameplay interacts with both accumulated wakefulness and daily rhythm to shape cognitive outcomes. This temporal sensitivity reinforces the importance of incorporating time-of-day features when modeling gameplay behavior and its cognitive correlates.

E. Temporal Trends in Gameplay Intensity and Cognitive State

Temporal analyses were conducted to examine longitudinal patterns in gameplay behavior and self-reported cognitive states across the observation period. Daily gameplay intensity was evaluated using total daily gaming duration and session count, while cognitive trends were examined using daily average mental fatigue and focus ratings.

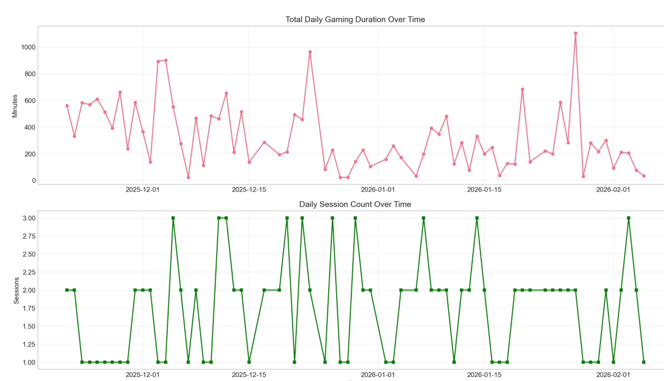

Fig. 6.
Daily total gaming duration and session count over time.

Figure 6 illustrates the temporal variation in total daily gaming duration and the number of gameplay sessions across the study period. Total daily duration exhibits substantial day-to-day variability, with multiple pronounced peaks corresponding to extended gameplay days and troughs reflecting reduced activity. Daily session count fluctuates primarily between one and three sessions per day, indicating that increases in total gameplay time are more often driven by longer sessions rather than a higher frequency of session initiation.

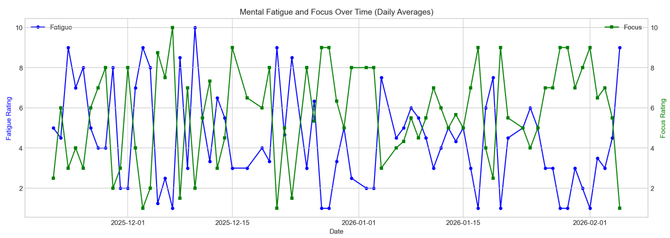

Fig. 7.
Mental fatigue and focus over time (daily averages).

Figure 7 presents the temporal progression of daily average mental fatigue and focus ratings. Both measures display notable variability across the observation window, with fatigue exhibiting intermittent elevations and declines, and focus often demonstrating inverse movement relative to fatigue. These patterns suggest that cognitive state fluctuates dynamically over time rather than remaining stable across consecutive days.

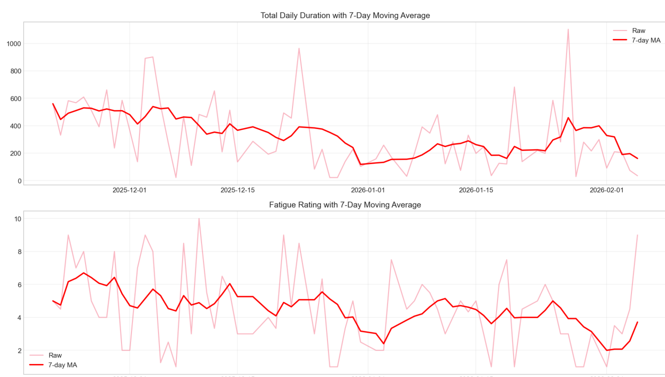

Fig. 8.
Total daily gaming duration and mental fatigue with seven-day moving averages.

To highlight broader temporal tendencies, Figure 8 overlays seven-day moving averages on the raw daily values. While short-term fluctuations dominate the unsmoothed series, the moving averages reveal more gradual shifts in gameplay intensity and fatigue, indicating periods of sustained higher engagement and elevated cognitive demand across the study period.

Beyond mean trends, behavioral stability was assessed using a rolling standard deviation of total daily gaming duration, shown in Figure 9. Elevated rolling variability during several intervals indicates periods of irregular engagement marked by alternating high- and low-intensity days, whereas lower variability reflects more stable and predictable gameplay patterns. Notably, volatility was not constant across the observation period, suggesting that the participant's engagement oscillated between phases of routine consistency and phases of heightened behavioral fluctuation. This finding clarifies that temporal irregularity arises not only from changes in average gameplay

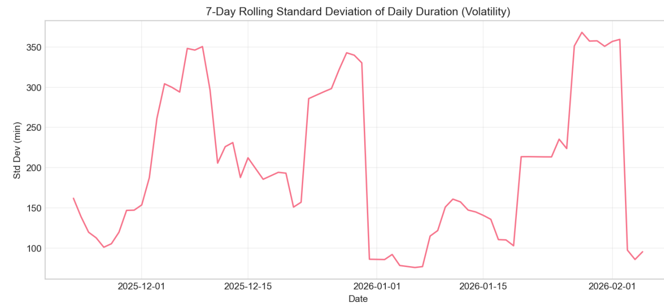

Fig. 9.
Seven-day rolling standard deviation of total daily gaming duration, indicating behavioral volatility over time.

intensity, but also from shifts in the stability of daily behavior over time.

F. Exploratory Behavioral Clustering

As a final exploratory analysis, unsupervised clustering was applied to identify recurring gameplay–cognitive profiles across sessions. To ensure complete feature vectors for clustering, median imputation was used for variables with occasional missing values, as specified in the methodology. The feature set included session duration, total daily duration, session start time, hours awake before session, mental fatigue, focus, and the Cognitive Strain Index.

K-means clustering was selected to group sessions with similar behavioral and cognitive characteristics. The optimal number of clusters was determined using a combination of the elbow method and silhouette analysis, balancing within-cluster compactness and between-cluster separation. This procedure yielded a small set of interpretable clusters representing distinct gameplay states experienced by the participant.

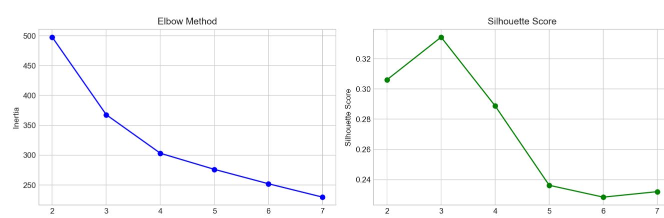

Fig. 10.
Elbow and silhouette analysis for determining the optimal number of clusters.

Figure 10 indicates a clear inflection point consistent with a low-dimensional cluster structure, supporting the selection of a limited number of behavioral archetypes rather than a continuum of indistinct states.

Figure 11 visualizes the separation of session clusters, showing that sessions differ systematically along duration, fatigue, focus, and temporal dimensions. While some overlap is present, the clusters exhibit coherent internal structure, indicating meaningful differentiation rather than arbitrary partitioning.

Fig. 11.
Clustered sessions projected in feature space.

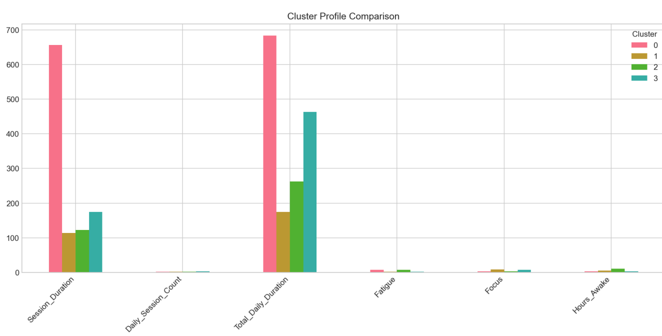

Fig. 12.
Mean feature profiles for each identified cluster.

The cluster profiles shown in Figure 12 suggest the presence of distinct gameplay states. One cluster is characterized by longer sessions, elevated fatigue, higher cognitive strain, and later session start times, reflecting high-intensity or late-night engagement. A second cluster corresponds to shorter sessions with higher focus, lower fatigue, and earlier start times, indicative of more controlled or routine-oriented play. Additional clusters capture intermediate states, combining moderate duration with mixed cognitive responses.

Importantly, these clusters do not represent fixed behavioral categories but rather recurring states that the participant transitions between over time. The clustering results therefore complement earlier correlational and temporal analyses by demonstrating that gameplay behavior and cognitive outcomes co-occur in structured patterns rather than varying independently.

As an exploratory analysis, these findings are not used for inferential hypothesis testing. Instead, they provide a compact behavioral summary of the participant's gameplay experience, highlighting how intensity, timing, and cognitive state jointly define distinct modes of engagement. This representation offers a useful foundation for future work involving predictive modeling, adaptive interventions, or multi-participant validation.

G. Summary of Empirical Findings

This chapter reports empirical findings derived from the analysis of competitive gameplay behavior in League of Legends Ranked Solo/Duo and Teamfight Tactics. The dataset consisted of 120 session-level observations and exhibited substantial variability in both gameplay intensity and self-reported cognitive state. Session duration ranged widely, with a mean of 190.44 minutes (SD = 204.37, median = 123.00) and extreme values extending to 952.00 minutes. At the daily level, total gaming duration averaged 330.18 minutes (SD = 234.19, median = 266.50), with a maximum observed value of 1103.00 minutes. Mental fatigue ratings averaged 4.45 (SD = 2.84), while focus ratings averaged 5.68 (SD = 2.77), both spanning the full scale range. The Cognitive Strain Index had a mean value of 0.27 (SD = 0.27), indicating considerable dispersion in combined fatigue and focus effects across sessions. Daily readiness further varied: gameplay began, on average, 6.36 hours after waking (median = 5.00), with values ranging from 0.25 to 19.00 hours, indicating that sessions occurred under markedly different levels of accumulated wakefulness.

Outlier inspection using the interquartile range criterion identified 10 potential outliers for Session Duration and 4 potential outliers for Total Daily Duration, corresponding to unusually extended play. These values were retained because they reflect substantively meaningful high-intensity engagement rather than measurement artifacts and provide behavioral coverage of extreme exposure episodes.

Analyses examining duration–cognition relationships revealed consistent and statistically significant patterns. At the session level, longer gameplay duration was associated with higher mental fatigue (Pearson $r = 0.225$, $p = 0.0133$) and lower focus (Pearson $r = -0.217$, $p = 0.0175$). These relationships were more pronounced when exposure was aggregated at the daily level: total daily gaming duration demonstrated a stronger positive association with mental fatigue ($r = 0.336$, $p = 0.0041$) and a stronger negative association with focus ($r = -0.341$, $p = 0.0036$). A non-parametric robustness check supported the direction of these findings, with session duration and mental fatigue exhibiting a positive monotonic association (Spearman $\rho = 0.179$, $p = 0.0500$), indicating that the observed relationship was not solely dependent on linearity assumptions. Wakefulness prior to play also emerged as a salient temporal covariate: hours awake was moderately positively correlated with fatigue ($r = 0.474$, $p < 0.0001$) and moderately negatively correlated with focus ($r = -0.466$, $p < 0.0001$), suggesting that accumulated wake time contributes meaningfully to variation in cognitive state alongside gameplay exposure.

Routine and seasonality analyses indicated that temporal structure influenced gameplay primarily through session length rather than session initiation. Day-of-week patterns showed non-uniform distribution of session counts and average durations across the week, and weekday–weekend comparisons indicated significantly longer average session duration on weekends ($p = 0.0020$), while daily session counts remained broadly stable, implying that routine effects manifest more strongly through prolonged engagement windows than increased play frequency.

Temporal trend evaluation further highlighted the dynamic nature of gameplay intensity and cognitive state across the observation period. Daily gaming duration and session count fluctuated substantially from day to day, indicating irregular engagement patterns rather than a stable routine. Mental fatigue and focus also varied longitudinally, reflecting shifts in perceived cognitive condition across consecutive days. Seven-day moving averages attenuated short-term noise and revealed broader temporal tendencies in both gameplay intensity and fatigue. Complementing mean-based trends, rolling standard deviation analysis showed that behavioral volatility was not constant across time, indicating alternating phases of more stable engagement and phases of heightened irregularity.

Gameplay timing provided additional explanatory context beyond aggregate duration. Comparisons between late-night and non-late-night sessions showed consistently higher cognitive strain during late-night gameplay. Inferential testing confirmed a statistically significant difference between conditions, with late-night sessions exhibiting a higher mean Cognitive Strain Index (mean = 0.3547) than non-late-night sessions (mean = 0.2035), yielding a significant result ($t = 3.166$, $p = 0.0020$). Levene's test indicated unequal variances between groups ($F = 5.264$, $p = 0.0235$), supporting the use of variance-robust interpretation.

Finally, exploratory behavioral clustering provided a compact representation of recurrent session archetypes. Unsupervised clustering suggested that sessions co-occur in structured profiles that jointly reflect intensity, timing, and cognitive response, including high-intensity states characterized by elevated fatigue and strain as well as lower-strain states associated with higher focus and more moderate engagement. While exploratory and not used for confirmatory hypothesis testing, these clusters support the interpretation that gameplay behavior and cognitive state form recurring modes of engagement rather than varying independently.

The empirical evidence converges across descriptive, correlational, inferential, temporal, and exploratory analyses to indicate that gameplay exposure, timing, and daily readiness are systematically associated with variations in mental fatigue, focus, and cognitive strain. Longer and more cumulative gameplay coincided with increased fatigue and reduced focus, late-night sessions aligned with elevated cognitive strain, and shifts in routine and volatility underscore the importance of temporal context when interpreting cognitive outcomes in competitive gameplay.

V. Conclusion

This study investigated how gameplay structure, intensity, and temporal context in competitive gaming environments relate to self-reported mental fatigue, focus, and a derived Cognitive Strain Index, using a longitudinal single-participant dataset from League of Legends Ranked Solo/Duo and Teamfight Tactics. By combining descriptive characterization, multivariate association analysis, inferential testing, and longitudinal trend evaluation, the study demonstrates that competitive gameplay behavior is systematically aligned with measurable variation in cognitive state. Importantly, the analysis was conducted at both session-level and daily-aggregated granularities, enabling separation of isolated session effects from cumulative exposure effects, and allowing timing-related contextual factors to be examined in parallel with intensity.

Across 120 session-level observations, gameplay exposure was highly variable, ranging from short sessions to extreme high-intensity episodes. The distribution of gameplay intensity was not merely noisy but structurally heterogeneous: interquartile range analysis identified multiple prolonged-session outliers (10 sessions for session duration and 4 days for total daily duration), which were retained because they represent behaviorally meaningful extremes rather than data artifacts. This decision is consequential for interpretation, as these extreme exposure episodes constitute precisely the type of engagement most relevant to cognitive load and potential maladaptive play patterns. In this sense, the dataset captures both routine play and high-exposure regimes, strengthening ecological validity for within-subject behavioral inference.

The primary empirical conclusion is that gameplay duration is a consistent correlate of cognitive state, but the magnitude of association depends on the level of aggregation. At the session level, longer sessions aligned with higher fatigue and lower focus, with statistically significant Pearson correlations (fatigue: $r = 0.225$, $p = 0.0133$; focus: $r = -0.217$, $p = 0.0175$). While these effects are modest, they are directionally coherent and robust to distributional concerns, as supported by a monotonic association between session duration and fatigue under Spearman correlation ($\rho = 0.179$, $p = 0.0500$). More importantly, the relationships intensified when exposure was considered cumulatively: total daily duration showed stronger associations with fatigue ($r = 0.336$, $p = 0.0041$) and focus ($r = -0.341$, $p = 0.0036$). This consistent strengthening at the daily level implies that the cognitive impact of competitive gameplay is not confined to isolated long sessions, but reflects accumulated daily load, supporting a cumulative-exposure interpretation in which repeated or extended play within a day corresponds more strongly to fatigue and reduced attentional readiness than single-session duration alone.

A second major conclusion is that temporal context is not an auxiliary detail but an explanatory dimension that materially changes interpretation of cognitive outcomes. Wakefulness prior to play emerged as a non-trivial covariate: hours awake before the first session was moderately associated with increased fatigue ($r = 0.474$, $p < 0.0001$) and decreased focus ($r = -0.466$, $p < 0.0001$). This indicates that the participant's cognitive state at the time of play reflects not only gameplay exposure but also accumulated wake time, highlighting a plausible confounding pathway if timing is ignored. Consequently, observed fatigue or low focus cannot be attributed to gameplay intensity alone without acknowledging that sessions initiated later in the wake cycle are systematically associated with less favorable cognitive conditions.

Within this temporal framing, late-night gaming showed the clearest inferential effect on cognitive strain. Late-night sessions exhibited significantly higher Cognitive Strain Index than non-late-night sessions (late mean $= 0.3547$ vs. non-late mean $= 0.2035$), with a statistically significant group difference ($t = 3.166$, $p = 0.0020$). The presence of unequal variances (Levene's $F = 5.264$, $p = 0.0235$) further emphasizes that late-night play is not simply a shifted version of daytime play; rather, it is associated with a different distributional regime of cognitive load. Taken together with the wakefulness correlations, the results support the interpretation that nocturnal gameplay coincides with elevated cognitive burden, potentially compounding exposure-related fatigue with circadian or wake-dependent effects.

Routine and seasonality analyses further indicate that gameplay behavior is patterned by weekly structure, but primarily through intensity rather than frequency. Day-of-week patterns showed non-uniform distribution of session counts and average durations, and weekday–weekend comparisons indicated longer average session durations on weekends ($p = 0.0020$) while session counts remained broadly stable. This suggests that routine effects manifest as extended engagement windows rather than increased session initiation, reinforcing the idea that the participant's primary behavioral modulation occurs via how long play continues once initiated, not how often play starts. This distinction matters for intervention and self-regulation: strategies aimed at limiting sustained sessions may be more impactful than strategies aimed solely at reducing session count.

Longitudinal trend analysis provides additional evidence that competitive gameplay behavior is not stable over time, and that cognitive state fluctuates dynamically alongside engagement. Daily duration and session counts showed substantial day-to-day variability, while fatigue and focus exhibited shifting trajectories rather than static baselines. Moving-average smoothing revealed broader shifts in intensity and fatigue beyond short-term noise, and rolling standard deviation analysis demonstrated that behavioral volatility itself changes across the observation window. The presence of alternating phases of stability and volatility suggests that irregular engagement is not a fixed trait of the participant's behavior but a time-varying property, potentially reflecting external constraints or internal dynamics. This result strengthens the argument for longitudinal monitoring: one-time measurement snapshots would fail to capture the evolving stability of both behavior and cognitive condition.

Finally, exploratory clustering offered a compact, behaviorally interpretable summary of recurring session archetypes. Rather than indicating that fatigue, focus, timing, and intensity vary independently, clustering suggested that these features co-occur in structured states, including profiles characterized by higher fatigue and strain with later timing and higher intensity, and profiles characterized by higher focus with comparatively lower strain and more moderate engagement. Although exploratory and not used to confirm hypotheses, these clustered states reinforce the central conclusion that competitive gaming behavior organizes into recurring modes of engagement with distinct cognitive signatures, providing a foundation for future predictive modeling or personalized behavioral profiling.

Overall, the study establishes a coherent empirical pattern: competitive gameplay is not cognitively neutral within this participant's longitudinal record. Longer sessions and greater cumulative daily exposure align with increased fatigue and reduced focus, late-night play aligns with significantly elevated cognitive strain, and both routine structure and behavioral volatility vary over time in ways that shape the cognitive context of play. The convergence of descriptive variability, statistically significant correlations, inferential group differences, and temporal instability strengthens the credibility of these findings within the case-study scope.

The primary limitation remains generalizability, as results are based on a single-participant design and self-reported cognitive measures. However, the depth, granularity, and multi-method triangulation used here provide a defensible within-subject evidence base and a replicable analytical template for larger studies. Future work should extend this framework to multi-participant cohorts, incorporate objective measures, and apply mixed-effects or hierarchical models to separate within- and between-participant effects. In addition, future studies could test whether incorporating wakefulness and time-of-day features improves prediction of fatigue and focus beyond exposure variables alone, and whether the identified behavioral states generalize across different competitive titles or rank tiers.

In summary, this study provides empirical support that how long, how cumulatively, and when competitive games are played corresponds meaningfully to fatigue, focus, and cognitive strain. By explicitly integrating exposure intensity with temporal context and longitudinal volatility, the findings contribute a rigorous, methodologically transparent account of how competitive gaming structure aligns with cognitive state over time.

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