Unfair Odds and Cognitive Illusions: The Role of the Conjunction Fallacy in Same Game Multi Betting Strategies

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Abstract

This report investigates the dynamics of sports betting, examining the impact of Same Game Multis (SGMs), which have significantly altered the betting landscape. Our study explores the behavioural factors that entice gamblers to consistently accept unfavourable odds driven by the allure of high-risk, high-reward strategies. Central to our analysis is the conjunction fallacy, hypothesised to induce overconfidence among SGM bettors through significant overestimations of winning probabilities caused by misunderstandings of interdependent event outcomes. This misjudgement demonstrates bettors' misplaced certainty in complex betting scenarios.

Our research assesses how well traditional decision-making frameworks like Cumulative Prospect Theory (CPT) capture actual gambling behaviours. While CPT effectively illustrates how gamblers might accept lower expected returns in favour of disproportionately valued higher payoffs, it does not fully address all financial outcomes of these biases, especially concerning the calculation of varying bookmaker margins. This limitation highlights the need for a more comprehensive theoretical model that accounts for psychological evaluations of outcomes and their precise economic impacts.

A critical aspect of our study is developing a novel utility model under the Expected Utility Theory (EUT) framework, which posits that SGM bets can appear rational by offsetting less favourable odds with non-monetary benefits such as entertainment and emotional engagement. However, this model also reveals a significant gap in gamblers' self-awareness: they often fail to recognise how cognitive biases distort their perception, leading them to underestimate the risks associated with more complex bets systematically. These misperceptions contribute to considerable player losses and impede informed and unbiased

decision-making. Furthermore, our findings suggest that bookmakers may strategically exploit these biases to enhance their profit margins, thus increasing the risks for gamblers.

Our study highlights the need to integrate psychological insights with quantitative analysis in gambling research. The findings aim to enhance the development of regulatory and consumer protection strategies by providing a more comprehensive understanding of gambling behaviours.

Table of Contents

List of Figures

List of Tables

Glossary

Term	Definition
Allais Paradox	A situation that demonstrates the inconsistencies in actual observed choices with the predictions made by expected utility theory, highlighting deviations from rational decision-making under risk.
Bookmaker Margin / Overround	The difference between the true probability of an event and the odds offered by the bookmaker, ensuring the bookmaker's profit regardless of the outcome.
Cumulative Prospect Theory (CPT)	An extension of Prospect Theory that accounts for how people perceive and distort probabilities, leading to non-linear probability weighting. It addresses the tendency to overweight small probabilities and underweight large probabilities, providing a more accurate model of decision-making under risk and uncertainty.
Ellsberg Paradox	A paradox in decision theory highlighting people's preference for known probabilities over unknown probabilities, demonstrating ambiguity aversion.
Expected Utility Theory (EUT)	A decision-making theory suggesting individuals choose options that maximise their expected utility, calculated as the weighted sum of utility from all possible outcomes, where the weights are the probabilities of each outcome occurring.
Expected Value (EV)	The average value of a bet over many trials, calculated by multiplying the probability of each outcome by its payoff and summing these products.
Favourite-longshot Bias	A bias where bettors disproportionately favour longshots (high-risk, high-reward bets) over favourites (low-risk, low-reward bets), leading to suboptimal betting strategies. Bookmakers typically underprice favourites and overprice longshots to ensure profitability.
Same Game Multi (SGM)	A type of bet combining multiple outcomes from a single game into one bet. It involves complex probabilities due to the interdependence of events.

1 Introduction

The evolution of gambling, from ancient games like Astragali to the probability theories of Gerolamo Cardano and Galileo, reflects society's complex relationship with chance (David, 1955). Casino games like slot machines, baccarat and roulette are the most well-known modern games of chance.

Sports betting, distinctively classified as a game of 'skill' rather than 'chance', contrasts with traditional casino games, where the bulk of academic research is concentrated. A significant reason for this oversight is that sports betting was legalised in the United States in 2018 when the US Supreme Court overturned the 1992 Professional and Amateur Sports Protection Act. US sports betting revenue grew from around US$900 million in 2019 to US$11 billion in 2023 (AGA, 2024). Globally, the sports betting market is estimated to be around US$161 billion and is forecast to grow to US$325 billion by 2031, indicating its mass appeal (DBMR, 2024). In Australia, gamblers incur around $25 billion annually in losses, the highest per capita globally (QGSO, 2022).

Most academic research on gambling focuses on Electronic Gaming Machines or slot machines. For instance, a Google Scholar search of 'gambling' yields approximately 1,280,000 results; 'electronic gaming machine' 349,000; 'slot machine' 850,000; 'sports betting' 155,000, 'parlay bet' 73 and 'same game multi' six.

SGMs have surged in popularity within sports betting markets, but their inherent complexity and the cognitive biases influencing bettor decisions pose substantial risks. Despite this, limited research examines these specific biases within the context of SGMs. Previous studies have extensively explored cognitive biases in general betting scenarios, yet only some have delved into the unique challenges SGMs pose. Traditional decision-making frameworks like CPT and EUT fail to explain the overestimation of winning probabilities in

SGMs, highlighting a significant gap in the literature. This study focuses on the conjunction fallacy, where bettors overestimate the likelihood of multiple events occurring simultaneously, leading to overconfidence and acceptance of unfavourable odds.

The critical feature of SGMs, compared to single-event or simpler multi-bets, is the combination of a low probability of a successful outcome with a low expected return to the player, resulting in a high ‘bookmaker margin’ and consequent player loss. Tversky and Koehler (1994) highlight that bettors tend to overestimate complex probabilities compared to simpler ones. This tendency appears to have contributed to the popularity of SGMs. We develop a comprehensive utility model incorporating psychological insights and economic analysis to understand better and mitigate the risks associated with SGMs. We examine the factors contributing to their popularity and their high rates of player losses. Our hypotheses are:

H1. Gamblers accept inferior odds in SGM scenarios primarily due to behavioural biases rather than market inefficiencies, influencing their decision-making process.

H2. SGM gamblers will exhibit overconfidence in their betting selections, stemming from misunderstanding the conjunctive probabilities. This means bettors overestimate the likelihood of multiple events occurring together, inflating their bets’ confidence.

H3. Participation in complex bets, perceived as ‘skilled’ betting, exacerbates behavioural biases such as the illusion of control, overweighting of low probabilities, and misinterpretations of mathematical concepts related to theoretical losses.

In the first part of this report, we outline the fundamental aspects of sports betting, focusing on SGM bets. We detail their structure, explain how bookmakers calculate their margins, and discuss the complexity inherent in these bets. Additionally, we introduce key concepts of conditional and dependent probability to illustrate how these complex betting products differ from traditional casino gambling. The second part of the report constitutes a comprehensive literature review examining SGMs through the lens of EUT and CPT. This section discusses gambler rationality and the decision-making models that describe how gamblers assess risk and reward in betting scenarios, focusing on the challenges posed by the high-risk nature of complex bets. We also consider the role of skilled gaming and the inherent risks involved, emphasising the increased complexity of decision-making in SGMs.

Our utility model emphasises that cognitive biases significantly influence the appeal of complex bets. While potential financial gains are a factor, the intrinsic pleasure and excitement derived from gambling and cognitive biases like overconfidence and heuristic misjudgments drive bettors' decisions. Integrating psychological elements into our economic framework, including varying bookmaker margins, provides a more nuanced understanding of gambling behaviours, illustrating how biases can skew perceptions of risk and reward.

Our experimental design will investigate the impact of the conjunction fallacy on gambling behaviour. By comparing betting selections in single, standard multi, and same-game multi bets, we expect to reveal that the conjunction fallacy leads to overconfidence among bettors, resulting in choices that are less favourable from a rational standpoint but psychologically compelling. These less advantageous decisions suggest that cognitive biases enhance the perceived utility of the bets, leading bettors to accept poorer odds. As a result, bettors overlook the improbability of winning and systematically overweight their chances due to cognitive distortions. This illustrates a deviation from rational decision-making models, highlighting the need for a utility model that incorporates both the psychological allure and the economic dynamics of betting. Results may also indicate that bookmakers exploit these biases to set higher profit margins, reflecting their understanding that such biases encourage bettors to engage with inferior odds.

This research aims to bridge the gap between theoretical models and gambling behaviours by merging traditional economic theories with psychological realities. Insights gained may inform more effective regulatory and consumer protection strategies, highlighting the importance of understanding the psychological underpinnings of gambling to mitigate risks and protect consumers. Having established the historical and economic context of sports betting, we now focus on the mechanics and specific challenges this form poses.

1.1 Sports Betting

In sports betting, the outcome is significantly influenced by the actions and traits of individual players rather than predominantly depending on random elements, thus requiring a degree of skill and knowledge (Getty et al., 2018). This form of wagering involves placing stakes on legally organised human sports activities accessible through a variety of platforms, both physical and increasingly digital (Hing et al., 2015).

The widespread popularity of sports betting, especially among 18-35-year-old males, can be attributed to three key factors: its 24/7 accessibility through online and mobile platforms; aggressive marketing and sponsorship tactics aligning it with popular sports teams and events; and targeted promotional strategies that integrate wagering into the social networks of its primary audience (Deans et al., 2019).

Unlike the more deterministic, probability-based outcomes of casino games, sports betting involves dynamic odds set by bookmakers who consider profit margins and employ a combination of skill, strategy, and psychological analysis. Sports betting necessitates more informed decision-making and analytical skills, setting it apart from the predominantly chance-based nature of casino games (Levitt, 2004).

In a 50:50 probability scenario (binary outcome), bookmakers might set odds at \$1.85 for each outcome. Betting \$1 on each side (total \$2) would return \$1.85, leading to a 15-cent loss, representing the bookmaker's ~8% margin and a ~92% return-to-player rate. Simple win/loss bets involve straightforward predictions, like who will win a game. They are easier to understand and offer more transparent odds. However, complex bets (parlays, multis) involve multiple contingencies, requiring gamblers to consider various interrelated events. In these types of bets, called *accumulators* in Britain, *parlays* in the US, or *multis* elsewhere, the bettor's stake is forfeited if any part of the bet fails. A win under a fixed-odds system typically results in a payout equal to the product of the individual games' gross payouts for each dollar staked. This format assumes that each game within the bet is independent (Grant et al., 2008).

The bookmaker margin, often called the 'overround' or 'win rate', is intrinsically subjective. It reflects the bookmaker's assessment of probabilities and their need to ensure a profit regardless of the event's outcome. This assessment involves subjective judgment in setting odds that might not necessarily align with the true probabilities, calculated as:

$$Bookmaker\ Margin = \frac{\Sigma(Implied\ Probabilities) - 1}{1}\ x\ 100\%$$

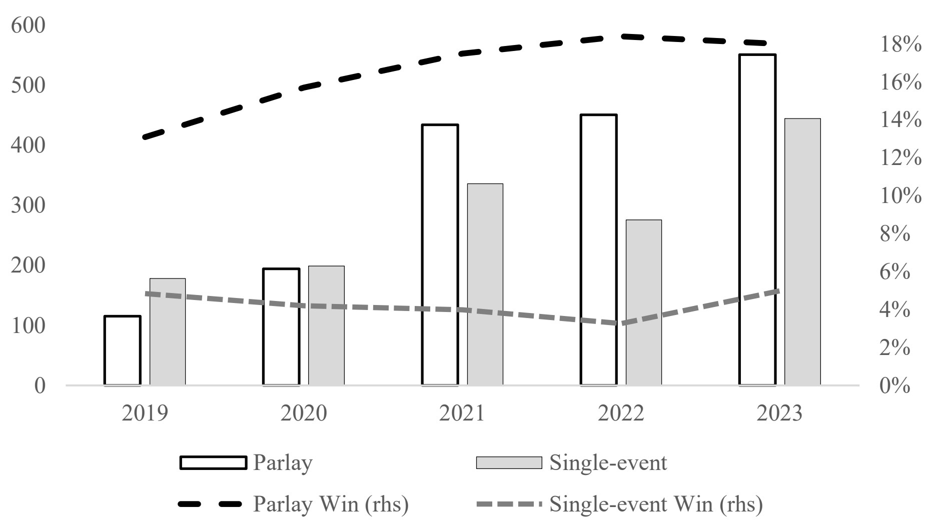
Bookmakers generate revenue primarily through complex betting schemes characterised by elevated overrounds (Newell, 2015), diminishing the bettors' value. Such bets, which are markedly advertised, maintain significantly higher margins (overrounds) in comparison to simple match-winner bets. This disparity in overrounds is likely a calculated strategy bookmakers employ to maximise their financial gains; that is, 'Bookies may know how to nudge bettors toward larger losses' (Newell, 2015).

1.1.1 Same Game Multis

Australian company Sportsbet is credited with pioneering SGMs, announcing the product in July 2016 (Golder & Wiseman, 2019). SGMs are not ‘independent’ bets but combined contingencies involving considering and analysing multiple interrelated events that may affect the bet’s outcome. Their odds are calculated differently from standard multis to account for the contingency between markets (Sportsbet, 2022). This challenges gamblers regarding accurate calculation and may be inadequately priced compared to their long odds (Rockloff et al., 2019).

To gauge this magnitude, we highlight one of the largest sports betting markets in the United States, New Jersey. In 2023, the bookmaker ‘win rate’ for single-event wagers was around 5% and 18% for parlay bets, a favourable margin (win rate) in a competitive market (Figure 1). This implies that for every $100 bet on parlay bets, players lost around $18 and for single events lost around $5.

Figure 1. New Jersey 2023 Sports Wagering Revenue



Source: New Jersey Office of Attorney General

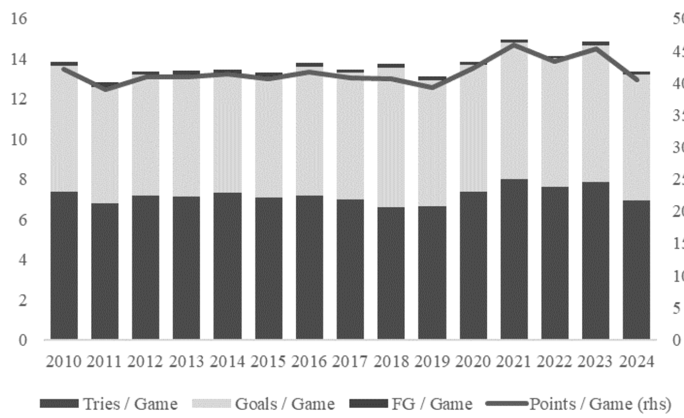
1.1.2 SGMs in Australia

Australian companies generally do not disclose details on individual betting products. Sportsbet, which holds approximately 50% of the online market share, reported that SGMs accounted for 55% of its active user base in 2021 (Flutter, 2021). With a total revenue of around A$2.5 billion and a net bookmaker margin of 12% in 2022 (Flutter, 2022), Sportsbet likely sees a substantial volume of SGM wagers, resulting in high player loss rates. Despite this significant market activity, Sportsbet has yet to disclose further detailed statistics on SGMs publicly.

1.1.3 Bookmaker Margins

The difficulty of calculating outcomes and accepting inferior odds are critical features of our analysis and hypotheses. The following example illustrates high bookmaker margins; as depicted in Figure 3 below, the bookmaker assigns the highest likelihood of tries scoring 7-8, offering the lowest odds for this range. This aligns with an average of 7.6 tries scored per game since 2021 (Dollin et al., 2024) (Figure 2).

Figure 2. NRL Statistics



Source: https://www.rugbyleagueproject.org/

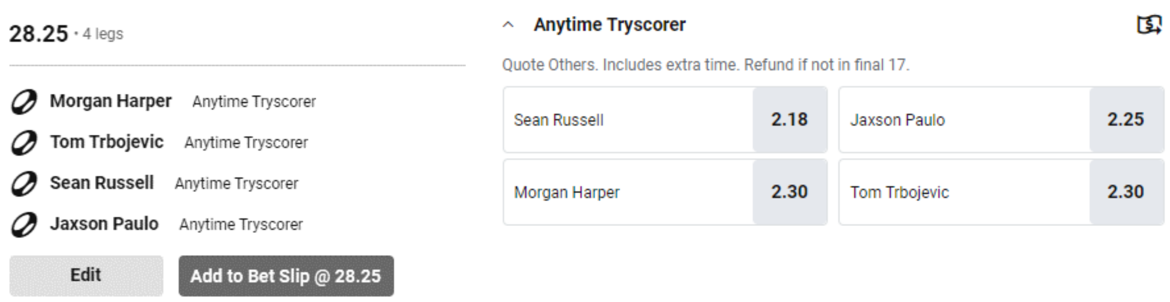
Figure 3: Total Try Odds

Source: Sportsbet

Based on the bookmaker odds (Figure 3), a ~16.2% profit is built in, assuming a balanced book. This is calculated by summing the implied probabilities (Implied Probability (IP) = 1 / Odds), where Total Market Percentage (TMP) = Σ_{allbands}IP and Margin = (TMP - 1) x 100% ≈ 16.2%. Consequently, betting on every outcome over time would lead to significant losses.

By examining a market's 'popular bet', the bookmaker offers $28.25 for the four players below to score a try (Figure 4). If these events were independent (meaning the outcome of one bet does not affect the outcome of another), multiplying the odds of each bet together implies $\text{Odds}_{\text{Harper}}$ x $\text{Odds}_{\text{Trbojevic}}$ x $\text{Odds}_{\text{Russell}}$ x $\text{Odds}_{\text{Paulo}}$ ≈ $25.95.

Figure 4. Sportsbet Popular Bet



The discrepancy between the simple multiplication of individual odds and those offered by bookmakers likely reflects more than event interdependencies; it may also suggest that bookmakers exploit cognitive biases. This is highlighted by Newell (2019), who posits a hypothetical scenario where a truthful gambling firm educates consumers about the exploitative nature of gambling. This results in informed consumers who refuse to gamble, explaining why no profit-maximising gambling firm operates in this manner. This exploitation is central to our proposed utility model discussed in Section 3.2.1, forming the basis of Hypothesis 1.

1.1.4 Complexity of Betting Dynamics

SGMs require a nuanced understanding of dynamic game events, as each shift can critically affect the outcome of a bet. This format heightens engagement and magnifies the stakes, merging excitement with increased risk. The substantial rewards SGMs offer are counterbalanced by their cumulative, high-risk nature. Experienced bettors drawn to this format likely perceive their in-depth game knowledge as a strategic edge in predicting outcomes.

Illustration of SGM Complexity

The complexity inherent in SGM betting can be exemplified using the try scorer market (Figure 4). The expected number of tries significantly impacts the likelihood of any individual try-scoring event. With 34 potential try-scorers and a game environment likely to see 7-8 tries, as predicted by bookmakers, selecting four specific players who will score becomes increasingly complex. This complexity can be quantified through the formula, where n represents the expected number of tries: P $(\text{scores at least once}) = 1 - (1 - \mathrm{p})^{\mathrm{n}}$.

Increasing n from 8 to 10 enhances each player's chances statistically, as $(1 - \mathrm{p})^{\mathrm{n}}$ diminishes, reflecting the increased opportunity each player has to score due to more overall scoring events. That is: $1 - (1 - \mathrm{p})^{10} > 1 - (1 - \mathrm{p})^{8}$.

This representation shows that the probability of any single-player scoring increases as the number of total tries increases. Still, it also highlights the challenges for bettors in accurately predicting outcomes for bets involving multiple players scoring. This integration of complex bet dynamics with cognitive biases, as outlined in Hypothesis 3, underscores the significance of exploring these bets within the broader economic behaviour and decision-making framework. It highlights how the allure of SGMs and their inherent complexities can significantly influence betting behaviour, driving the need for a deeper understanding of both the strategic and psychological aspects of sports betting.

1.1.5 Dependent vs Simple Probabilities: Sports vs Casino Gambling

Conditional and Dependent Probabilities

Conditional probability is essential to comprehend complex bets, and the dependence of events in a game is difficult to quantify. Differentiating dependency from bookmaker margin is also complicated.

Consider a practical example from an NFL game between the Los Angeles Chargers and Las Vegas Raiders, focusing on touchdown scorers:

- Austin Ekeler (Chargers) priced at $2.50
- Josh Palmer (Chargers) priced at $5.10

The independent combined odds of both Ekeler and Palmer scoring a touchdown would theoretically be calculated by multiplying their individual odds:

- Combined Odds (Independent) = $2.50 × $5.10 = $12.75

However, the bookmaker offers a slightly adjusted combined odds of $12.50, reflecting a nuanced adjustment for dependency and bookmaker margin. We make the essential assumption here that if Ekeler scores a touchdown, the probability of another player on his team, such as Palmer, scoring in the same game is reduced due to the limited number of scoring opportunities and the turnover of possession.

This interaction can be quantified using a dependency factor *f*, where:

- $f = 1$ would imply complete independence between the events (Ekeler's scoring has no impact on Palmer's chances).
- $f < 1$ indicates dependency (Ekeler's scoring decreases Palmer's chances of scoring).

The conditional probability of Palmer scoring, given that Ekeler scores using the dependency factor f, is P (P | E) = P (P) x f, where f represents the adjustment factor for dependency. Without any dependency between events:

- Combined Odds (Independent) = \$2.50 x \$5.10 = \$12.75 or 7.8% probability

Introducing a dependency factor f (where f<1) indicates that Ekeler scoring a touchdown decreases the likelihood of Palmer scoring. Consequently, the actual probability of both scoring together is less than the independent probability of 7.8%.

The new formula, considering that f < 1 makes the event less likely, increases the theoretical odds:

- Combined Odds (Dependent) $= \$2.50\ x\ \$5.10\ x \frac{1}{f} = \$12.75\ x \frac{1}{f}$

As f is less than 1, dividing by f (a fraction) results in a number greater than \$12.75. If the bookmaker offers odds lower than \$12.75, it implies one of two things:

- The odds are assuming a higher probability of Palmer scoring if Ekeler scores, which contradicts our assumption of dependency (f<1).
- A higher bookmaker margin is being included, essentially increasing the cost of the bet for gamblers.

Simple or Objective Probabilities

In casino games like American roulette, the house edge is typically fixed, averaging 5.26%. This means the ‘house edge’ or ‘player loss’ remains constant regardless of the player’s risk preferences. For instance, betting on a more likely outcome like red or black $\left(\frac{18}{38}\right)$ chance, or a less likely event of picking an exact number $(\frac{1}{38})$, results in the same expected loss (EV) over time:

Colour: $EV = \left(\frac{18}{38} x\ 1\right) + \left(\frac{20}{38}\ x(-1)\right) = \frac{18}{38} - \frac{20}{38} = -\frac{2}{38} = -5.26\%$

Number: $EV = \left(\frac{1}{38} x\ 35\right) + \left(\frac{37}{38}\ x\ (-1)\right) = \frac{35}{38} - \frac{37}{38} = -\frac{2}{38} = -5.26\%$

A rational agent looking to maximise expected value would consistently avoid bets with a negative expected value. Since both the colour and number bets in roulette have a negative expected value, a rational agent focused solely on expected value would prefer not to place either bet, opting to preserve their wealth or seek investments with positive expected values. However, according to Expected Utility Theory (EUT), individuals may have different risk preferences and utility functions, meaning that their decisions depend on these factors rather than on expected value alone. While most rational agents, especially risk-averse or risk-neutral, would avoid bets with negative expected value since their utility would generally decrease with expected losses, risk-seeking behaviour might lead a player to prefer the bet on a specific number. Despite having the same negative expected value as the colour bet, the number bet offers a higher potential payout, which could provide higher utility to a risk-seeking individual, even in the face of expected losses.

Transitioning from the predictable environment of casino games, we observe a contrast in sports betting. Here, especially in SGMs, bookmaker odds are not fixed and often require a sophisticated analysis that accounts for multiple interdependent variables. This complexity introduces significant room for cognitive biases such as overconfidence and heuristic misjudgments, which are less prevalent in the straightforward probability assessments of casino gambling.

Neither EUT nor CPT seems fully equipped to account for the observed variance in bookmaker margins or the positive relationship between bet complexity and margin. In these environments, bettors often engage with bets that objectively appear to have inferior returns. Our study posits that this seeming paradox can be explained by integrating non-monetary benefits such as entertainment and emotional engagement, suggesting that under certain conditions, seemingly irrational choices within the framework of SGMs can appear rational. This analysis forms the basis for Hypotheses 2 and 3, which propose that the intricate nature of sports betting not only permits but exacerbates behavioural biases like overconfidence, the illusion of control, and misinterpretation of mathematical concepts related to theoretical losses.

The rise of SGMs necessitates a deeper examination of existing theoretical frameworks and empirical studies. The following literature review scrutinises previous research to identify gaps and establish the theoretical underpinnings for our analysis.

2 Literature Review: Cognitive Biases and Decision-Making in Sports Betting

2.1 Gambler rationality and decision-making

The expected utility theory (EUT) initially posited by Bernoulli in 1738 was that individuals base their betting decisions on the expected monetary value of outcomes. It was refined by Von Neumann and Morgenstern (1944), introducing a more nuanced version, acknowledging that decisions under uncertainty are influenced by potential monetary outcomes and individual risk preferences encapsulated within diverse utility functions.

As Pratt (1964) discusses, utility functions can be concave, indicating risk-averse behaviour where the marginal utility of wealth decreases with increasing wealth. This perspective is pivotal in understanding why some bettors prefer safer bets with lower odds. However, this view has been criticised for oversimplifying the complexity of betting behaviour (Diecidue et al., 2004). For example, Diecidue et al. argue that real-world gambling often deviates from these theoretical predictions, as evidenced by violations of transitivity and stochastic dominance in practical scenarios.

Conversely, Kahneman and Tversky (1979) discuss how convex utility functions in the domain of losses depict risk-seeking behaviour, where the marginal utility of wealth increases with wealth accumulation, particularly when facing potential losses. This model is further challenged by empirical findings suggesting that bettors' risk preferences are context-dependent and influenced by cognitive biases such as overconfidence and the illusion of control (Erceg & Galić, 2014).

This framework explains why high-risk, high-reward bets in sports betting are attractive despite their lower expected returns. The psychological impact of potential substantial gains disproportionately influences bettors' decisions, outweighing a rational assessment of the likelihood of achieving them. This is compounded by probability weighting, where individuals tend to overweight small probabilities, leading them to undervalue the risk of losses in favour of the exaggerated perceived likelihood of significant wins. Thus, even if these bets offer objective expected returns that are lower than safer bets, the subjective utility derived from the possibility of a substantial win is perceived as higher by some bettors, overcoming inherent loss aversion.

In sports betting, traditional EUT often fails to explain the nuanced decision-making behaviours observed among bettors, notably in high-risk environments. Starmer (2000) argues that EUT does not fully capture the complexities of real-world gambling, where known and unknown risks frequently influence decisions. Echoing this sentiment, Tversky and Kahneman (1992) highlight that gambling behaviours often oscillate between risk-averse and risk-seeking tendencies, which EUT does not adequately predict.

Responding to these limitations, Luce et al. (2008) propose a modified utility model that integrates entropy to better account for the uncertainties typical in betting scenarios. This model is relevant for examining complex bets where gamblers face ambiguous probabilities akin to the scenarios described by the Ellsberg paradox. By incorporating an entropy-modified form of 'subjective expected utility', this approach offers a more realistic framework for understanding how bettors evaluate risks and make decisions when confronted with the differential treatment of known and unknown probabilities. Building upon this foundation, we propose an extended utility model incorporating expected financial outcomes and subjective psychological experiences to provide a more comprehensive understanding of SGM betting behaviour (H1).

This context sets the stage for exploring how cognitive biases might influence the perceived utility of complex bets like SGMs, where cognitive biases like the conjunction fallacy play a critical role (H1, H2).

Le Menestrel (2001) introduces the concept of 'process utility', which highlights the intrinsic entertainment value of gambling, independent of financial outcomes. This model is crucial for understanding the broader allure of gambling, as it acknowledges that motivations extend beyond mere financial risks and rewards to include the enjoyment derived from the act itself. This perspective is particularly relevant when considering the Allais paradox, which demonstrates gamblers' deviation from purely financial motivations in their decision-making processes. Such deviations align with Hypothesis 1, which suggests that cognitive biases can significantly influence betting behaviour by enhancing the perceived utility of gambling. These biases make the gambling experience subjectively more appealing, irrespective of the objective financial expectations.

Understanding 'process utility', we can better appreciate how non-financial rewards contribute to the persistence of irrational gambling behaviours as postulated under H1. In contrast, Cain et al. (2005) found that many adults regularly participate in gambling, placing sizeable bets on 'favourites', primarily motivated by financial gain rather than entertainment.

However, this does not capture the intricacies of complex sports bets at 'underdog' (low) probabilities, which we investigate in H2 and H3.

Marfels (2001) extends this understanding by analysing the rationality of gambling, emphasising that utility in gambling goes beyond monetary gains. Marfels argues that gambling rationality also encompasses entertainment value and complimentary services offered by casinos, challenging traditional views that focus solely on financial outcomes.

Finally, Miceli (2023) examines sports betting by introducing a contest utility function $V[pa(1-p)^{1-a}]$, which uses the probabilities 'p' and '1 – p' to denote the chances of each of the two teams winning. It demonstrates how fans can enhance their experience through betting, particularly in uneven contests, by aligning their preferences with contest odds ($p=a$). However, this binary nature limits its use in more complex betting dynamics like SGMs.

Our proposed utility model (H1) addresses this limitation by reflecting multiple outcomes, accommodating a broader spectrum of preferences and multiple possible results within a single event. This allows it to capture better the diverse betting behaviours and preferences observed in real-world sports betting scenarios, providing a more comprehensive framework for analysing fan engagement and betting strategies.

2.2 Betting Behaviour and Biases

Bettor behaviour can be understood through psychological theories like the illusion of control (Langer, 1975), hindsight bias (Fischoff & Beyth, 1975), decision-making based on availability heuristics (Tversky & Kahneman, 1973) and social dynamics (Cialdini & Goldstein, 2004; Nyemcsok et al., 2023). We concentrate primarily on the conjunction fallacy (Tversky & Kahneman, 1983) and the overweighting of small probabilities (Prospect Theory).

These concepts are pertinent to the patterns and paradoxes observed in sports betting. This choice of focus allows us to delve deeper into the cognitive biases that specifically influence sports bettors, especially in the context of high-risk and complex betting scenarios like SGMs. We acknowledge that this represents a specialised subset within the broader array of psychological factors influencing gambling.

2.2.1 Conjunction Fallacy

Tversky and Kahneman (1983) ascribed the conjunction fallacy to the 'representativeness heuristic', a similarity-based intuitive reasoning. As they explained in 1974 (p. 1124), this heuristic involves judging the likelihood of an event (A) by its resemblance to another event (B). People often estimate probabilities based on how representative A seems of B.

In their classic illustration, Tversky and Kahneman presented the following description:

'Linda is 31 years old, single, outspoken and very bright. She majored in philosophy. As a student, she was deeply concerned with issues of discrimination and social justice and also participated in anti-nuclear demonstrations.'

Participants were then asked to rank two options based on probability:

1. Linda is a bank teller.

2. Linda is a bank teller and is active in a feminist movement.

Around 85% chose the second option, illustrating the conjunction fallacy. That is, the likelihood of two events happening together cannot be greater than that of either event occurring individually.

2.2.2 Conjunction Fallacy in Sports Betting

In sports betting, particularly in SGMs, we hypothesise that the conjunction fallacy influences bettor behaviour (H1). For example, bettors might believe that the likelihood of a favoured team winning and a star player from that team scoring in the same match is higher than the mathematical joint probability, leading to overconfident betting decisions. This overestimation makes complex bets seem more appealing, mainly because of the higher potential rewards they promise.

Conversely, disjunctive bets - successful if any of multiple possible events occurs - tend to be underestimated in their likelihood. Despite offering a greater chance of winning, these more straightforward betting options are often overlooked in favour of more elaborate, high-reward bets. This prevalent misjudgement of probabilities, where complex outcomes are valued excessively and simpler ones are diminished, exemplifies how cognitive biases skew bettors' decision-making processes, steering them towards more intricate and ostensibly lucrative betting strategies.

Nilsson and Andersson (2010), in one of the few investigating the conjunction fallacy in sports betting, analyse how bettors evaluate football game outcomes. They found that bettors often mistakenly judge the probability of combined low or intermediate-likelihood events (like Stoke City defeating Manchester United) and high-probability events (such as Liverpool FC beating Wigan) as greater than the likelihood of the low-probability event alone. This misjudgement is not seen when two low-probability events are combined, indicating the context-sensitive nature of bettor assessments. Our study concentrates on the representativeness heuristic, a primary theory from Nilsson and Andersson that elucidates the conjunction fallacy, extending these concepts to SGMs to examine Hypothesis 2.

Representativeness Heuristic

Representative events in sports betting, such as an NRL match, are the favourite team winning (match-winner bets), the favourite winning by a high margin (margin bets), or a star player scoring a try (anytime try scorer). Conversely, representative events for underdog teams are less diverse as they are generally less expected and less frequent, meaning fewer popular bets are associated with them.

This is likely why bookmakers predominantly advertise complex bet types with high expected losses for bettors (Newell, 2015). Newell concluded that bookmakers exploit the representativeness heuristic, where bettors are influenced by the perceived likelihood of an event occurring based on its representation in the media or advertising. Nilsson and Andersson (2010) indicate, however, that the representativeness heuristic does not fully explain the occurrence of the conjunction fallacy in sports betting. This means the fallacy still occurs even when bettors do not rely on this ‘matching to a prototype’ approach. In other words, other factors at play lead bettors to incorrectly assess the likelihood of combined events in sports betting. This suggests that the decision-making process is more complex than being influenced by representativeness.

Andersson and Nilsson (2015) provide a contrasting perspective, revealing that bettors generally make well-calibrated judgments when interpreting betting odds, suggesting a realistic grasp of the odds’ probabilistic information. However, sports bettors show a limitation in adjusting judgments for different margins, indicating a potential gap in probabilistic reasoning in complex betting scenarios. This applies directly to our investigation of the popularity of SGMs and the high rates of player losses (H1, H2, H3).

Newall (2017) examines the behavioural aspects of British gambling advertising, specifically the prevalence of complex football bets. He notes that these bets often feature high bookmaker margins, dominate advertising and pose dual challenges: they confuse consumers and exploit cognitive biases. Newall's findings indicate that football fans frequently misjudge probabilities by assigning cumulative probabilities to game events that collectively exceed 100%, reflecting the conjunction fallacy (H1). This tendency to overestimate the likelihood of simultaneous events suggests gambling advertisements may skew bettor perception, leading to irrational betting decisions influenced by an exaggerated sense of winning probabilities.

2.2.3 Skilled vs Non-skilled Gaming

Skill-based wagering in sports betting involves complex decision-making processes, highlighting the unique challenges and mathematical intricacies inherent in this form of gambling. This examination is essential as it contextualises the cognitive biases discussed earlier and provides a deeper understanding of why bettors are drawn to complex bets like SGMs despite the heightened risks and lower expected returns (H3).

Sports betting relies on an in-depth knowledge of individual players' characteristics and behaviours rather than mere chance (Getty et al., 2018). This reliance underscores the importance of knowledge and analytical skills in predicting outcomes, enhancing the perceived control bettors feel over the betting process. Custom sports betting products, such as 'request-a-bet', exemplify this intersection between perceived skill and gambling behaviour. These services allow bettors to design their wagers, reinforcing the perception of skill over chance, particularly among younger male bettors (Newall et al., 2021a).

High-Risk, High-Reward Bets

The preference for high-risk, high-reward bets within these custom services suggests a belief in personal skill to craft successful strategies, often involving long-odds bets on star players from top teams (Newall et al., 2021b). Hassanniakalager and Newall (2019) indicate that sports betting outcomes can be influenced by skill, as bettors leverage their knowledge and strategic planning to improve their winning odds. This contrasts with games of pure chance, such as roulette, where no legal strategies can overcome the house advantage.

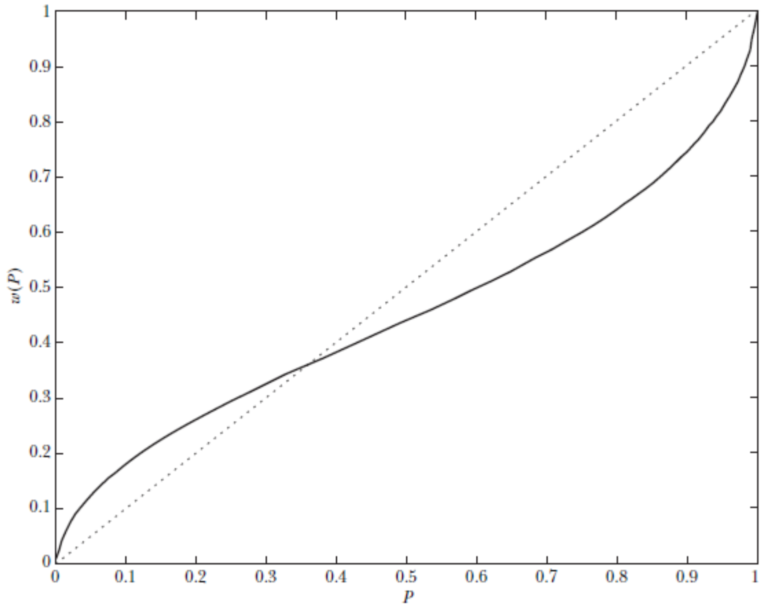
Perceived Proficiency vs. Actual Outcomes

Gamblers often categorise their betting activities as skill-based, attributing their perceived proficiency to understanding historical statistics and betting data (Winters & Derevensky, 2019). However, this perception is complicated by findings that, over time, success rates in sports betting do not significantly differ from those in chance-based gambling, suggesting an overestimation of skill involvement (Phua et al., 2022). Sports bettors likely exhibit more erroneous beliefs than those involved in games of pure chance, reflecting a cognitive disparity between skilled and non-skilled betting (Mercier et al., 2018). Additionally, research highlights different predictors of problem gambling severity between sports and non-sports bettors, pointing to unique risks in skilled betting activities (Cooper et al., 2021). This suggests that bettors may incorrectly assess the likelihood of combined events or overweight low probabilities in complex bets (H3).

2.2.4 Overweighting of Low Probabilities

Tversky and Kahneman (1992) expanded Prospect Theory by developing Cumulative Prospect Theory (CPT) to better handle scenarios with more than two outcomes. CPT uses cumulative decision weights instead of separable ones, allowing different weighting functions for gains and losses (Figure 5). This provides a more nuanced understanding of how individuals evaluate probabilities, particularly in complex betting scenarios.

Figure 5. The Probability Weighting Function



Notes: The graph plots the probability weighting function proposed by Tversky and Kahneman (1992) as part of cumulative prospect theory, namely $w(P) = P^{\delta}/(P^{\delta} + (1 - P)^{\delta})^{1/\delta}$, where P is an objective probability, for two values of δ. The solid line corresponds to $\delta = 0.65$, the value estimated by the authors from experimental data. The dotted line corresponds to $\delta = 1$, in other words, to linear probability weighting.

Source: Barberis (2013)

In SGMs, where multiple interrelated outcomes contribute to the final result, the rank-dependent utility model of CPT is relevant. This model considers the order of probabilities and their cumulative impact, leading to a tendency to disproportionately overweight low-probability events. This deviation from linear probability weighting can explain why bettors often favour high-risk, high-reward bets, as the perceived utility of potential large payouts overshadows the rational evaluation of their actual likelihood.

Both Kahneman and Tversky (1979) and Barberis (2013) delve into the concept of probability weighting, with Barberis expanding its application to financial decision-making. Despite these advancements, Barberis' work still falls short in accounting for the interactive environments of betting, particularly in complex bets. A significant methodological gap in these studies is their reliance on controlled, simplified environments that may not reflect the real-world complexity of sports betting. Existing research often neglects the dynamic and interactive nature of betting, where multiple contingent events must be considered simultaneously.

The attractiveness of gambling on longshots, akin to SGMs, can be partially explained by CPT despite the actuarially unfair odds (Cain et al., 2005). Cain et al. argue that psychological factors beyond those captured by CPT are crucial for understanding gambling behaviour, especially in bets with objectively inferior returns. For example, Prelec (1998) discusses the misestimation of win probabilities in lotteries, driven by loss aversion and the unrealistic appeal of large rewards. These insights support our hypothesis (H3) that complex bets exacerbate behavioural biases, leading to poor decision-making. However, CPT falls short of fully describing the variability in how individual gamblers perceive expected returns and bookmaker margins. This subjective perception appears to influence betting behaviour, underscoring a gap in CPT's ability to fully capture the complex decision-making processes in gambling.

2.3 Summary and Future Directions in SGM Betting Behaviour Research

The popularity of SGMs is significantly influenced by gamblers' risk attitudes and cognitive biases, such as the conjunction fallacy. Existing studies provide valuable insights but often overlook the real-world complexities and compounded cognitive biases specific to SGMs, leading to a wide range of gambling behaviours from rational to highly irrational (Stetzka & Winter, 2021). Our study employs an experimental design with real monetary stakes and complex bet scenarios, reflecting realistic betting environments. This approach is crucial for examining Hypothesis 1, which focuses on psychological factors influencing betting decisions. By integrating psychological insights with economic analysis, we aim to enhance our understanding of betting behaviour in SGMs.

This research highlights the conjunction fallacy within sports betting, revealing significant gaps in understanding how SGM bettors strategise around complex event combinations. By distinguishing between skilled and non-skilled gaming, we demonstrate how perceptions of skill influence betting behaviour and susceptibility to cognitive biases. Our experimental design provides nuanced insights into these biases, enriching the gambling literature by examining the interplay between cognitive biases and economic decision-making in sports betting.

3 Methodology

Following the review of the existing literature, we outline a robust methodology to investigate our hypotheses. This section outlines the experimental design and procedures employed to test the impact of cognitive biases in SGM betting.

3.1 Experimental Design

We introduce real monetary stakes to improve the ecological validity of our study, ensuring our findings can be generalised to real-world settings. Each participant knows that one of their bets, randomly selected after all bets are placed, will be actualised with a $10 stake. Inspired by Camerer and Hogarth (1999), this approach aims to evoke genuine cognitive and emotional responses typical of real betting scenarios, providing a more accurate reflection of betting behaviour under realistic conditions. The experiment randomises phases to avoid order effects and minimise biases (Gigerenzer, 2005). By changing the order of simple and complex bets, we aim to reduce decision-making biases.

There are four phases in the experiment:

1. **Component Phase**: Simple betting scenarios (win/loss) where participants select and rate their confidence in individual bets.
2. **Conjunction Phase**: The individual bets from the Component Phase will be combined in two and three-game 'multi' bets.
3. **Same Game Multi Component Phase**: Complex bet scenarios (win/loss and try scorers) where participants select and rate their confidence in individual bets.
4. **Same Game Multi Conjunction Phase**: The individual bets from the Same Game Multi-Component Phase will be combined into two and three-scenario 'same game multi' bets.

Presentation of Participant Information

We collect participant predictions and confidence levels for each bet during each trial phase, using a 0-100% confidence scale. This scale spans from complete uncertainty to absolute certainty, ensuring an accurate assessment of all possible confidence levels. By utilising this comprehensive approach, we can detect overestimation of bet success, underestimation, and precise prediction accuracy. This allows us to effectively isolate and analyse cognitive biases, such as overconfidence, and the impact of the conjunction fallacy on betting behaviour.

In the Component and Same Game Multi Component Phases, participants record their confidence levels for individual betting scenarios, including simple win/loss bets and more complex bets involving try scorers. This data provides the foundation for the subsequent Conjunction and Same Game Multi Conjunction Phases, where individual bets are combined into two and three-game multi-bets. During the conjunction phases, we compare the confidence levels assigned to individual bets with those assigned to aggregated multi-bets.

This dual rating system quantitatively captures how the aggregation of bets into multis alters the perceived likelihood of winning and influences bettor confidence, enabling a detailed analysis of how perceptions shift when individual outcomes are combined into compound betting scenarios.

3.1.1 Component Phase

We present the eight games of an upcoming round of NRL that engage participants' subjective beliefs about team strengths and outcomes, ensuring the representativeness heuristic is effectively tested (Table 1).

Table 1. Game Winning Classifications

Game	Classification	Home	Away	Classification
1	Unlikely	Dolphins	Manly Sea Eagles	Intermediate
2	Likely	Penrith Panthers	Canterbury Bulldogs	Unlikely
3	Unlikely	Parramatta Eels	Brisbane Broncos	Likely
4	Intermediate	Wests Tigers	Newcastle Knights	Intermediate
5	Intermediate	St George Dragons	South Sydney Rabbitohs	Intermediate
6	Likely	Melbourne Storm	Cronulla Sharks	Unlikely
7	Likely	Sydney Roosters	NZ Warriors	Unlikely
8	Unlikely	Gold Coast Titans	Nth Queensland Cowboys	Likely

Participants are asked:

'In this part of the study, you will be presented with a set of bets, each consisting of a game and its predicted outcome. Your task will be to predict whether these bets will win or lose and then rate your confidence in each prediction on a scale of 0-100%'.

Bets are presented as the Home team winning, and participants use a scale to mark their confidence, for example:

'Dolphins (Head to Head Winner) vs Manly Sea Eagles'

'Bet Wins' or 'Bet Loses'

'How confident are you?'

3.1.2 Conjunction Phase

We test combinations with lower likelihood components in the multi and same-game multi-conjunction phases, as people often overestimate combined event probabilities (Nilsson & Andersson, 2010). Testing Intermediate-Likely (IL) combinations is crucial for this purpose.

This overestimation occurs even though the conjunction rule states that the probability of a conjunction should not exceed the probability of its least likely component. In addition, testing Unlikely-Likely (UL) combinations is essential. Like IL combinations, the conjunction fallacy can manifest here when an unlikely event is combined with a likely event. Participants may irrationally increase their confidence in the combined bet's success due to the presence of the possible event, which contradicts probability theory.

Synthetic Results Using Bookmaker Odds

To enhance our experimental setup's effectiveness and ensure it aligns with participants' subjective beliefs about team strengths and potential match outcomes, we incorporate 'market odds' from Sportsbet as an objective metric to categorise the events into different likelihood categories (Tables 1 and 2). This also allows us to look for patterns that suggest overestimating control or misinterpreting odds (H3). This is executed by delineating bets into three distinct likelihood categories:

- 'Likely' for odds from $1.01 to $1.51
- 'Intermediate' for odds from $1.52 to $2.20
- 'Unlikely' for odds greater than $2.21

These categories correspond to the probability of a bet's success, with the benchmark odds of $1.85 as the reference point, indicating an even 50:50 chance (including bookmaker margin). The approach allows for a controlled examination of the decision-making processes and the cognitive biases that may manifest when individuals evaluate risks in isolation compared to in combination. This structured categorisation based on objective odds surrogates the direct collection of individual confidence levels in the Component Phase to create bets in the Conjunction Phase (Table 2).

Throughout the experiment, we deliberately refrain from presenting actual market or objective odds to participants to focus on cognitive biases rather than numerical literacy. This approach allows us to isolate the influence of the representativeness heuristic and test for the conjunction fallacy without the confounding factor of participants' ability to understand and calculate probabilities (H2 & H3).

We record predictions and confidence ratings for each multi-bet in the conjunction phases for multi and SGM bets. This phase's primary aim is to investigate the presence of the conjunction fallacy by comparing confidence levels in single bets to those in multi-bets and SGM bets.

Table 2. Conjunction Phase Set-up

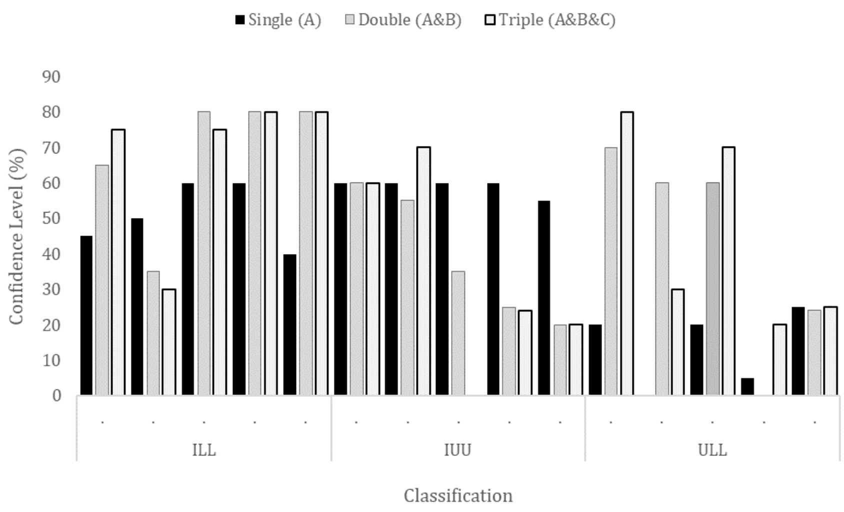
Classification	Betting Components
IL	Wests Tigers + Penrith Panthers
	St George Dragons + Melbourne Storm
UL	Gold Coast Titans + Penrith Panthers
	Parramatta Eels + Melbourne Storm
ILL	Wests Tigers + Penrith Panthers + Melbourne Storm
	St George Dragons + Melbourne Storm + Penrith Panthers
ULL	Gold Coast Titans + Penrith Panthers + Melbourne Storm
	Parramatta Eels + Melbourne Storm + Penrith Panthers

We remind participants of the study's structure, emphasising their multi-bet evaluation task. Bets are depicted with the home team as the predicted winner, and participants indicate their confidence. Participants are presented with the components in

Table 2 and respond with ‘Bet Wins’ or ‘Bet Loses’ followed by their confidence level: ‘How confident are you?’

To illustrate how our data would be interpreted to investigate the presence of the conjunction fallacy, we have analysed a single participant’s data from Nilsson and Andersson’s (2010) study (Figure 6). This analysis compares confidence levels in single bets to those in multi-bets, examining confidence levels in single, double, and triple bets across three classifications: ILL (Intermediate-Likely-Likely), IUU (Intermediate-Unlikely-Unlikely), and ULL (Unlikely-Likely-Likely).

Figure 6. Example of Data Collected (Participant 1)



Note: The chart uses actual participant data sourced from Nilsson and Andersson (2010)

In the IUU category (Figure 6), confidence decreases with the inclusion of unlikely outcomes. However, Participant 1 deviates from rational choice by exhibiting the conjunction fallacy in the ILL and ULL categories. Specifically, when combining intermediate or unlikely events with likely outcomes, Participant 1 demonstrates irrationally high confidence levels in multiple-event bets, contrary to probability theory, which predicts lower confidence in these complex bets than in single bets.

Our experiment examines mean confidence ratings across the participant cohort. We expect to find similar results as Nilsson and Andersson (2010), noting these results were on ‘standard’ multis (independent events), not same-game multis (Table 3). The results of the paper indicate that the likelihood of an outcome initially evaluated as immediately likely (I(L)) increases when combined with a highly likely prediction (IL). This likelihood is further enhanced when an additional highly likely prediction is included (ILL).

Table 3. Mean Confidence Rating for the Evaluations

Bet Type	Category	Confidence Ratings
Single	I(L)	49.2%
Multiple-2	IL	50.9%
Multiple-3	ILL	53.7%

Source: Nilsson and Andersson (2010)

3.1.3 Same Game Multi-Phase

Component Phase - SGM

Participants will perform two actions: predict whether a player will score a try and which team will win, and then rate their confidence in each prediction. These predictions and confidence ratings will be evaluation benchmarks in the subsequent SGM Conjunction Phase.

Table 4. Component Phase - SGM

Classification	Betting Component	Bookmaker Odds	Implied Bookmaker Probability
Likely	Roosters (Win) vs Warriors	$1.28	78%
	Dragons (Win) vs Rabbitohs	$1.51	66%
Intermediate	Young - Roosters (ATS)	$1.66	60%
	Watene-Zelezniak - Warriors (ATS)	$2.18	46%
	Tupou - Roosters (ATS)	$1.89	53%
	Lomax - Dragons (ATS)	$1.67	60%
	Thompson - Rabbitohs (ATS)	$2.15	47%
Unlikely	Tedesco - Roosters (AS)	$2.35	43%
	Tuivasa-Sheck - Warriors (ATS)	$3.70	27%
	Mitchell - Rabbitohs (ATS)	$2.40	42%
	Suli - Dragons (ATS)	$2.60	38%

This phase's cornerstone is compiling an array of individual judgments on the likelihood and certainty of each discrete betting component's success. This data collection aims to capture the essence of participants' evaluative strategies in isolation before confronting the complexities of combined betting scenarios in the later stages of the study.

Conjunction Phase - SGM

The Conjunction Phase evaluates how participants combine different betting components into an SGM, focusing on the conjunction fallacy. Each component - match winners and anytime try scorers (ATS) - is categorised into three likelihood levels (likely, intermediate, unlikely) using 'market odds' (section 3.1.2). Participants predict the overall success of each multi-bet and rate their confidence in these predictions.

Table 5. SGM Conjunction Phase Summary

Classification	Betting Components	Bookmaker Odds	Implied Bookmaker Probability
IL	Young - Roosters (ATS) + Roosters (Win) vs Warriors	$2.05	49%
IL	Watene-Zelezniak - Warriors (ATS) + Roosters (Win) vs Warriors	$3.20	31%
UL	Montoya - Warriors (ATS) + Roosters (Win) vs Warriors	$5.25	19%
UL	Suli - Dragons (ATS) + Dragons (Win) vs Rabbitohs	$3.50	29%
Complex	Roosters (Win) vs Warriors + Montoya - Warriors (ATS) + Tedesco - Roosters (AS)	$8.25	12%
Complex	Dragons (Win) vs Rabbitohs + Mitchell - Rabbitohs (ATS) + Suli - Dragons (ATS)	$10.00	10%

As summarised in Table 5, we address Hypothesis 2 by testing for the conjunction fallacy by compiling 2-event (Double) betting combinations into Intermediate-Likely (IL) and Unlikely-Likely (UL). Acknowledging the challenge of distinguishing between cognitive biases and event dependencies, our design includes try scorers from teams expected to lose, creating scenarios with a presumed negative correlation between the team's victory and the player's scoring. This setup aims to minimise dependencies and sharpen our analysis, allowing evaluation of how participants' confidence levels reflect potential cognitive distortions.

For Hypothesis 3, which aims to explore the impact of added complexity on betting decisions, we combine three bets from the component phase, which include a team winning and the most likely scorer from each side, a similar mechanism to deal with dependency bet and a team winning and next-best likely scorers from each side to create the Complex bets (Triple).

This setup provides a clearer view of how complexity alone can affect bettor behaviour by adding a variable that should not influence the probabilities of the other two components within these bets. These selections are summarised in Table 4, and the full betting options are in Table 1a of the appendix.

3.2 Testing Hypothesis 1

H1. Gamblers accept inferior odds in SGM scenarios primarily due to behavioural biases rather than market inefficiencies.

Newall (2017) highlights the role of cognitive biases in betting behaviour but does not explicitly address the acceptance of inferior odds in SGMs. By focusing on behavioural biases leading to the acceptance of inferior odds, our study addresses a specific gap in the literature concerning the psychological underpinnings of betting behaviour in SGM scenarios. This hypothesis extends Le Menestrel's (2001) concept of process utility, suggesting that intrinsic motivations and cognitive biases significantly influence betting behaviour. Cognitive biases such as the conjunction fallacy lead to overestimating combined probabilities, contributing to the acceptance of less favourable odds.

To test H1, we have developed a novel utility model to explain the differentiation between the act of the bet itself and the expected outcome.

3.2.1 Utility Model for SGMs

We define the total utility (OU_{SGM}) of engaging in an SGM bet as a composite measure that incorporates the expected financial outcomes and the subjective psychological experiences associated with the betting activity:

$$OU_{SGM} = EU + PU$$

This utility metric is structured to include the following:

Expected Utility (EU)

EU is calculated from the expected monetary returns of the bet, which are adjusted for the bookmaker's odds and margin. This component reflects the rational financial assessment of the bet.

$$EU = E[_{correctprobability} [u_{convex} ((1 - BM_{Margin}) \times Theo_{Odds} \times Stake)]$$

Here, the term u_{convex} represents the utility function that captures the risk-seeking nature of gamblers, where potential high rewards are disproportionately valued, characteristic of a convex utility curve.

This utility function is applied to the expected returns (EV) from the bet:

$$EV = ((1 - BM_{Margin}) \times Theo_{Odds} \times Stake)$$

Process Utility (PU)

This captures the SGM betting process's intrinsic motivations and psychological experiences. Intrinsic motivations include the thrill of risk-taking and the enjoyment of supporting a favourite team and betting event. Cognitive biases include the conjunction fallacy, the illusion of control, and the overweighting of low probabilities.

These motivations enhance the emotional and psychological satisfaction from participating in SGM bets, providing non-monetary value that enriches the betting experience, calculated as:

$PU = u_{IM}(IM) + u_{CB}(CB)$

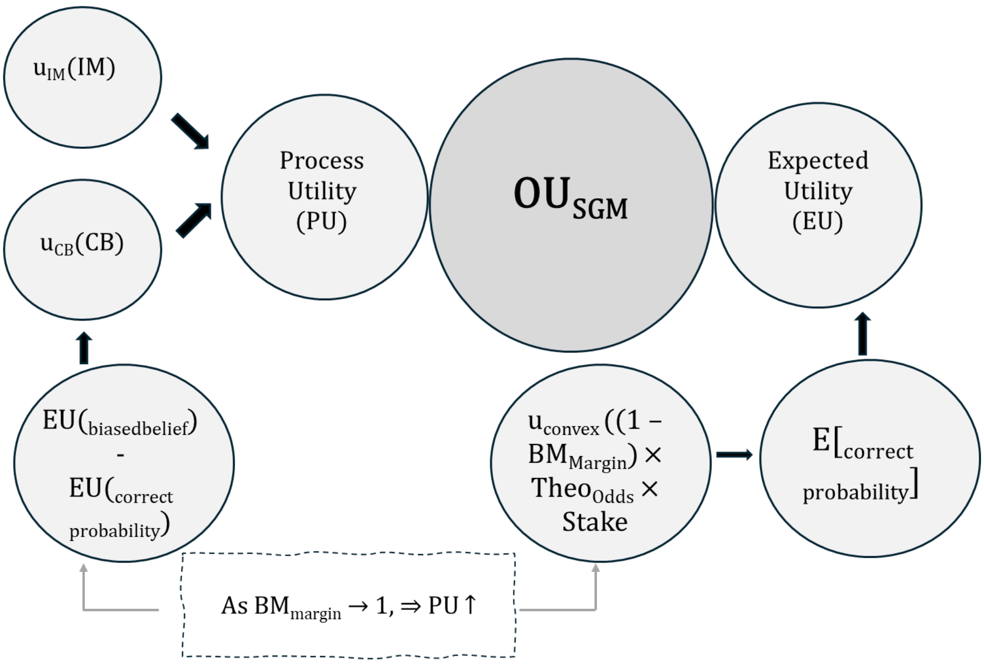
- u_{IM} (IM) represents the utility function that quantifies the psychological benefits derived from intrinsic motivations, emphasising how much personal satisfaction contributes to the overall utility of betting.
- u_{CB} (CB) represents cognitive biases, defined as the difference between the EU from biased beliefs and correct probability:
  - $u_{CB}(CB) = E[_{biasedbelief}]\ [u_{convex}((1 - BM_{Margin}) \times Theo_{Odds} \times Stake)] - E[_{correctprobability}\ [u_{convex}((1 - BM_{Margin}) \times Theo_{Odds} \times Stake)]$
- Biased beliefs $[_{biasedbelief}]$ refer to deviations from rational expectations, where individuals' perceptions and predictions of outcomes are influenced by their cognitive biases rather than objective data or statistical probabilities. These biases can stem from cognitive distortions, causing individuals to misestimate probabilities and potential outcomes.
- The convex nature of the utility function $(_{uconvex})$ significantly influences SGM gamblers' decision-making by appealing to risk-seekers who favour the potential for large rewards. This function emphasises larger gains more than equivalent losses, making high-risk, high-reward bets particularly attractive to these individuals.

$\therefore OU_{SGM} = EU_{biased\ belief} + PU$

$\therefore OU_{SGM} = E[_{biasedbelief}\ [u_{convex}((1 - BM_{Margin}) \times Theo_{Odds} \times Stake)] + u_{IM}(IM)$

This utility model emphasises the dual role of financial and psychological factors in shaping betting behaviour, forming the SGM bet's total utility. Here, the bookmaker margin influences the expected and process utility, integrating rational financial assessments with psychological experiences.

Figure 7. SGM Utility Model



As bookmaker margin (BM_{margin}) approaches 1, reducing potential financial returns, the importance of process utility (PU) becomes more pronounced. This dynamic highlights how bettors continue to engage in high-risk bets, driven by both expected monetary gains and the psychological rewards of the betting experience.

Impact of Bookmaker Margins on Betting Behaviour

Higher margins often deter bettors due to reduced potential financial gains. However, for gamblers who derive significant psychological satisfaction from betting, the intrinsic motivations can offset the less attractive odds, maintaining their interest and participation in

SGM betting. Given the typically high bookmaker margin in SGM bets, the role of process utility becomes crucial in maintaining the appeal of the bet.

The non-monetary benefits - such as the excitement of risk-taking and the psychological satisfaction from betting - play a pivotal role in influencing a bettor's decisions. Cognitive biases further compound this influence, which alters bettors' perceptions of the odds and potential payouts. These biases cause gamblers to believe they have a better chance of winning than the odds objectively indicate.

Interplay Between Margins, Biases, and Motivations

This relationship underpins our testing of Hypothesis 1, suggesting that as bookmaker margins increase, there must be a corresponding increase in both process utility and the impact of cognitive biases to maintain the attractiveness of the bet. These biases skew gamblers' risk perceptions, intensifying their involvement by making the bets appear more attractive than they are statistically. Consequently, the betting experience remains engaging for risk-seekers, who are attracted to the potential for significant rewards despite substantial financial risks. This demonstrates a critical interaction between rising bookmaker margins, stronger cognitive biases, and the underlying motivations that propel betting behaviour.

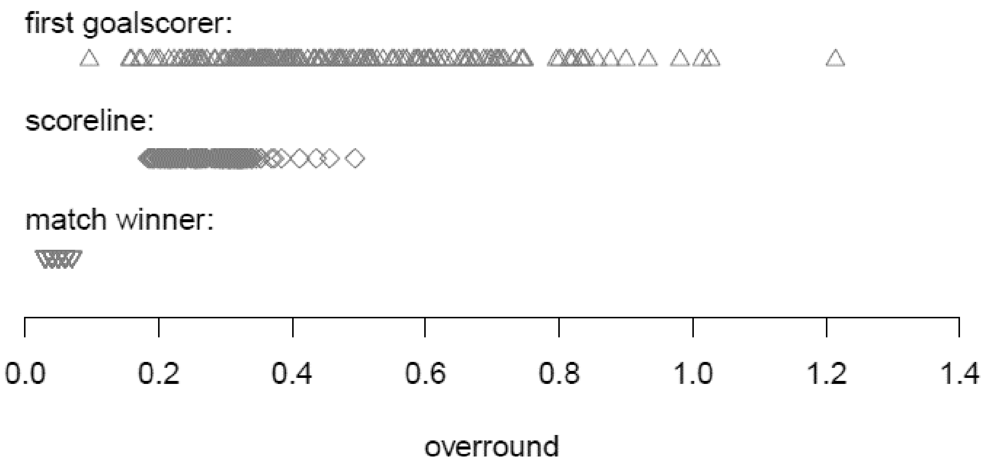
Cognitive Bias Impact

It is crucial to recognise that individuals are often unaware of how cognitive biases influence their betting decisions and compensate for less favourable odds $[EU(_{biasedbelief}) - EU(_{correctprobability})]$. This lack of awareness can significantly contribute to player losses. By testing the impact of these biases, we aim to understand their role in gamblers' decision-making processes, which is central to our investigation in Hypotheses 2 and 3.

3.2.2 Practical Illustration – FIFA World Cup

To illustrate the practical implications of this theoretical framework, we consider an example from the 2014 FIFA World Cup. The betting margins set for different types of bets varied significantly (Figure 8), providing a clear example of how bookmaker margins can influence the utility gamblers derive from their betting activities. Specifically, the margin for first-goal-scorer (FSG) bets was approximately 48%, compared to a much lower 5% for match-winner bets (H2H).

Figure 8. Overrounds in three bet types over the 2014 World Cup



Source: Newall (2015)

The significant disparity in these margins shows that while higher bookmaker margins reduce the financial appeal of bets, this effect can be overshadowed by the enhanced process utility from the thrill and potential high payouts. This scenario also highlights a key issue: gamblers may overlook how cognitive biases like overconfidence and illusion of control affect their decisions. This lack of awareness can lead them to underestimate the poor odds offered by high-margin bets, mistakenly perceiving these bets as more attractive.

Addressing this misconception is crucial, as it influences our understanding of Hypothesis 1, asserting that cognitive biases, rather than precise market assessments, often drive gambling decisions. We address the implications of cognitive bias impact on betting decisions by testing for overconfidence (H2) and analysing skill vs randomness (H3).

3.2.3 Utility Model Limitations

Our model aims to represent the factors influencing gambling decisions by distinguishing between EU and PU. While this helps to simplify complex interactions for analytical clarity, it inherently comes with limitations. The model may not fully capture how gamblers integrate emotional satisfaction with financial outcomes. This simplification is necessary to frame these factors clearly but does acknowledge that real-world decision-making processes may be more complex. Acknowledging these limitations is crucial as it underscores the need for further empirical research to refine our understanding of how these utilities interact and influence gambler behaviour in practical scenarios.

3.3 Testing Hypothesis 2

H2. SGM gamblers exhibit overconfidence in their betting selections due to a misunderstanding of conjunctive probabilities.

Nilsson and Andersson (2010) found that bettors often misjudge the likelihood of combined events, leading to overconfidence. However, their study does not explicitly address SGM scenarios. By applying these findings to SGM betting, our research fills this gap in understanding how bettors' confidence is influenced by misjudging conjunctive probabilities. This hypothesis connects the representativeness heuristic and the conjunction fallacy to overconfidence in betting. According to Prospect Theory, individuals tend to overweight low probabilities, contributing to overconfidence in their predictions - our experimental design tests this overconfidence by comparing confidence levels in individual bets to those in multi-bets.

3.3.1 Experimental Task

In the SGM phase, we directly test the representativeness heuristic by requiring participants to predict and combine multiple outcomes within a single game. We observe whether predictions become more optimistic when outcomes are combined rather than considered individually. This could indicate a reliance on representativeness and support H2 that SGM bettors overestimate compound event probabilities. For example, in NRL games, the interrelation between a team winning and a specific player scoring introduces complex dynamics into betting decisions. This complexity is highlighted by the high likelihood assigned to star players scoring compared to the collective probability for non-star players.

3.4 Testing Hypothesis 3

H3. The perception of skill in betting exacerbates behavioural biases, particularly in complex bets like SGMs.

Research by Newall et al. (2021) suggests that bettors perceive sports betting as skill-based. This perception can exacerbate cognitive biases, as bettors overestimate their ability to predict outcomes accurately. In contrast, research has consistently shown that over time, the success rates of sports bettors are indistinguishable from random chance (Phua et al., 2022), challenging the view that sports betting is skill-based. Phua et al. focused on sports bettors, non-sports gamblers, and non-gamblers to compare these groups, finding no significant difference in success rates.

To test H3, we propose a sub-hypothesis (H3a): if it is possible to outperform randomness, then some element of skill is present.

We analysed the last six seasons of NRL matches (1,073 matches), treating the bookmaker's odds as expert opinions. Backing every favourite for a $1 stake would have yielded a loss of $14.90 (2019-2024) at a 70% win rate. We used this as a benchmark for evaluating betting strategies through Monte Carlo simulations (Table 1b appendix). Alternatively, picking every underdog yields a $69.36 loss.

The first simulation (n=10,000) used a purely random selection strategy, resulting in a mean loss of $77.17, significantly higher than the benchmark loss of $14.90 (p-value < 0.0001). The second simulation (n=10,000) adopted a mixed strategy, selecting short-priced favourites (odds < $1.30) and randomly selecting the rest, resulting in an average loss of $45.40. Although this mixed strategy outperforms the pure random strategy, it still underperforms compared to the benchmark (p-value < 0.0001).

These simulations demonstrate that consistently backing favourites involves some skill, as this approach significantly outperforms a purely random strategy. Additionally, despite not reaching the benchmark of consistently backing all favourites, the mixed strategy still outperforms pure randomness, indicating a greater element of skill (H3a). However, the consistent loss, even when backing favourites, highlights the impact of bookmaker margins and the favourite-longshot bias, where bookmakers typically underprice favourites and overprice longshots to ensure profitability.

As hypothesised in H1, gamblers accept inferior odds in SGM scenarios primarily due to behavioural biases rather than market inefficiencies. This underscores the potential for cognitive biases to be amplified in complex betting scenarios like SGMs, where the perception of skill can exacerbate these biases. Newall et al. (2021) support this, indicating that the perception of betting as skill-based can lead to overestimating one's predictive abilities and acceptance of less favourable odds.

To further investigate, we will test confidence levels of single, double, and triple SGM bets to examine the role of the illusion of control and overweighting of low probabilities in perceived skill-based betting. This investigation will assess the impact of adding complexity to betting selections, with overestimating probabilities aligning with CPT's assertion of the conjunction fallacy.

With the methodology clearly defined, we can anticipate the potential outcomes of our experimental approach. The following section discusses the expected results and the implications for understanding betting behaviours in SGMs.

4 Expected Results

The study anticipates demonstrating significant cognitive biases among participants when making complex bets, specifically in SGMs scenarios. It is expected that:

- Participants will tend to violate the conjunction rule, overestimating the probability of combined events occurring simultaneously, leading to systematic errors in their betting decisions (H1, H2).
- Overconfidence in conjunctive probabilities and misunderstanding the actual odds will manifest prominently in more complex betting scenarios (H2).
- The complexity of the bets will enhance cognitive biases like the illusion of control, overweighting of low probabilities, and misinterpretations of mathematical concepts related to theoretical losses (H3).

4.1 Hypothesis 1

As defined in H1, the equation for the overall utility from an SGM bet assumed is:

$$OU_{SGM} = \mathrm{E}[_{\text{biasedbelief}} [\mathrm{u}_{\text{convex}} ((1 - \mathrm{BM}_{\text{Margin}}) \times \mathrm{Theo}_{\text{Odds}} \times \mathrm{Stake})] + \mathrm{u}_{\text{IM}} (\mathrm{IM})$$

In this model, $E_{biasedbelief}$ accounts for the expected utility derived from the gamblers' perceptions, which are influenced by cognitive biases, and $u_{IM}(IM)$ represents the utility from intrinsic motivations such as thrill and entertainment.

We anticipate that the experiment will show participants violating the conjunction rule during standard multi and SGM multi-phases of betting, indicating that cognitive biases enhance the perceived utility of the bet. This suggests that bettors influenced by these biases might disregard less favourable odds due to cognitive distortions. Further, a higher bookmaker margin (BM_{margin}) might indicate bookmakers exploiting these cognitive biases to increase their profit margins. The rationale is that bookmakers, understanding that cognitive biases skew bettors' judgment, might set higher margins with the expectation that these biases will cause bettors to accept poorer odds. This sets up an exciting direction for future research examining betting advertisements and inducements for SGMs and their financial outcomes. Researchers could explicitly value process utility by examining varying bookmaker margins within simple and complex bets.

4.2 Hypothesis 2

H2 posits that participants will exhibit overconfidence in conjunctive bets, particularly when evaluating scenarios involving statistically independent or negatively correlated events, thereby highlighting instances of the conjunction fallacy.

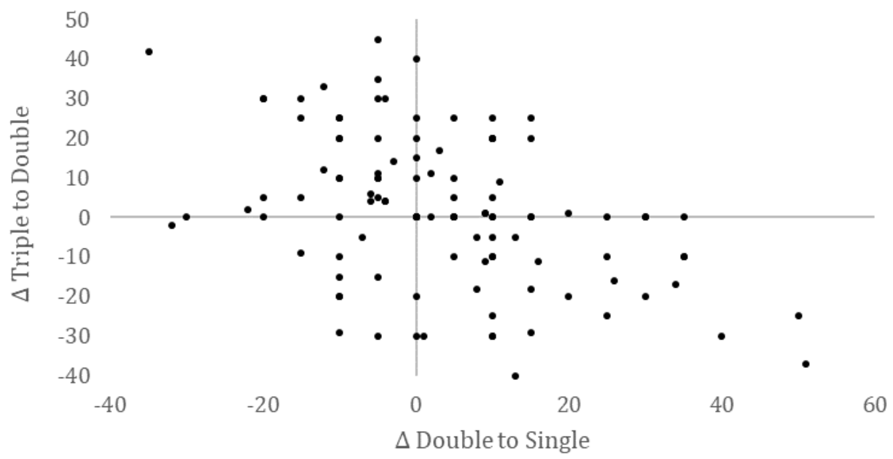
For independent bets, consider an 80% confidence rating of the Roosters winning and 60% for Watene-Zelezniak (Warriors) scoring. The joint probability (confidence) of both events occurring is calculated by multiplying the individual probabilities: $P(A \cap B) = P(A) \times P(B) = 0.80 \times 0.60 = 48\%$.

Confidence ratings above 48% suggest overestimation and a misunderstanding of how independent probabilities combine, revealing overconfidence. While we assume statistical independence, real-world game dynamics might alter these relationships. For example, a leading team may adopt conservative tactics, reducing their scoring probability, whereas a trailing team may escalate risks, potentially increasing their scoring chances. These dynamics could foster a positive correlation between events, challenging our initial assumptions.

For dependent bets, such as the combination of the Roosters winning (80%) and Young (Roosters) scoring (60%), the lower limit is set by the least probable event, in this case, 60%. Game dynamics could also influence these probabilities. A leading team might reduce scoring efforts, while a trailing team could become more risk-seeking. This dynamic can introduce positive correlations even in dependent scenarios, complicating our initial categorisations. This requires a nuanced analysis to correctly interpret confidence ratings between 48% and 60%, as these may not strictly indicate a conjunction fallacy but rather an adjustment to interdependencies. This limits our ability to compare dependent and independent scenarios directly and affects our interpretation of results under Hypothesis 3.

Our experiment contains the confidence rating data for all betting scenarios - single, double, and triple bets. This dataset will allow us to examine how participants' perceived probabilities of conjunctive outcomes evolve as more events are added to the betting scenario. From the data presented by Nilsson and Andersson (2010), we observed an increase in confidence levels when participants moved from evaluating single bets to double bets and from double bets to triple bets (Figure 9). Such increases in confidence levels, despite the decreasing likelihood of more complex conjunctive events occurring, suggest a systematic overestimation consistent with the conjunction fallacy.

Figure 9: Change in Confidence Ratings



Note: The chart uses actual participant data sourced from Nilsson and Andersson (2010)

If Hypotheses 2 and 3 hold, we expect a similar pattern in our data. We can quantify the extent of overconfidence and conjunction fallacy by comparing the transitions in confidence levels from single to double bets and from double to triple bets. The crucial comparison here is between the actual combined probabilities under independence (or appropriate adjustments for dependency) and the confidence levels expressed by participants. An increase in confidence ratings beyond mathematically justified indicates that participants are influenced by cognitive biases, such as the conjunction fallacy, supporting H2.

4.3 Hypothesis 3

H3 investigates how enhanced complexity within betting scenarios affects cognitive biases like the illusion of control, the overweighting of low probabilities, and the misinterpretation of loss probabilities. This hypothesis posits that incorporating multiple betting outcomes, particularly from different categories, amplifies cognitive distortions due to the increased complexity of decision-making.

CPT offers a valuable framework for understanding these phenomena, notably the tendency to overweigh small probabilities and underweight large ones, especially in complex betting environments like SGMs. This theoretical approach is highly relevant here, as it predicts that the more complex the betting scenario, the more likely bettors are to display these non-linear probability assessments.

Table 4. Component Phase - SGM

Classification	Betting Component	Bookmaker Odds	Implied Bookmaker Probability
Likely	Roosters (Win) vs Warriors	$1.28	78%
	Dragons (Win) vs Rabbitohs	$1.51	66%
Intermediate	Young - Roosters (ATS)	$1.66	60%
	Watene-Zelezniak - Warriors (ATS)	$2.18	46%
	Tupou - Roosters (ATS)	$1.89	53%
	Lomax - Dragons (ATS)	$1.67	60%
	Thompson - Rabbitohs (ATS)	$2.15	47%
Unlikely	Tedesco - Roosters (AS)	$2.35	43%
	Tuivasa-Sheck - Warriors (ATS)	$3.70	27%
	Mitchell - Rabbitohs (ATS)	$2.40	42%
	Suli - Dragons (ATS)	$2.60	38%

Using the examples in Table 4 (reproduced above) and assuming a participant's confidence ratings:

I. Team Winning: Roosters (80% confidence); Try Scorers: Montoya from Warriors (20% confidence); and Tedesco from Roosters (40% confidence).

II. Team Winning: Dragons (60% confidence); Try Scorers: Mitchell from Rabbitohs (20% confidence); and Suli from Dragons (40% confidence).

This strategy involves players from both opposing and the same teams to enhance complexity and reduce dependency effects. Mixing inter-team and intra-team dynamics tests a range of probabilities to assess cognitive biases in SGM betting more effectively.

Assuming three dependent events, the least likely individual events of Montoya (Bet I) and Mitchell (Bet II) scoring are at 20% confidence. Thus, under the conservative assumption, the least likely event dictates the upper bound of rational confidence for the entire combination: $\mathrm{P}(\mathrm{A} \cap \mathrm{B} \cap \mathrm{C}) \leq \min(\mathrm{P}(\mathrm{A}), \mathrm{P}(\mathrm{B}), \mathrm{P}(\mathrm{C})) = \mathrm{P}(\mathrm{A} \cap \mathrm{B} \cap \mathrm{C}) \leq 20\%$. Alternatively, we can view the events as independent. Although true independence between events is unlikely considering the dynamics of a team sport, including try scorers from both competing teams helps minimise interdependencies that typically skew probabilities in more straightforward betting scenarios.

The confidence level for all three events occurring together in this multi-bet scenario should be implied by multiplying the individual probabilities: $P(A \cap B \cap C) = P\ (A) \times P\ (B) \times P\ (C) = 6.4\%$ (Bet I) and 4.8% (Bet II).

Suppose participants' confidence in this conjunctive outcome exceeds 6.4% and 4.8%. This is a critical intersection with CPT, which predicts that individuals do not evaluate probabilities linearly but instead tend to overweigh small probabilities and underweight larger ones (Figure 5). This overestimation, where participants' confidence exceeds the objective probabilities, aligns with CPT's assertion of the conjunction fallacy. However, CPT primarily focuses on how individuals psychologically value outcomes and probabilities rather than directly considering the extent of return-to-player or bookmaker margin.

Advancing CPT with Complex Bets

Our study focuses on the impact of cognitive biases on betting behaviour without presenting actual market odds to avoid confounding factors related to numerical literacy. As such, we did not explore how CPT handles situations with unfair odds. To address this gap, future studies should examine how CPT predicts behaviour in scenarios where bookmaker margins vary, assessing whether actuarially unfair odds exacerbate cognitive biases. Testing in such conditions could also reveal if bookmakers exploit these biases to set higher margins, as suggested in H1. This would enhance our understanding of strategic behaviours in betting markets and provide a more comprehensive application of CPT in real-world SGM scenarios.

4.3.1 Contingency Plan

Should the results reveal participants making rational decisions with minimal influence from cognitive biases (H1, H2, H3), this unexpected outcome might indicate higher levels of gambling literacy or the effectiveness of educational interventions than previously recognised. Research shows that gambling awareness and susceptibility to cognitive biases can vary significantly based on education, experience, and individual cognitive styles (Shi & Li, 2023). To investigate the root causes of these rational behaviours, examining participants' access to gambling education and their primary information sources and analysing demographic data such as age, betting experience, and educational background will be essential.

If participants' confidence levels align closely with theoretical probabilities (H2), this could suggest an improved understanding of betting odds. This improved understanding may be due to the influence of digital tools and platforms that provide detailed information. Such tools can aid individuals with varying levels of education and experience in accurately assessing probabilities. Moreover, exploring the role of interactive educational tools will be crucial, as these can effectively convey complex probabilistic concepts to individuals with different cognitive styles, helping them understand and mitigate cognitive biases.

Should complex bets not exacerbate behavioural biases as anticipated (H3), it may indicate that bettors with higher education and more experience are better equipped to navigate these biases. Understanding the impact of cognitive styles on susceptibility to biases can offer valuable insights into how different bettors process information and make decisions. Further exploration in this area should focus on examining how educational interventions and personalised betting tools can be tailored to enhance decision-making capabilities, thereby reducing the impact of cognitive biases across different segments of the betting population.

4.4 Practical Implications

The anticipated results from our study contribute to academic discourse and bear significant practical implications, informing regulatory policies and consumer protection strategies in the gambling industry.

Recognising cognitive biases, especially the conjunction fallacy, is crucial as sports betting grows more complex, particularly with SGMs. This knowledge advances academic discourse and informs responsible gambling practices and policies (Rockloff et al., 2019). Research in this area provides foundational strategies to mitigate irrational and harmful betting behaviours, potentially leading to significant improvements in consumer protection (Newall, 2017).

The interaction between the presentation of betting options and bookmakers' exploitation of cognitive biases likely leads to less informed and riskier betting decisions. Furthermore, studies highlight the relationship between demographics, such as gender and income, and the preference for skilled or non-skilled gambling activities (Stevens & Young, 2010). This correlation suggests that factors like access to gambling opportunities and life stage can significantly influence the preference for skill-based over chance-based gambling. Understanding these demographic influences can provide valuable insights into targeted interventions for problem gambling.

Educational Interventions

Educational campaigns addressing cognitive biases, such as the overvaluation of low-probability events and the conjunction fallacy, can encourage bettors to adopt more rational and analytical approaches to SGMs. Developing self-regulation tools, such as applications that alert users to potential bias-driven decisions or decision fatigue, can effectively prevent problematic gambling behaviours (Hing et al., 2017). These tools help bettors manage their gambling activities responsibly and enhance their overall gambling literacy, enabling them to recognise and counteract cognitive biases (Keen et al., 2017; Keen & Blaszczynski, 2019).

Regulatory Measures: Probability Display

Regulators could implement policies that require more transparent communication of the risks associated with complex bets. For instance, requiring bookmakers to display the true probabilities of winning SGM bets alongside offered odds will help bettors make more informed decisions, fostering rational decision-making. This transparency can lead to more rational decision-making among bettors, aligning their strategies with the probabilistic realities of betting events and reducing the risks associated with high-stakes, complex bets (Rockloff et al., 2019).

In addition, regulatory bodies, including the ACCC, could mandate that bookmakers disclose detailed odds calculations, including explicit margins. Implementing such transparency measures would ensure fairness and bolster the betting industry's long-term viability by promoting a more equitable playing field. This measure is crucial for maintaining consumer trust and ensuring bettors can make informed decisions based on fair and transparent betting practices.

4.4.1 Summary of Practical Implications and Future Directions

The methodologies and insights from this research extend beyond the betting industry. These findings can enrich financial education, helping individuals recognise and counter biases in investment decisions. Additionally, the principles from this research can guide public policymakers in designing interventions that account for irrational decision-making processes, potentially leading to healthier lifestyle choices and more effective economic policies.

The strategies developed to elucidate betting odds and decision-making processes are adaptable to educational curricula, enhancing numeracy and statistical literacy. This adaptation can empower individuals to navigate diverse life decisions more effectively, from healthcare to retirement planning, fostering a society capable of making more informed and rational choices. Moreover, in technology and artificial intelligence, these insights can inform the design of interfaces and systems that help users overcome cognitive biases, promoting more rational decision-making and preventing the exploitation of these biases.

4.5 Limitations

While our study offers valuable insights, it is crucial to acknowledge its limitations. Addressing these constraints provides a balanced perspective and highlights areas for future research. Our experiment used real monetary stakes to enhance decision-making realism but retains limitations. While we intentionally omitted odds information to control biases and simulate betting conditions as per Nilsson and Anderson (2010), this setup does not fully mimic a typical betting environment, potentially affecting ecological and external validity. Future improvements could include disclosing odds and using a dynamic, interactive platform to replicate authentic gambling behaviours better and yield more representative findings.

The considerable length and complexity of the trial might cause participant fatigue, potentially leading to disengagement or non-deliberative responses as the experiment progresses. Streamlining the experimental procedures and segmenting the tasks into shorter, manageable parts could mitigate this issue. Moreover, this complexity might lead to decision fatigue, where participants make poorer decisions later in the experiment. This aspect skews interpretations towards cognitive biases without considering more straightforward explanations.

Based on prior research, we used confidence ratings instead of probability assessments and omitted odds information to minimise influence on participants' responses. However, these methods may have unintentionally affected their behaviour. Future research could explore alternative methods of presenting bets and assessing probabilities to verify the effects observed in this study and allow more direct testing of CPT. This would provide an ability to examine how CPT predicts behaviour in scenarios where bookmaker margins vary, assess whether actuarially unfair odds exacerbate cognitive biases, and potentially reveal if bookmakers exploit these biases to set higher margins.

In addition, while this study emphasises the role of cognitive biases such as the conjunction fallacy in influencing betting behaviour, future work should also consider alternative explanations for why bettors accept inferior odds. Factors such as misinformation, peer influence, marketing tactics, and a general misunderstanding of odds and probability could play significant roles. Exploring these factors would provide a more comprehensive view of the decision-making processes in sports betting.

5 Conclusion

This research explored how the conjunction fallacy and overconfidence influence decision-making processes among SGM bettors, highlighting the complex interplay between cognitive biases and betting behaviour. The experimental design investigates how gamblers, confident in their analysis, often overestimate the likelihood of interdependent events. This propensity underscores the deep-rooted impact of cognitive biases, notably the representativeness heuristic, on gambling strategies.

Furthermore, our findings underscore the critical role of a novel utility model under the EUT framework that helps explain why gamblers may accept suboptimal bets, a factor that traditional models like CPT fail to capture fully. Additionally, our study reveals potential exploitation by bookmakers, who may leverage cognitive biases to enhance profits, highlighting regulatory requirements. Moving forward, we advocate for developing a comprehensive theoretical model that melds psychological and economic perspectives to reflect the complexities of gambling behaviour accurately.

Investigating how inflated confidence impacts bettors' assessments of event interdependence sheds light on critical decision-making flaws. This exploration focuses on revealing the influence of cognitive biases, especially the conjunction fallacy, on the propensity of bettors to accept suboptimal odds. By analysing how perceived confidence and understanding might mask the complexities of combined probabilities, we expect our findings to enrich our comprehension of decision-making dynamics in sports betting substantially. The trial could serve as a foundation for testing additional factors, such as the utility derived from entertainment, in explaining why bettors accept significantly actuarially unfair odds.

While our research draws on robust theoretical frameworks and simulates empirical scenarios, it acknowledges the limitations of isolating cognitive biases within the multifaceted domain of sports betting. The dynamic nature of sports events and individual differences among bettors introduce variables that could obscure the clarity of causal relationships between observed betting behaviours and the conjunction fallacy. Moreover, the interdependence of events in SGMs, while statistically quantifiable, often resists simplistic probabilistic calculations, adding a layer of complexity to the analysis.

This study's implications extend into academic and practical dimensions of gambling studies. Academically, it contributes to a nuanced understanding of how cognitive biases influence gambling behaviour, particularly within complex betting environments. The findings advocate for developing targeted interventions to educate bettors about cognitive biases and the true nature of probabilities in SGMs. Given our proposition that misjudgments due to cognitive biases are common, we recommend that policymakers enforce regulations to ensure that odds and betting terms are communicated more transparently, helping protect bettors from misleading practices.

Building on the insights garnered, further research is recommended to explore the efficacy of educational programs in mitigating the impact of the conjunction fallacy in sports betting. Such studies could utilise experimental designs to test the effectiveness of different instructional approaches, potentially incorporating real-time feedback and decision aids to enhance bettors' understanding of probabilities and risk.

In conclusion, this research delineates a critical junction in behavioural economics and gambling studies, where the intricate dance of chance, choice, and cognition coalesces. By demystifying the conjunction fallacy in SGM betting, we deepen our understanding of bettor psychology and expose ethical concerns with bookmaking practices. The industry must consider these ethical dimensions to promote fairer gambling environments that are entertaining and ethically sound.

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Appendix

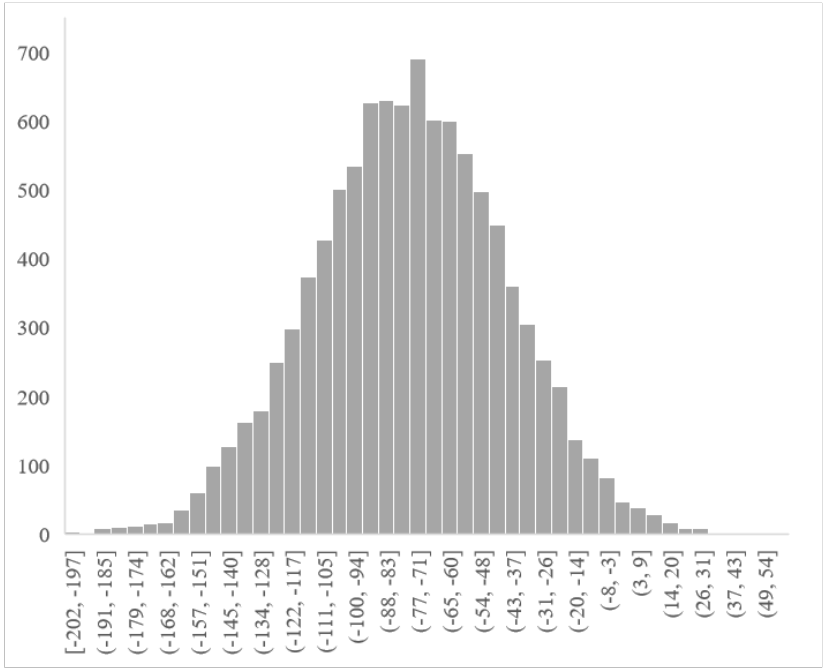
Table 1a. Summary of Odds

Classification	Betting Components	Combined Odds Calculation	Theoretical Probability (BM margin of ~8%)	Bookmaker Odds	Implied Bookmaker Probability
Likely	Roosters (Win) vs Warriors		72%	$1.28	78%
Intermediate	Young - Roosters (ATS)		56%	$1.66	60%
Intermediate	Watene-Zelezniak - Warriors (ATS)		42%	$2.18	46%
Intermediate	Tupou - Roosters (ATS)		49%	$1.89	53%
Unlikely	Tedesco - Roosters (AS)		39%	$2.35	43%
Unlikely	Montoya - Warriors (ATS)		35%	$2.65	38%
Likely	Dragons (Win) vs Rabbitohs		61%	$1.51	66%
Intermediate	Lomax - Dragons (ATS)		55%	$1.67	60%
Intermediate	Thompson - Rabbitohs (ATS)		43%	$2.15	47%
Unlikely	Mitchell - Rabbitohs (ATS)		39%	$2.40	42%
Unlikely	Suli - Dragons (ATS)		36%	$2.60	38%
IL	Young (ATS) + Roosters (Win)	$2.12	45%	$2.05	49%
	Watene-Zelezniak (ATS) + Roosters (Win)	$2.79	29%	$3.20	31%
	Tupou (ATS) + Roosters (Win)	$2.42	40%	$2.30	43%
	Lomax (ATS) + Dragons (Win)	$2.52	39%	$2.37	42%
	Thompson (ATS) + Dragons (Win)	$3.25	25%	$3.75	27%
UL	Montoya (ATS) + Roosters (Win)	$3.39	18%	$5.25	19%
	Tedesco (AS) + Roosters (Win)	$3.01	33%	$2.80	36%
	Mitchell (ATS) + Dragons (Win)	$3.62	21%	$4.33	23%
	Suli (ATS) + Dragons (Win)	$3.93	26%	$3.50	29%
Complex	Roosters (Win) + Young (ATS) + Watene-Zelezniak (ATS)	$4.63	19%	$4.75	21%
	Dragons (Win) + Lomax (ATS) + Thompson (ATS)	$5.42	16%	$5.75	17%
	Roosters (Win) + Montoya (ATS) + Tedesco (ATS)	$7.97	11%	$8.25	12%
	Dragons (Win) + Mitchell (ATS) + Suli (ATS)	$9.42	9%	$10.00	10%

Table 1b. Monte Carlo Simulations

Metric	Simulation 1: Pure Random Selection	Simulation 2: Mixed Strategy
Mean Loss	$77.17	$45.40
Standard Deviation	$34.93	$27.10
Benchmark Loss	$14.90	$14.90
Sample Size	10,000	10,000
p-value	< 0.0001	< 0.0001
Statistical Significance	Highly significant	Highly significant

Histogram of Payouts: Pure Random Selection Strategy



Histogram of Payouts: Mixed Strategy