Master's Degree Program in Marketing
Major in Marketing Analytics and Metrics

Course of Statistics for Marketing

The Role of Fatigue in Decision-Making: Evidence from Online Poker Games

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Academic Year 2023/2024

Abstract

The increasing engagement in online poker necessitates a deeper understanding of the factors influencing decision-making under risk, particularly the choice to purchase the newest insurance option available on Omaha Poker cash games. This study investigates the influence of mental fatigue, induced by prolonged engagement in repetitive tasks, on insurance purchase decisions among online poker players. Leveraging a robust dataset comprising over 5 million showdown situations from Pokerstars' Omaha Poker cash games, logistic regression models were employed to test the relationships. Increased fatigue significantly elevates the probability of opting for insurance, reducing player’s attitude toward risk. Furthermore, the analysis shows that player expertise mitigates this effect, while higher stakes amplify it. These results contribute to the extension of traditional risk models by incorporating dynamic states, emphasizing the interplay between short-term cognitive fatigue and long-term skill development in high-stakes environments. Online gambling platforms can enhance user experience and promote responsible gambling through real-time fatigue monitoring and personalized interventions. This study offers valuable insights for marketers aiming to improve player retention and Customer Lifetime Value (CLV) by tailoring strategies to individual player states. Recommendations for future studies should explore additional drivers and methods to assess the broader generalizability of findings.

Keywords: Online poker, decision-making, choice under risk, fatigue, expertise, stakes.

Table of contents

Chapter 1 - Introduction

1.1 Problem background

Online gambling is a rapidly growing industry that counts more than 100 million online poker players worldwide[1], with poker platforms continually innovating their interfaces and features, to enhance player engagement and revenues. Risky choices and decisions permeate this game and beyond its realms, various aspects of daily life such as critical sectors of the economy from financial investments and healthcare decisions are driven by the principles of risk-taking and decision-making under uncertainty. Poker games give a real-world setting to understand how people behave when they make risky choices. When the uncertainty comes from a choice under risk as the decision to buy insurance in a gambling context, more precisely online poker games on web platforms, the choice is influenced by supplementary variables pertinent to the specific circumstances at hand. Indeed, beyond a player's ability, understanding of probabilities, or utility maximization reasoning, fatigue plays a relevant role in this context, as can significantly impair one's ability to process information and make optimal choices. Particularly in poker, a domain characterized by extended play sessions and high stakes, fatigue emerges as a critical factor that can skew decision-making processes. During extended sessions of playing poker, it is highly probable to get fatigued as players have to process a lot of information in a short time frame under pressure, especially when the stakes involved are high, as the prospect of winning money serves as the primary motivation for poker players (Hayano, 1984). Overall, past research has shown that attitude toward risk and choice under risk are multi-shaped: there are rational, irrational, behavioral, mathematic, probabilistic, and subjective aspects that play a role in making final decisions. However, remains unstudied whether and how fatigue affects the decision process when buying or not an insurance option. It is interesting to examine this relationship in poker games, to make the findings applicable also in other risky decision environments. By dissecting the impact that fatigue has on insurance purchasing decisions under risk in online poker, this study aims to shed light on broader behavioral patterns that define human interactions with risk and uncertainty across various fields.

[1] WTP, World Poker Tour, 2022

1.2 Relevance for theory – Additional contribution

Existing studies suggest that a player's decision-making process can be interpreted through the lens of Prospect Theory, considering how each player weighs the risks and rewards of his choices (Kahneman, Tversky, 1979). This study instead centers on fatigue, as a decrement in performance due to prolonged engagement, and learning, as an improvement over time through experience, as variables that have a relevant impact on decision-making and will provide a clean test of risk-taking behavior in a real-world setting, leveraging the advantages of observational studies. Prolonged work results in both learning and fatigue effects, with learning dominating speed improvement and fatigue dominating accuracy reduction (Gonzalez, Best, Healy, Kole, Bourne, 2011), these elements are both consequences of time that passes, but they spread their effect in different, opposite directions. Typically, with repetitive tasks, individuals initially improve in performance due to learning, but excessive repetitions lead to fatigue, negatively impacting performance (Asadayoobi, Jaber, Taghipour, 2021). The exploration of fatigue and learning as influential factors in decision-making processes extends beyond the realm of online poker, encompassing a wider spectrum of risk-taking behaviors in various settings. These elements are crucial in understanding how individuals assess and respond to risks. Examining the impact of fatigue on players' decision to purchase insurance in online poker, this study not only contributes to the field of online gambling literature but also offers valuable insights into the broader dynamics of risk assessment and decision-making. Indeed, it is crucial to understand how a player's decision-making process evolves through extended sessions and repeated exposure to game scenarios. This investigation can reveal how fatigue influences players' choices to opt for insurance, an aspect that has not been explored in the context of online poker so far.

1.3 Relevance for practice

Problem gambling is a worldwide phenomenon that occurs when gambling is out of control and it start causing social, personal, and interpersonal problems to gamblers (Raylu, Po Oei, 2004). This phenomenon developed even more with the emergence of online platforms and the European Union is moving toward a more continued expansion of gambling characterized by the legalization and liberalization of gambling markets (Kingma, 2008). Problem gambling prevalence rates vary from 2% to 5% in North America, 0.5% to 5.8% in Asia, and in Europe from 0.1 to 3.4% (Calado, Griffiths, 2016). The emergence of online platforms has contributed to the expansion of the gambling market in recent years, but technology can also be leveraged as a regulatory and surveillance tool. Indeed, insights into how fatigue and learning over time affect risk-taking can be crucial for developing strategies to promote responsible gambling, like the use of pop-up messages encouraging self-awareness to effectively increase responsible gambling and reduce the incidence of problem gambling (Monaghan, 2009). Identifying points at which players are more prone to making less rational decisions and performance decreases (Asadayoobi, Jaber, Taghipour, 2021), platforms can implement protective measures such as alerts or mandatory timeouts. Targeting different clusters of players is fundamental as seniors prefer messages about limit setting, while young adults and frequent gamblers better respond to messages about their play and expertise (Giansbury, Abarbanel, Philander, Butler, 2018). This knowledge can lead to a more tailored and responsible gaming experience, where platforms can offer guidance or alerts based on a player's engagement level and decision-making patterns (Ladouceur, P. Shaffer, Blaszczynski, J. Shaffer, 2017). It would enhance the overall customer experience and security, as creating an online environment where platforms try to avoid the issue of problem gambling through the data they collect from their customers, would result in a more reassuring and safe setting for the users.

Regarding the platform's side, understanding how these behavioral aspects drive and impact the decisions of players is essential in designing and promoting online poker platforms from a marketing perspective. Indeed product success requires a great amount of detail from many stakeholders and sources of information (Xu, Frankwick, Ramirez, 2016). Insights into how fatigue and learning over time influence decision-making can aid in developing personalized marketing strategies, such as when to present the insurance options to maximize engagement and satisfaction, through models that provide insights and diagnostics (Wedel, Kannan, 2016). An effective personalization of the marketing offer in this context can be enhanced both on individual and segment levels of granularity (Wedel, Kannan, 2016). By understanding the behavioral patterns underpinning insurance decisions, firms can tailor their features and marketing communications to align with players' psychological states and learning curves. This can enhance the user experience, potentially increasing player retention and Customer Lifetime Value (CLV), that is the present value of the future profits associated with a particular customer’s present value (Fader, Hardie, 2010), or Residual Lifetime Value (RLV) in case of a yet retained customer, for the company. Beyond the online poker industry, the findings of this research can have broader implications in the realms of digital marketing and consumer protection.

1.4 Problem statement

To assess the role of fatigue in decision-making, the dynamic nature of online gambling like poker games offers a unique platform to study human behavior under risk and build a framework of findings useful to be applied in practical fields, better understanding underlying trends and patterns.

Therefore, the study aims to answer the following research question: *How and to what extent does fatigue influence poker players' decision to buy insurance in online poker games? Additionally, how do moderating effects of learning over time and the stakes involved impact the effect of fatigue on insurance choice?*

1.5 Scope and Feasibility

One of the leading platforms for online poker, *Pokerstars*, introduced the "*All-in Cashout*” in 2019. This functionality offers players an insurance option in the most critical moment of the game: the showdown. In poker, the showdown is the final phase of a particular hand where the remaining players reveal their cards to determine the winner. The showdown represents a critical decision point, particularly in hands where the outcome is still influenced by cards yet to be revealed. This is where the “*All-in Cashout*” option comes in. This feature allows players in a showdown to opt for a safe payout instead of participating in the binary lottery. Each player in a showdown situation has to make a strategic choice between:

- Taking the safe insurance option (*“All-in Cashout"*) with a known payout.
- Participating in the binary lottery with the risk and reward of potentially winning or losing the entire pot.

This development has added a new dimension to the decision-making process in online gambling, blending traditional risk-taking with options for risk mitigation, and this study will focus on the factors influencing the purchase decision of insurance. Traditional models of risk and reward do not fully encapsulate these complex decision-making processes. There is an opportunity to contribute to filling this knowledge gap by comprehending how fatigue, which increases the effort in decision-making (Iodice, Calluso, Barca, Bertollo, Ripari, Pezzulo, 2017), and learning over time, that instead make it less exhausting (Gonzalez, Best, Healy, Kole, Bourne Jr., 2011), shape players' insurance purchase decisions in online poker.

By leveraging a comprehensive dataset from Pokerstars, which encompasses 5,063,505 hands from Omaha poker cash games, where the insurance choice in a showdown situation involving two opponents is shown, the study will employ quantitative analysis methods and logistic regression models, to investigate how these factors interact with the decision-making process, and how their effect is moderated. The feasibility of the research is underpinned by access to a rich dataset (Kalt, Kasinger, Schneider, 2022; Dertwinkel-Kalt et al., 2020), allowing for a detailed examination of player behavior in real-world, high-pressure situations. However, the study will not include the broader spectrum of online gambling behaviors, nor will it address the psychological features of gambling addiction or the efficacy of consumer protection measures. Additionally, while the study will consider the moderating role of learning over time and the stakes involved, it will not delve into other potential influencers such as demographic variables or external economic or social factors. By setting these boundaries, the study aims to contribute meaningful insights into the fields of marketing, consumer behavior, and online gambling research, while acknowledging the limitations inherent in the scope of the study and the data available.

1.6 Research approach and data

The primary focus of the analysis of the study is on the existing dataset of online poker players. Given the width and breadth of the dataset, the emphasis will be on extracting and analyzing the most relevant information that can directly address the hypotheses concerning insurance purchase decisions, fatigue, learning over time, and the stakes involved.

Chapter 2 - Theory (Literature Review)

2.1 General context

Beyond investigating the impact of fatigue on the insurance choice, it is important to resume the existent literature standpoint, that has extensively charted the landscape of choice under risk, to grasp the foundational elements of the context.

When faced with uncertainty individuals choose the action that maximizes their expected utility (Abdellaoui, 2002), and the subject's cognitive abilities intended as the understanding of probability and expectations, financial motivations, and consistency influence the decision-making process (Mongin, 1998). But probability has to be further interpreted by customers, who will give different meanings to a certain likelihood, as subjective experience and prior outcomes influence future choices, i.e., prior gains can increase players' willingness to accept gambles, while prior losses can decrease the willingness to take risks (Barberis, 2013; Thaler, Johnson, 1990). Demographic attributes such as age and sex impact significantly the tendency to take risks. An older person commonly requires a larger probability of expected success than a younger person to make a decision (Greene, 1963). Additionally, if an individual has a choice between two alternatives, one risky and one less risky, he will probably reject the risky option unless the possible reward for assuming the risky alternative is sufficiently high (Greene, 1963). Indeed the stakes involved in the hand, intended as monetary value, moderate the impact of fatigue with the choice to opt for an insurance option. It appears that a player may be less risk-averse in his decision-making process if the potential outcome is deemed valuable enough. On the other hand, people tend to underweight outcomes that are barely probable in comparison with outcomes that are obtained with certainty (Kahneman, Tversky, 1979), generating risk aversion behavior in choices involving sure gains, unless the possible gain of the risky option is outstanding. Risk aversion is a basic assumption also for endowment effect (Barberis, 2013), which highlights the gaps between willingness to accept and willingness to pay, and disposition effect (Andrikogiannopoulou, Papakonstantinou, 2020), which is the tendency of individuals to sell or retain stocks whose value has increased or decreased since the purchase.

The nature of insurance products is strictly linked with the concept of risk. People tend to buy more insurance against events that have a moderately high probability of inflicting a relatively small loss than against low-probability and high-loss events (Slovic, Fischhoff, Lichtenstein, Corrigan, Combs, 1977), because they devote their capacity to dealing with likely events instead of focusing on large losses but rare events. This stands under the expected utility [E(U)] maximization view, while under a behavioral model standpoint for low-probability, high-consequence events, those at risk may buy coverage to reduce their anxiety about experiencing a large financial loss (Kunreuther, Pauly, 2018). In the gambling context, there's a tendency for low-probability events to be relatively overbet and high-probability events to be underbet, a phenomenon known as the favorite–longshot bias (Williams, Sung, Mackenzie, Peirson, Johnson, 2016).

2.2 Impact of fatigue, learning, and stakes on decision making

Fatigue is a many-sided concept that overlaps multiple areas of science. Although it is usually associated with decrements in performance, there are at least three different types of fatigue that are active areas of scientific research: sleep deprivation (Gawron, French, Funke, 2001; Gunzelmann, et al., 2007), physical fatigue (Gawron, 2014), and mental fatigue that results in a reduction of the capacity to perform an activity as a result of extended time spent on mental work (Bartlett, 1953). The last one will be the focus of this study since the accumulation of mental fatigue is frequently responsible for the increase in errors in repetitive tasks (Gonzalez, Best, Healy, Kole, Bourne Jr., 2011). Different degrees of mental fatigue can affect players, leading to an impaired ability to use cognitive processing and to regulate and experience emotions (Pignatiello, Martin, Hickman Jr, 2020), also considering that the pure act of decision-making is exhausting and effort-consuming (Augenblick, Nicholson, 2016). What may trigger the decrease in performance is prolonged work on repetitive tasks, as can deplete an individual's physical and cognitive resources, which can result in both skill acquisition and performance decrements (Healy, 2008). The cognitive performance of carrying out a demanding task is often described by an inverted-U-shaped function, in which performance will improve up to a threshold point, after which, continuing the task will result in impaired performance (Asadayoobi, Jaber, Taghipour, 2021). A higher number of decisions to make probably leads to a more articulated process used to make choices, increasing the difficulty of decision-making. Indeed, as the complexity of a decision rises, the more decision fatigue an individual experiences (Hatami, Sarkhan, Nikpeyma, 2022). Development in the research has shown that during mental fatigue shifts in motivation, the G parameter in the ACT-R model (Jongman, 1998), drives performance more rather than reductions in mental energy. This suggests that people can overcome their state of fatigue and reengage in the cognitive task, and mental fatigue is mostly a motivationally driven mechanism (Hopstaken, van der Linden, Bakker, Kompier, Leung, 2016). In the context of online poker games, fatigue has not been studied so far. It can be considered a short-term development factor and reflects the immediate and short-lived impact of weariness and tiredness on a player's decision-making abilities during the game. Plus, decision-making is dependent on the time of the day (Kouchaki, Smith, 2014) and the higher the number of choices people have to make throughout the same day, the harder each one becomes for the human brain, which eventually looks for shortcuts (Tierney, 2011).

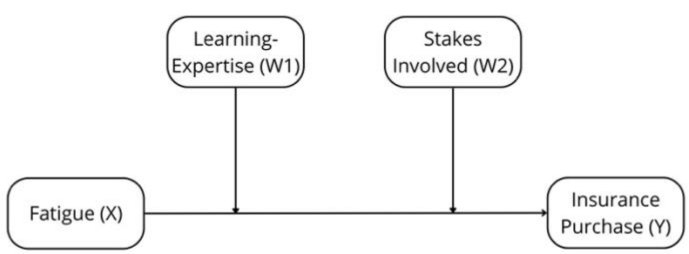
The study aims to test whether fatigue has a significant effect on the decision-making process of poker players regarding the insurance purchase decision, and it will explore how different levels of fatigue, as measured by the duration of playing sessions, impact the likelihood of opting for insurance. Based on the previous stream of research, follows *Hypothesis 1 (H1)*: *An increase in the degree of fatigue leads to an increase in the likelihood of taking the insurance choice*.

In the context of online poker games, in stark contrast with fatigue, learning over time spans across weeks, months, or even years, encapsulating a player's long-term growth and adaptation in the realm of poker. This aspect represents the progressive accumulation of experience and knowledge gained by players over an extended period, beyond individual playing sessions, i.e., player expertise, and it is mainly embodied by profits for a player. Online gamblers are more likely to perceive themselves as skilled at poker than offline players and have more distortions on the GBQ (Steenbergh, Meyers, May, Whelan, 2002), which is a widely used measure of gambling-related cognitive distortions that is grounded in theory. Having skill is certainly a powerful tool to succeed in poker games, indeed from the World Series of Poker of 2010 emerged that players a priori considered as highly skilled achieved an average return on investment (ROI) of +30%, compared to the -15% for other players (Levitt, Miles, 2014). When people retain attention selectivity they maintain or even improve accuracy in repetitive tasks, rather than exhibit a decline in accuracy. These positive effects, represented by a decrease in response latency over time, result from general skill acquisition in a prolonged time frame and specific learning or repetition priming attributable to the repeated occurrence of stimuli and responses (Gonzalez, Best, Healy, Kole, Bourne Jr., 2011). Wright’s model’s (WLC) learning curve (Jaber, 2016; Glock, Grosse, Jaber, Smunt, 2019) assumes a constant learning rate, but it is not realistic to assume in real life, as many other factors influence the learning process. Therefore, as fatigue accumulates within every repetition in a short-term time frame, it eclipses the long-term improvements resulting from learning. A revised version of Wright's model (WLC) states that fatigue not only accumulates exponentially over time in the same session, and is influenced by the increasing number of repetitions, but does so according to a positive exponent, which contributes to creating the U-shaped pattern (Jaber, 2016; Glock, Grosse, Jaber, Smunt, 2019). Because of the experience and learning degree gained, more experienced poker players might approach decision-making in insurance choice differently from novices, based on their expectations and past experiences with similar situations (Barberis, 2013). The study seeks to investigate the impact of a player's long-term experience and skill development in poker on his insurance purchasing behavior and test whether learning over time has a significant moderating effect between fatigue and insurance purchase decisions. Based on the stream of research mentioned above, *Hypothesis 2 (H2)*: *Learning Over time (Player Expertise) moderates the relationship between fatigue and the likelihood of taking the insurance choice such that higher levels of learning attenuate the effect of fatigue*.

When during a poker game stakes move up to higher levels, the number of passive players decreases (Siler, 2010). This may be linked to the fact that the win rate coefficient for passive strategies decreases at higher stakes, instead both uncertainty about the strategic play of opponents and chances for profit increase (Siler, 2010). Hence, assessing uncertainty into precise quantitative risk becomes more difficult. When the stakes are smaller players have more trouble in properly weighting incentive structures characterized by frequent small gains and occasional large losses (Siler, 2010). Consequently, the relationship between winning a large proportion of hands and profitability is negative (Siler, 2010). Therefore, the pressure of playing a high-stakes hand is much more elevated. The prospect of winning money serves as the primary motivation for poker players (Hayano, 1984), even if also other incentives exist like sharpening skills, sociability, and gaining the status of a regular player (Bradley, Schroeder, 2009). Moreover, the psychological value of virtual or physical representations of money, as chips in poker, is less than real money (Lapuz, Griffiths, 2010), a phenomenon known as "payment transparency" (Lapuz, Griffiths, 2010; Thaler 1999). Gambling with chips may lead to a suspension of judgment (Lapuz, Griffiths, 2010), a state in which the gambler's financial value system is distorted and can stimulate further gambling. Playing at higher stakes entails a greater mental commitment and can weigh in deciding whether to choose an insurance option or not. While the payment transparency effect surely has an impact on online poker games, the particular game the study is based on uses real money and not chips. Due to the setting of the data for the analysis, the increasing effect of high-stakes hands on the pressure perceived by players is of higher relevance. This study indeed aims to test whether the Stakes Involved moderate the relationship between fatigue and the insurance purchase decision. Specifically, it is hypothesized that the impact of Fatigue on the decision to purchase insurance varies depending on the monetary value at risk in each hand. This hypothesis aims to explore the dynamic interaction between the cognitive state of the player and the financial implications inherent in the stakes of the game. Follows *Hypothesis 3 (H3): The stakes involved moderate the relationship between fatigue and the likelihood of choosing the insurance option, with higher stakes intensifying the effect of fatigue.*

2.3 Conceptual model

Considering the hypotheses presented above, an overall view of the double moderation model of the study is graphically represented:



- Insurance purchase decision is the dependent variable (DV), indicating whether a player decides to buy the "All-in Cashout" insurance option during a poker hand.

- Fatigue (short term development) is the independent variable (IV) of the model and is measured by the duration of a playing session, reflecting the immediate short-term effects of exhaustion on decision-making about insurance choice.
- Learning over time – Player expertise (long term development) is the first moderator (W-1) on fatigue in the model. It represents the long-term accumulation of poker experience and monetary gains over time (number of showdowns faced and profit earned).
- The stakes involved represent the monetary value at risk in each hand and moderate (W2) the effect of fatigue on the decision to buy insurance, positing that the impact of fatigue may be greater at higher stakes, potentially leading to a higher propensity to insure.

The conceptual model integrates psychological, behavioral, and economic findings to understand the multifaceted decision-making process regarding insurance purchases in the context of online poker gambling. It considers the interplay of short-term cognitive states, like fatigue, and long-term developments, such as learning, within the framework of varying financial stakes, both within the same player and between different players.

Chapter 3 - Data and Methodology

3.1 Background

Omaha Poker cash games

The data set used to develop the study builds data and setup by Dertwinkel-Kalt et al. (2020), and gathers data on Omaha Poker cash games, a variation of the popular Texas Hold'Em, with some notable differences. The main one is the number of private (*hole*) cards that players receive at the start of each hand, namely two in Texas Hold'Em and four in the case of Omaha Poker cash games. Additionally, instead of using chips, that are perceived to be worth less than real money (Lapuz, Griffiths, 2010), like in poker tournaments, this game is played with the use of real money. This helps the gambler to better understand the value of his spending and avoid the pitfall of "payment transparency" (Lapuz, Griffiths, 2010). Along with the four private cards, five community cards are dealt face-up on the board. The objective of the game is for each player to select two of their private cards, combine them with three community cards, and form the best possible five-card poker hand. Each hand is composed of five betting rounds: i) *Pre-flop*: the player sees the hole cards and decides whether to enter the hand by calling the value of the big blind; ii) *Flop*: the first three community cards are dealt face up on the board and a betting round ensues; iii) *Turn*: the fourth community card is dealt and follows another round of betting; *River*: the last community card is dealt and the last round of betting takes place; *Showdown*: occurs if there is more than one player left after the *river* turn[2]. The player with the best five-card hand wins the *pot*, which is the sum of money that they wager during a single hand. On the Pokerstars platform, a percentage fee for providing the service is collected from the pot, namely the *rake*, which ranges from 3.5% to 5% depending on the *stake* (Kalt, Kasinger, Schneider, 2022). The player who wins the hand is awarded the *net pot*, resulting from the difference between the *pot* and the *rake*.

Insurance option

The so-called *All-in-cashout* is a feature added to the Pokerstars platform on August 13, 2019. It allows players who face a showdown situation to choose a safe alternative against the risky one

[2] Information about the functioning of Omaha Poker cash games can be retrieved from: https://www.pokerstars.it/en/poker/games/omaha

of going all-in. The website software calculates each player's chance of winning the hand, based on their hole cards and the ones on the board. Considering these percentages, Pokerstars offers a cash amount corresponding to the equity of each player in the pot, from which a fee is subtracted for using the option. The overall payout when choosing the insurance option is calculated as $\$(\text{pot - rake}) \times \pi \times 0.99$, which is the expected value of the lottery minus a fee of 1% charged by the platform (Dertwinkel-Kalt et al., 2020; Kalt, Kasinger, Schneider, 2022).

3.2 Data

The source of this data is a study about players' skewness preferences (Dertwinkel-Kalt et al., 2020; Kalt, Kasinger, Schneider, 2022). The data set contains 5,063,505 observations, composed of decisions of 85,326 distinct players, each identified by a unique ID number. Each row of observation pertains to a unique situation of showdown between two or more players.

Data are extracted from 2,445,464 distinct Omaha Poker cash games showdown situations played on the Pokerstars website between January 01, 2020, and June 30, 2021. The number of distinct hands is 48.3% of the total observations as they represent showdown situations between two players. The variables of the data set encompass pieces of information about the actions of players in the various rounds of the poker hand (*Pre-flop, Flop, Turn, River)*, the position on the table (*BB*: big blind, *SB*: small blind, *CO*: cutoff, *MP*: middle position, *EP*: early position, *BTN*: button), which are important for understanding the context of each decision. Additionally, performance and strategy metrics are reported as the winning probabilities in showdown situations, which highlight players' success rate and efficacy, the participation levels in different hands of the game, and the profits obtained, as the ones expected. Also, the value of the pot and the rake are listed, as representing the most important financial information about the cost of playing. The focus of the analysis is on the variable *insurance*, namely a dummy variable, which is the dependent variable of the study. The value 1 is assigned if the player chooses to insure against the risk of following the showdown (safe option), instead, the value 0 is assigned to the variable whether the player chooses to face the risk and does not take the insurance option. Considering that there are no missing values on this variable, players choose the safe option in 17.2% of cases with a standard deviation of 0.377 (Table 1), which is a rather low share of the overall choices. This may result from the assumption that most of the gamblers involved in the analysis are risk-seeking as a trend, or by other decision-making mechanisms.

Table 1: Summary statistics on insurance choice

Statistic	N	#(Choice=1)	#(Choice=0)	Mean	St. Dev.
Insurance choice	5,063,505	871,821	4,191,684	0.1722	0.377

Along the four betting rounds of a single hand, players have the chance of folding, i.e., decide not to follow a raise and exit the game for that hand. They reach the last betting round on 50.9% of the cases and face 59.34 showdown situations on average. When the safe option is chosen, the average payout of the insurance is 35.03$, ranging from 0.01$ as the minimum value to 63,599.99$ as the highest payout of insurance. When a player reaches the showdown and decides not to buy the insurance, the times he wins are 48.12% of the cases.

To develop additional robustness checks, some hand, player, and time-specific unique characteristics were derived from the original data, as expected value and variance that allow controlling for individual hand effects, a unique player identifier which is used to group observations at the player level, the count of distinct hand for each player, the profits gained along the games joined, the amount of money every player start the hand with, the average win probability, and several time-specific controls.

The winning probability at showdown and the net pot size are used to calculate the expected value, $E = \pi$x, and the variance, $V = \pi(1 - \pi)x^2$, of binary outcome gamble that players face in showdown situations (Kalt, Kasinger, Schneider, 2022). The lotteries in the data set have an average expected value of 61.68$ (SD 323.24), a standard deviation of 323.24, and a median of 13.78$. Variance, as the percentile distribution includes a very large set of values mainly in the direction of the higher values, shows a tendency to be highly skewed.

Table 2 – Summary statistics on Expected Value and Variance

Statistic	N	Mean	St. Dev.	Pctl(25)	Median	Pctl(75)
Expected Value	5,063,505	61.68	323.24	5.41	13.78	36.4
Variance	5,063,505	80,407.7	2,834,408	35.43	178.69	1,140.75

All other relevant summary statistics are reported in Appendix A.

3.3 Methodology

This study utilizes a double moderation analysis to evaluate the impact of fatigue on the insurance purchasing decision in online poker games. The analysis takes into account the moderating influences of learning over time and the stakes involved. By using this approach, the relationship between fatigue and the decision to purchase insurance is designed, while controlling for the player's level of expertise and the stakes of the poker game.

Empirical strategy

The study employs a logistic regression analysis to test the hypotheses derived from the moderated moderation model. This choice is predicated on the binary nature of our dependent variable, the insurance purchase decision, which necessitates a methodological approach capable of handling dichotomous outcomes effectively. The logistic regression model is estimated with the following reduced-form equation:

$$Y_{i,j(h,m)} = \beta_0 + \beta_F F_j + \beta_L L_j + \beta_S S_j + \delta_h + \gamma_m + \varepsilon_{i,j} \quad (1)$$

Where the dependent variable $Y_{i,j(d,h,m)}$ is a binary indicator of whether player i chooses the insurance option in decision moment j, that refers to a specific hour of the day h[3], since decision-making is dependent on the time of the day (Kouchaki, Smith, 2014), and month of a year m[4]. The variable F_j represents fatigue as a continuous score, which is calculated as follows: for each player, on each unique game day in the data set, the number of distinct showdown situations faced is counted. This is the total gameplay activity for each player on each specific day. Next, an average threshold of daily showdowns faced is calculated for every single player across all game days available. This average represents the typical daily activity level serving as a personal threshold. For each game record then, it is classified whether the player's activity for each hand (showdown) played was above or below the average threshold, and consequently, if the player was low-fatigued or high-fatigued in that decision moment. To derive a unique fatigue score for

[3] Hours of the day are divided into three moments: Morning (from 6 a.m. to 11.59 p.m.), Afternoon (from 12 p.m. to 5.59 p.m.), and Evening (from 6 p.m. to 11.59 p.m., and from 12 a.m. to 5.59 a.m.). This division ensures that the entire 24-hour day is covered by these three categories.

[4] Months and years values are extracted from the dates and combined into a single string, formatted as "Month_Year", and converted into a factor with levels ordered chronologically to ensure proper sequencing in subsequent analyses.

each hand at the player level, a ratio between the particular hand count (number of showdown hands) within the same day and the average threshold for each player is calculated [5]. L_j, on the other hand, denotes learning over time, encapsulating the cumulative experience and improvement in a player's performance. Within the data set is measured with a continuous variable, which provides an expertise score, to catch a broad spectrum of in-game dynamics. Grouping by player identifiers to ensure that the subsequent summaries are computed for each player individually rather than for the data set as a whole, the count of distinct showdown hands for each player and the profits over hundreds of hands for each player are standardized using z-score normalization, to avoid extremely high skewed results, and combined (averaging)[6]. These two variables represent one skill proxy (profits) and an experience proxy (total showdowns), providing a balanced measure. Averaging the standardized scores permits each of the dimensions to contribute equally to the final score, despite originally having different scales and ranges of values. The expertise is calculated as a time-invariant value within the data set since it is not possible with actual settings to address extended time-related features, e.g., how many years a player has been playing before the data collection. S_j represents the stakes involved in the game, quantified by the monetary value at risk. The variable that encapsulates this concept in the data set is a continuous stakes levels score, which is calculated as the ratio between the *"pot"* (prize of the lottery) and the average pot that each player is used to face. This ratio provides a measure of the risk that a player is taking in a particular hand, compared to his average. Higher ratios suggest that a significant portion of the player's stack is at risk[7]. δ_h variable controls for the time of the day (morning-afternoon-evening) fixed effect toward specific behaviors affecting risk-

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[5] Example: if a player has a fatigue score < 1 in a certain showdown hand, it means that his fatigue level is low, as he is playing below his average number of showdowns per day (e.g., if a player's average number of showdowns on the same day is 4, and he is playing the second showdown of the day, his fatigue score will be 0.5, and he is considered low-fatigued). Whether the fatigue score is > 1, the showdown hand at stake is above the average threshold for that player, who is intended as fatigued (e.g., if a player's average number of showdowns on the same day is 4, and he is playing the fourth showdown of the day, his fatigue score will be 1.5, and he is considered high-fatigued).

[6] After standardization the metric variables are now on a similar scale, giving equal weight to both variables in the final expertise score regardless of their original units or distributions. The averaging process to obtain the expertise score is calculated as follows: (*Total_hands_per_player* + *profit_per_hundred_hands_noins*) / 2.

[7] If a player has a stakes level score < 1 in a certain showdown hand, it means that he is facing a low stake hand, as the price of the lottery is below the average price faced by that player (e.g., if a player's average pot is 20, and the price of the hand is 15, his stakes score will be 0.75, which is considered a low-stake hand for that player). Whether the stakes level score is > 1, the price of the lottery at stake is above the average threshold for that player, and the hand is considered a high-stakes one (e.g., if a player's average pot is 20, and the price of the hand is 40, his stakes score will be 2.0, which is considered a high-stake hand for that player).

taking, and γ_m accounts for effects of seasonality, comprehending months and year-specific factors. Finally, $\varepsilon_{i,j}$ captures the error term, encompassing the influence of unobserved factors on the insurance purchase decision.

$$Y_{i,j(d,h,m)} = \beta_0 + \beta_F F_j + \beta_L L_j + \beta_S S_j + \rho \boldsymbol{E}j + \mu \boldsymbol{V}j + \sigma \boldsymbol{W}_j + \delta_h + \gamma_m + \varphi \boldsymbol{P}_j + \varepsilon_{i,j} \tag{2}$$

To account for potentially misleading factors related to particular moments in hand scenarios this extended equation adds two hand control variables: expected value Ej [8] and variance Vj [9]. Controlling for expected value accounts for the inherent profitability or risk associated with each hand, ensuring that the decision to take insurance is not a reflection of the profitability of the hand. Controlling for variance instead accounts for the risk associated with each hand, since hands with higher variance are riskier because of the outcomes being less predictable. W_j represents a control variable for hand-specific characteristics as the day of week[10], the position at the table of the player ("BB", "SB", "CO", "MP", "EP", "BTN")[11], and the amount of money the player started the hand with (stack)[12]. These three control variables contribute to addressing hand-specific features. Finally, $\boldsymbol{P}_j$ includes player controls as loss and profits per hundred hands and the average win probability at showdown.

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[8] Calculated as $E = \pi$x, where π are the winning probabilities and x is the net pot size (pot – rake)
[9] Calculated as $V = \pi(1-\pi)x^2$, where π are the winning probabilities and x is the net pot size (pot – rake)
[10] A factor variable with different levels representing days of the week (Monday, Tuesday, Wednesday, Thursday, Friday, Saturday, Sunday).
[11] The relative position at the table impacts the range of hands played, bet sizing, and overall strategy, as players in later positions can exploit the information gained from earlier actions.
[12] Player's stack is the total amount of chips/money they have in front of them at the table. The size of a player's stack can significantly influence strategy and decision-making during the game.

Chapter 4 - Results

4.1 Descriptives

Fatigue

A descriptive analysis of insurance choice is developed for varying fatigue levels, assuming constant player expertise and stakes.

First, the number of showdowns by each player when fatigued or not (above or below the fatigue threshold) is counted and hands played below and above the threshold levels are divided into two groups, representing low and high fatigue levels respectively[13]. Lastly, the percentage of people who chose *'1'* for insurance in each of the two groups is computed. The overall average percentage of insurance chosen by more fatigued players is 17.6%, while for less fatigued players the share of insurance choice is 16.4 % (Table 3). This difference is in line with *Hypothesis 1 (H1)* of the study, as a rise in the degree of fatigue corresponds to a higher amount of insurance taken since the average insurance choice in the data set is 17.2 %. Fatigued players exceed this average share by 0.4 percentage points, while low-fatigued ones fall short by 0.8 percentage points, highlighting different behaviors tied to converse moments of fatigue.

Table 3 – Insurance rate with Fatigue effect

FatigueLevelDaily	TotalHands	InsuranceChosen	InsuranceRate
Above Mean	3483207	612455	17.6
Below Mean	1580298	259366	16.4

Table 3 compares the insurance scores for both low and high-fatigue groups.

The majority of hands in the data set (68.79%) are high-fatigue showdown hands, which leads to higher insurance choice rates. In comparison, 31.21% of hands are played under a state of low fatigue (Table 4, Appendix A.1). The prevalence of showdowns played above the mean threshold underlines the importance of studying the impact that fatigue has on insurance choice, and how the decision making develop in fluctuating fatigue scenarios. Although the results support a preference for insurance choice among more fatigued players, a regression analysis will address additional variables that influence the choice outcome, including the moderators of the model

[13] High fatigue group is composed of players with a fatigue continuous score > 1, while low fatigue group observations have a fatigue score < 1.

learning – player expertise and stakes involved. The aim is to understand how different degrees of player expertise and stakes involved impact the likelihood of choosing the insurance option for fatigue levels.

Learning over time (Player Expertise)

The degree of expertise is expected to moderate the impact of fatigue on insurance choice. Players were assigned a personal expertise score, calculated on the count of total hands played and profit per hundred hands. This moderator is operationalized as a continuous variable, on a scale ranging from -48.30588 as the minimum value and 31.07426 as the maximum one (Table 5, Appendix A.1). To build descriptive statistics on the continuous variable assessing its distribution and behavior at the minimum and the maximum, players below the 25 percentile and above the 75 percentile are divided into two groups. The average insurance choice rate (i.e., the proportion choosing insurance) is then calculated for the two expertise groups.

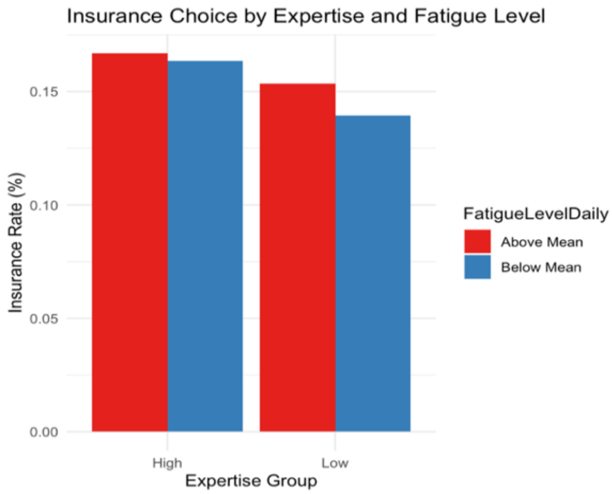
Table 6 – Insurance Choice rates in Expertise groups

ExpertiseGroup	InsuranceRate	Count
Low Exp	14.8	1265859
High Exp	16.6	1264659

The lowest insurance choice rate is for the Low Expertise group, with 14.8% of people choosing the insurance option, while more expert players choose it in 16.6% of the cases. The varying insurance rates across different expertise levels suggest that player confidence and risk assessment capabilities could be influencing their decision to choose insurance. More experienced players (High Exp) might decide to opt for insurance more frequently as a safety net due to perceived higher risks or due to a deeper understanding of gaming scenarios. However, both groups purchase insurance with a reduced frequency compared to the data set average (17.2%).

As a moderator in the model, is interesting to control for the effect of player expertise on the players more and less fatigued. While the Low Expertise group shows more than one percentage point difference in insurance rates between fatigue levels (1.4%), this difference is notably less in magnitude (0.3 %) in the High expertise group (Table 7, Appendix A.1). In Figure 1 insurance choice among different levels of expertise and fatigue is displayed.

Figure 1 – Insurance Choice Expertise ~ Fatigue



Stakes involved

The stakes involved moderate the relationship between fatigue and the likelihood of choosing the insurance option and is expected that higher stakes enhance the effect of fatigue. This moderator is operationalized as a continuous variable, on a scale ranging from 0.00025 as the minimum value and 72.53313 as the maximum one (Table 8, Appendix A.1). To assess the distribution of the variable and its behavior at minimum and maximum players below the 25 percentile and above 75 percentile are divided into two groups (Table 9).

Table 9 - Insurance Choice rates in Stakes percentiles

StakesCategory	InsuranceRate	Count
Low Stakes	13.2	1265877
High Stakes	21.3	1265876

The mean of 21.3% of insurance taken in High Stakes hands is higher by 4.1% on the average insurance choice (17.2%) and is the group with the highest share among all the ones in the various variables of the model. This behavior is indicative of increased risk aversion when players face higher potential losses, as the pressure of playing a high-stakes hand is much more elevated since the prospect of winning money serves as the primary motivation for poker players (Hayano 1984).

Figure 2 – Insurance Choice Stakes ~ Fatigue

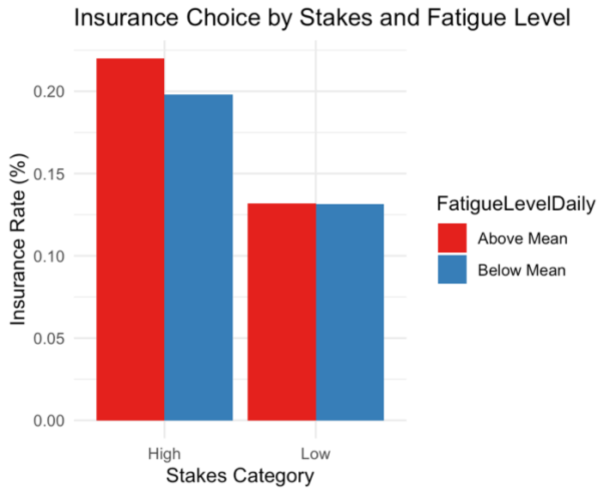


Figure 2 shows that players categorized under "Above Mean" fatigue consistently show higher insurance choice rates compared to their "Below Mean" counterparts, also across stakes categories, reinforcing *Hypothesis 1 (H1)* of the study. In the high fatigue group, the proportion of people choosing insurance grows by 2.2 percentage points as the stakes rise (Table 10, Appendix A.1). This pattern suggests that players are more inclined to choose insurance as the potential loss (or risk) increases, which is consistent with risk-averse behavior. For players with "Below Mean" fatigue the variations in insurance rates across different stakes are significantly smaller compared to those in the "Above Mean" fatigue category. This suggests that in low-stakes scenarios the fatigue effect is mitigated while being under high-stakes pressure increases the impact of fatigue on insurance choice, and this aversion is further amplified when they are fatigued.

4.2 Regression analyses

Results

Table 11 shows marginal effects from the logistic regression estimated on equation (1) and (2). To compare the magnitude of the different coefficients more consistently, the variables in the main specifications are log-transformed and standardized (z-scores). The regression coefficients (Table 12, Appendix A.2) represent the change in the log odds of the dependent variable for a one standard deviation change in the log-transformed predictors. To obtain marginal effects average predicted probabilities ($\hat{p}$) are calculated, which represent the average probability that the dependent variable equals one (e.g., choosing the insurance option) for each observation. Then marginal effects are computed using the following formula: $ME_i = \hat{p}(1-\hat{p})\beta_i$ [14]. Standardized variables allow probability to be interpreted as the average insurance choice share in the sample at stake in the regression.

Column 1 (Table 11) shows marginal effects for the model without control variables. It emerges that a one standard deviation rise in fatigue increases the probability of choosing insurance by 0.5 percentage points. The coefficient is highly statistically significant (p-value<0.0001). This finding underpins the pivotal role of fatigue in decision-making, suggesting that individuals are more likely to choose insurance when they experience higher levels of fatigue.

The interaction term between fatigue and learning (expertise) reveals a significant (p-value<0.0001) negative effect. Increasing expertise by one standard deviation reduces the impact of fatigue on the probability of choosing insurance by 0.3 percentage points. Therefore, higher levels of expertise mitigate the influence of fatigue, potentially due to more informed decision-making processes and developed knowledge about gaming scenarios.

The interaction term between fatigue and stakes involved shows a positive and highly significant (p-value<0.0001) effect. An increase in stakes involved by one standard deviation amplifies the impact of fatigue on the probability of choosing insurance by 0.4 percentage points. This result suggests that the perceived stakes enlarge the effect of fatigue, leading to a higher likelihood of choosing insurance under higher-stakes conditions.

In Column (2) hand-specific characteristics are included as control variables. The estimated magnitude of marginal effects of the independent variable and the moderators do not change considerably compared to Column (1), and the variables remain highly statistically significant (p-value<0.0001). Fatigue impact on insurance choice increased by 0.1 percentage points, the learning effect on fatigue decreased by 0.1 percentage points, and the stakes' impact on fatigue remained stable. When including player-specific controls, see Column (3), results consistently show similar effects as Column (2). The results of the fixed effect regression model, controlled by hand and player-specific characteristics are shown in Column (4) of Table 11. Here, a one standard deviation rise in fatigue increases the probability of choosing insurance by 0.6 percentage points, differing from basic specification by 0.1. Also, the learning effect shows a 0.1

[14] Where $\hat{p}$ are the predicted probabilities by the model, consistently taking a value 0.172, and β_i is the predictor coefficient from GLM logistic regression.

decrease compared to the basic specification while the stakes moderator's magnitude of effect remained unchanged between models (1) and (4).

Overall, the results are consistent in direction and statistically significant (p-value<0.0001) across the four different model specifications, demonstrating the robustness of the findings.

Table 11 – GLM Regression marginal effects

	Dependent Variable: Insurance choice dummy			
	(1)	(2)	(3)	(4)
Fatigue	0.005***	0.006***	0.006***	0.006***
	(26.483)	(34.767)	(34.692)	(35.163)
Fatigue * Learning	-0.003***	-0.004***	- 0.004***	-0.004***
(Expertise)	(-16.810)	(-22.388)	(-22.328)	(-22.303)
Fatigue * Stakes	0.004***	0.004***	0.004***	0.004***
Involved	(22.551)	(23.694)	(23.940)	(23.827)
Constant	-1.589***	-1.721***	- 1.722***	-1.758***
	(-1326.993)	(-422.304)	(-422.423)	(-255.026)
Hand-specific controls	No	Yes	Yes	Yes
Player-specific controls	No	No	Yes	Yes
Time fixed effects	No	No	No	Yes
Observations	5,063,505	5,063,505	5,063,505	5,063,505

Note: The table reports the GML regression marginal effects of the empirical equations (1) and (2). The dependent variable is a binary indicator matching 1 if a player chooses the insurance option and 0 otherwise. The independent variable of interest is Fatigue. Learning (Expertise) and Stakes Involved represent the interaction term between the independent variable and the moderators, being the proxy for the moderation effect of the model. Additionally, controls for hand-specific and player-specific are added, along with the fixed effect of time, to control for unobserved heterogeneity across games, players, and over time. The independent variable and moderators enter the regression as log-transformed and standardized z-scores. Corresponding z-values are provided in parentheses. Specifications (1)-(3) differ in the control variables used in the regression: (1) does not contain any additional control variable, (2) amplify the basic specification by adding hand-specific characteristics as controls, (3) take both hand and player-specific characteristics into account. Column 4 shows the time-fixed effect regression results, which comprehend all the aforementioned control variables and fixed effects. P-value significance levels: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1.

Positive and significant fatigue marginal effect on insurance choice confirms *Hypothesis 1* (*H1*) statement, as a growth in fatigue leads to an increase in the likelihood of taking the insurance choice. Constant negative and significant marginal effects of learning validate *Hypothesis 2 (H2)*, considering that higher levels of expertise decrease the impact of fatigue on binary choice. Finally, positive and statistically significant marginal effects of stakes on the relationship between fatigue and the twofold outcome support *Hypothesis 3 (H3)*, as higher stakes enhance the effect of fatigue increasing the probability of opting for insurance.

4.3 Robustness checks of results

In this section robustness checks are provided to address potential limitations and issues of the framework. First, to ensure the robustness of the logistic regression findings, a Linear Probability Model (LPM) is estimated. While logistic regression is generally preferred for binary outcomes as predicted probabilities remain between 0 and 1, LPM provides a straightforward interpretation of coefficients as marginal effects. Comparing the marginal effects obtained from the logistic regression with the Ordinary Least Squares (OLS) estimates from the LPM allows to assess the consistency of the results. They remained qualitatively robust. In both specifications, estimated marginal effects are almost unchanged (Table 13, Appendix A.2). Fatigue marginal effects on insurance choice in the GLM model range from 0.5 to 0.6, and in the LPM one assumes a constant value of 0.5. The expertise moderation effect shows a decrease of 0.1 from specification (1) to (4) in the GLM model and remains stable in the LPM model (takes a constant marginal effect of 0.3 percentage points), while stakes record a 0.1 difference in specification (4) across the two models (0.4 in the GLM, 0.5 in the LPM). The marginal effects from the logistic regression are similar to the OLS estimates, strengthening the confidence in the findings, also considering that all the coefficients are statistically significant (p-value<0.0001).

Second, a Fixed Effect logistic regression (FEGLM) is developed to control for unobserved heterogeneity at the player level, accounting for player-specific characteristics that may influence the decision to choose insurance, thanks to the variable "*playername",* which is a unique identifier for every single player. It helps isolate the within-player variation and reduces potential biases arising from omitted variables, ensuring that the estimated effects are not confounded by individual-specific factors that remain constant over time at the player level. Results, displayed in Table 15 (Appendix A.2), show consistency for marginal effects between the GLM and FEGLM. In specification (4) Stakes effect varies by 0.2 percentage points in the fixed effects model respect to the GML one, while the other variables accounted for remained equal in magnitude and direction. Due to the nature of fixed effects in consideration, some observations are removed because they only have one outcome category (either all 0s or all 1s). For a specific player in the data set, if all recorded instances are 0 or 1 and there is no variation in the outcome to estimate, it means that he never or always chose insurance. For this reason, 44,434 fixed effects (1,046,254 observations) were removed, but despite this reduction, the results remain robust and provide valuable insights, relying on 4,017,251 observations. All results stick to a high significance level (p-value<0.0001). Therefore, including player-fixed effects enhances the robustness of the results, by guaranteeing that they are not driven by unobserved individual heterogeneity, and by observations with only one outcome category.

Third, a regression with the same specifications (1), (2), (3), (4) is run on a model that includes fatigue as a factor variable (until now was coded as a continuous fatigue score) with two levels: "Below Mean" and "Above Mean", to classify players into two groups. Below and above refer to a particular moment in the game: each hand played is labeled with one of the two levels depending on the personal threshold of fatigue of every player, on every unique day. Table 16 and Table 18 of Appendix A.2 report the coefficients of the logistic regressions representing the change in the log odds of the dependent variable for a one standard deviation change in the predictors. In the first one "Below Mean" level is set as a reference level, to compare how players behave when their fatigue level shifts from low to high, conversely in the second "Above Mean" is set as a reference level of the factor variable to catch effects of fatigue level changing from high to low. Tables 17 and 19 (Appendix A.2) show marginal effects for fatigue labeled as a factor variable. When moving from the "Below Mean" to "Above Mean" group the probability of choosing insurance increases by 0.9 (1) to 1.1 (4) percentage points (p-value<0.0001), confirming that being fatigued increases the likelihood of choosing the insurance option. When shifting from "Below Mean" to "Above Mean" fatigue, a one-unit increase in expertise leads to a decrease in the probability of choosing insurance by 0.5 (1) to 0.8 (4) percentage points (p-value<0.0001). Finally, higher stakes intensify the positive effect of increased fatigue on choosing insurance. For each unit increase in stakes, the increase in the probability of choosing insurance when moving from "Below Mean" to "Above Mean" fatigue is enhanced by 0.8 (1) - (4) percentage points (p-value<0.0001). The results show consistency in terms of the direction and significance of the effects of the model's variables since higher fatigue increases the probability of choosing insurance, expertise moderates this effect negatively, and stakes moderate this effect positively. However, the magnitude of the effects is slightly different when treating the fatigue variable as continuous versus factor. Indeed, treating fatigue as a continuous variable allows for a detailed understanding of its incremental effects on the probability of choosing insurance while handling it as a factor variable with two levels captures the broader shifts in behavior across the groups. Therefore, the continuous treatment results in smaller magnitude effects due to its fine-grained sensitivity to incremental changes. In contrast, the factor handling highlights changes associated with moving from "Below Mean" to "Above Mean" fatigue levels, resulting in larger magnitude effects. Finally, is relevant to give prominence to the fact that even if results show some little differences in magnitude, direction and statistical significance of the model's predictors are still consistent, and findings are consequently reinforced.

Fourth, the predictor variables used within the GML, LPM, and FEGLM are log-transformed and standardized. A log transformation rescales the actual measurements to return a more homogeneous variability of some responses and a normal distribution consistent with the theoretical distribution of the sample mean. In each situation, a log transformation helps the sample observations better satisfy the assumptions of statistical analysis, making the model more robust to outliers (Curran-Everett, Douglas, 2018). The standardization process was handled using the z-score formula $Z = (X - \bar{X})/s$ [15] (Dubes, Jain, 1980). The standardized variables have a mean of zero and a standard deviation of one, allowing for coefficients to be interpreted on a consistent scale and directly compared to assess the relative importance of different

[15] Where X is the original data value, $\bar{X}$ and s are respectively the sample mean and the standard deviation. The transformed variables will have a mean of 0.0 and a variance of 1.00.

predictors. It also helps mitigate potential multicollinearity issues. These transformations ensure that the variables are correctly distributed and suitable for regression analyses. In Figure 3 (Appendix A.2) the histograms represent the distribution of the log-transformed and standardized variables. Fatigue and stakes variables show a normal distribution while the learning variable's histogram shows a moderate negative skew, with a skewness value of -1.158. The variable remains useful and reliable to use in the analysis since most of the data are clustered around zero and the skewness value is not extreme. Overall applying these transformations to the predictor variables helps reduce the impact of outliers and allows for a more straightforward and meaningful comparison of the coefficients.

4.4 Summary of Results

The analyses conducted in this study aimed to test three main hypotheses regarding the decision-making process of poker players in the context of choosing insurance options.

Hypothesis 1 (H1) posited that a rise in fatigue would lead to an increased likelihood of taking the insurance choice. Results from the regression analyses confirm this hypothesis: across all model specifications, the marginal effects of fatigue on the probability of choosing insurance are positive in direction and statistically significant (p-value < 0.0001). In the base specification without control variables and fixed effect (Table 11, Column 1), a one standard deviation increase in fatigue increases the probability of choosing insurance by 0.5 percentage points when treated as a continuous variable and 0.9 when treated as a factor (Table 17, Column 1, Appendix A.2). This effect remains consistent and even slightly increases when additional control variables are included. In the final model with all controls and fixed effect (Table 11, Column 4), the marginal effect of fatigue on insurance choice is 0.6 percentage points for continuous, and 1.1 for factor predictor (Table 17, Column 4, Appendix A.2). Therefore, is possible to confidently state that fatigue has a meaningful relationship with insurance choice behavior. Players with different activity levels within a daily period show different propensities to opt for insurance, as reiterated activity leads to more fatigue, potentially impacting decision-making processes, since the cognitive performance of carrying out a demanding task an inverted-U-shaped function (Asadayoobi, 2021) that results in a reduction of the capacity to perform an activity as a consequence of extended time spent on mental work (Bartlett, 1953).

Hypothesis 2 (H2) put forward that learning over time (player expertise) moderates the relationship between fatigue and the likelihood of taking the insurance choice, with higher levels of learning weakening the effect of fatigue. The interaction term between fatigue and learning (expertise) shows a significant negative effect (p-value < 0.0001) across all model specifications. Precisely, increasing expertise by one standard deviation reduces the impact of fatigue on the probability of choosing insurance by approximately 0.3 percentage points (0.5 if the Fatigue variable is handled as a factor, see Table 17, Appendix A.2) in the basic model (Table 11, Column 1) and by 0.4 percentage points (0.8 with Fatigue as a factor, see Table 17, Appendix A.2) in the model with all controls and fixed effect (Table 11, Column 4). Therefore, the results validate Hypothesis 2, as the more the expertise level increases, the less pronounced the effect of fatigue on the decision to opt for insurance is. Higher expertise players have better strategies or risk assessments that make them less reactive to changes in their fatigue state.

Hypothesis 3 (H3) proposed that the stakes involved would moderate the relationship between fatigue and the likelihood of choosing the insurance option, with higher stakes magnifying the effect of fatigue. The interaction term between fatigue and stakes involved is positive in direction and highly significant (p-value < 0.0001) in all models. A one standard deviation increase in stakes amplifies the impact of fatigue on the probability of choosing insurance by approximately 0.4 percentage points (0.8 if the Fatigue variable is labeled as a factor, see Table 17, Appendix A.2) in the basic model (Table 11, Column 1) and remains consistent across other specifications (when fatigue is handled as a factor variable last specification (4) reports a value of 0.8 percentage points). This behavior is indicative of increased risk aversion when players face higher potential losses. Findings, validating Hypothesis 3, suggest that the perceived stakes of the decision significantly inflate the effect of fatigue, leading to a higher likelihood of choosing insurance under higher-stakes conditions, as the pressure of playing a high-stakes hand is much more elevated since the prospect of winning money serves as the primary motivation for poker players (Hayano 1984).

Chapter 5 – Survey Design and Results

5.1 Introduction

Building on the theoretical framework established in the earlier chapters and to further validate the findings obtained, a survey was designed to catch quantitative data from poker players in a different experiment setting. The survey aims to investigate the elements that influence decision-making in online poker by studying how fatigue affects choice under risk and how expertise and stakes interact with fatigue in this scenario. The inquiry subjects hover the same as the main study of this research, whereby the poker players. At the same time, the context of data collection changes: in this section, participants were provided with a survey, while the main study is built on observational data gathered directly from players' actions during games. The latter setting, combined with the main one of the research project (observational data collection), permits a deeper knowledge of the phenomenon at stake since, in the questionnaire, players have to auto-assess the various statements of the design. There are some benefits of conducting online data collection through a survey that reinforces the decision to enrich the actual setting with this research method. Indeed, there is the possibility of reaching a potentially illimited population in terms of geographic distribution, within the boundaries of the research scope and aim, targeting the fittest sample to answer the research questions (Lefever, Dal, Matthíasdóttir, 2007). Additionally, it is a time and cost-efficient method for researchers to gather answers, unlike the observational method, which requires a longer time frame to be developed and actuated. Lastly, it enables double-checking whether the findings based on observational data are consistent with ones based on auto-assessed answers about specific behaviors in determined conditions. In particular, the aim is to test the hypotheses that higher levels of fatigue increase the likelihood of choosing insurance, while expertise mitigates, and stakes intensify this tendency.

This section will first describe the survey design, explaining how key variables were measured and how was structured to test the study's hypotheses. It will then present the results, offering descriptive statistics and exploring the relationships between fatigue, expertise, stakes, and insurance purchase behavior.

5.2 Survey Design and Measurements

The survey was developed to explore how fatigue, expertise, and stakes influence decision-making in online poker. It was implemented using the Qualtrics platform. The questionnaire was divided into five sections: demographics, fatigue, player expertise, stakes, and interaction between variables (Item 20, Appendix A3). The questions included in each section were formulated to be aligned with the research questions and derived from the related literature on the key constructs (fatigue, expertise, and stakes). Each section was tailored to tackle its specific hypothesis on how the variables mentioned above influence the decision to purchase insurance in online poker games.

Section 1 – **Demographics**. Basic demographic information such as age (Q1) and gender (Q2) are collected to assess eventual relevant results fluctuations depending on them.

Section 2 – **Fatigue**. This branch includes two statements regarding fatigue to which respondents are asked to agree or disagree, concerning insurance purchase decisions under mental struggle. Q4 is composed of two questions: firstly, investigates the degree to which every single player perceives fatigue during a playing session that lasts longer than his/her average ("I feel mentally fatigued after playing online poker for longer than my average time"), then explores the relationship between increasing fatigue and the decision to purchase insurance ("When I am mentally fatigued, I am more likely to take the insurance option in poker"), as *Hypothesis 1* (H1) states. Participants indicated their level of agreement on a 5-point Likert scale. This section allowed a detailed understanding of players' cognitive states and how they influence subjective risk assessment, knowing that fatigue can have different antecedents (decisional, self-regulatory, situational), i.e. something happening before as the origin of something happening later, (Pignatiello, et.al., 2020).

Section 3 – **Player Expertise**. Expertise was measured using both objective and subjective components. Firstly, participants were asked how long they had been playing online poker (Q3). The variable player expertise gains a new shape of measurement: if in the observational data gathering method expertise was composed of a skill proxy (profits) and an experience proxy (total showdowns), now, a time-related measure is added to the previous setting, whereby the time they had been playing poker. The experience levels range from less than a year to more than five years. Q3 represents the objective component of expertise. Furthermore, Q5 captures the self-assessed expertise level with a validated Likert scale for that kind of measurement, ranging from 1 (novice) to 7 (expert) (MacKay, Bard, Bowling, Hodgins, 2014). This represents a subjective measure of players' confidence in their poker skills. These two proxies of expertise were then used to develop a unique weighted measure: 60% of the weight was given to the number of years of experience (Q3), and 40% to the self-assessment score (Q5). This approach allowed the creation of a robust measure of expertise by integrating both objective and subjective assessments. This section ends with Q6 ("I am less likely to choose insurance because my expertise helps me better evaluate the risks"), which evaluates the impact that expertise has on fatigue and refers to *Hypothesis 2* (H2) of the study, which states that higher expertise should mitigate fatigue effects for online poker players.

Section 4 – **Stakes**. This section is devoted to assessing how the value of money involved in poker games impacts decision-making. Q7 ("I tend to take less risks when playing for higher stakes"), and Q8 ("How much does the value of money at stake influence your decisions during a poker game?") ask to what degree stakes influence decisions and propensity to take risks, assessing a personal sensibility level to financial risk in poker. The latter two questions are based on the DOSPERT scale (Blais, Weber, 2006), which was specifically designed to measure risk-taking behavior across various domains, including gambling, as reflected in the gambling subscale. To conclude, Q9 ("How likely are you to opt for insurance when playing for high stakes?") evaluates how likely are players to opt for insurance when playing for higher stakes, and how pronounced is stakes' impact on fatigue, when have to choose or not the insurance option, which corresponds to the target of investigation of *Hypothesis 3* (H3). This question relates closely to the Gambling-Related Cognitions Scale (GRCS) (Raylu, Oei, 2004) and to the Risk Propensity Scale (Meertens, Lion, 2008), which both focus on decision-making under high-risk and high-stakes scenarios. These items are crucial to understanding the interaction between financial risk and cognitive strain (e.g., fatigue) when making insurance decisions in risky environments.

Section 5 – **Interaction between variables**. Respondents are asked to agree or disagree to two sentences that examine how fatigue, expertise, and stakes interact in poker decisions.

5.3 Data Collection and Sample

The sample gathered through the survey is composed of 168 participants of various ages and genders. The respondents' ages ranged from 18 to 40 years (Mean 24.56, SD 3.41), with an uneven distribution between males, accounting for 95.24% of the sample, and females (4.77%).

The data for this survey was collected from a sample of online poker players drafted through various channels. The recruitment method was indeed two-folded: firstly, reaching out to active online poker players via dedicated group chats and online communities and, secondly, approaching students at the university level who had some experience in playing online poker. Group chats and forums about online poker, where players regularly communicate, provided direct access to a sample that was consistently aligned with the necessities of the research, while university students widened the variety of the sample. This approach has the potential to yield more detailed findings, offering a deeper understanding of the underlying dynamics. Allowing for greater variability and complexity in the data enables a more comprehensive exploration of the subject. The use of different recruitment channels ensured a diverse participant pool, enhancing the robustness of the data and the generalizability of the findings. The survey was scatted through Qualtrics, an online platform that allowed for efficient data collection and distribution.

5.4 Results

5.4.1 Descriptives

Fatigue

The descriptive statistics for the fatigue-related items (Q4_1, Q4_2) furnish insights into how mental fatigue affects decision-making in the online poker context.

Table 21 – Summary Statistics Q4_1

Min.	1st Qu.	Median	Mean	3rd Qu.	Max.
1	2	3	3.293	4	5

Summary statistics for Q4_1 ("I feel mentally fatigued after playing online poker for longer than my average time") highlight that players commonly experience moderate levels of mental fatigue during prolonged sessions. Indeed, the mean response is 3.29 on a 5-point Likert scale (SD 1.17), showing participants leaning slightly toward agreement with the statement, with the score of 4 being the one with the highest distribution of responses (31.4%). Furthermore, the median value is 3. When calculating cumulative percentages for responses below (1-2) and above (4-5) the median, it appears that 44.31% of players report feeling mental fatigue during prolonged sessions, compared to 28.74% who do not. This finding aligns with the theory that the accumulation of mental fatigue is often a contributing factor to the increased occurrence of errors in repetitive tasks and decreased performance (Gonzalez, Best, Healy, Kole, & Bourne Jr., 2011), confirming that it is a quite common event for many players during extended poker sessions.

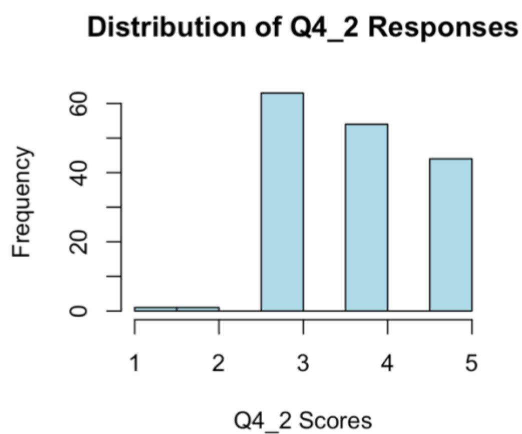
The second item of this section of the survey, Q4_2 (“When I am mentally fatigued, I am more likely to take the insurance option in poker”), inspects the relationship between fatigue and the likelihood of choosing the insurance option on a 5-point Likert scale.

Table 22 – Summary Statistics Q4_2

Min.	1st Qu.	Median	Mean	3rd Qu.	Max.
1	3	4	3.88	5	5

On average, players tend to agree with that statement (Mean 3.88, SD 0.86), confirming that fatigue increases their propensity to take insurance. This finding is relevant since it confirms the statement of *Hypothesis 1* (H1) of the main study: “*An increase in the degree of fatigue leads to an increase in the likelihood of taking the insurance choice”*, enhancing risk-averse behaviors. The distribution of responses is also meaningful, as it is possible to observe in Figure 4 very few participants selected the lowest scores (1-2), namely the 1.2% of the entire study's sample. At the same time, all the answers converged to the highest values, demonstrating that fatigue has a notable impact on decision-making, with almost the entire respondent's group endorsing the tendency to take with higher frequency the insurance option when feeling fatigued.

Figure 4 – Distribution of responses Q4_2



Player Expertise

The descriptive statistics for the expertise-related questions offer insights into the perception of players about their own skill level, and how expertise impacts fatigue on the decision to take the insurance option. This branch of the survey consists of three items that contribute to meeting the study's inquiries.

Q3_1 (Item 20, Appendix A3) is intended to label players' expertise through the years of experience. The results show a quite heterogeneous sample comprised of players with both low and high experience levels. Indeed, 16.77% of respondents had been playing online poker for less than one year, and 22.75% for 1-2 years. Then, the larger part of gamblers in the study's sample had been playing online poker for 2-5 years and the more experienced ones, who played for more than 5 years, represent the 22.15% of the entire group. Therefore, diverse levels of expertise are represented, whether it is deducted by years of experience, enhancing the significance and reliability of the results gained, due to the high within variance of the sample for this variable.

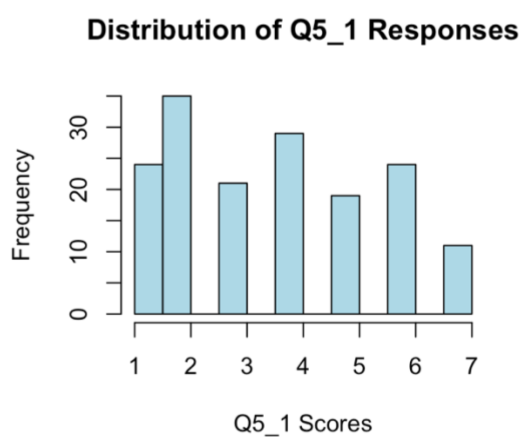
The second relevant item in this section is Q5_1 ("How would you rate your expertise in online poker?"). Asking players to self-assess their skill level represents a complementary measure of expertise coupled with Q3_1 since adds a subjective evaluation to one that should be objective. Q5_1 indeed, captures the self-assessed expertise level with a validated Likert scale, ranging from 1 (novice) to 7 (expert) (MacKay, Bard, Bowling, Hodgins, 2014).

Table 23 – Summary Statistics Q5_1

Min.	1st Qu.	Median	Mean	3rd Qu.	Max.
1	2	4	3.61	5	7

Being the mean 3.61 (SD 1.87), the first quartile 2, and the third quartile 5, it is deductible that a vast part of the players consider themselves to be at a mid-level expertise. The distribution of responses (Figure 5) reports that the more frequent value chosen on the Likert scale is 2 (21.47%), suggesting that a significant portion of the sample identifies with a lower level of experience.

Figure 5 – Frequency distribution Q5_1



The distribution reveals distinct clusters of expertise levels within the sample. Specifically, values 1 and 2 on the Likert scale correspond to self-assessed low levels of expertise, values 3 to 5 represent players with mid-level expertise, and values 6 and 7 indicate high self-assessed expertise. Low-expertise participants comprise 36.19% of the sample, while the mid-expertise group, representing 42.35%, forms the largest cluster. In contrast, 21.47% of respondents self-assessed as highly expert players, being the group with the fewest unities. The aim of the latter clustering will be explained later in this chapter.

The last item of the second branch of the survey is Q6_1 ("I am less likely to choose insurance because my expertise helps me better evaluate the risks"), which evaluates how expertise impacts decision-making in relation to insurance purchases. The statement of this question is formulated based on the results obtained in the main study of this research, which shows that higher experience levels mitigate the impact of fatigue on insurance choice (*Hypothesis* 2).

Table 24 – Summary Statistics Q6_1

Min.	1st Qu.	Median	Mean	3rd Qu.	Max.
1	2	3	2.96	4	5

The mean response for this item is 2.96 (SD 1.23) on a 5-point Likert scale, which indicates that participants tend to moderately agree with the statement of the question. That scenario confirms that expertise can have a mitigating effect on the decision-making process, with some variability shown by the standard deviation, which is expected to justify the development of different expertise levels across the sample.

Stakes

The descriptive statistics developed for the stakes-related questions shed light on how financial risk shapes and impacts decision-making in online poker. The current section is composed of three items.

Q7_1 ("I tend to take less risks when playing for higher stakes") and Q8_1 ("How much does the value of money at stake influence your decisions during a poker game?") analyze how respondents behave when facing high stake hands and more generally, how the level of the stakes drive the decision-making process when playing. Both are measured on a 5-point Likert scale.

Table 25 – Summary Statistics Q7_1 and Q8_1

	Min.	1st Qu.	Median	Mean	3rd Qu.	Max.
Q7_1	2	3	4	3.80	4	5
Q8_1	2	3	4	3.87	4	5

The mean score for Q7_1 is 3.80 (SD 0.78) (Table 25), which suggests that players tend to take fewer risks when facing higher stakes. The standard deviation value indicates that there's not a relevant variability in answers, and players behave quite homogeneously in this context. Moreover, 42.33% of the participants selected a score of 4, which is also the median value, reinforcing the general agreement level for this item, and no one chose a score of 1, which aligns with expectations that financial risk can lead to more cautious decision-making. Q8_1 explores a similar condition but with a broader spectrum than the previous one. The mean response of 3.87 (SD 0.74), with a median of 4 (Table 25), indicates that the value of money at stake is an important factor in almost all participants' decisions. Therefore, the more money at risk, the more players are influenced in their decision-making process.

The last item, Q9_1 ("How likely are you to opt for insurance when playing for high stakes?") directly addresses the likelihood of opting for insurance when the stakes are high.

Table 26 – Summary Statistics Q9_1

Min.	1st Qu.	Median	Mean	3rd Qu.	Max.
2	3	4	4.03	5	5

The mean response for this question is 4.03 (SD 0.86), suggesting a strong agreement of participants regarding the increased likelihood of taking insurance with increasing stakes. The low value of the standard deviation highlights consistency across player's beliefs. Additionally, the frequency distribution shows that many players (37.1%) selected the highest score of 5. Finally, it is possible to infer that the *Hypothesis* 3 (H3), is confirmed by these statistics.

Interactions between variables

The final section of the descriptive statistics examines the interactions between fatigue, expertise, and stakes, with a particular focus on how expertise moderates the influence of fatigue and high stakes on decision-making in online poker. Specifically, two questions in this section explore the role of expertise in mitigating impulsive decisions under fatigue (Q10_1: "When I am fatigued, my expertise helps me avoid making impulsive decisions, such as buying insurance unnecessarily") and the effect of high stakes on insurance decisions, independently or not of expertise (Q10_2: "When the stakes are high (i.e., 1000€), compared to low (i.e., 10€), I am more likely to buy insurance, regardless of my expertise").

Table 27 – Summary Statistics Q10_1 and Q10_2

	Min.	1st Qu.	Median	Mean	3rd Qu.	Max.
Q10_1	1	2	3	3.04	4	5
Q10_2	1	3	4	3.56	4	5

The mean response of 3.04 (SD 1.31) of Q10_1 suggests that participants perceive their expertise as moderately helpful in avoiding impulsive decisions when fatigued. The standard deviation value advises a relatively high variability in responses. Indeed, while some players appear confident that their expertise helps them make the right decision, others do not feel the same effect, suggesting that the interaction between fatigue and expertise is not homogeneous across all players. Q10_2 has a mean response of 3.56 (SD 1.09), indicating that participants generally agree that high stakes increase the likelihood of purchasing insurance, even if they consider themselves experts. These results suggest that, although expertise significantly influences decision-making, the financial risk associated with high stakes can supersede expertise, leading players to adopt more conservative strategies, such as purchasing insurance. This supports *Hypothesis* 3 (H3) which states that elevated stakes amplify risk-averse behavior, irrespective of a player's skill level or self-confidence.

5.4.2 Expertise Score Measure and Quantile Analysis

To create the most explanatory and comprehensive measure of expertise in this study, as in the main one of the research project, some measures are combined to obtain a new score for each player. Expertise was operationalized by blending two related components: the number of years a player has been involved in online poker (measured by Q3_1) and the self-assessed skill level (measured by Q5_1). This approach allowed for the creation of a weighted composite expertise score, which considers the objective experience embodied by the time spent playing and the subjective confidence in one's skills. To carry out this process, numeric labels were assigned to each of the response options in item Q3_1, from 1 (<1 year) to 4 (>5 years). The self-assessed skill level was measured by Q5_1 on a 7-point validated Likert scale. Since the measure expressed by the years of experience is objective, within the calculation process of the combined expertise score was given more weight to that variable than the self-assessed expertise, which could be influenced by personal biases, even if remains a valuable indicator to use coupled. Pointedly, the expertise score was calculated for each player using the following formula:

$$\boldsymbol{Expertise\ Score\ Weighted = 0.6 \times Q3\_1\ Numeric + 0.4 \times Q5\_1}$$

The latter formula assigns 60% importance to the player's poker experience measured by time and 40% to the self-assessment of skill. The weighted score provides a more robust measure of expertise, balancing both the player's objective time spent playing and the perceived competence.

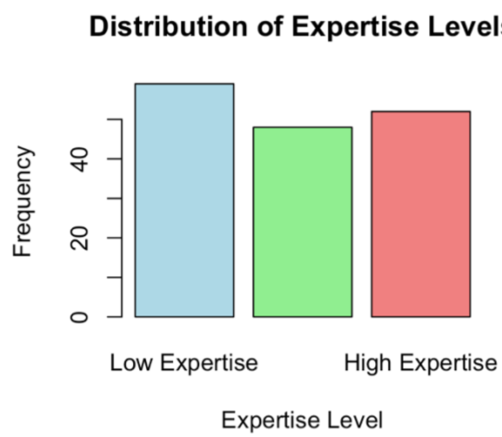
Table 28 – Summary Statistics Expertise Score

Min.	1st Qu.	Median	Mean	3rd Qu.	Max.
1	2	3	3.04	3.80	5.20

The summary statistics for the variable reveal a range of values between 1.0 and 5.2, with a median of 3.0 and a mean of 3.04 (SD 1.31). The first quartile (Q1) is 2.0, indicating that 25% of respondents scored below this threshold, while the third quartile (Q3) is 3.8, demonstrating that 75% of participants scored below this value. The interquartile range (IQR) from 2.0 to 3.8 suggests a moderate spread in expertise, as the standard deviation is above one, with a slight positive skew indicated by the mean being higher than the median. These values reflect a broad distribution of expertise levels, with most respondents clustering around mid-level expertise, but with a portion extending into both lower and higher expertise levels.

After the assignment of an expertise score for each respondent, the observations of this variable were further categorized into three quantiles to inspect how different levels of expertise interact with other variables and the decision to buy insurance, such as fatigue and stakes. The low-expertise group is composed of 59 participants, and it is the most plentiful, medium-expertise cluster counts 48 respondents, and lastly, more expert players are 52 in the entire sample. The distribution shown in Figure 6 emphasizes the mostly equal representation of every group within the sample, enhancing the reliability of the findings regarding the typical behaviors of players coming from the latter categorization.

Figure 6 – Expertise levels distribution



Then, the principal items of the survey, namely the ones representing the likelihood of taking insurance under different conditions of the variable of the main model, are analyzed following the quantile division of expertise.

Table 29 – Fatigue Likelihood Insurance ~ Expertise Quantiles

	Min.	1st Qu.	Median	Mean	3rd Qu.	Max.
Low Expertise	3	4	5	4.58	5	5

Medium Expertise	3	3	4	3.62	4	5
High Expertise	1	3	3	3.31	4	5

Table 29 summarizes the relationship between fatigue and the likelihood of purchasing insurance, segmented by expertise quantiles. Low-expertise participants exhibit the highest likelihood of choosing insurance under fatigue, with a mean score of 4.58, and a median of 5, showing a minimal variation between quartiles. This suggests a strong tendency among this group to perceive fatigue as a significant factor influencing insurance decisions. In contrast, participants in the medium and high-expertise groups show lower mean values (3.62 and 3.31). This implies that as expertise increases, the likelihood of choosing insurance under fatigue decreases, which could imply that more experienced players have better cognitive strategies or resilience in fatigue-driven decision-making.

Table 30 – Expertise Likelihood Insurance ~ Expertise Quantiles

	Min.	1st Qu.	Median	Mean	3rd Qu.	Max.
Low Expertise	1	1	2	1.63	2	2
Medium Expertise	2	3	3	3.12	3	4
High Expertise	3	4	4	4.31	5	5

The likelihood of purchasing insurance due to expertise also varies significantly across expertise quantiles, as shown in Table 30. Participants with low expertise have a mean score of 1.63, indicating that this group is least likely to feel confident in avoiding insurance, potentially due to a lack of perceived risk evaluation skills. Conversely, participants in the high expertise group exhibit a much higher mean (4.31), reflecting a strong perception that their expertise enables them to manage risk without the need for insurance. This stark contrast between low and high expertise levels highlights how expertise may mitigate the influence of external factors like fatigue, allowing for more calculated decision-making in high-risk scenarios.

Table 31 – Stakes Likelihood Insurance ~ Expertise Quantiles

	Min.	1st Qu.	Median	Mean	3rd Qu.	Max.

Low Expertise	4	5	5	4.93	5	5
Medium Expertise	3	3	4	3.69	4	5
High Expertise	2	3	3	3.31	4	4

The likelihood of purchasing insurance when stakes are involved is also stratified by expertise levels. As in Table 31, players with low expertise show a notably high mean of 4.93, indicating that they are highly likely to opt for insurance when stakes are high and likely driven by risk aversion. The median for this group is also consistently 5, further emphasizing their risk-averse behavior. On the other hand, participants with medium and high expertise display lower means of 3.69 and 3.31, respectively. This trend suggests that more experienced players are less likely to be influenced by stakes when making insurance decisions, as they may possess better risk management skills and are less reliant on external protections such as insurance.

Find a visual representation of the latter Quantile analysis in Appendix, A.3 (Figure 7).

The differences observed across the tables underscore the significant role that expertise plays in decision-making under conditions of fatigue and varying stakes. As expertise increases, players tend to demonstrate greater confidence in their ability to evaluate risks, which decreases their dependence on external safeguards like insurance. Furthermore, the low-expertise group consistently exhibits more risk-averse behavior across different conditions and variables. These findings align with theoretical models of decision-making that suggest more experienced individuals develop cognitive mechanisms that mitigate the effects of external pressures, leading to more stable and less emotionally driven choices. Consequently, these patterns reinforce the hypothesis that expertise serves as a buffer against the influences of fatigue and high stakes, enabling players to make more informed and deliberate decisions.

5.4.3 Regression Results

A regression analysis examines how expertise and stakes impact a player's likelihood of purchasing insurance under mental fatigue conditions. The model is developed on the following regression equation:

$$\boldsymbol{Q4_2 = \beta_0 + \beta_1 Q7_1 + \beta_2 expertise_{weighted} + \varepsilon}$$

Within the formula, $Q4_2$ is the continuous dependent variable of the model, whereby the self-reported likelihood of choosing the insurance option for a player under mental fatigue. The independent variables of the model are two: the first numerical term is $Q7_1$[16], which measures the effect of stakes on risk aversion in poker games, and the second is $expertise_{weighted}$, which is the composite measure of poker expertise, that combines objective (years playing), and subjective factors (self-assessed score). Finally, ε is the error term of the equation, encompassing the influence of unobserved factors on the insurance purchase decision. The design of the regression formula permits the evaluation of the impact of the two independent variables, taken separately one from another, on the dependent variable, which is the likelihood of choosing insurance when fatigued. The dependent variable, as formulated based on the survey's results, implies that fatigue has a significant effect on the decision to take insurance, enhancing the likelihood of happening (Mean 3.88, SD 0.86, Table 22), further confirming *Hypothesis* 1 (H1) of this study, which posits that an increase in the degree of fatigue leads to an increase in the likelihood of taking the insurance choice.

The regression model output is reported as follows:

Table 32 – LM Regression results

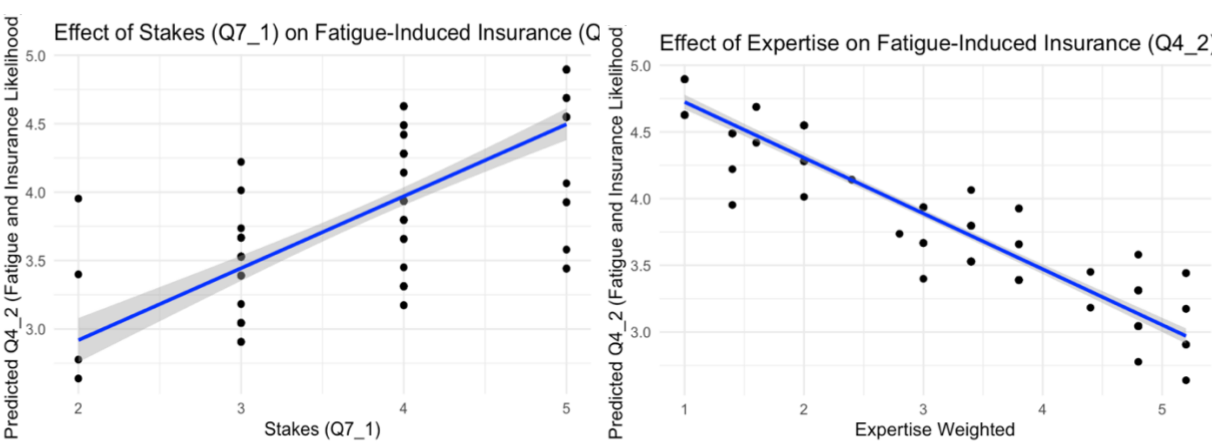
Predictor	Estimate	Std. Error	t-value	p-value
(Intercept)	3.90	0.35	11.19	<2e-16***
Expertise Weighted	0.27	0.07	3.80	0.000201***
Stakes	-0.35	0.04	-8.21	7.77e-14***

The regression analysis results provide insightful insights concerning the research question and hypothesis posed in this study.

[16] This item was assessed on a 5-point Likert scale, with a mean score of 3.80 (SD = 0.78), implying a general tendency toward increased risk aversion as stakes rise. The relatively low standard deviation suggests homogeneity in responses, with most participants converging toward moderate-to-high levels of agreement. No participants chose the lowest option on the scale, underscoring the general expectation that higher financial stakes promote more cautious decision-making.

The intercept is significant (p-value < 0.001) and indicates the baseline level of likelihood for taking insurance fatigued when both stakes and expertise are zero. The first independent variable of the model, expertise-weighted, shows a negative and highly significant (p-value <0.001) relationship with the likelihood of taking insurance when fatigued. Precisely, as expertise increases, the likelihood of taking insurance decreases by 0.35 units per point of expertise. This finding put forward that higher expertise has a mitigating effect on the fatigue effect on insurance purchase decisions, further confirming *Hypothesis* 2 (H2). The latter outcome suggests that players may benefit from improved cognitive skills related to higher experience in playing poker, making them less likely to make impulsive decisions like opting for insurance when it is not needed. The second independent variable of the model, stakes, which measure how participants tend to take fewer risks as the stakes increase, shows a positive and highly significant (p-value <0.001) relationship with the likelihood of taking insurance when fatigued. The coefficient tells that for each unit increase in stakes, the likelihood of choosing insurance increases by 0.27 units on the Likert scale. This finding supports *Hypothesis* 3 (H3), which postulated that the stakes involved would moderate the relationship between fatigue and the likelihood of taking the insurance option, with higher stakes intensifying the effect of fatigue on this decision.

Figure 8 – Effect plots of Independent Variables



The effect plots illustrate the relation between the independent variables and the dependent variable. Each black dot represents an observation, and the blue line is the linear relationship between stakes or expertise with the predicted probability of taking insurance when fatigued. The grey-shaded area near the blue line is the confidence interval (C.I.), which indicates the uncertainty around the estimated line. The positive slope for stakes and the negative one for expertise support the moderating role of these two variables. The spread in the data points indicates some variability in the results, more pronounced in stakes than in expertise. Additionally, the tightness of the confidence interval means a reasonably precise estimate of the effect on the dependent variable, with a good degree of precision. The model has an R-squared of 0.4678, explaining the 46.8% of the variance of the dependent variable, which highlights two main things: the first is that still half of the variance has to be explained in the model, but it is significant that just two factors combined can cover such a big portion of the variance. Both expertise and stakes play a primary role in moderating the effect of fatigue on decision-making, confirming the results obtained in the first study of this research project, under different experiment settings. Finally, the latter findings further confirm that fatigue significantly affects decision-making in poker games, particularly in high-stakes situations, but also that expertise can serve as a mitigating factor, reducing the likelihood of risk-averse decisions such as purchasing insurance.

Chapter 6 - Conclusions

The introduction of the insurance option on online platforms allows testing and evaluating the impact of fatigue on decisions under risk in online poker scenarios, shedding light on broader behavioral patterns that define human interactions with risk and uncertainty in a real-world setting. Strong, significant, and robust effects of fatigue on risk-taking are caught.

The research contributes to enriching the framework of literature and filling the gap of knowledge related to fatigue in decision-making under uncertainty. The actual stream of research regarding fatigue describes it as a decrement in performance due to prolonged engagement, which can be mainly physical or mental. This study builds upon the concept of mental fatigue as continuous task repetition, to assess the unstudied impact on decision-making in high-risk contexts. The findings expand behavioral risk models (as Kahneman and Tversky's Prospect Theory) by providing empirical evidence that fatigue can alter risk preferences. As a development, future models of decision-making under risk should consider including dynamic psychological states to better predict behavior, instead of focusing only on cognitive and rational factors. Moreover, it is shown that the long-term cognitive adaptations (experience gained) mitigate the short-term impairments caused by fatigue, enriching the complex framework that the relationship between experience and fatigue has with the decision-making process in uncertain scenarios. Finally, money represents the primary outcome of interest for players when playing poker games and enhances the pressure that an individual feels when playing. This is well-grounded knowledge in gambling-related literature but it was not studied so far whether the perceived value of stakes exacerbates or not the impact of fatigue on players. The study contributes to the field of online gambling literature but also offers valuable and generalizable insights into the broader dynamics of risk assessment and decision-making, relative to the the impact of fatigue on decision-making under uncertainty, explaining to what extent the relationship between fatigue, experience, and money at stake influences players' choices to opt for insurance. The interplay of such factors concerning the decision-making process is an unstudied aspect in the actual literature framework of the aforementioned areas of research, that is addressed in this study in the context of online poker.

The practical implications of this study are substantial for online gambling industry regulators, marketers, and consumers. Online gambling regulators can develop responsible gambling measures for consumer protection such as real-time fatigue detection algorithms to prompt players to take breaks or provide warnings about the risks of continued play. The algorithms would use inherent players' data retrieved from the platforms as the personal average length of a gaming session and fluctuations in the personal assets to assess whether is needed to send a warning message to the player, avoiding issues that can arise due to prolonged game sessions. It would be a concrete solution to better face issues related to problem gambling, which is an increasing phenomenon that online platforms could even stress, since the psychological value that representations of money assume, such as chips in poker, is less than real money (Lapuz, Griffiths, 2010), and players do not have physical barriers, i.e, a person do not have to reach a casino to play poker.

Marketers could exploit insights gained from this study to improve user experience (e.g., personalized marketing strategies based on player fatigue patterns can increase retention and Customer Lifetime Value). Indeed, machine learning algorithms may be leveraged to trigger personalized interventions, identifying real-time indicators of fatigue, such as slowed decision-making, increased error rates, or a substantial raise of insurance chosen based on specific players thresholds (as it is a consequence of increased fatigue). Personalized time-limited offers could encourage players to return to the game after a break, ensuring they come back refreshed and less fatigued. Tailoring the gaming experience to each player's current state ensures that they remain engaged and enjoy the game, enhancing their overall satisfaction with the platform and reducing the likelihood of negative experiences, which could potentially lead to a loss of customers. Moreover, fatigue-based promotions could be developed to reward players for maintaining healthy gaming habits, i.e., offer bonuses for players who take regular breaks or maintain shorter session times as good habits. To enhance the platform experience gambling companies could also collaborate with health and wellness apps to offer players tools for monitoring and managing mental and physical well-being, sharing data, and building personal profiles with player-specific thresholds and attitudes, to help gamblers be more self-aware and consequently more responsible, reducing burnout and encouraging longer-term engagement. This approach aims to offer a more engaging and safe experience. Indeed, personalized marketing strategies that leverage fatigue insights can lead to higher satisfaction and loyalty among the customer base, resulting in increased Customer Lifetime Value (CLV) as players are more likely to continue gambling on the current platform and making in-game purchases, also increasing the potential traffic on the platform. To monitor the effectiveness of the proposed strategies, platforms should regularly gather feedback from more frequent players on fatigue-based interventions, occasionally adjusting strategies accordingly to players' behavior.

However, there are some limitations due to the framework of the study: it does not delve into additional potential influencing factors such as demographics or external economic or social factors that catch the broader spectrum of online gambling behaviors, psychological features of gambling addiction, and the efficacy of consumer protection measures. Additionally, even if the sample of the study (85,326 distinct players) is wide and relevant, it is possible that poker players are not representative of the general population's behavior, as could result more accustomed to risky environments with respect to the general population. By setting these boundaries, the study aims to contribute meaningful insights into the fields of marketing, consumer behavior, and online gambling research while acknowledging the limitations inherent in the scope of the study and the data available.

Building upon the insights gained, several extensions could further enrich the understanding of decision-making in online gambling and its relationship with fatigue. Future research could: i) integrate biometric data (e.g., heart rate, eye tracking) during data gathering sessions to measure fatigue and its impact on decision-making more accurately; ii) extend the period of observation and data collection to offer deeper insights on long-term patterns between and within players; iii) expand the research field including other contexts where decision-making under uncertainty plays a pivotal role (e.g., financial trading platforms, sports betting, e-sports betting), further validating the actual findings and assessing their generalizability across various domains; iv) implement controlled experiments to test the effectiveness of promoting responsible gambling and improving user experience based on fatigue attitudes of different players; v) incorporate external economic (e.g, income, employment status), social (e.g., cultural attitudes toward gambling and risk taking), and demographic (e.g., age, sex, martial status, education level, geographic location) variables into the analysis to reveal how broader environmental factors influence the interplay between fatigue and decision-making.

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Appendix

Appendix A

Summary statistics on relevant variables

Statistic	Mean	St. Dev.	Min.	Pctl(25)	Median	Pctl(75)	Max.
Winning prob. at showdown	47.59417	5.594842	0	44.52	48.08	51.22	100
Profits	-21.00625	237.937	-145158.4	-20.45	-5.57	0.58	36620
Stack	111.0053	611.0035	0.1	10.37	25	62.33	81643.93

Appendix A.1

Table 4 - Overall Fatigue level distribution

	Number of hands	Percentage hands (%)
Less Fatigued	1580298	32.21
More Fatigued	3483207	68.79

Table 5 – *ExpertiseScore* summary

Min.	-48.30588
1st Qu.	0.02957
Median	0.50892
Mean	2.28035
3rd Qu.	2.49086
Max.	31.07426

Table 7– Insurance by Learning (Expertise) and Fatigue

ExpertiseGroup	FatigueLevelDaily	InsuranceRate	Count
Low Exp	Above Mean	15.3	804,281
Low Exp	Below Mean	13.9	461,634
High Exp	Above Mean	16.7	900,179
High Exp	Below Mean	16.4	364,480

Table 8 – *StakesInvolved* summary

Min.	0.00025
1st Qu.	0.44706
Median	0.80137
Mean	1.00000
3rd Qu.	1.29694
Max.	72.53313

Table 10 – Insurance by Stakes Involved and Fatigue

StakesCategory	FatigueLevelDaily	InsuranceRate	Count
Low Stakes	Above Mean	13.2	856765
Low Stakes	Below Mean	13.1	409112
High Stakes	Above Mean	22	891752
High Stakes	Below Mean	19.8	374124

Appendix A.2

Table 12 – GLM Regression results (coefficients)

	Dependent Variable: Insurance choice dummy			
	(1)	(2)	(3)	(4)
Fatigue	0.032***	0.042***	0.042***	0.043***
	(26.483)	(34.767)	(34.692)	(35.163)
Fatigue *Learning	- 0.021***	- 0.031***	- 0.031***	- 0.031***
(Expertise)	(-16.810)	(-22.388)	(-22.328)	(-22.303)
Fatigue *Stakes	0.028***	0.030***	0.030***	0.030***
Involved	(22.551)	(23.694)	(23.940)	(23.827)
Constant	-1.589***	-1.721***	- 1.722***	-1.758***
	(-1326.993)	(-422.304)	(-422.423)	(-255.026)
Hand-specific controls	No	Yes	Yes	Yes
Player-specific controls	No	No	Yes	Yes
Time fixed effects	No	No	No	Yes
Observations	5,063,505	5,063,505	5,063,505	5,063,505

Table 13 – LPM Regression results (coefficients)

	Dependent Variable: Insurance choice dummy			
	(1)	(2)	(3)	(4)
Fatigue	0.005***	0.005***	0.005***	0.005***
	(30.163)	(32.339)	(32.403)	(32.544)
Fatigue *Learning	- 0.003***	- 0.003***	- 0.003***	- 0.003***
(Expertise)	(-15.376)	(-15.994)	(-15.884)	(-15.770)
Fatigue *Stakes	0.004***	0.005***	0.005***	0.005***

Involved	(27.147)	(27.862)	(28.051)	(27.966)
Constant	0.172***	0.167***	0.167***	0.165***
	(1028.320)	(300.203)	(300.170)	(173.917)
Hand-specific controls	No	Yes	Yes	Yes
Player-specific controls	No	No	Yes	Yes
Time fixed effects	No	No	No	Yes
Observations	5,063,505	5,063,505	5,063,505	5,063,505

Table 14 – Fixed Effect GLM Regression results (coefficients)

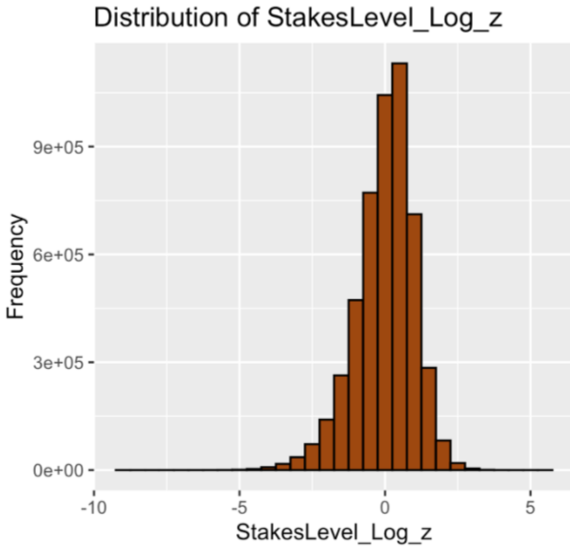
	Dependent Variable: Insurance choice dummy			
	(1)	(2)	(3)	(4)
Fatigue	0.026 ***	0.026 ***	0.026 ***	0.027 ***
	(5.716)	(5.717)	(5.907)	(6.444)
Fatigue *Learning	- 0.031 **	- 0.032 **	- 0.032 **	- 0.032 **
(Expertise)	(-2.855)	(-2.953)	(-3.092)	(-3.074)
Fatigue *Stakes	0.009 ***	0.009 ***	0.009 ***	0.010 ***
Involved	(3.823)	(3.662)	(3.588)	(3.945)
Hand-specific controls	No	Yes	Yes	Yes
Player-specific controls	No	No	Yes	Yes
Time fixed effects	No	No	No	Yes
Player fixed effects	Yes	Yes	Yes	Yes
Observations	4,017,251	4,017,251	4,017,251	4,017,251

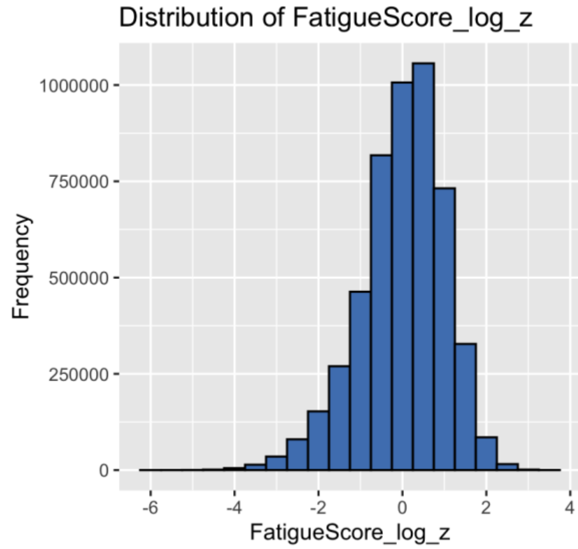
Table 15 – Fixed Effect GLM Regression results (marginal effects)

	Dependent Variable:

	Insurance choice dummy			
	(1)	(2)	(3)	(4)
Fatigue	0.004 ***	0.004 ***	0.004 ***	0.005***
	(5.716)	(5.717)	(5.907)	(6.444)
Fatigue * Learning	-0.005**	-0.005**	- 0.005 **	-0.005**
(Expertise)	(-2.855)	(-2.953)	(-3.092)	(-3.074)
Fatigue *Stakes	0.002 ***	0.002 ***	0.002 ***	0.002 ***
Involved	(3.823)	(3.662)	(3.588)	(3.945)
Hand-specific controls	No	Yes	Yes	Yes
Player-specific controls	No	No	Yes	Yes
Time fixed effects	No	No	No	Yes
Player fixed effects	Yes	Yes	Yes	Yes
Observations	4,017,251	4,017,251	4,017,251	4,017,251

Figure 3 – Distribution Histograms of predictor variables





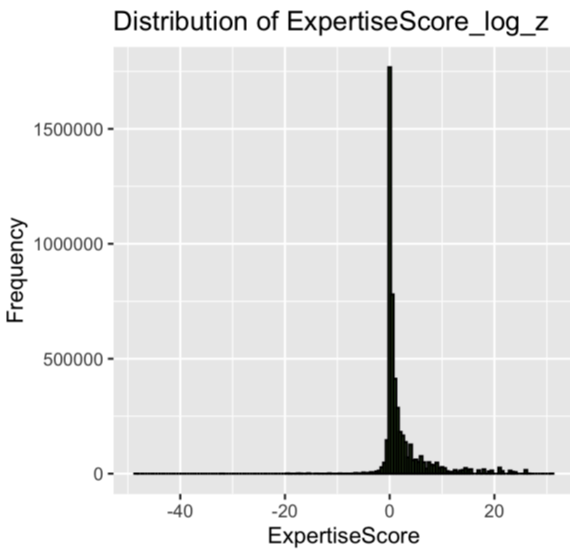


Table 16 - GLM Regression results FatigueAboveMean (coefficients)

	Dependent Variable:			
	Insurance choice dummy			
	(1)	(2)	(3)	(4)
Fatigue Above Mean	0.063 ***	0.078***	0.079***	0.079***
	(24.271)	(30.172)	(30.076)	(30.167)
Fatigue *Learning	-0.038 ***	-0.053***	-0.053***	-0.053***
(Expertise)	(-14.640)	(-18.935)	(-18.918)	(-18.963)

Fatigue *Stakes	0.055 ***	0.058***	0.058 ***	0.058***
Involved	(20.160)	(20.767)	(20.909)	(20.783)
Constant	-1.631 ***	-1.774***	-1.775***	-1.808***
	(-753.930)	(-397.947)	(-397.988)	(-252.916)
Hand-specific controls	No	Yes	Yes	Yes
Player-specific controls	No	No	Yes	Yes
Time fixed effects	No	No	No	Yes
Observations	5,063,505	5,063,505	5,063,505	5,063,505

Table 17 - GLM Regression results FatigueAboveMean (marginal effects)

	Dependent Variable: Insurance choice dummy			
	(1)	(2)	(3)	(4)
Fatigue Above Mean	0.009 ***	0.011***	0.011 ***	0.011 ***
	(24.271)	(30.172)	(30.076)	(30.167)
Fatigue *Learning	-0.005 ***	-0.008 ***	- 0.008 ***	-0.008 ***
(Expertise)	(-14.640)	(-18.935)	(-18.918)	(-18.963)
Fatigue *Stakes	0.008***	0.008 ***	0.008 ***	0.008***
Involved	(20.160)	(20.767)	(20.909)	(20.783)
Constant	-1.631 ***	-1.774***	-1.775***	-1.808***
	(-753.930)	(-397.947)	(-397.988)	(-252.916)
Hand-specific controls	No	Yes	Yes	Yes
Player-specific controls	No	No	Yes	Yes
Time fixed effects	No	No	No	Yes
Observations	5,063,505	5,063,505	5,063,505	5,063,505

Table 18 - GLM Regression results FatigueBelowMean (coefficients)

	Dependent Variable: Insurance choice dummy			
	(1)	(2)	(3)	(4)
Fatigue Below Mean	- 0.063***	-0.079 ***	-0.079 ***	-0.079***
	(-24.271)	(-30.172)	(-30.076)	(-30.167)
Fatigue *Learning (Expertise)	0.038 ***	0.053 ***	0.053 ***	0.053***
	(14.640)	(18.935)	(18.918)	(18.963)
Fatigue *Stakes Involved	-0.055 ***	-0.058 ***	-0.058 ***	-0.058***
	(-20.160)	(-20.767)	(-20.909)	(-20.783)
Constant	- 1.568 ***	-1.695 ***	-1.696 ***	-1.729***
	(-1092.076)	(-408.110)	(-408.239)	(-249.617)
Hand-specific controls	No	Yes	Yes	Yes
Player-specific controls	No	No	Yes	Yes
Time fixed effects	No	No	No	Yes
Observations	5,063,505	5,063,505	5,063,505	5,063,505

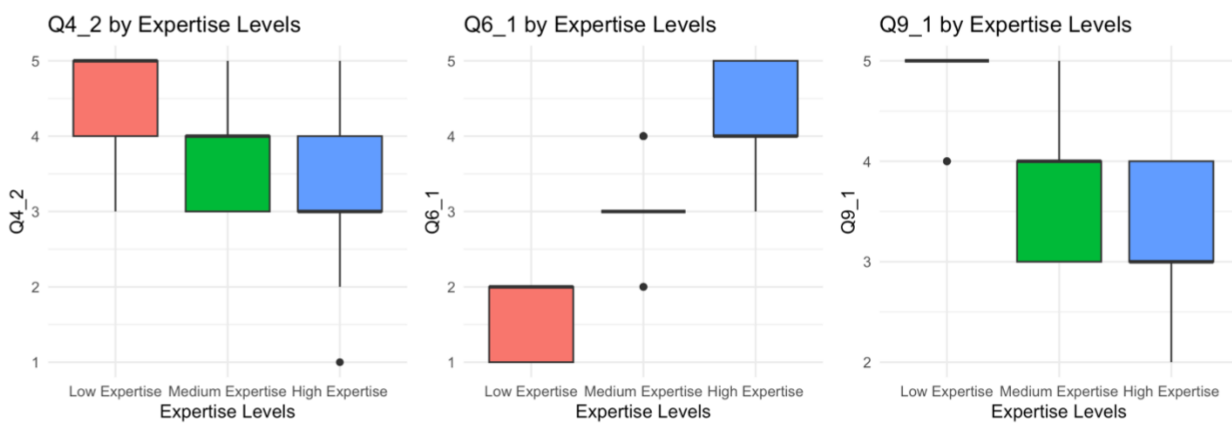
Table 19 - GLM Regression results FatigueBelowMean (marginal effects)

	Dependent Variable: Insurance choice dummy			
	(1)	(2)	(3)	(4)
Fatigue Above Mean	-0.009 ***	-0.011***	-0.011 ***	-0.011 ***
	(-24.271)	(-30.172)	(-30.076)	(-30.167)
Fatigue *Learning (Expertise)	0.006 ***	0.008 ***	0.008 ***	0.008 ***
	(14.640)	(18.935)	(18.918)	(18.963)
Fatigue *Stakes Involved	-0.008***	-0.008 ***	-0.008 ***	-0.008***
	(-20.160)	(-20.767)	(-20.909)	(-20.783)

Constant	- 1.568 ***	-1.695 ***	-1.696 ***	-1.729***
	(-1092.076)	(-408.110)	(-408.239)	(-249.617)
Hand-specific controls	No	Yes	Yes	Yes
Player-specific controls	No	No	Yes	Yes
Time fixed effects	No	No	No	Yes
Observations	5,063,505	5,063,505	5,063,505	5,063,505

Appendix A.3

Figure 7 – Fatigue, Expertise, and Stakes mean values ~ Expertise Quantiles[17]



Item 20 – Main study survey

[17] The reason some groups do not have a colored bar in the boxplot is that the range of the values in that group is very narrow. This can happen when the minimum, first quartile (Q1), median, third quartile (Q3), and maximum values are very close to each other. In such cases, the boxplot may not display a visible bar (or box) because there isn't enough variation between the values.

Start of Block: intro

Thank you for participating in this research study on decision-making in online poker. This survey aims to explore how factors such as fatigue, player expertise, and the stakes involved influence your decisions during a game, particularly regarding the option to purchase the insurance option in high-risk situations. As insurance is intended the so-called "All-in Cashout" option on Pokerstars. Your responses will contribute valuable insights to better understand decision-making processes in online gaming environments. The survey will take approximately 3-5 minutes to complete, and all responses will remain anonymous. Your participation is voluntary, and you may withdraw from the survey at any time. Please answer the questions based on your personal experiences. There are no right or wrong answers, and your honest responses are highly appreciated.

End of Block: intro

Start of Block: Section 1: Demographics

Q1 What is your age?

____

Q2 What is your gender?

○ Male (1)

○ Female (2)

○ Non-binary / third gender (3)

○ Prefer not to say (4)

Page Break

Q3 How long have you been playing online poker?

◯ Less than 1 year (1)

◯ 1-2 years (2)

◯ 2-5 years (3)

◯ More than 5 years (4)

End of Block: Section 1: Demographics

Start of Block: Section 3: Fatigue

Q4 Agree or disagree with the following statements about mental fatigue during poker sessions

	Strongly disagree (1)	(2)	(3)	(4)	Strongly agree (5)
I feel mentally fatigued after playing online poker for longer than my average time (1)	◯	◯	◯	◯	◯
When I am mentally fatigued, I am more likely to take the insurance option in poker (3)	◯	◯	◯	◯	◯

End of Block: Section 3: Fatigue

Start of Block: Section 2: Player expertise

Q5 On a scale from 1 to 7, evaluate your expertise level in online poker

	Novice					Expert	
	1	2	3	4	5	6	7
How would you rate your expertise in online poker? ()							

Page Break

Q6 Does your expertise level impact fatigue effect on insurance choice?

	Strongly disagree (1)	(2)	(3)	(4)	Strongly agree (5)
I am less likely to choose insurance because my expertise helps me better evaluate the risks (1)	○	○	○	○	○

End of Block: Section 2: Player expertise

Start of Block: Section 4: Stakes Involvement

Q7 Evaluate stakes level impact on risk during online poker games

	Strongly disagree (1)	(2)	(3)	(4)	Strongly agree (5)
I tend to take less risks when playing for higher stakes (1)	○	○	○	○	○

Q8 On a scale from 1 to 5, evaluate the impact of the stakes involved on your decision making process

	Not at all			A great deal	
	1	2	3	4	5
How much does the value of money at stake influence your decisions during a poker game? ()					

Page Break

Q9 Does stakes level impact the fatigue effect on insurance choice?

	Extremely unlikely			Extremely likely	
	1	2	3	4	5
How likely are you to opt for insurance when playing for high stakes? ()					

End of Block: Section 4: Stakes Involvement

Start of Block: Section 5: Decision-Making Under Fatigue and Expertise

Q10 Answer the following questions

	Strongly disagree (1)	(2)	(3)	(4)	Strongly agree (5)
When I am fatigued, my expertise helps me avoid making impulsive decisions, such as buying insurance unnecessarily (1)	○	○	○	○	○
When the stakes are high (i.e., 1000€), compared to low (i.e., 10€), I am more likely to buy insurance, regardless of my expertise (2)	○	○	○	○	○

End of Block: Section 5: Decision-Making Under Fatigue and Expertise