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AI-Assisted Bettors: Analyzing AI-Driven Betting Behavior through Cluster Analysis

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Abstract

The use of artificial intelligence (AI) systems in consumer-facing decision-support systems (DSS) such as predictive analytics and automated recommendation platforms is growing in popularity in numerous domains, including sports betting. The degree to which users interact with the output of automated systems, calibrate trust, and exhibit automation bias–consistent behavior is largely unknown. In this study, we investigate the behavioral segments formed by bettors using AI-powered predictive sports betting DSS based on their shifts in confidence, risk-taking behavior, and bankroll management practices.

We use survey data from a sample of 200 U.S.-based bettors and SPSS TwoStep Clustering to identify three distinct behavioral profiles: Traditional Bettors, AI-Influenced Confident Bettors, and AI-Adopting Risk-Takers, each with their own unique set of interactions with and through predictive DSS. The findings show that bettors can engage in responsible adoption through strategic bankroll management practices and a tempering of AI trust, while overreliance behaviors can be mitigated or amplified, respectively, by counter or co-aligning with individual differences.

Framing betting platforms as real-time, in-the-wild, and consumer-deployed DSS contributes to IS research on algorithmic decision environments, user trust, and human–computer interaction. The results advance IS theory by contributing to the discussion of how cognitive biases, human decision behaviors, and confidence amplification in and through automated systems manifest in such domains. We conclude the paper with implications for responsible DSS design and deployment as well as practical guidelines for user segmentation in predictive analytics DSS environments.

Keywords: Design Science, AI-Assisted Betting, AI-Driven Decision-Making, Gambling Psychology, Machine Learning in Betting.

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1. Introduction

Artificial intelligence (AI) has seen a swift uptake as an integral component of decision-support systems (DSS), facilitating enhanced processing power, accuracy, and speed across a variety of domains and industries, including banking, healthcare, and logistics (Power, 2002; Davenport & Harris, 2007). Betting tools have been extended to the consumer with the integration of artificial intelligence, and the intersection of real-time odds calculations, predictive modeling, and personalized risk assessments reflects several key DSS components. As bettors increasingly rely on predictive platforms to inform wagering decisions, they are engaging with consumer-facing DSS characterized by data-driven recommendations that leverage structured data and probabilistic forecasting to guide their betting decisions. In other words, users of AI-powered tools interface with AI-assisted DSS for their decision-making tasks, an IS-related feature observed in professional settings.

The gamification of gambling has also created and sustained two opposed bettor categories. Recreational bettors participate in sports to bet on them. They are aware of the poor return on investments for most bets; however, they enjoy the risk-taking as a component of their entertainment (Humphreys & Perez, 2012). The social norms of this culture involve rec bettors. These gamblers enjoy the social aspect of team loyalty and playing with their "friends." Rec bettors also rely on general football knowledge as a precursor to wagers, often employing an intuitive approach in their betting strategies (Humphreys & Perez, 2012). In contrast, sharp bettors use statistical modeling to find value and make bets for long-term profit. To achieve profitability, sharp bettors play the sports betting market as a long-term investment opportunity, implementing bankroll management strategies and algorithms to uncover market inefficiencies (Wong, 2001; Šír & Lábaj, 2021; Donahue, 2022). Market inefficiencies occur when an investment, like a wager, has a higher expected value than the original cost of the investment (Donahue, 2022). Smart bettors use money management and hedging techniques to minimize risks and lower the volatility of their bankrolls.

In more recent years, a new hybrid category has emerged, AI-Assisted Bettors. AI-assisted bettors utilize AI in their betting decision-making, but not to the extent of fully implementing all the components used by sharp bettors (Galekwa et al., 2025; Skrill, 2024). To fully understand the basis of each bettor category, one must look at the decision support with which each category of bettors interacts. Rec and sharp bettors have begun using more AI-empowered betting tools, and there is growing evidence that bettors using these tools show a higher volume of bets per day and overconfidence in their betting decisions (Elder et al., 2022). Decision theory and human–computer interaction (HCI) research offer insight into the relationship between user behavior and the use of DSS. Excessive trust in the output of machine learning systems, overconfidence, and the over-reliance on automation without independent verification are known as automation bias (Mosier & Skitka, 1996; Elder et al., 2022). Cognitive and social psychology research has been used to explain the decision-making processes that bias humans when making financial choices in situations with uncertain outcomes (Kahneman & Tversky, 1979; Nickerson, 1998; Tversky & Kahneman, 1971). The behavioral tendencies of people making wagers that rely on AI DSS could be a useful area of exploration. How do bettors trust AI-powered prediction systems? The AI-powered betting platforms function as consumer-deployed DSS in these types of use cases and can be analyzed with IS principles for this work. This raises an interesting IS research question: how do people make decisions in predictive systems where they balance human and AI augmentation?

The use of IS to understand how to develop artifacts, how people use artifacts, and how artifacts can be integrated and networked for decision-making has a long history. A behaviorally informed IS would apply relevant human and HCI research to how users of predictive betting platforms think, act, and relate to one another. The use of information systems in gamification technologies has a significant history, but the specific use of DSS to inform gambling decisions within betting apps has not been a focus of prior work.

Gambling on sports has a range of purposes in American life. It can serve as entertainment, a hobby, a source of income, or an identity-defining process for professional bettors. The accessibility of betting in most American states has fostered a diverse user base that would be the prime subjects of clustering analysis in IS. As user-generated content, online betting forums, such as Reddit, have been used to capture some initial descriptions of bettor types with the use of latent semantic analysis (Salari et al., 2022). However, the adoption of DSS has not been used to investigate bettor profiles. This raises an interesting question for IS research. With significant consideration given to the integration of decision environments, how do people think when choosing from predictive DSS, and what role does decision-making theory play in these environments? We know that people tend to fall into categories of sharp or recreational. We also know that bettors are using AI-powered systems to inform betting decisions. However, the intersection of identity with these platforms has not been explored. This study approaches these issues by investigating a US-based sample of 200 active AI bettors to study and segment their use of AI-based betting platforms using SPSS Two-Step Cluster Analysis.

Aim: In this paper, we investigate the heterogeneity in confidence, risk-taking, and strategic engagement among bettors who employ AI-augmented decision-support tools. We seek to answer the following IS research question: "What are the patterns of confidence, risk-taking, and AI reliance that lead to different user segments in bettors using predictive decision-support systems?"

Method: We leverage survey-based data from 200 US bettors and unsupervised clustering methods to identify unique profiles of AI interaction – bettors who are using AI as a delegate for their decisions, confidence amplifier, or a secondary resource. We discuss implications for understanding how users trust and calibrate automated recommendations in high-stakes decision contexts and for designing and deploying responsible DSS in consumer-facing settings.

2. Literature Review

One of the original foci of IS scholarship has been on the intersection of AI and decision support systems (DSS). The classic DSS literature has analyzed how structured decision environments "augment" human judgment with data-driven decision support, predictive modeling, and ex ante scenario evaluation (Power, 2002; Davenport & Harris, 2007). At the same time, the expanded availability of consumer-facing AI has pushed the DSS "ecology" beyond its traditional enterprise use cases (Jarke et al., 2019; Rai, 2020). Commercially-deployed DSS that directly support consumer micro-decisions now include various types of AI-powered betting systems, which provide both real-time forecasts and probabilistic confidence estimates, automated "expert" recommendations, and multiple-choice scenario selection. Betting platforms thus present a valuable real-world use case for examining DSS theory at the intersection of prediction markets, AI, and consumer behavior.

A more recent IS research stream has highlighted how users engage with machine-produced advice and interact with AI models, focusing particularly on the calibration of algorithmic trust (Glikson & Woolley, 2020; Jussupow et al., 2022). If a user lacks the ability or motivation to understand a particular AI output, or if they misperceive the capabilities of the system as being more or less accurate than it actually is, their level of trust will be miscalibrated. Excessive trust in an AI system has also been conceptualized as "automation bias" (Mosier & Skitka, 1996; Lee & See, 2004). In IS, several experimental studies have demonstrated that over-trust in algorithms leads to less critical processing, delegation of effort and attention, and even responsibility-shifting from the human user to the machine (Logg et al., 2019; Castelo et al., 2022). By contrast, people can also avert their trust in machine suggestions in the presence of AI errors, even when the system is demonstrably more accurate than most humans (Dietvorst et al., 2015). As a final caveat, DSS are perhaps more likely to be adopted for consumer-oriented decision making where users have more limited capacity to check system accuracy and access system explanations.

In a parallel literature within HCI and IS design science traditions, a small number of recent studies have turned attention to individual differences in how users respond to AI tools. This work highlights the role of moderators in how end users think and act in decision environments—extending the basic propositions about calibration, confidence, and mental effort (Shin, 2021; Ehsan & Riedl, 2020). In addition to varying by system type, user experience, and self-perceived expertise, AI-enabled decision-making can also boost confidence when a system makes a recommendation—even if those predictions are uncertain or probabilistic in nature (Jussupow et al., 2022). This so-called "confidence boost effect" has been previously documented in IS research on various types of financial and medical decision support (Söllner et al., 2021; Longoni et al., 2019; Pourebrahim et al., 2023). Empirical work in this area has not yet been done on fast-paced, high-stakes domains like sports betting, despite high levels of heterogeneity in bettor behavior, psychology, and sophistication (Hägg et al., 2022).

Betting behavior has of course been extensively studied in the domain of behavioral finance, usually by reframing conventional cognitive biases like Prospect Theory (Kahneman & Tversky, 1979), overconfidence bias (Elder et al., 2022), or the Gambler's Fallacy (Tversky & Kahneman, 1971) in the context of sports betting (Hur et al., 2018; Bechmann et al., 2023; Yildiz & Gurel, 2014). The work in this thesis augments this research by examining how digital technologies can shift how those biases are expressed, and how trust and confidence are calibrated with respect to personalized, algorithmic predictions. As users shift more of the cognitive load to betting platforms, their cognitive framing of gains and losses, perceived risk, and sensitivity to feedback can all change. For example, algorithmic forecasts may introduce or amplify confirmation bias, as bettors seek out system outputs that confirm their prior beliefs (Nickerson, 1998). Personalized recommendations may also help reframe decisions from deliberative to reactive, if users act on expert suggestions less critically or treat the system as the default choice (Shin, 2021).

Finally, a large subfield of IS research on user segmentation and personalization may also be relevant to this study.

Prior work has performed cluster analyses to segment users by behavior, cognitive style, or trust dispositions across multiple use cases—including e-learning systems (Gupta & Pathak, 2020), insurance claims (Leidner et al., 2017), and even algorithmic pricing tools (Castelo et al., 2022). These frameworks all provide a lens for empirically understanding heterogeneity in how users approach AI-powered decision environments. In the case of AI-assisted betting, user clustering can be useful not only for distinguishing between frequent and infrequent users, heavy and light users, or system-dependent and system-independent users, but also for profiling user types that adopt different strategic postures (e.g., risk vs. reward orientation) and self-regulation tactics (e.g., confidence calibration, bankroll management).

In sum, the current IS literature on AI and DSS offers a rich theoretical framework for understanding both the generic mechanisms and individual differences in how AI-powered betting systems function as consumer-facing DSS. The literatures also justify the present research and methodological need to empirically test for segmentation into different types of bettors based on a combination of behavioral and psychological measures—especially in an algorithmic setting where end users are presented with a high degree of confidence, placed at risk with real money, and lack full system transparency.

3. Methodology

Survey Instrument

Items were selected from a larger survey instrument used in a larger research project on generative AI and sports betting behavior. Items were mapped to four primary behavioral constructs of interest for this analysis:

1. AI reliance,
2. Confidence shift post-AI adoption,
3. Risk-taking behavior, and
4. Bankroll management practices.

These constructs were selected based on prior research on decision-support technology (Mosier & Skitka, 1996), automation bias (Elder et al., 2022), and gambling studies (Kahneman & Tversky, 1979; Donahue, 2022).

Respondents provided ratings to a series of items using a five-point Likert scale, ranging from 1 (Strongly Disagree) to 5 (Strongly Agree). Many items were included in a pre/post format to identify changes in behavior post-adoption of generative AI tools, such as ChatGPT. For instance, users were asked to provide agreement ratings to paired statements such as:

- Pre-AI: “I followed a strict bankroll management plan.”
- Post-AI: “I followed a strict bankroll management plan.”

Responses to these items were used to create change-score variables for cluster analysis (e.g., Δ confidence, Δ bankroll discipline)

Post-AI variables also included:

- Confidence amplification: “I feel more confident in sports betting after using AI.” (Q15_4)
- Increased betting activity: “I increased the number of bets I make.” (Q15_1), “I increased the average size of bets I make.” (Q15_2)
- AI interaction type: “I use generative AI to analyze raw data,” “I use paid or free AI analytics platforms to make decisions.” (Q11 block)
- Self-identification: “I consider myself more of a recreational, semi-sharp, or sharp bettor after using AI.” (Q16 block)

Demographics, AI experience, and fantasy app use items were also included, along with attention-check items to screen for data quality. The instrument was IRB-approved by the University of Wisconsin–Oshkosh and fielded on the

CloudResearch platform to pre-screen U.S. adults.

The survey's constructs and representative items are listed in Table 1.

Table 1 - Survey Constructs and Representative Items

Construct	Measurement Source	Sample Items (Likert Scale)	Pre/Post Format?
AI Reliance	Developed for this study (Q11, Q12)	"I use generative AI tools to analyze raw data for sports bets. "I used paid analytics to inform bets."	Post only
Confidence Shift	Developed for this study (Q15_4)	"I feel more confident in sports betting after using AI."	Post only
Bankroll Management	Adapted from prior gambling strategy literature (Q8_6 / Q9_6)	"I followed a strict bankroll management plan."	Pre & Post
Risk-Taking Behavior	Adapted from financial decision literature (Q15_1, Q15_2)	"I increased the number of bets I make. "I increased the average size of bets."	Post only
Sharp/Semi-Sharp Identity	Adapted from Donahue (2022); custom developed (Q16)	"I consider myself more of a sharp bettor. "I consider myself more of a semi-sharp bettor."	Post only
AI Perceived Competence	Developed for this study (Q12_1, Q12_2)	"I understand what generative AI is. "I understand how to use generative AI."	Post only
Betting Frequency	Behavioral indicator (Q10_1)	"How many sports bets did you place per week on average in 2023?"	Post only

Notes: All items were measured on a 5-point Likert scale unless otherwise noted. Pre- and post-difference scores were used to assess changes in constructs such as bankroll management and strategic alignment.

Data Collection

The Connect platform from CloudResearch served as the recruitment system for participants, enabling high-quality data collection (Hartman et al., 2023). The research initially recruited 310 U.S. adult participants. However, after screening for AI usage and other quality checks (attention check, time to complete, etc), 200 participants who actively used AI in their sports betting decisions were retained for analysis. The final sample included participants between 21 and 65 who identified as 62.3% male, 36.8% female, and 0.9% non-binary or other genders. Participants received a nominal payment from CloudResearch after finishing the survey, which required 10 to 15 minutes. The survey gathered data regarding bettors' dependence on AI systems and monitored their betting frequency and changes in confidence and financial control practices.

Cluster Analysis Approach

The research utilized SPSS TwoStep Cluster Analysis to categorize bettors according to their AI usage patterns and confidence shifts in betting behaviors, as this method automatically identifies the optimal number of clusters and handles both categorical and continuous data types (SPSS, 2001; Bacher, Wenzig, & Vogler, 2004; IBM, 2025). Three distinct clusters emerged from the analysis, categorizing bettors according to their use of AI systems for decision-making and their tendency to take risks. The study examined variables of AI dependency, betting frequency, confidence variations, and bankroll management principles. The Bayesian Information Criterion (BIC) analysis proved that the three-cluster solution provided the optimal data fit.

Validation Tests

The research evaluated the clustering solution's robustness by applying chi-square tests to measure categorical variations between clusters while using ANOVA to examine continuous variable mean differences across clusters. Statistical tests demonstrated significant differences between groups in AI reliance, betting behavior, and confidence shifts ($p < 0.05$), which validates the cluster identification.

4. Results

Resulting Clusters:

The cluster analysis identified three groups of bettors based on their AI usage, betting confidence, and risk-taking tendencies. Traditional AI Bettors showed limited engagement with AI insights, maintaining lower betting frequency and small changes in confidence levels after adopting AI technology. These bettors preferred to trust their instincts and basic evaluation methods instead of using AI analytics. Bettors who moderately used AI tools reported higher confidence in their bets due to the insights provided by AI technology. Through their structured betting system, they continued to be cautious by combining AI-generated data with traditional research methods to guide their decisions. AI-driven risk-takers exhibited the highest reliance on AI-generated insights. They used AI regularly to inform their betting decisions. Members of this category placed bets more frequently and at higher stakes, exhibiting heightened confidence following AI integration. The increased risk-taking tendencies of these bettors reduced their ability to maintain disciplined bankroll management compared to AI-assisted bettors, who follow more strategic approaches.

Cluster One – Traditional Bettors

Traditional Bettors are more risk-averse and cautious participants in the betting world. Traditional Bettors use AI tools less because they base their betting choices on intuition, personal experience, and publicly available information. Traditional Bettors participate in wagering activities only occasionally because they treat betting as an informal hobby instead of a strategic or analytical exercise. Their trust in betting decisions does not increase significantly following the introduction of AI tools because they either omit AI from their strategies or implement it only marginally. Traditional Bettors avoid experimenting with AI-generated insights and do not modify their betting approaches based on external analytical data. This group maintains its resistance to technological advances by adhering to traditional sports betting methods that do not rely on data-driven techniques.

Cluster Two – AI-Influenced Confident Bettors

AI-Influenced Confident Bettors form a bridge between Traditional Bettors who resist technological change and aggressive AI adopters who fully embrace AI tools for betting. They moderately use AI tools during their betting processes by applying AI insights to improve their decision-making while avoiding complete reliance on automated systems. Incorporating AI tools into their strategies lets these bettors evaluate matchups and value bets more effectively while reducing uncertainty, which results in higher confidence levels than Traditional Bettors. These bettors preserve a systematic betting strategy by combining AI analysis with traditional methods, including personal research and expert viewpoints. This group practices careful bet sizing and bankroll management to avoid reckless gambling despite using AI, unlike high-risk AI-adopting bettors. These bettors demonstrate strong potential to develop into AI-assisted bettors through their balanced use of AI technology and disciplined betting practices.

Cluster Three – AI-Adopting Risk Takers

The most aggressive betting group regarding AI applications and wagering patterns consists of AI-adopting risk-takers. The group depends on AI to make betting choices without verifying predictions through manual examination. AI-powered insights boost their confidence, which results in a noticeable rise in the number of bets they place while increasing their wager volume. The increased confidence from AI-generated predictions results in these bettors taking bigger risks by making substantial wagers without traditional research or expert advice.

AI-Influenced Confident Bettors maintain structured decision-making processes, whereas AI-Adopting Risk-Takers display impulsive betting patterns that deviate from bankroll management standards. Gamblers who rely too heavily on AI tools develop unwarranted trust in AI predictions, as they believe these predictions cannot make mistakes.

5. Key Findings

To better understand the differences among AI-assisted bettors, Table 2 provides a comparative overview of the three identified clusters: Three distinct groups of bettors emerge when studying AI-assisted betting patterns: Traditional Bettors, who use minimal AI support; AI-Influenced Confident Bettors, who blend AI insights with their decisions; and AI-Adopting Risk-Takers, who fully embrace AI technology. The differentiation between clusters relies on their use of AI, level of betting confidence, approach to risk-taking behavior, bankroll management strategies, and decision-making

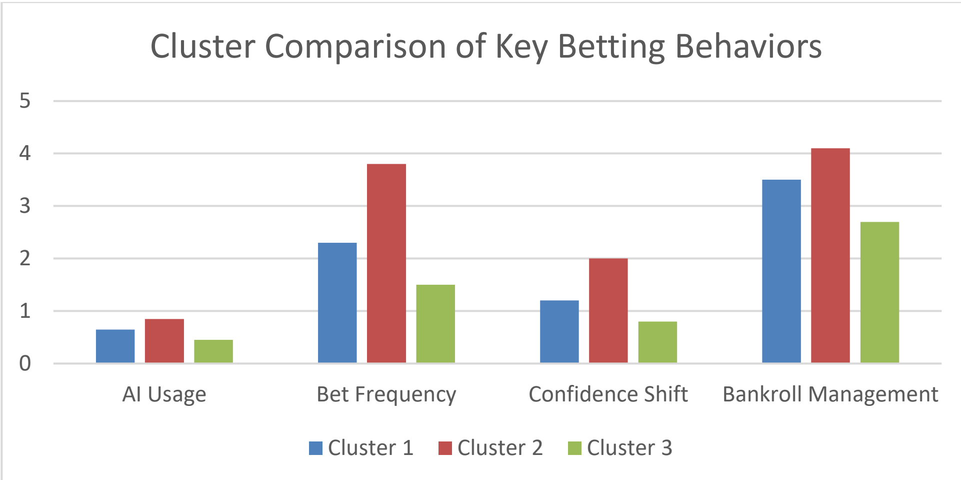

Figure 1 - Cluster Comparison of Key Betting Behaviors

Notes: Figure 1 displays the predictor importance scores from the SPSS TwoStep Cluster Analysis, indicating the relative contribution of each variable to the formation of the three-cluster solution. Higher values signify a stronger influence on cluster differentiation.

methodologies. Traditional Bettors utilize AI tools minimally because their approach is mainly driven by intuitive judgment. AI-Influenced Confident Bettors use AI analysis to guide their decisions but remain strategic and balanced in their betting approach. AI-Adopting Risk-Takers rely entirely on AI-generated forecasts, which increases their confidence but often leads to reckless betting practices. Identifying these distinct groups highlights AI's impact on betting behaviors and how various bettors utilize AI within their betting strategies. The primary attribute of these bettor clusters involves bankroll management, which represents the methods people employ to handle their betting money (Intellias, 2025). These bettors who practice solid bankroll management distribute their betting money carefully while establishing betting boundaries and varying stakes according to risk factors. Bettors with poor bankroll management often place bets driven by overconfidence, engaging in high-risk wagering strategies.

Table 2 - Clusters Defined

Cluster	**AI Usage**	**Betting Confidence**	**Risk-Taking Behavior**	**Bankroll Management**	**Decision-Making Approach**
Traditional Bettors	Low	Minimal change after AI adoption	Risk-averse, occasional betting	Cautious, conservative	Intuition-based, relies on personal experience and public data
AI-Influenced Confident Bettors	Moderate	Increased confidence with AI insights	Balanced risk-taking, controlled bets	Disciplined, strategic	Uses AI insights but verifies with traditional research and expert opinions
AI-Adopting Risk-Takers	High	Overconfident due to AI reliance	Frequent betting, larger stakes	Poor, often reckless	Fully depends on AI-generated predictions without manual verification

The use of AI-driven confidence significantly influences predictions about AI-assisted behavior. Following AI adoption, bettors who showed increased confidence levels shifted towards data-driven betting strategies, utilizing insights generated from AI systems to make their decisions. Bettors who relied solely on AI-generated confidence failed to achieve strategic success because they neglected disciplined betting practices. Not all AI users become AI-assisted bettors. AI-assisted bettors distinguish themselves through their capability to integrate elevated AI confidence levels with effective bankroll management techniques. A segment of AI users engaged in reckless betting practices, while another group used methodical decision-making patterns to demonstrate the critical nature of disciplined financial planning for success. These key findings are summarized in Table 3.

Table 3 - Summary of Key Findings

Key Finding	Description
AI-Driven Confidence	Increased confidence correlates with data-driven betting shifts.
Bankroll Management as a Differentiator	Strategic bankroll management separates AI-assisted bettors.
Paid AI Tools as a Stronger Predictor	Paid AI users are more likely to transition into AI-assisted bettors.

This study's conclusions provide essential guidance for IS creators and organizations that utilize AI-based decision-support systems. IS developers need to create features that encourage users to critically assess AI recommendations due to the demonstrated overconfidence in AI-assisted betting. AI-powered decision environments like financial forecasting and automated investment platforms face similar challenges. When organizations create AI systems that improve user comprehension of probabilistic results and risk assessment, they reduce automation bias risks and enhance decision-support capabilities.

Cluster Validation and Model Selection

Researchers analyzed the clustering solution with ANOVA and chi-square tests, demonstrating that the groups have distinct behavioral patterns. The ANOVA analysis presented in Table 4 reveals significant differences in Perceived AI Competence (10_1) and Betting Frequency (15_5) among clusters, where p-values are less than 0.001, indicating that these continuous variables effectively separate different bettor segments. Chi-square tests (Table 5) validate the cluster structure by showing significant associations ($p < .001$) across the categorical variables Trust in AI Recommendations (11_3), Risk-Taking Behavior (15_1), and use of AI Tools (16_2).

The SPSS Two-Step Clustering process utilized the Bayesian Information Criterion (BIC) and Akaike Information Criterion (AIC) to establish the best number of clusters, resulting in a three-cluster solution that optimally balances model complexity with interpretability. Figure 1 demonstrates which key predictors drive cluster formation and identifies AI reliance (16_2), Confidence Shift (15_4), and Betting Frequency (15_1) as the top influential variables.

Table 4 - ANOVA Results

Variable	Cluster 1 Mean (SD)	Cluster 2 Mean (SD)	Cluster 3 Mean (SD)	F-Value	p-Value	Effect Size (Eta²)
Perceived AI Competence (10_1)	3.27 (1.51)	4.63 (1.51)	5.38 (1.41)	30.474	**<.001**	0.238
Betting Frequency (15_5)	4.20 (1.10)	5.05 (0.73)	5.44 (0.92)	28.533	**<.001**	0.226

Table 5 - Chi-Square Test Results

A	Chi² Value	df	p-Value
Trust in AI Recommendations (11_3)	60.543	8	**<.001**
Risk-Taking Behavior (15_1)	124.715	8	**<.001**
Betting Strategy Type (15_4)	138.072	8	**<.001**
Use of AI Tools (16_2)	142.151	8	**<.001**
Willingness to Adopt AI (16_3)	105.59	8	**<.001**

The predictor importance scores quantify the extent to which each variable contributes to distinguishing the identified clusters. SPSS TwoStep Cluster Analysis calculates scores between 0 and 1 for each variable's impact on cluster formation. Scores that approach 1 show a variable's greater impact on cluster formation. Variables receive lower scores (approaching 0) because they contribute minimally to cluster separation.

The scores shown in Figure 2 illustrate the contribution of each variable towards creating the three-cluster solution. The variables AI reliance (16_2), Confidence Shift (15_4), and Betting Frequency (15_1) achieved the highest scores, which demonstrated their significance in differentiating bettor types.

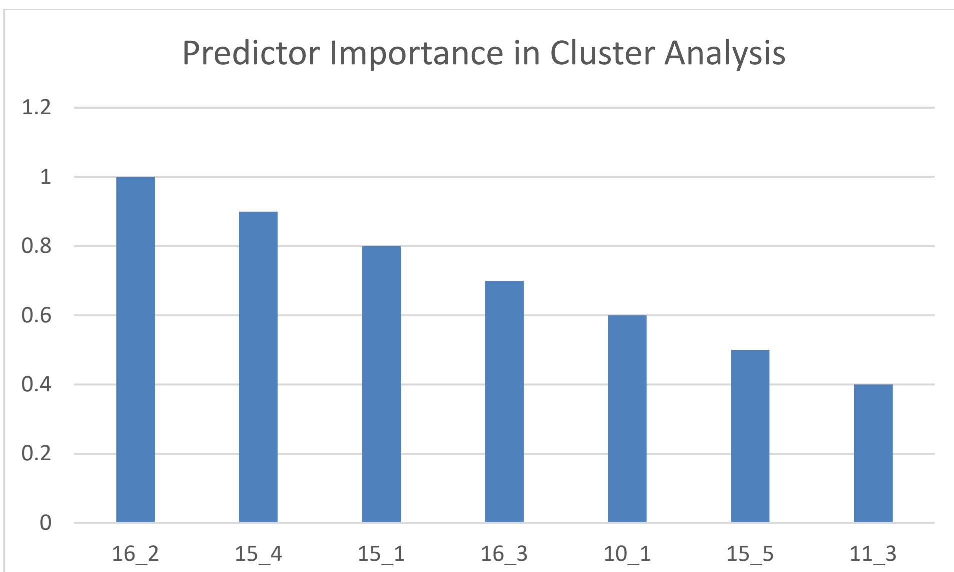

Figure 2 - Predictor Importance in Cluster Analysis

Notes: displays the predictor importance scores from the cluster analysis, highlighting the relative influence of key behavioral variables in distinguishing between bettor segments. The variables include Use of AI Tools (16_2), Betting Strategy Type (15_4), Risk-Taking Behavior (15_1), Willingness to Adopt AI (16_3), Perceived AI Competence (10_1), Betting Frequency (15_5), and Trust in AI Recommendations (11_3). Higher scores indicate a stronger role in shaping the three-cluster solution, emphasizing differences in AI reliance, betting behaviors, and strategic decision-making.

6. Discussion

Information systems research sees a significant evolution through the adoption of AI-powered predictive analytics in sports betting for data-driven decision-making. Research in Information Systems demonstrates that decision-support systems improve organizational decision-making capabilities by utilizing structured data analysis and predictive modeling techniques (Davenport & Harris, 2007). AI delivers these functionalities to decision-makers through instant market analysis and customized betting recommendations. The research findings illustrate how AI-powered information systems applications shape bettor behavior by increasing their decision confidence and creating segmentation patterns comparable to those in business intelligence systems for enterprise analytics.

This research advances human-computer interaction knowledge in information systems by studying user interactions with decision tools powered by artificial intelligence. Studies in information systems have demonstrated that decision-making in critical situations is influenced by automation bias and dependence on AI recommendations, as noted by Mosier and Skitka (1998). Bettors show increased trust in AI forecasts, which causes them to change their risk-taking behavior and betting strategies. This study examines how AI influences decision-making processes, which adds to IS literature by exploring HCI elements, algorithmic trust concepts, and how users adapt their behavior.

Theoretical Contributions

This study makes several contributions to the IS theory literature on DSS, algorithmic trust calibration, and user segmentation in AI-augmented decision environments.

First, the current work contributes to DSS theory by utilizing the contextual domain of predictive, AI-augmented, high-stakes, real-time decision support tools to investigate the deployment of such decision support principles in a new context: namely, AI-augmented betting platforms for consumer decision-makers. While much of the extant DSS literature has focused on formally constrained and regulated enterprise decision environments (Power, 2002; Arnott & Pervan, 2014), the current work provides novel evidence that the DSS constructs of probabilistic modeling, recommendation logic, and real-time processing now power betting apps and websites that are used by individual consumer actors, and by users in a behavioral environment that is far less regulated and less predictable than the decision context for which DSS systems were initially developed. This study thus helps to close a gap in the IS consumerization of enterprise technology literature (Alder et al., 2018) by empirically articulating the core principles of DSS as they are currently implemented to support individual, real-time decisions in an environment where user behavior is more complex and variable than originally theorized.

Second, the current study contributes to IS theories of algorithmic trust calibration and automation bias by empirically identifying three latent user segments that map onto three unique orientations towards the system. Traditional Bettors, in showing aversion to using the system in the first place, are indicative of the DSS phenomenon of algorithm aversion (Dietvorst et al., 2015). AI-adopting risk-takers, by placing their trust in the system's recommendations, are demonstrating a lack of calibration and exhibiting automation bias (Mosier & Skitka, 1996). AI-Influenced Confident Bettors, in contrast, have shown well-calibrated trust in the predictions of the system (Jussupow et al., 2022). The differences among these three user groups thus provide an important behavioral validation of a set of extant IS theories that describe user trust in algorithmic systems as non-uniform, dynamic, context-specific, and psychologically mediated (Glikson & Woolley, 2020).

Third, by employing unsupervised clustering to detect latent subgroups of users based on differences in AI usage, shifts in confidence levels, and self-regulation of gambling behavior, the study contributes to IS literature on user segmentation and personalization in technology-mediated decision environments. This methodology builds on prior IS work on user segmentation, which in this context is used to model heterogeneity in system adoption decisions, systems interaction style, and risk preferences (Gupta & Pathak, 2020; Leidner et al., 2017). In doing so, it provides a replicable method for DSS and HCI scholars interested in how different types of users engage with and experience semi-autonomous, complex decision support systems.

In this way, this study advances IS theory by providing empirical evidence that connects key aspects of user cognition in AI-augmented systems—trust in AI and self-regulatory behavioral differences—to real-world engagement with complex decision-support technologies. The resulting theoretical contributions provide an explanatory lens with which to view current user behavior in DSS contexts, as well as normative design implications for the more responsible development of AI-based systems.

Practical Implications

Results demonstrate numerous implications for the operation of sportsbooks and betting platforms. Betting platforms can develop AI-driven tools that cater to AI-assisted bettors, improving their strategic decision-making abilities while promoting responsible gambling practices. Sportsbooks can create premium AI analytics services for bettors who use AI in a structured manner to place confident bets.

Sportsbooks should modify their betting odds or enforce limits to address the heightened risk-taking tendencies of bettors using AI technologies. Sportsbooks should consider implementing personalized betting limits and educational tools about bankroll management for groups known for aggressive betting practices. Platforms can optimize engagement methods through better segmentation analysis while balancing user experience and risk management.

Limitations & Future Research

This study makes important contributions but also presents numerous limitations. The dataset depends on self-reported survey responses, which could lead to response biases, especially in evaluating confidence and risk-taking behaviors. Actual betting data should be used in future research to validate these findings. The research captures bettor behavior during one specific moment while betting strategies develop dynamically. Longitudinal research would provide valuable insights into how AI-assisted bettors adjust or refine their betting strategies over time.

Future research should focus on regulatory issues as a major area of investigation. The increasing sophistication of AI-driven betting tools could prompt policymakers to pass new regulations influencing bettors' behavior. Research into how prospective AI regulations affect bettor segmentation will shed light on the changing dynamics between AI technology and gambling decision processes. While this study focuses exclusively on AI-using bettors, future research should compare AI and non-AI users to determine whether AI adoption significantly alters betting behavior or enhances pre-existing tendencies. Future investigations require analysis of AI-assisted bettors using new theoretical models to understand the effects of AI adoption on extended betting methods and segmentation of bettors. Subsequent research should examine how Generative AI influences betting decisions to establish a more robust theoretical base for understanding AI-based betting activities.

7. Conclusion

This study contributes to IS research by demonstrating how AI-powered information systems shape decision-making behaviors, reinforcing the importance of IS frameworks in predictive analytics, decision support, and Human-Computer Interaction (HCI). Advanced betting behaviors driven by AI technology are establishing new categories of bettors that extend beyond conventional classifications. This research demonstrates that AI-assisted bettors are primarily differentiated by their confidence levels, Betting Frequency, and dependence on AI support. AI-adopting risk-takers utilize technology to expand their betting activities and risk limits, whereas AI-influenced confident bettors maintain a systematic strategy that supports disciplined bankroll control.

AI advancements in sports betting demand a comprehensive analysis of bettor behavioral changes and the elements that create lasting, successful betting methods. Future investigations should examine the relationship between sportsbooks and AI systems in conjunction with changing bettor profiles, and analyze the extended financial and psychological outcomes of betting choices enhanced by AI technology. A deeper understanding of these dynamics will enable the development of responsible betting structures while also enhancing bettors' comprehension of AI-based decision-making processes.

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