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INTERNATIONAL GAMING INSTITUTE

# AI AND PLAYER RISK IDENTIFICATION AND RESPONSE

RESEARCH REPORT

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# PREFACE

## AUTHORSHIP

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## FUNDING

This project was financially supported by the Massachusetts Gaming Commission. The one-year project was competitively bid and awarded to IGI in July 2024. As with all contracted research and related projects at IGI, the research team retains final editorial control over content disseminated via this report and any related presentations and publications that may follow.

## REPORT STRUCTURE

IGI assembled a team to execute the research plan detailed in our RFP response to the Massachusetts Gaming Commission. This included a focus group study on artificial intelligence use cases, a systematic literature review on behavioral risk indicators, and an in-depth interview study on financial risk identification. Accordingly, the report is presented in three primary sections corresponding to each study, preceded by an executive summary highlighting key findings from across the project.

The report is intended for a broad audience of policymakers, regulators, gambling operators, and academics. We therefore aimed for a more accessible writing style and report structure, less detailed than a formal academic manuscript but without compromising the rigor and analytical depth of the research. As the reader will observe, the issues explored are complex and often without straightforward solutions. These topics warrant continued dialogue, and any associated regulatory actions should be paired with careful evaluation.

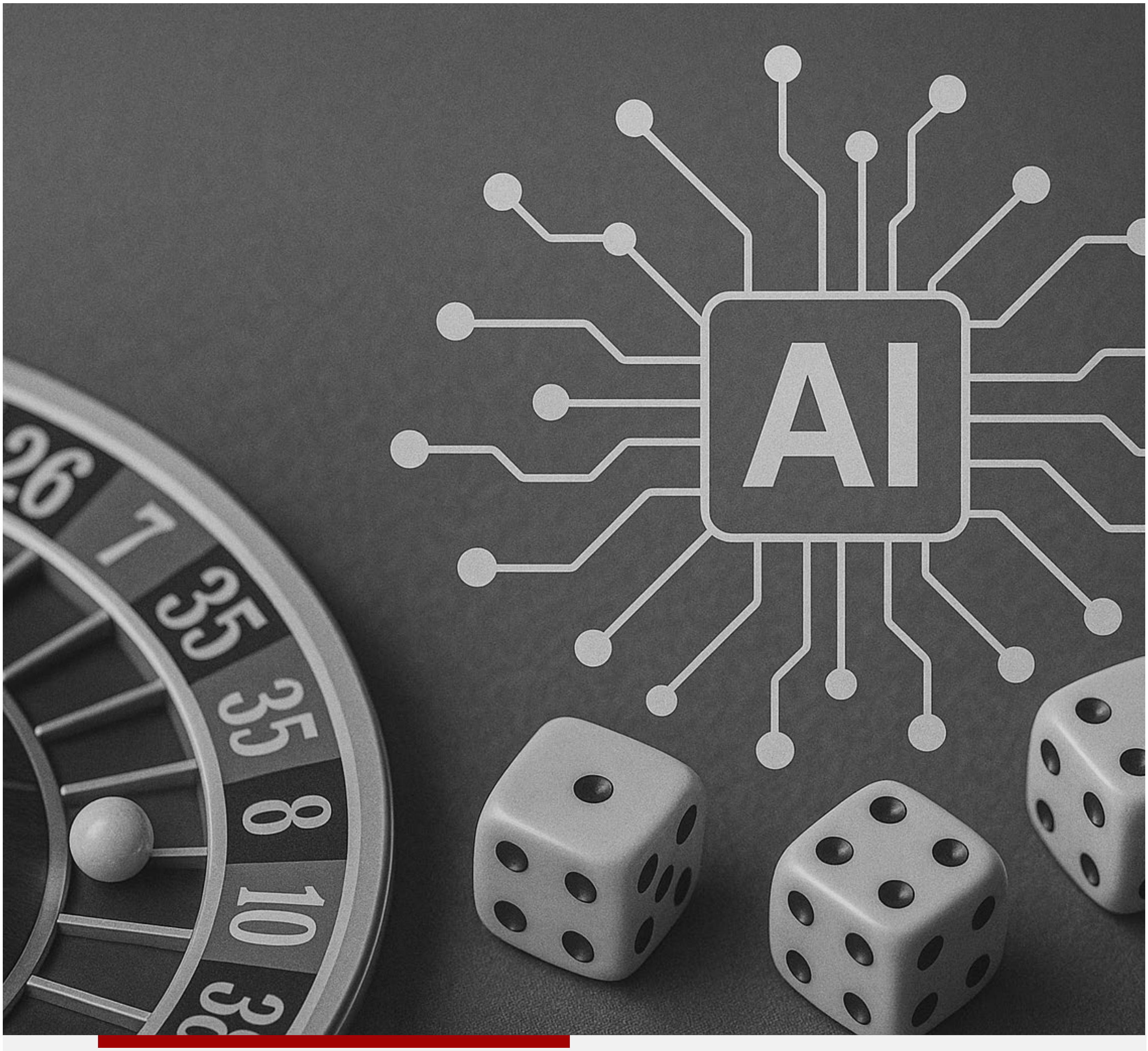
## ACKNOWLEDGEMENTS

We would like to acknowledge the research assistants and scientists at IGI who contributed to this project, particularly in assisting with data extraction and coding as part of the systematic literature review. Their diligence and attention to detail were instrumental to the success of this work.

We thank the members of the Commission's Research Review Committee for their helpful and constructive comments.

We thank the Massachusetts Gaming Commission for its leadership at the frontier of gambling regulation and for supporting this important and timely work. As artificial intelligence continues to evolve and influence society, research support is essential to ensure the benefits of this technology are maximized while minimizing potential risks and harms.

We acknowledge that, while this report was authored by human researchers, the writing process was supported by the use of AI tools. Specifically, the authors used ChatGPT to assist with tightening language and copy-editing early drafts. The workflow involved researchers drafting the original content, with AI tools used as part of the revision and editing process. In addition, some aesthetic report images were generated using ChatGPT.




# OVERVIEW

This report focuses on three timely and highly relevant areas as the gaming sector experiences two intersecting lines of growth: the continued expansion of the U.S. gaming market and the rapid advancement of artificial intelligence (AI).

In response to these developments, this report provides a commentary on current and potential *AI use cases* in the gaming sector. It includes a focused assessment of one specific and increasingly prevalent application: *player risk detection*. Specifically, we establish an evidence base for behavioral indicators used to identify at-risk players, supported by a structured database that links each indicator to the quality and strength of existing evidence. Finally, we explore an emerging frontier in this space – leveraging financial data to assess players' *financial risk*.

# EXECUTIVE SUMMARY

The purpose of this report was threefold. First, via a focus group study, to identify use cases and associated ethical concerns of current and future applications of AI in the gaming industry. Second, to complete a systematic review of evidence related to behavioral risk identification. Third, via in-depth interviews, to obtain a targeted understanding of financial risk identification and the technology that exists to track individual players across operators and gaming modalities. The overarching intent is to provide data and evidence to support informed decision-making regarding regulatory involvement and potential action in each of these areas.

Accordingly, the report is structured into three primary sections, each corresponding to one of the studies. For each study, we provide a brief introduction, followed by the methods and results, and conclude with a concise summary of key findings, limitations, and recommendations.

## REPORT HIGHLIGHTS

**Study 1**
AI Use Cases

- **AI is embedded across four major operational areas: Operational Efficiency, Customer Relationship Management, Player Experience and Engagement, and Compliance and Risk.** Use cases include everything from GenAI for game asset generation and customer service chatbots, to machine learning for AML detection and offer optimization.

- **Land-based and online operators are converging in their AI capabilities.** Participants noted rapid innovation in land-based settings, challenging the traditional assumption that online operators are inherently more advanced.

- **Advanced personalization is viewed as a double-edged sword.** While improving engagement, it also raises ethical risks around targeting vulnerable individuals, especially if demographic or behavioral data is misused.

- **Concerns were raised about the use of foundation models (e.g., GPT-n series, Claude, etc.).** Risks such as prompt manipulation, opaque training data, and use in customer facing applications suggest a need for sector-specific safeguards and governance strategies.

- **Regulatory gaps are evident.** While the European Union's AI Act represents the most comprehensive regulatory effort to date – setting a high bar with its risk-based governance framework – it remains unclear how gambling-specific AI applications will be classified. In particular, use cases involving marketing, personalization, and behavioral nudging may fall into "high-risk" or even "prohibited" categories due to their potential to cause psychological and financial harm.

- **AI maturity varies significantly across the sector.** Third-party providers and specialized companies appear to lead innovation, likely due to greater agility and technical expertise. However, many operators remain cautious, and overall, AI literacy and preparedness, particularly among regulators, lags behind the pace of technological change.

**Study 2**
BRIDGE – Systematic Review

- **A total of 68 studies were included in the review**, consisting of 25 descriptive studies and 43 predictive studies. Descriptive studies focused on identifying behavioral patterns and player subgroups, while predictive studies aimed to classify players at risk of gambling harm using machine learning or statistical models.

- **Sixty-five unique behavioral indicators were identified**, categorized into five overarching domains: Play, Engagement, Profile Information, Responsible Gambling (RG) Tool Use, and Payments. Each indicator was assigned a BRIDGE Score, which reflects both the frequency of its appearance and the methodological quality of the supporting studies.

- **Payment-related indicators emerged as the strongest category in terms of evidence.** While play indicators appeared most frequently across the literature, payment indicators – such as deposit number and amount – consistently ranked highest in BRIDGE Score, reflecting both frequency and evidentiary quality. Five of the top ten indicators were related to payment transactional behaviors.

- **Several high-profile recommended indicators lack strong academic support.** For example, "customer-led contact" and RG tool use are frequently cited in guidance documents but appear infrequently and are poorly supported in the literature. There may be various reasons for this disconnect, including industry practice outpacing scientific inquiry or challenges in academic access to the breadth of available data.

- **Study quality and reporting practices vary widely.** Many predictive modeling studies used large datasets and sophisticated methods but failed to disclose adequate performance metrics or data-processing procedures. Standardized reporting and greater openness with data and code are needed to improve transparency and reproducibility.

- **Commercial systems remain opaque.** Many proprietary algorithmic risk detection tools could not be included in the review due to a lack of methodological transparency. This presents a challenge for independent evaluation and regulatory oversight.

## Study 3
Financial Risk Identification

- **Financial risk in gambling remains underdefined and underexplored.** While financial harm is widely recognized as a core dimension of gambling-related harm, there is no consensus on what constitutes "financial risk."

- **Tracking players across operators remains limited but evolving.** While single-wallet systems in monopolistic markets allow centralized tracking, most jurisdictions lack the infrastructure or legal frameworks to enable seamless cross-operator data sharing. Emerging models, such as the UK's GamProtect and the U.S. Responsible Online Gaming Association's clearinghouse, offer promising paths forward.

- **A range of technologies, including FinTech, could enhance harm detection.** Open banking, credit reference agencies, and global self-exclusion programs were identified as underutilized tools for identifying financial distress related to gambling.

- **Open banking presents both promise and pitfalls.** While it enables granular analysis of consumer financial behavior, concerns remain around data quality, user adoption, and operator accountability. Some operators may be disincentivized from leveraging such tools, fearing increased scrutiny or regulatory liability. Additionally, open banking frameworks vary in their maturity across jurisdictions.

- **Barriers to implementation are significant.** Interviewees cited outdated systems, fragmented data, legal constraints, and low regulatory technical capacity as key obstacles. Cultural and political resistance, especially in the U.S., was also noted, with participants pointing to a reluctance to regulate personal financial behavior.

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# STUDY 1 – AI USE CASES

In 1950, Alan Turing posed the question: "Can machines think?" (Turing, 1950). Six years later, a group of researchers convened at Dartmouth College to formalize the study of this question and settled on the term *artificial intelligence*. Interestingly, this term won out over alternatives like "automata studies," as it was better able to attract academic interest and, perhaps most importantly, funding. The term reflected the scale of the field's ambitions and positioned itself in deliberate competition to human intelligence. Thus, as Hao (2025) pointedly suggests, the term was a "marketing tool from the very beginning" (p. 90).

While advances in AI had been accelerating during the first decades of the 21st Century, OpenAI's development of the "GPT-n" series (and subsequent release of ChatGPT in November 2022) brought AI (and the foundational technique behind it – deep learning) into the mainstream[1]. Since then, the marketing power of the term "AI" has erupted. AI is now used to describe a vast range of technologies and applications, many of which precede ChatGPT (Hue & Hung, 2025). Companies are branding with "AI" in their names and using ".ai" domains (Munjal, 2024). Analytics firms that have leveraged machine learning and statistical techniques for years are now re-labeling their work as AI, whether by choice or a competitive necessity. And when people say they're "using AI," they're likely not writing code or building algorithms; they're using chatbots (e.g., ChatGPT, Claude, Gemini, etc.) built for mass adoption.

This makes for an interesting moment in the gambling industry, where the term "AI" is increasingly used but not always well understood, particularly given the diverse range of stakeholders in the sector and the wide array of potential applications. Additionally, while gambling is enjoyed as a recreational activity by most individuals, for a small minority it can lead to serious negative consequences (Potenza et al., 2019). Given this, the sector already faces heightened regulatory scrutiny, and the adoption of AI can introduce new ethical considerations and risks, which may or may not be accommodated by existing regulatory frameworks (Ghaharian et al., 2024). Compounding this is the uncertain and evolving landscape of broader AI regulation: from multi-national to state-level efforts.

At the international level, the European Union's Artificial Intelligence Act (EU AI Act) stands out as the first comprehensive and enforceable AI-specific law (for a high-level summary of the Act see: Future of Life Institute, 2024). It implements a risk-based framework, categorizing AI systems across four tiers: (1) unacceptable, (2) high, (3) limited, and (4) minimal. Under the Act, practices like social scoring and exploiting vulnerabilities are prohibited, and strict compliance obligations are enforced for systems categorized in the high-risk tier. It also differentiates between the type of entity and their AI systems[2]. Importantly, like the EU's General Data Protection Regulation (GDPR), the EU AI Act has an extra-territorial scope, meaning that it will impact companies using AI systems who are based outside of EU jurisdiction.

In the US, AI regulation is fragmented and its future increasingly uncertain. Federal agencies like the National Institute of Standards and Technology (NIST) have provided voluntary standards, but it is at the State-level where we are seeing the introduction of more enforceable approaches. For example, Tennessee's Ensuring Likeness Voice and Image Security (ELVIS) Act was enacted in 2024 to protect artists from AI-generated media (e.g., music, performances, etc.). While a comprehensive review of State-level AI regulations is out of scope for this report, we recommend Lozoya Martinez (2025) for an in-depth analysis. However, at the time of writing, the future of State-level efforts remains uncertain, as a

[1] OpenAI is an artificial intelligence company that developed the Generative Pre-trained Transformer (GPT) series of language models. These models are trained on vast amounts of text and can generate human-like responses to questions and prompts. The release of ChatGPT in 2022 made this technology widely accessible to the public (reaching 100 million users in just 2 months) and significantly accelerated interest and use of AI across industries.

[2] The EU AI Act defines two principal actors: *providers*, who develop AI systems or general-purpose AI models, and *deployers*, who use these systems under their authority in professional contexts. For example, companies like OpenAI and Google (developers of general-purpose systems ChatGPT and Gemini) would be considered providers. In the gambling sector, most operators are likely to be deployers, implementing AI systems developed by third parties. But there are also many specialist providers creating AI tools to support specific functions discussed later in this report (e.g., fraud detection, player protection, etc.). However, some operators may also act as providers if they develop AI systems in-house to support business functions.

recent provision in a federal budget bill would prohibit states from enacting or enforcing their own AI regulations for the next 10 years (Bhuiyan, 2025), potentially shifting the onus of responsibility to sector-specific regulatory bodies.

## OBJECTIVES

Given the rapid pace of development in AI and its increasing adoption within the gambling sector, this study comes at a critical time. To support regulatory decision-making and distinguish real-world applications of AI from marketing rhetoric, this study had two core objectives:

- To explore uses of AI in the gambling industry.
- To explore the associated risks and ethical considerations.

While we took a broad exploratory approach to these objectives, we also made an effort to examine the use of AI in specific areas (as requested in the RFP): marketing, player acquisition, and the detection of underage gambling. We employed a focus group study design and the following research questions guided our approach:

- RQ1: How do participants define the current uses of AI in the gambling industry?
- RQ2: What do participants believe are the possible future uses of AI in the gambling industry?
- RQ3: How do participants perceive the applications of AI specifically to support marketing, player acquisition, and the detection of underage gambling?
- RQ4: What do participants believe are the risks and ethical considerations associated with current and future AI applications in the gambling industry?
- RQ5: How do participants believe forthcoming or proposed AI regulations (e.g., the EU AI Act) will impact the gambling industry?

## METHODS

We pre-registered our research questions and analysis plan prior to data collection and analysis. The full pre-registration, which outlines our methodology in detail, is available at https://osf.io/snqwt. For brevity, key methodological details are summarized below. The study's protocol was reviewed and approved by the University of Nevada, Las Vegas Institutional Review Board.

We employed a qualitative focus group design to address our research questions. Given the specialist nature of the topic, we recruited participants via a purposive and convenience sampling approach. Participants were recruited and selected to represent one of three key profiles:

- *Gaming industry AI experts* with direct experience developing or deploying AI tools in gambling contexts.
- *Gaming industry domain experts* with expertise across the breadth of gaming operations including marketing, player acquisition, responsible gambling, or detecting underage gambling.
- *General AI experts* from industry, academia, or policy settings with advanced knowledge of AI systems and/or AI governance.

A diverse sample was recruited, which allowed us to structure each focus group with at least one participant from each of the three profiles. This allowed for productive exchanges across domain areas and encouraged interdisciplinary discussion.

Participants' professional experience spanned a range of jurisdictions (including North America, Europe, Asia, and Australia) and covered both online and land-based gambling operations. The two focus group participants are described in Table 1.

Table 1 - Focus Group Participants

| Participant (group) | Profile | Key experience and expertise |
|---|---|---|
| 1 (A) | Gaming AI expert | ▪ >10 years experience online gaming (North America & Europe).<br>▪ Founded an AI-based player risk detection software company.<br>▪ Advisor to gambling regulators and harm prevention non-profits.<br>▪ AI-based work in journals and conferences. |
| 2 (A) | Gaming AI expert | ▪ >30 years experience online gaming with C-level roles (Europe).<br>▪ CEO AI services start-up.<br>▪ Advisor to gambling regulators and harm prevention non-profits. |
| 3 (A) | General AI expert | ▪ >10 years experience of practice in AI law, advising US & EU companies.<br>▪ Partner at an international law firm.<br>▪ Written on AI and serves on government advisory boards related to AI. |
| 4 (A) | Gaming domain expert | ▪ >30 years experience in gaming (US).<br>▪ Manages US gaming practice for global consulting firm.<br>▪ Experience and focus on land-based operations. |
| 1 (B) | Gaming AI expert | ▪ >30 years experience in gaming (US, Asia, Australia).<br>▪ CEO gaming analytics consulting firm.<br>▪ Experience and focus on land-based operations and CRM. |
| 2 (B) | General AI expert | ▪ >10 years experience in AI (Europe).<br>▪ CEO Technology Due Diligence platform.<br>▪ CTO AI consultancy firm (including finance, healthcare, retail, marketing). |
| 3 (B) | Gaming AI expert | ▪ >20 years experience in online gaming (North America & Europe).<br>▪ Founded an AI-based player risk detection software company.<br>▪ AI-based work in journals and conferences. |
| 4 (B) | Gaming domain expert | ▪ >10 years experience in gaming (US).<br>▪ VP at nation-wide gaming operator.<br>▪ Focus on marketing and analytics in land-based gaming. |

Two researchers were present during each focus group. KG led the discussion using a structured interview protocol, while MS observed and contributed follow-up questions. Both researchers probed for clarification or elaboration as needed. Following the sessions, three members of the research team (KG, MS, and JB) analyzed the audio recordings and transcripts independently. Coding was applied to categorize AI use cases, and for the remaining research questions, coding was used to highlight key points and insights raised by participants. Findings were discussed collaboratively to ensure consistency and mitigate potential individual biases. We wrote up the results based on this analysis and included selected participant quotes to illustrate key themes or ideas. We did adjust some quotes, but this was limited to small edits to ensure clarity, grammar, and length without altering meaning. In the results that follow, where applicable, we support and contextualized our findings with relevant real-world examples. These examples were either provided by participants or identified during the writing phase of this report. These examples help visualize how such use cases are being implemented.

## FINDINGS

### Current AI Use Cases

Focus group participants described a wide range of current AI applications in the gambling industry. These ranged from more “traditional” approaches – such as predictive analytics and machine learning – to newer developments like natural language processing (NLP) and large language models (LLMs)[3]. But as we noted in the introduction, participants acknowledged that the term “AI” is now widely used. As one participant remarked:

[3] For a primer on machine learning see Bi et al. (2019). For a primer on Generative AI, including LLMs, see Feuerriegal et al. (2024).

> “The same methods have been applied in the 1990s and early 2000s. But the computational power simply wasn’t there. Now you have that power, and you can process so many different data points. What we used to call machine learning, now we gravitate to the term AI.”

Our analysis of the transcripts identified four core themes representing current AI use cases in the gambling industry. These are presented in Table 2, alongside corresponding use case areas and example applications identified by the focus group participants.

Table 2 – AI Use Case Themes Identified by Focus Group Participants

| Theme | Use Case Areas | Example applications |
|---|---|---|
| **Operational Efficiency and Workforce Augmentation** | Policy and documentation | Using LLMs to draft internal HR policies |
| | Coding | Analysts using Copilot to write and review code |
| | Content generation | GenAI tools to create slot machine assets (e.g., graphics) |
| | Task support / communication | Drafting emails and copywriting, troubleshooting, etc. |
| | Reporting and analytics | LLMs used to interpret analyses and extract key findings |
| | Business optimization | Staffing forecast models integrated with LLMs |
| **Customer Relationship Management** | Player valuation | Using machine learning to identify high value players |
| | Offer optimization | Using predictive models to calculate elasticity estimates |
| | Campaign personalization | GenAI to tailor content using player data and preferences |
| | Acquisition strategy | Models to optimize cost per acquisition |
| | Asset optimization | Models for allocation of room comps |
| **Player Experience and Engagement** | Personalization | Automatically select coin sizes for online slots |
| | Recommender systems | Recommending games based on peer groups |
| | Augmented content | Using vision AI to overlay data on live sports feeds |
| | Customer support | Customer service chatbots trained on policies and FAQs |
| | Behavioral nudging | Automated prompts to influence deposit behavior |
| **Compliance and Risk** | RG – risk identification | Machine learning models to assess player harm potential |
| | RG – messaging | Automated based on thresholds (e.g., spending or time) |
| | AML | Detection of suspicious transactions and bonus abuse |
| | KYC | Vision AI for player identity verification |
| | Security | Vision AI to detect firearms |
| | Bad actors (customers) | Using AI for location spoofing and deepfakes |

### *Theme 1: Operational Efficiency and Workforce Augmentation*

When asked about the current uses of AI in the gaming industry, some interviewees started by highlighting the lack of investment in technological innovations that has characterized the gambling industry, especially land-based casinos, over the past several decades. In such a context, companies are starting to welcome AI-based solutions positively. One of the most prominent themes in current AI applications is back-office operations, with respondents mentioning activities such as human resources management, cybersecurity, technology development, procurement, finance, marketing, and customer support being augmented by AI-based solutions.

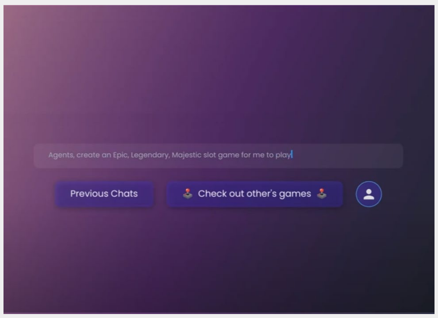
Interviewees explained that gaming stakeholders are increasingly adopting AI-based strategies for efficiency reasons, noticing a growing trend in the use of LLMs. A participant underlined that, compared to human labor, LLMs can accomplish complex tasks, such as coding, in a much shorter amount of time. An example in this sense was game design and graphics. Firstly, in a context where employees work under pressure to continuously and quickly create new content, AI can provide prompt solutions – generating outputs in a fraction of the time it would take a team of workers to accomplish. Secondly, the use of AI can reduce the high costs associated with hiring, for example, artists and graphic designers.

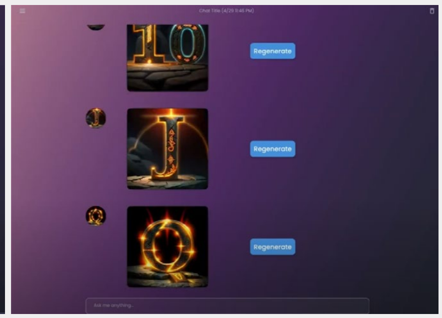
> “The pressures to get new content out at speed is huge. AI is perfect. Suddenly you’ve got a room full of developers.”

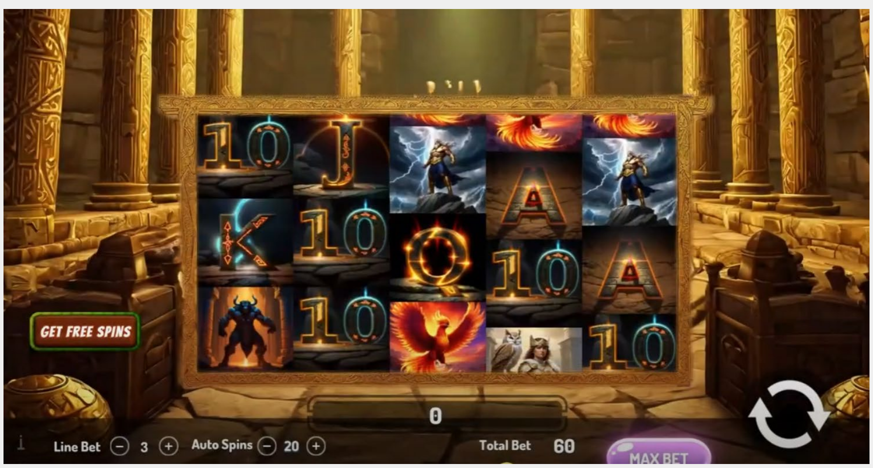
Box 1 highlights a current example of this trend, where a company has developed a generative AI based solution to support slot game design.

**Box 1 – AI for game design**

XGENIA is a third-party provider that uses generative AI to rapidly produce slot games. Their website advertises the ability to “Design, build and deploy your game ideas within minutes, eliminating legacy development times and costs” and slogans like “New games in minutes. Not months.” (XGENIA, Inc, 2025). Their YouTube channel[4] present product demos, demonstrating “text to game”:




Beyond design and development, participants shared a range of use cases demonstrating how LLMs are already being integrated into daily workflows. Human resources and compliance teams, for example, are using LLMs to draft internal policies. Copywriters are using multiple consumer-facing chatbots, such as ChatGPT, Claude, and Perplexity, to generate marketing copy, often combining outputs and editing them for tone or brand alignment. One participant also described how a compliance team was experimenting with LLMs to identify potential loopholes in regulatory language.

### *Theme 2: Customer Relationship Management*

This theme captures how operators use AI to manage player relationships, value, and lifecycle to optimize business outcomes. Participants’ discussion touched on themes such as analyzing both player preferences and customer value. While there is some overlap with Theme 1 – particularly in the use of AI to support internal functions – here the focus is on how these tools specifically enhance customer relationship management (CRM). For example, participants noted how AI (particularly GenAI and LLMs) can assist with tasks like copywriting and interpreting player data within marketing and CRM contexts.

[4] https://www.youtube.com/@xgenia

Notably, participants highlighted important differences between online and land-based settings. Land-based casinos, in particular, have historically struggled with fragmented and legacy data systems that limit the ability to build a complete view of the customer. However, participants described how new AI systems are beginning to overcome these limitations. One participant explained that the industry is moving away from the long-held aspiration of building a "360-degree view" of each customer – a single, unified record that aggregates all customer information. Instead, today's AI systems are enabling operators to extract only the relevant insights from disparate and legacy data sources without the need to harmonize them into a central system. Thus, AI is driving a paradigm shift in how customer data is managed and applied.

A recurring theme across the focus groups was the use of AI to improve efficiency, and this was particularly salient in discussions on CRM. As one participant explained, the most durable and successful applications of AI have involved "scaling insights and best practices across the entire player database." For example, AI systems are now being used to automate many of the tasks traditionally performed by casino hosts, such as estimating what players are likely to spend on their next visit, determining where players sit within their lifecycle, and tailoring reinvestment offers accordingly. AI-based techniques allow operators to model player value and elasticity in ways that are more precise and that streamline decision-making. Much like the earlier observation that AI transforms a single designer into a "room full of developers," here it could transform a single expert host into a whole team of CRM experts.

A broader takeaway from participants was the use of AI to leverage the multitude of data points that characterize customer behavior and preferences. Many of these applications, such as analyzing frequency of visits, spend levels, and recency of play, are already well-established in marketing, but participants emphasized how AI now enables operators to use this information in a more automated and dynamic fashion. For example, to optimize the timing of marketing interventions, tailor offers more precisely, and improve cost-per-acquisition (CPA) models across both online and land-based settings. In addition to gaming-specific behaviors (e.g., game preferences, typical bet sizes), there is growing interest amongst land-based operators in using AI to understand non-gaming behaviors including, for example, resort usage, dining habits, and other ancillary spend to inform marketing and asset allocation decisions. One participant suggested that such data helps "asset optimization," ensuring room comps are provided to the "right player." In online settings, one participant described the use of AI to generate what they referred to as the "next generation of clickbait," content designed to strategically direct players to specific websites (in the case of affiliate marketing) or offers using personalized statistical insights.

*Theme 3: Player Experience and Engagement*

This theme focuses on how AI enhances the real-time player experience through personalization and support. Participants described a range of applications focused on personalization, tailored support, and dynamic content delivery, many of which aim to mirror or build upon AI applications seen in other consumer industries such as retail and streaming services (e.g., Netflix).

A commonly cited example was the use of "hyper-personalization" to tailor the gambling experience to individual players. Interviewees described how AI systems are now capable of personalizing aspects of the experience such as recommended games (drawing comparisons to Netflix-style recommender engines), optimal coin sizes on slots, and suggested deposit amounts based on individual player behavior. As one participant put it:

> "What is the sweet spot of deposit value that keeps the player depositing? You don't want to try and squeeze too hard. You don't want to leave money on the table."

Several current examples illustrate how these personalization strategies are already being used. For example, 888.com outlines how its AI-driven recommendation engine tailors content based on players' past activity and preferences (888.com, 2025). Golden Matrix Group has launched a system that separates suggested games into "Games You've Tried" and "Games You Might Like," updated daily based on a player's latest behaviors (Bentham, 2024).

Sports betting was described as a particularly advanced area for AI-driven engagement. Participants highlighted use cases involving real-time data overlays, predictive analytics for event outcomes, and “snippets of auto-generated news.” One participant specifically pointed to Sportradar – a leading sports data company – as being at the frontier of leveraging AI in the gaming sector. As noted on their website: “Our engagement tools take historical and live data and present it in an eye-catching, intuitive way. So your customers stay longer, click more and bet more” (Sportradar, 2025). Among their innovations, Sportradar has used AI to support the development of micro-bets, which describe opportunities to wager on discrete in-game events rather than overall outcomes. For instance, the company claims its systems can generate approximately 1,500 new betting opportunities per tennis match (e.g., the next break point, who will serve the next ace, and the last stroke type) (Sportradar, 2024). Additionally, its “4Sight Streaming” product integrates AI vision technology to overlay real-time statistics and insights directly onto live video, giving players instant access to dynamic, personalized betting options.

Participants also emphasized the growing role of AI in customer service and support. LLMs are increasingly being trained on internal resources – e.g., company policies, training manuals, and FAQs – to power multilingual chatbots capable of delivering consistent, 24/7 assistance. This functionality is particularly valuable in regulated markets with diverse player bases, where the demand for scalable, multilingual support is high. As one participant put it:

> “LLMs will take all your training literature, and it will give you a customer service agent with the equivalent of 3 to 6 months experience out of the box.”

Importantly, AI-powered support is not limited to text-based web chats. Companies like Poly.ai are demonstrating how lifelike voice assistants can be deployed to enhance customer interactions across various different sectors (PolyAI Ltd., 2025). Among Poly.ai’s gaming clients are Caesars Entertainment, Boyd Gaming, and Landry’s. In a case study featuring The Golden Nugget hotel and casino, Poly.ai implemented an AI voice assistant to handle room reservations, guiding customers through the booking process in a way that “feels natural and friendly but still follows business logic.” (PolyAI Ltd., 2025).

### *Theme 4: Compliance and Risk*

This theme captures how AI is being applied to support compliance functions and mitigate risk across key areas, including responsible gambling (RG), anti-money laundering (AML), know-your-customer (KYC), and security.

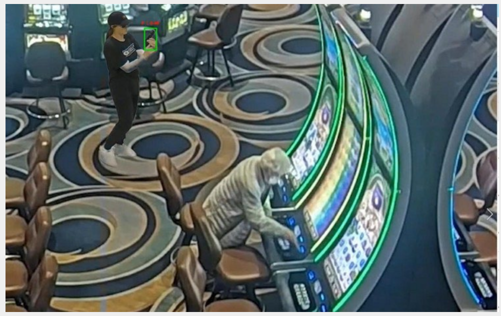
RG was one of the most frequently discussed areas. While participants acknowledged that AI is being used to detect gambling-related harm, they noted that the level of sophistication varies widely. As one participant put it, some current practices remain relatively “primitive,” relying on traditional statistical methods. For instance, FanDuel launched a consumer dashboard called My Spend in December 2024, which simply displays players’ spending and winnings (Betfair Interactive US LLC, 2025). In contrast, more advanced examples referenced algorithmic risk detection systems – developed both in-house and by third-party vendors – that analyze behavioral tracking data to identify potentially problematic play patterns.

Participants highlighted that AI use is prevalent in online settings to support AML efforts, prevent bonus abuse and account takeovers, and improve identity verification. These practices may be performed in-house or via third party providers. For example, Frogo.ai is a technology provider that claims to use AI to detect fraudulent activity in the online gambling sector (Davies, 2025).

In land-based casinos, participants spoke to how AI-powered computer vision is increasingly used to enhance surveillance and customer tracking. Box 2 provides some examples that support the participants’ statements.

**Box 2 – AI in land-based settings**

ZeroEyes has developed AI technology that can detect the presence of firearms on patrons, which is currently in use at the River Spirit Casino in Tulsa, Oklahoma (Takahashi, 2023).



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Xailient, a company specializing in computer vision applications, has partnered with Konami to develop a product entitled “SYNK Vision,” which they claim replaces the need for physical player cards through facial recognition. Additionally, this system is advertised to support harm minimization by alerting staff to signs of distress and enabling timely interventions (Konami Gaming, Inc, 2024).

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Viso.ai partnered with a casino to implement a real-time crowd-counting application using computer vision, which tracks occupancy via existing surveillance cameras to ensure compliance with capacity limits (Viso.ai, 2025).

Finally, participants raised concerns that AI can be exploited by bad actors to circumvent compliance processes. The UK Gambling Commission recently flagged this issue in its updated guidance on terrorist financing and financial crime (Gambling Commission, 2025b). They note a rise in the “scale and sophistication of attempts to bypass customer due diligence checks using false documentation, deepfake videos and face swaps generated by artificial intelligence.” Notably, it appears that accounts created using such methods are more likely to be linked to criminal activities such as money laundering and terrorism financing.

## Future Use Cases

### *Novel Data Sources Powering Novel Use Cases*

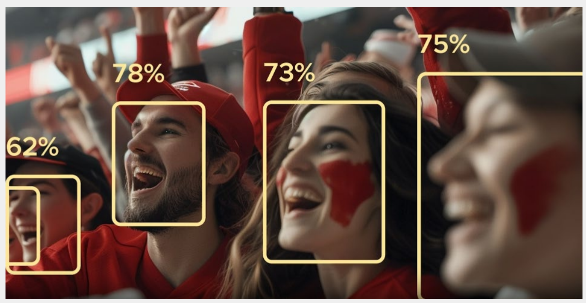
While not AI applications in themselves, participants spoke to how novel data sources are enabling new and more advanced AI use cases. A clear example comes from the land-based sector, where tracking player behavior at table games has historically been a challenge due to the absence of mechanisms – like those in online or electronic gaming machines – that capture player activity on a bet-by-bet basis. But with the introduction of radio frequency identification (RFID)-enabled chips and tables, as well as computer vision systems, this gap is beginning to close. For example, one participant highlighted Walker Digital Table Systems as an example of a company at the frontier of this space, who have developed “smart table” technology that allows for detailed tracking of wagering activity. These data can be used not only to enhance player ratings and support loyalty and marketing initiatives but also to bolster compliance and harm prevention (as discussed earlier) (Walker Digital Table Systems, LLC, 2025).

Moreover, data is no longer limited to numbers in spreadsheets. Text, video, audio, and visual feeds can all be used as inputs for "multi-modal" AI systems. As highlighted earlier, camera feeds are already being leveraged for compliance and risk purposes, and participants expect these applications to expand. Interestingly, several participants speculated that the players themselves may become a source of input data, with systems capable of extracting information from a person's "static" appearance (e.g., via an image) as well as their real-time emotional states (e.g., via video).

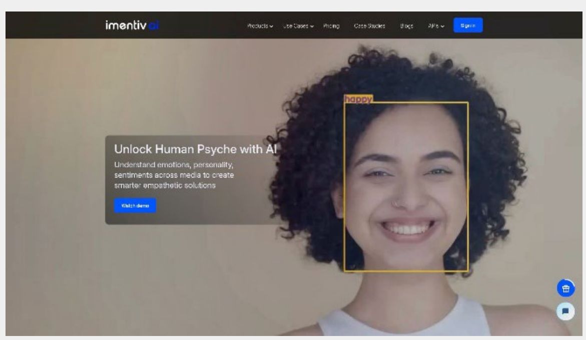
Building on the theme of "hyper-personalization," one participant described how companies in the retail sector are already using vision AI systems to recommend products based on customers' visual appearances. Another suggested that facial expression analysis during gambling play could be used to detect emotional states in real time, enabling applications ranging from personalized marketing to player protection (e.g., identifying signs of distress). In Box 3 we highlight some existing commercial and academic efforts, which provide examples that support these participants' forecasts.

**Box 3 – AI and facial recognition: commercial and academic efforts**

MoodMe has developed "AI facial emotion recognition" (MoodMe, 2025). One of their product features include an "Emotion FanCam" that identifies moments in live sporting events – such as the joy of a goal or the tension of a close match – to enhance brand engagement on digital signage and in-stadium advertisements. Such content could be leveraged by any brand – including gaming companies – to use in promotional materials. Perhaps, the use case could be re-purposed for the casino floor or other gaming environments.




Imentiv AI advertises a product designed to augment the work of mental health professionals by providing real-time emotional assessment using AI (Imentiv, 2025). This AI-driven and real-time feedback could help clinicians better understand a patient's emotional state and reactions during therapy sessions.




Sadeghi et al. (2024) explored automated depression detection, using LLMs to extract depression-related indicators from interview transcripts. Their prediction model was trained on PHQ-8 scores, and they further incorporated facial data extracted from video frames to build a multimodal model. Interestingly, they found that a text-only approach yielded robust performance. Nepal et al. (2024) developed MoodCapture, which uses images to detect signs of depression. In their study, researchers collected more than 125,000 naturalistic images – captured from participants' front-facing smartphone cameras during daily life – from 177 individuals diagnosed with major depressive disorder. By linking photo features such as angle, lighting, and color to self-reported PHQ-8 depression scores, they trained a random forest model to effectively predict raw PHQ-8 scores.

*Instantaneous Information Delivery*

Participants highlighted the growing role of AI in enabling instant access to relevant information, both for internal operator use and customer-facing applications. Several participants emphasized how LLMs could assist customer support staff by translating complex model outputs into natural language, which would be particularly useful in supporting safer gambling interactions. For example, while risk detection systems may be effective at flagging a potential at-risk customer, the reason for the flag may not be clear to individuals unfamiliar with the model's development process, variable naming conventions, or underlying logic.

One participant also emphasized the value of using LLMs to "pull out what's important" from large-scale marketing analyses, highlighting how this capability could enhance both communication and decision-making (e.g., between analysts and customer service agents). While this use case is already emerging, it has the potential to become more widespread. For example, Gaming Analytics.ai currently offers an AI platform tailored for land-based casinos, featuring an "AI-driven search" function that enables users to query casino databases using natural language (Gaming Analytics, 2025).

This instant access to information is not limited to staff. Participants also envisioned a future where players themselves interact with conversational interfaces instead of navigating static menus. As one participant described:

> "So instead of the user having to navigate around the website, they can just ask what they want. And then, basically, the website comes back, is this what you want, or even place a bet."

*Agentic AI*

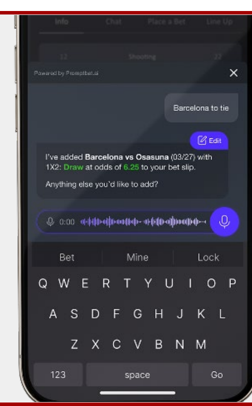
Agentic AI can be described as "a category of AI systems capable of independently making decisions, interacting with their environment, and optimizing processes without direct human intervention" (Hosseini & Seilani, 2025). This was viewed by participants as being particularly transformative with applications across a wide array of gaming industry functions. Importantly, agentic systems have the potential to not only make one-time decisions but orchestrate entire workflows for both operators and customers.

Examples included AI agents that autonomously analyze live sporting events and generate real-time micro-betting markets, agents that handle marketing workflows by assessing player eligibility, crafting offers, and distributing communications, and agents that interact directly with players to conduct personalized safer gambling conversations.

Some participants imagined AI agents acting on behalf of the player themselves: analyzing odds, recommending bets, or even placing wagers on behalf of bettors using "function-calling" capabilities. In fact, this may already be a reality, as highlighted in Box 4.

**Box 4 – Sports Betting AI Agent**

Promptbet.ai may be an early example of this shift to agentic solutions, offering a conversational interface that responds to user inputs (typed or spoken) with betting options and product suggestions (Unblocked Labs GmbH, 2025).



Participants also discussed how agentic AI could be used to develop and test new game variants, including optimizing features like return-to-player (RTP) rates dynamically, thereby reducing the need for manual design and testing.

## Risks and Ethical Considerations

Throughout the focus groups, participants were asked to reflect on the potential risks and ethical considerations associated with both current and emerging AI applications in the gambling sector. These conversations revealed several concerns related to marketing practices, model outputs, agentic and conversational AI, data provenance, explainability, and human understanding of AI systems.

### *Marketing and Personalization*

While the use of AI for targeted messaging was widely acknowledged as an effective marketing tool, participants also expressed concerns about its ethical implications. In particular, several participants warned that advanced personalization strategies (if left unchecked) could contribute to the exploitation of vulnerable groups. One participant emphasized that certain populations, such as younger individuals or those with a history of gambling problems, may be more susceptible to persuasive marketing techniques. When demographic or behavioral data (e.g., cultural background, social media activity, or prior play behavior) are used to train models, there is a risk that AI systems could produce highly tailored offers that inadvertently or, perhaps, purposefully increase harm. Additionally, as one participant noted, these data points could be used to target "potential" customers using data points that are unrelated to gambling behavior:

> "Target people based on what they look like, and perhaps some of the things that they've said on social media. Nothing to do with betting and gambling."

This dynamic touches on what Strümke et al. (2023) refer to as "inadvertent algorithmic exploitation," where machine learning models unintentionally leverage characteristics associated with human vulnerabilities – such as depression, young age, or gambling addiction – in pursuit of their optimization objectives (e.g., maximizing engagement or spend). While such outcomes may not be intentional, the consequences can be ethically problematic and raise important questions about responsibility, transparency, and human oversight in AI-driven marketing practices.

Importantly, AI could be used to safeguard against this. One participant proposed a mechanism involving the use of "adversarial models" layered onto marketing systems. These adversarial components would effectively act as a check, flagging or preventing offer designs that produce play patterns associated with compulsive gambling. As the participant put it, a system could be instructed to "design an offer, but don't create patterns of play that are associated with compulsive gambling." Thus, AI could be used to embed harm reduction principles directly into the architecture of marketing systems in a proactive rather than reactive manner.

### *LLMs, Agentic AI, and Human Agency*

Participants expressed concern about how LLMs could be manipulated to produce harmful outputs. One participant noted that, while most LLMs are trained to reject unsafe queries (e.g., requests for dangerous instructions), users can sometimes circumvent these safeguards through indirect or iterative prompting. As one participant put it:

> "You can get them [LLMs] to answer questions that they wouldn't necessarily ordinarily answer through a series of very carefully targeted prompts and follow-ups."

Such vulnerabilities have implications for the gambling sector, where malicious actors might seek to steer chatbot outputs to their advantage. This could be particularly problematic in scenarios where conversational agents have access to tools, APIs, and/or internal data sources for function calling (i.e., AI agents). This could be manipulated and lead to the generation of inappropriate content, leakage of confidential information, and execution of unauthorized actions (Farrar, 2025). One participant noted that this could be particularly problematic on the supplier side (e.g., machine manufacturers and game studios), where intellectual property provides a key competitive advantage. Breaches of this intellectual property may lead to legal action, as seen in a recent case between Aristocrat and Light & Wonder (Fletcher, 2024a). Additionally, another participant noted that affiliates are already experimenting with methods to manipulate LLM outputs to influence user behavior – akin to search engine optimization – as traditional search engines lose ground to LLM-based chatbots (Gartner, 2024).

Notably, even without prompt engineering, LLMs may not be capable of handling gambling-related queries adequately. A recent preprint from our research team found that two widely used foundation models were often unable to provide appropriate or accurate responses to questions related to problem gambling in sports betting contexts (Ghaharian, Soligo, et al., 2025). This brings into question the suitability of leveraging foundational LLMs for customer facing solutions. One participant drew a parallel to this kind of issue that is exhibited by generative image models, noting:

> "The image generation models have been tarnished by the original data sets that they were trained on, which is porn in part. So, when you use a lot of the image generation models…they always have output, which is a little bit raunchy, for lack of a better word."

This training data problem applies to LLMs as well, which are often trained on very large and opaque datasets. In many cases – including models developed by leading developers like OpenAI, Anthropic, and Google – the exact composition of training data is not disclosed. As a participant noted, problematic outputs may be difficult to fully "train out," especially if these issues are embedded in the foundational pretraining phase.

Ideally, language model developers would use curated and filtered datasets for pre-training, particularly when models are intended for sensitive domains like gambling. However, given that these foundation models have already been developed, current efforts largely focus on post-training alignment. While techniques like prompt engineering and system message design offer some control, these methods are not always robust. A more promising approach may be domain-specific fine-tuning.

For example, OpenAI recently introduced HealthBench, a dataset of question–answer pairs related to health, evaluated by clinicians around the world, to help align models when they respond to medical-related questions (Arora et al., 2025). Similar approaches could be adapted to the gambling domain, as proposed in Ghaharian et al. (2025), to ensure LLMs are capable of delivering appropriate and safe responses.

Related to Agentic AI, one participant described a hypothetical but plausible future in which AI agents interact autonomously, such as a gambling agent attempting to persuade a banking agent to authorize a large transaction. While acknowledged as speculative, the example underscores the importance of governance structures that keep a "human-in-the-loop" for certain decisions.

Conversational agents were similarly viewed as carrying risks. Participants worried that, without adequate oversight, chatbots could become subtly predatory, nudging users toward "dark patterns" or exploiting moments of vulnerability. One participant commented on the need for regulation in this regard:

> “AI could be used to present a potential bet or an opportunity as a friend. Now, unless there is regulation that explicitly prevents operators from doing this, you will inevitably get some bad actors going down that route”

*Human Understanding and Operational Preparedness*

While predictive models have long been used in gambling, the introduction of generative AI represents a significant shift in complexity and accessibility. Participants voiced concern that many industry stakeholders are not yet equipped to responsibly adopt these systems. One participant worried that supplier-side staff, in particular, could inadvertently expose IP by using generative tools to create or iterate on existing assets: for example, by feeding proprietary game mechanics into AI systems to generate new concepts. This underscores the need for clear internal policies around employee use of generative AI.

Others noted a broader lack of understanding about how generative models work. As one participant put it:

> “It’s fine for us to do car research online using ChatGPT. It’s another thing to write policies that run a company right?”

This gap in understanding can lead to inappropriate trust in model outputs. Some stakeholders – employees and customers alike – may fail to question the validity of AI-generated content or may sign off on it without adequate scrutiny. Several participants advocated for AI-specific training for industry professionals and emphasized the need for internal review mechanisms, such as requiring senior staff to sign off on critical AI-generated documents or policies.

A related concern is the presence of automation bias and complexity bias. As one participant explained:

> “We are victims of our own fallibility, and as far as machines are concerned, we suffer from automation bias and complexity bias. So, we don't understand how it works, and we therefore ignore it, and we automatically assume that if it’s generated by a machine it’s going to be correct.”

Finally, it was uncovered that this kind of bias could have implications in relation to player risk detection algorithms. While advanced models may offer improved predictive power, their complexity can undermine trust, particularly in contexts where explainability is essential. As one participant observed, the demand for transparency from operators and regulators often results in a preference for simpler models, even if more complex approaches might offer greater efficacy. At the same time, there is a risk that stakeholders may over-rely on model outputs, treating them as objective or definitive assessments, despite the inherent uncertainty in identifying gambling-related harm. One participant reflected:

> “Can you tell me exactly how much [players] must lose, how much they must deposit? But you can’t really tell, because one metric depends on all the other metrics, right? It’s all connected to each other. So, that’s why I think we gravitate towards simple algorithms, because operators and regulators demand explainability.”

Taken together, these ethical considerations and risks raised by participants underscore the need for thoughtful governance of AI technologies in the gambling sector. These discussions also point to a potential role for regulation in ensuring responsible development and deployment, an issue explored in the next section.

### Regulatory Roles and the EU AI Act

When asked about the role of regulators in overseeing and enforcing AI-related rules in the gambling industry, participants expressed a diverse set of views. A prominent theme was the EU AI Act, the world’s first comprehensive and binding piece of legislation that governs the development and deployment of AI. While some participants focused on specific provisions of the Act, others reflected more broadly on regulatory responsibilities, multi-level governance, sensitive data protection, the role of AI audits, and the preparedness of regulators themselves.

#### *The EU AI Act and Gambling: A Prohibited Use?*

Participants described how the EU AI Act provides specific details on what it prohibits including, for example, the use of harmful, deceptive, and manipulative techniques to induce distorted behavior. Harm, in this sense, may be interpreted as psychological, physical, or financial. As such, a participant explained that the use of AI in some gambling contexts could be interpreted as an unacceptable risk and thus fall under the category of “prohibited use” – the highest level of risk. The participant noted that certain AI-driven marketing techniques in gambling could potentially be classified as an “unacceptable risk” under the Act, commenting:

> “Gambling operators might be deploying techniques like dark patterns…digital nudging…structuring games…making it hard for a player to remove themselves. So, they’re inducing addictive behaviors and addiction is a potential psychological harm. And they’re causing them to spend money that they don’t necessarily want. So, gambling addiction is squarely within the sights of this measure.”

Although, others did not share quite the same view. Another participant commented that any marketing activities in gambling would likely be considered a “medium risk,” but if certain use cases were considered as “health applications” more stringent requirements could be enforced.

While it is unlikely that the EU intends to ban AI use in gambling outright, participants viewed the Act as an instrument to impose greater statutory responsibility on stakeholders (operators and regulators) to mitigate potential harms. In this light, the Act could serve as a “legal lever” for reshaping how AI is used in gambling, particularly where AI interacts with players. As noted, each EU member state will designate a national regulator with authority to enforce the Act, including oversight of “prohibited” and “high-risk” use cases. Thus, a participant warned that operators will need to carefully scrutinize their AI use cases to ensure none inadvertently meet the definition of a prohibited system:

> “The gambling industry is going to need to dissect all of its use cases for AI and make it pretty clear that none of the use cases fall within the category of prohibited AI.”

This participant went further, suggesting that some stakeholders could choose to avoid using AI entirely in certain contexts in order to sidestep regulatory obligations, highlighting the need to weigh the benefits of AI against its potential risks and costs.

*Existing Gambling Regulations: Already Equipped?*

Not all participants agreed that new legislation like the EU AI Act would fundamentally alter regulatory expectations in gambling. One participant suggested that existing regulatory frameworks may already be sufficient to cover AI-related harms, regardless of the technology used. Referring to the UK Gambling Commission’s three licensing objectives, they remarked:

> “If you look at the UK, the regulator’s objectives are to keep crime out of gambling, keep gambling fair, and to prevent harms to vulnerable people. So, you could argue they already have the mandate to police this, regardless of if you’re using AI, or if you’re calling someone up on a telephone betting account.”

This view suggests that the EU AI Act may not introduce entirely new expectations but rather amplify the need for regulators to consider AI as a novel pathway through which existing harms might manifest.

*Defining AI: What Falls Under AI Regulations?*

Participants also discussed the broad scope of the EU AI Act’s definition of AI. As one explained, the Act distinguishes between: *AI models* as the underlying engines or algorithms, and *AI-powered systems* as applications that rely on those models, ranging from conventional machine learning to generative AI. From the participants’ perspective, as long as a system exhibits the characteristics of AI (e.g., autonomy, learning, or adaptivity), it is subject to the Act, even if it doesn’t use cutting-edge generative techniques. This expansive definition means that many existing systems in gambling (e.g., recommendation engines or risk scoring algorithms) could fall within its purview.

*Regulatory Culture and Enforcement Models*

Participants contrasted different regulatory environments. Several found the UK’s approach insightful. One participant explained that the UK Gambling Commission is increasingly encouraging the use of technology, particularly in the context of consumer protection. Thus, operators are expected to demonstrate use of data related to players’ gambling behavior and how systems built on this data support player protection goals. Operators who do not adhere to this guideline are subject to financial penalties (e.g., see: Gambling Commission, 2025a). Still, a key concern remained: regulation often lags behind innovation. Currently there has been no effort on the part of a gambling regulator to address AI safety via legislative action. One participant suggested this absence may stem less from unwillingness than from a lack of confidence and knowledge among regulators:

> “Regulators tend to be…civil servants, you know, people who’ve worked in certain sectors of government. Maybe in the US you have former police officers who become gambling regulators. They’re not really technologists.”

Participants also drew comparisons to other industries – particularly financial services – where regulatory oversight of AI and algorithmic models is more advanced. In that sector, models used for credit scoring or risk assessment are routinely disclosed to regulators, stress-tested for reliability, and linked to tangible incentives; for example, institutions may be permitted to hold less capital if their models meet established regulatory standards.

In some jurisdictions, participants described a multi-tiered regulatory environment where gambling operators are subject to both sector-specific and cross-sectoral rules. For example, data privacy or cybersecurity may fall under national or federal laws, while responsible gambling is overseen by industry regulators. In this context, regulators could act in a complementary manner, adapting broader regulations into tailored expectations for the gambling sector.

## CONCLUSIONS AND RECOMMENDATIONS

This study highlights the expanding use of AI across the gambling industry, with four key themes (around current use cases) emerging from the focus group participants: (1) Operational Efficiency and Workforce Augmentation, (2) Customer Relationship Management, (3) Player Experience and Engagement, and (4) Compliance and Risk.

Participants emphasized both the opportunities and the risks that AI presents, particularly with regard to marketing practices, risk detection, and customer-facing conversational agents. Importantly, emerging technologies such as agentic AI, vision systems, and LLMs are expected to accelerate these developments, while also introducing new ethical and regulatory challenges.

### Key Findings

- **AI is already embedded in core business functions**, including back-office and customer facing use cases. While traditional machine learning and predictive analytics are well established, more novel generative AI applications are emerging.
- **Advanced personalization and agentic AI present challenges**. While they offer potential benefits for customer experience, they may simultaneously increase the risk of harm to vulnerable populations.
- **Regulatory expectations are evolving.** The EU AI Act’s risk-based framework appears to be influential in shaping global practices and could have important implications for how AI is governed in gambling contexts.
- **AI maturity varies across the sector.** While online operators may be further ahead, land-based casinos are rapidly adopting new AI capabilities. Third-party providers and more “niche” companies (e.g., Sportradar) appear to sit at the frontier of innovation – possibly due to greater agility and specialization – but also because operators may be reluctant to assume the associated risks or make the necessary investments themselves. Similarly, AI literacy and preparedness differ widely across stakeholder groups, with regulators appearing to lag behind the industry.

### Recommendations

The findings of this study point to a number of practical steps that gambling regulators, particularly in the absence of broader AI regulation, can begin to take now. While the full development of AI-specific gambling regulations may take time, there are several actions that can help lay the foundation for effective oversight, promote industry accountability, and build regulatory capacity. The recommendations below are sequenced from short-term and immediately actionable, to longer-term goals that may require broader policy shifts or inter-agency collaboration (see Figure 1).

Figure 1 – Regulatory Actions Timeline


1. **Appoint an internal AI champion or task force.** Dedicate time and resources to building AI literacy among regulatory staff. This could include internal training sessions, ongoing education, or the formation of an AI-specific working group. Alternatively, regulators may consider establishing external advisory panels focused on AI, modeled after the UK Gambling Commission's use of expert advisory groups in specialized areas (e.g., see the Digital Advisory Panel: Gambling Commission, n.d.).

2. **Support industry training and internal governance.** In the absence of specific AI regulations, regulators can encourage licensees to establish internal governance policies that cover, for example, generative AI use, employee training, and risk review protocols. Regulatory bodies might direct licensees to established frameworks like the EU AI Act or the NIST AI Risk Management Framework and promote a "best foot forward" approach that encourages proactive rather than reactive alignment.

3. **Survey Licensees' AI Use.** Establish a structured and repeatable process to map how licensees are currently using AI systems. Such a framework has been proposed by Lozoya Martinez (2025) and is currently being piloted by our research group. An ongoing understanding of AI adoption across the sector will be essential to inform future policy decisions. Additionally, this process should be explored as a regulatory mandate to ensure transparency, and could include additional reporting requirements for other AI practices such as safeguards and testing protocols.

4. **Engage in cross-agency dialogue.** Partner with regulators from adjacent sectors to share learnings and develop harmonized principles around AI governance. This could also lead to shared technical standards and avoid duplicating efforts.

5. **Develop sector-specific AI guidance.** Over the longer term, regulators may consider issuing formal guidance or policies outlining expectations for the use of AI in gambling. This could draw from broader legal frameworks (e.g., the EU AI Act) and adapt them to gambling-specific contexts, particularly around high-risk systems like behavioral nudging or risk prediction models. For instance, regulators could require a human-in-the-loop for AI systems that produce outputs with potential consumer welfare or compliance implications.

## Limitations, Future Work, and Emerging Issues

This study was exploratory in nature and based on two qualitative focus groups with subject-matter experts. As such, findings reflect perceptions and experiences rather than a comprehensive or representative industry assessment. We acknowledge the interpretive limitations of qualitative analysis; however, reflexivity was considered at every stage of data collection and analysis. We remained aware that individual belief systems influence how we interpret reality (Schiffer, 2020; Wilson et. Al, 2022), which necessitated constant reflection on how biases and preconceptions might have affected processes such as recruitment and data collection (Bourke, 2014). In this regard, the co-authored nature of this work helped to avoid the personal biases of the researchers from affecting the data. We are also aware that sometimes a hierarchical relationship between the interviewer and interviewee can occur, with the interviewer assuming a position of privilege and authority (Mason-Bish, 2019). Thus, during the focus groups, we aimed to establish equal dynamics and foster a collaborative atmosphere.

Future research could replicate this methodology with a larger and more diverse sample. Alternatively, a survey-based design may be appropriate for gathering broader insights in areas that require less contextual depth. Given our finding that AI maturity varies across the industry (particularly within regulatory bodies) it may be worthwhile for future academic work to assess AI literacy across stakeholder groups. This could help identify where training or education is needed, as well as inform the development of appropriate educational materials.

While participants acknowledged both the benefits and potential harms of AI applications for customers (e.g., enhanced personalization, privacy risks, etc.), future research should incorporate the perspectives of customers themselves. Understanding how end-users perceive AI in gambling, including those with lived experience of gambling harms, could yield valuable insights. Individuals with lived experience have been shown to contribute meaningfully to other areas of gambling research (Jenkins et al., 2024).

A deeper dive into the technical limitations of AI-based systems may also be warranted. While focus group participants highlighted various important considerations , such as ethical concerns around targeted marketing and the limitations of language model training data, other technical concerns lacked in-depth discussion. For example, false positives or misclassifications could be particularly problematic in marketing or player risk assessments, potentially resulting in wrongful advertising to players (e.g., those who have self-excluded) or incorrect risk identification. Similarly, model drift (where a model's performance degrades over time) and algorithmic bias (where algorithms unfairly discriminate against certain populations) are other important avenues for future work. Prior work in the gambling studies field has begun to emerge in these areas (e.g., see: Murch et al., 2024, 2025; Percy et al., 2020), but more is certainly warranted given the rapid growth in this field.

Additionally, there were two emerging areas that we feel require further attention from a multi-stakeholder standpoint.

*Governance Gaps in the AI Supply Chain*

Although the EU AI Act is widely considered the most robust AI governance framework to date, gaps may emerge in its application to the gambling sector. Operators may not fall under the jurisdiction of the Act or may choose not to adhere to its provisions, due to, for example, oversight, ambiguity, or operating outside the EU. Furthermore, many operators procure AI systems from third-party vendors, some of whom may be based in jurisdictions with less stringent or non-existent AI regulation. This creates a fragmented governance landscape, particularly in the absence of gambling-specific AI guidance. As a result, AI accountability may vary significantly across operators and suppliers, increasing the risk of inconsistent safeguards, poor documentation, and transparency.

*A Note on Foundation Models*

As identified in our findings, many emerging AI applications in gambling (e.g., customer-facing tools like chatbots) are built on large foundation models (e.g., from OpenAI, Google, Anthropic). These models are trained on proprietary datasets that are not publicly disclosed, raising transparency and reliability concerns, particularly in sensitive domains such as gambling.

Our research, along with evidence from other sectors, shows that foundation LLMs can produce inappropriate, misleading, false (i.e., hallucinations), or harmful outputs, and often fail to abstain from responding to sensitive queries. Despite these risks, there are currently no regulatory requirements for gambling operators to disclose their use of such systems or to implement safeguards. This raises key questions:

- Is a foundation model being used in a customer-facing feature (e.g., chatbot)?
- Has it been fine-tuned, and if so, using what data?
- Have any safeguards (e.g., red teaming, alignment, or output filtering) been implemented?
- Can the system reliably abstain from answering sensitive or off-topic questions?

For instance, if a chatbot is deployed to handle account management tasks, has it been tested to ensure it doesn't provide advice on gambling strategies or financial decisions? Similarly, if a chatbot is provided as a "betting assistant," has it been evaluated for risks like information leakage, manipulation, or persuasive nudging (e.g., encouraging harmful play)? At present, there are no established benchmarks or transparency requirements governing these implementations. This lack of oversight highlights the critical need for regulatory approvals and clear guidelines to protect consumers.

# STUDY 2 – BRIDGE SYSTEMATIC REVIEW

The increased digitization of gambling over the past two decades has enabled the collection of increasingly granular behavioral data on players. Online gambling platforms and casino management systems in land-based environments now routinely capture detailed information about player activity, for example, time spent gambling, transaction frequency, and the use of responsible gambling tools. These data have provided opportunities to identify early warning signs of gambling-related harm through data science techniques, including machine learning and predictive modeling.

Now, there is a burgeoning field of study focused on this player risk detection problem, with engagement from both academe and industry. Regulatory bodies are also increasingly mandating the use of such data-driven approaches. For example, the UK Gambling Commission introduced new requirements in September 2022 obligating operators to monitor a specific set of behavioral indicators and implement automated processes for strong indicators of harm (Gambling Commission, 2022).

However, an ongoing challenge is providing guidance and determining which indicators are most effective for modeling risk. To address this, standardization efforts have begun to emerge. One such initiative is the development of a European standard on “markers of harm” for online gambling by the European Committee for Standardization (CEN, French: Comité Européen de Normalisation). This initiative aims to define a set of behavioral indicators that can be used consistently across jurisdictions to identify problematic gambling behavior more quickly and accurately. A presentation at ICE London in February 2024 revealed that CEN’s technical committee is considering nine key markers of harm: losses, changes in the use of responsible gambling tools, gambling product preferences, time spent gambling, customer-initiated contact, canceled withdrawals, depositing behavior, speed of play, and volume of stakes. However, details about the methodology and progress of this remains limited.

A similar effort was led by the UK’s Senet Group, which convened a series of meetings between five major gambling operators (McAuliffe et al., 2022). The group agreed on a minimum of nine markers of harm, including: spend from norm, frequency of play, late-night play, deposit frequency, failed deposits, withdrawal reversals, multiple payment methods, and credit cards.

Additionally, both the UK Gambling Commission and Dutch regulator (Kansspelautoriteit, Ksa) have published lists of indicators that they recommend should be used to monitor players and detect risk (Gambling Commission, 2022; Kansspelautoriteit, 2025). The UK Gambling Commission’s list, includes: customer spend, patterns of spend, time spent gambling, gambling behavior indicators, customer-led contact, use of gambling management tools, and account indicators. However, the development process behind this list is unclear.

In contrast, the Ksa provided greater transparency in their methodology. Their report references a literature review by Delfabbro et al.(2023), and describes a consultation process involving workshops led by Focal Research Consultants. The Ksa categorizes its indicators into five domains: intensity, loss of control, increase in gambling, operator behavior, and features of the games.

Despite these promising developments, there is still a need for greater clarity on which indicators are most effective. While grounding decisions in available evidence is essential, drawing strong inferences from existing research remains challenging. As noted in the Ksa report, “some indicators have been studied extensively, while others have only been studied a few times,” and “even when indicators were studied multiple times, they were often operationalized in different ways and that makes comparisons difficult.”

This study sought to address these challenges by contributing empirical evidence and greater methodological consistency to the evolving discourse on behavioral risk indicators.

## OBJECTIVES

The objective of this study was to systematically collect and evaluate existing evidence on behavioral risk indicators used to identify at-risk gamblers based on objective tracking data. Importantly, this is not the first review conducted in relation to this topic; at least five reviews have been published in the past six years. Thus, to justify our approach and clarify our contribution, we briefly summarize these prior efforts.

Chagas and Gomes (2017) conducted an early critical review of 55 studies using behavioral tracking data to understand online gambling behavior. While this review was broad in scope and seminal in identifying early applications of behavioral data, it did not follow a standardized literature review framework such as PRISMA[5]. At the time, the review provided a valuable snapshot of the field and helped shape subsequent research agendas. However, the pace of technological advancement and methodological innovation in this domain has accelerated significantly since then.

Deng et al. (2019) conducted a narrative review examining the application of data science techniques to online gambling behavioral tracking data, including machine learning for early detection of high-risk gamblers. While narrative reviews are useful for synthesizing findings and proposing future research directions, they are not required to follow structured methodologies for search, inclusion, or synthesis, which introduces potential bias through omission of relevant literature (Grant & Booth, 2009).

Mak et al. (2019) conducted a systematic review of machine learning applications in addiction research more broadly. While methodologically rigorous, the review included only two gambling-specific studies and was not tailored to the gambling context.

More targeted reviews have emerged in recent years. Ghaharian et al. (2022) conducted a scoping review guided by the PRISMA-ScR framework, focusing on data science applications in the context of responsible gambling. The review identified 37 studies spanning a wide range of methodological approaches and data types. While intentionally broad in scope, the review provided a valuable mapping of current applications and offered a detailed assessment of methodological components.

A year later, Delfabbro et al. (2023) published a review focused specifically on behavioral tracking data collected by online gambling operators. Their primary aim was to summarize trends in the literature and identify areas for future research. While they provided some methodological detail, the review did not appear to follow a standardized framework. Their key inclusion criterion was that studies use objective online behavioral data. Of the 58 studies included, 45 (78%) focused on individual player risk, while the rest examined product-level factors. Although the review provides useful insight into indicators for player risk detection, the broad inclusion criterion (any use of online behavioral data) meant that the included studies varied widely in their aims, ranging from identifying predictors of account closures and other proxies of harm to evaluating responsible gambling tools such as messaging and limit setting.

Most recently, Marionneau et al. (2025) conducted a PRISMA-ScR-based scoping review of 31 academic studies, with a particular focus on the methodological stages involved in developing player risk assessment models. Their aim was to inform the development of a regulator-led risk prediction model, and to support this goal they focused on evaluating studies based on three key stages: (1) the selection of training data; (2) decisions on model estimation; and (3) the assessment and interpretation of prediction results. The review made a valuable contribution by offering a structured and detailed methodological evaluation of the current evidence base.

However, while Marionneau et al. noted that they extracted information on predictors used in these models, their summary of the predictor sets was presented at a relatively high level. For example, predictors were broadly categorized

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[5] Literature review frameworks, such as the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA), were developed to improve the transparency, consistency, and methodological rigor of evidence syntheses. Originally introduced in health sciences, PRISMA has since been widely adopted across disciplines, including psychology, public health, and gambling studies. Reviews that follow PRISMA use predefined eligibility criteria, structured search strategies, and standardized reporting protocols to reduce bias and improve replicability.

as “gambling behavioral variables” or “demographics,” without detailed breakdowns of specific indicators. Their accompanying commentary noted that behavioral indicators typically included variables related to time and money spent, gambling frequency, transactions, or use of gambling management tools. Demographic characteristics such as age, gender, and country of residence were also commonly reported. As with Ghaharian et al., Marionneau et al. observed that the number and nature of predictors were often unclear or inconsistently reported, ranging from fewer than ten to over one hundred across studies.

This high-level treatment of predictor sets was also observed in the Delfabbro et al. and Ghaharian et al. reviews. However, both these reviews made a more detailed attempt to name individual variables in their commentary and provided tables listing specific indicators used across studies. However, it is difficult to draw firm conclusions about indicators from these efforts, as the primary objectives of both reviews were not specifically focused on evaluating studies focused risk identification or assessing the predictive validity of individual indicators – Ghaharian et al. focused on mapping the breadth of data science applications for responsible gambling generally, and Delfabbro et al. focused on mapping the evidence that had leveraged online behavioral tracking data.

### Aims of this Review

Given the coverage of these current reviews, this study aimed to provide a more detailed synthesis that targets specific behavioral indicators being used, and the strength of evidence supporting each. As highlighted by most of the reviews here: indicators need to be more thoroughly investigated and methodologies need to be better assessed and compared. As new regulatory and industry efforts aim to define standardized predictors for risk detection, a clearer understanding of the current indicator landscape and the quality of supporting evidence becomes increasingly important. Our review aims to fill this gap by attempting to generate a user-friendly “catalogue” of behavioral risk indicators to help audiences understand their evidentiary support: The **B**ehavioral **R**isk **I**ndicators **D**atabase of **G**ambling **E**vidence (BRIDGE).

We believe BRIDGE complements and builds upon the foundations of prior scoping and narrative reviews by adopting a more targeted and systematic approach, where we prioritize a focus on behavioral risk indicators derived from objective player tracking data. Our specific pre-registered research questions were as follows:

- RQ1: What methods are used to identify at-risk individuals with behavioral tracking data?
- RQ2: How do the methods perform?
- RQ3: What behavioral indicators are used within these methods?
- RQ4: What is the level of support and the quality of evidence for these behavioral indicators?

Additionally, we aimed to lay the foundation for a “living review,” where this evidence base can be regularly updated – negating the need for multiple fragmented efforts – and offering a collaborative resource for academic, regulatory, and industry stakeholders.

## METHODS

This review was pre-registered in advance of data collection and analysis, and conducted in accordance with the PRISMA guidelines. The full pre-registration document details all stages of the review’s methodology (available at: https://osf.io/rj92s). Here, we provide a more concise summary of the methods used, along with supplemental rationale for any deviations or decisions made during the development of the review methodology and/or during the execution of the review process.

As stated in our pre-registration, we adapted the PICO framework to guide the development of the review’s methods. Specifically, we defined our Population as gamblers (P), Intervention as methods and indicators of behavioral risk identification (I), and Outcome as gambling-related harm (O). We also included a data component to ensure the review captured studies using objective tracking data (essential for generalizing to practical applications), and excluded the Comparison element, as it was not relevant to our research questions.

### Eligibility Criteria

To be included in the review, studies had to meet the criteria detailed in Table 3.

Table 3 – Eligibility Criteria

| Criteria | Description |
|---|---|
| **Language** | Published in English. |
| **Publication type** | Published in a journal, conference proceedings, technical reports, grey literature, and others. |
| **Data** | Must leverage some form of objective tracking data to support player risk identification. This may include, but is not limited to, data sources such as bet-level information tracked by gambling operators (online or land-based), financial transactions recorded by, for example, third-party service providers, banks, and other financial institutions, or text records from customer interactions. Studies that use exclusively self-reported data to construct indicators to predict risk will not be included in the review. |
| **Objective** | One of the objectives (stated or inferred) of included studies must be the creation of a data science model for the identification and/or prediction of players at a potential risk of gambling-related harm, and/or the understanding of markers/indicators of gambling-related harm. |

We deliberately took an inclusive approach to defining objective behavioral tracking data, rather than limiting inclusion to gambling operator datasets alone. This decision reflects the evolving nature of the data ecosystem available to support player risk detection. For example, financial transaction data was recently mandated for players' financial risk assessments by the UK Gambling Commission as of February 2025. Similarly, advances in natural language processing (NLP) and large language models (LLMs) enable the analysis of text, and studies are beginning to emerge leveraging this source of data (Smith et al., 2024). Moreover, advances in data collection in land-based environments have closed the gap in terms of leveraging machine learning and predictive modeling for behavioral data analysis[6].

Given the wide range of ways that gambling-related harm has been defined across the literature (as evidenced in prior reviews), we clarified this eligibility criterion by specifying that included studies must have an objective (preferably explicitly stated in the manuscript or report) to develop a model for predicting gambling-related risk or to identify and understand behavioral indicators associated with harm.

## Search Strategy

Three search components connected with an 'AND' statement were used to carry out the literature search across two databases: Scopus and Web of Science. The completed search term, with appropriate syntax included, was as follows:

*( gambling OR wagering OR "sports betting" ) AND ( data OR "player tracking" OR online OR internet ) AND ( predict* OR "Artificial intelligence" OR algorithm* OR "Machine learning" OR identif* OR detect* OR markers OR cluster* OR self-exclu* OR "Neural network*" ).*

Additionally, we restricted our database searches to articles published from 2022 onward, as pre-existing literature reviews on this topic had already comprehensively collected studies published up to at least 2021. To ensure continuity and avoid duplication, we manually scanned the final included studies of two recent reviews – Delfabbro et al. (2023) and Ghaharian et al. (2022) – to identify any relevant earlier studies. We also performed an adapted search on Google Scholar.

## Screening and Selection

A team of three reviewers conducted the screening process for article inclusion. All articles identified through the search strategy were imported into Covidence. Duplicate records were automatically flagged using Covidence and resolved manually by the research team as needed.

Each reviewer independently screened the titles and abstracts of all retrieved records. Articles were categorized as 'include', 'exclude', or 'TBD' (to be determined). A citation was marked as include if its title and abstract indicated that it met the eligibility criteria. A TBD designation was used when abstracts were missing or the content was too vague to allow a clear decision. Records were marked as exclude if they clearly failed to meet one or more eligibility criteria or were not relevant to the review's aims.

[6] Commercial technology providers enable the collection of granular bet-level information for each player (e.g., see www.axes.ai and www.acrestechnology.com). Additionally, radio frequency identification (RFID) technology and vision-based systems can facilitate granular tracking of players' betting activity on table games (e.g., see www.wdtablesystems.com and www.cogniac.ai).

After the initial title and abstract screening, all TBD articles were reviewed and resolved by consensus. The research team then conducted full-text reviews of all articles marked as include or TBD-approved, ensuring that each met the inclusion criteria and was relevant to the research questions. The final set of studies included in the review was based on this full-text screening process as well articles identified from prior reviews that met the eligibility criteria.

### Data Charting and Synthesis

In our pre-registration, we indicated that data extraction and quality assessment of include studies would be guided by two established tools: the CHARMS (**CH**ecklist for critical **A**ppraisal and data extraction for systematic **R**eviews of prediction **M**odelling **S**tudies) and TRIPOD+AI (**T**ransparent **R**eporting of a multivariable prediction model for **I**ndividual **P**rognosis **O**r **D**iagnosis – **AI** extension) checklists. These tools were developed to support the evaluation and reporting of prediction modeling studies, specifically in clinical and medical domains. Both focus on assessing the completeness and transparency of reporting in studies using AI and machine learning.

However, we encountered several limitations when applying these tools in their original form. Chief among our concerns was that both checklists are designed as binary frameworks – assessing whether specific items are reported – rather than offering a mechanism for "grading" the quality or relevance of studies. Additionally, several checklist items were either inapplicable or poorly aligned with studies in the gambling and behavioral risk detection literature.

As a result, we used CHARMS and TRIPOD-AI as initial guides but developed a customized data extraction form. The final data charting template incorporated selected elements from both checklists while introducing structured fields specific to player risk detection research.

Our final extraction form included 25 items:

- **Study and publication details**: Article title, author(s), publication year, publication journal, publication identifier (DOI/PMID)
- **Sample and data characteristics**: Data source, gambling type, sample specification, sample size, data collection period (age of data), time horizon, and geographic location
- **Study design and modeling**: Study objective, data science category, model/analysis method, outcome, outcome class, outcome type
- **Indicators**: Names of predictors, Number of predictors, indicator selection (prior to modeling), indicator selection (during modeling), algorithm/model selection
- **Model evaluation**: Metric coverage and quality (each scored on a 3-point scale – weak, moderate, or strong)
- **Transparency**: Open science practices (e.g., availability of code or data)

To facilitate usability and future analysis, two members of the research team (KG and JB) collaboratively defined possible values for as many data entry fields as possible. While not feasible for every variable, we aimed to keep field values simple, consistent, and intuitive. This approach served two purposes: (1) it reduced the cognitive load on the data extraction exercise, and (2) it enabled consistent entries across team members, making downstream synthesis and comparison more efficient. To further promote accuracy and mitigate fatigue bias during the data extraction phase, five researchers from IGI independently extracted data from subsets of the included studies using the structured form. After this initial extraction phase, all entries were cross-checked by the principal investigator (KG) for accuracy and completeness. Researchers were also asked to provide rationale for certain fields, in particular, justification for decisions related to each studies' objectives (i.e., descriptive vs. predictive) and their metric coverage and quality scores.

To standardize indicator classification across studies, we implemented a two-level categorization system. The research team extracted all reported predictors, then one author (KG) reviewed and harmonized terminology. Because the same indicators were often labeled inconsistently across studies (e.g., number of bets, frequency, wager count) and/or varied in terms of computation or aggregation (e.g., median, means, totals), we grouped them into lower-level indicator categories (n = 65). These were further collapsed into five higher-level behavioral dimensions (play, engagement, payment, RG tool use, profile information). Descriptions of higher-level categories are provided in Table 4 and the list of lower-level indicators in Table A1.

Table 4 – High-level Indicator Categories

| Indicator | Description |
|---|---|
| **Play** | Indicators related to betting/wagering behavior, such as bet frequency and size. |
| **Profile information** | Static account or demographic attributes, such as age, gender, or registration date. |
| **Engagement** | Indicators of when, how often, and how broadly a player interacts with games or platforms. |
| **RG tool use** | The use of responsible gambling tools, such as deposit limits, time-outs, or self-exclusion. |
| **Payment** | Financial transactions related to the gambling account, e.g., deposits, withdrawals, payment methods. |

To enhance the accessibility and utility of this review for stakeholders, we implemented a simple scoring system to summarize key methodological features and reporting practices across studies. While 25 fields were extracted, scoring focused on a targeted subset (n = 9) deemed most relevant for assessing the evidentiary strength of player risk indicators (Table 5).

Table 5 – BRIDGE Scoring Rubric

| Criterion | Scoring Approach |
|---|---|
| **Study objective** | Descriptive studies = 1; Predictive studies = 2 + scoring on all fields below |
| **Outcome class** | Validated screener = 4, Proxy of harm = 3, Group of thresholds = 2, Single behavior = 1 |
| **Indicator selection (prior to modeling)** | Not stated/unclear/subjective = 0, Otherwise = 1 |
| **Indicator selection (during modeling)** | Not stated/unclear/subjective = 0, Otherwise = 1 |
| **Algorithm/model selection method** | Not stated/unclear/subjective = 0, Otherwise = 1 |
| **Metric coverage** | Weak = 0, Moderate = 1, Strong = 2 |
| **Metric quality** | Weak = 0, Moderate = 1, Strong = 2 |
| **Open science** | 0-1 practices = 0, 2-3 practices = 1, 4+ practices = 2 |
| **Peer-review** | No = 0, Yes = 1 |

We assigned "descriptive" studies a baseline score of 1 because their primary aim is often to explore or characterize data rather than build or test models specifically for risk prediction. While these studies are valuable for identifying candidate indicators, the absence of a defined outcome variable linked to player risk inherently limits the strength of evidence they provide. In contrast, studies with a "predictive" objective were scored higher and assessed across the remaining eight domains of the rubric, as they typically included an outcome variable directly associated with player risk. We'd like to note, this scoring framework is not intended to function as a formal quality appraisal tool. Rather, it serves as a practical and intuitive mechanism to help stakeholders quickly evaluate included studies[7].

## RESULTS

A total of 68 studies were included in the final review. The number of records identified, screened, assessed for eligibility, and ultimately included are detailed in the PRISMA flow diagram (Figure 2).

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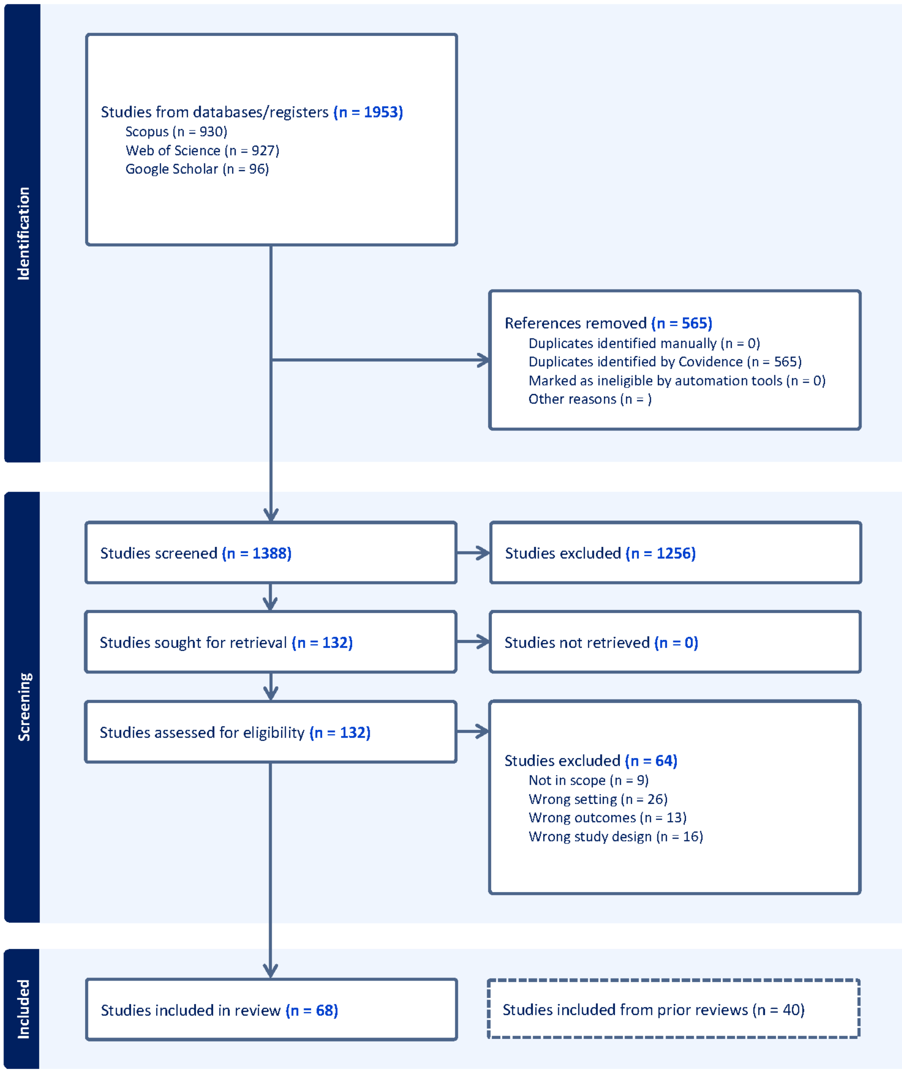
[7] While formal risk of bias tools exist, these were primarily developed for clinical trials and are thus not well-suited for this specific context. Tools such as PROBAST have emerged for evaluating prediction models but, again, are focused on clinical applications. Considering these limitations, we propose this custom scoring system tailored to the specific objectives of this review. We acknowledge that this approach is inherently subjective and was shaped by the consensus of our review team. Nonetheless, we did use existing tools to inform its design and view it as an important first step toward greater consistency in evaluating this evolving evidence base. Given our aim to maintain this review as a living resource, we look forward to inviting feedback and engagement from the broader research community to iteratively refine and validate this framework over time.

Figure 2 – PRISMA Flow Diagram




Descriptive and predictive studies were summarized separately to reflect their differing objectives and methodological characteristics. Completed raw data extraction forms, including metadata for each study, for the descriptive studies (n = 25) and the predictive studies (n = 43) are available on Google Drive in the "BRIDGE Data Extraction" file.

## Descriptive Studies

Among the studies classified as descriptive, 12 employed some form of cluster analysis, an unsupervised machine learning technique. The remaining 13 studies used a variety of analytical approaches, which we grouped into three categories: concentration analysis (n = 6), statistical analysis (n = 3), and regression analysis (n = 4). The overarching goal of these studies was to identify distinct player subgroups or behavioral patterns using variables engineered from objective tracking data.

Sample sizes ranged from 398 to 195,318 players, with observation periods spanning 1 to 70 months. Of the 25 studies, 19 used data from players located in European countries. The gambling product verticals analyzed included casino games, sports betting, poker, lottery, daily fantasy sports (DFS), horse racing, and electronic gaming machines (EGMs). The distribution of behavioral indicators across the five high-level categories is presented in Figure 3. The top 20 most frequently used indicators (according to the low-level categorization scheme) are presented in Table 6[8].

[8] Raw count data for each indicator is available on Google Drive in the "BRIDGE Score Data" file.

Figure 3 – Distribution of Indicators for Descriptive Studies Across High-level Categories

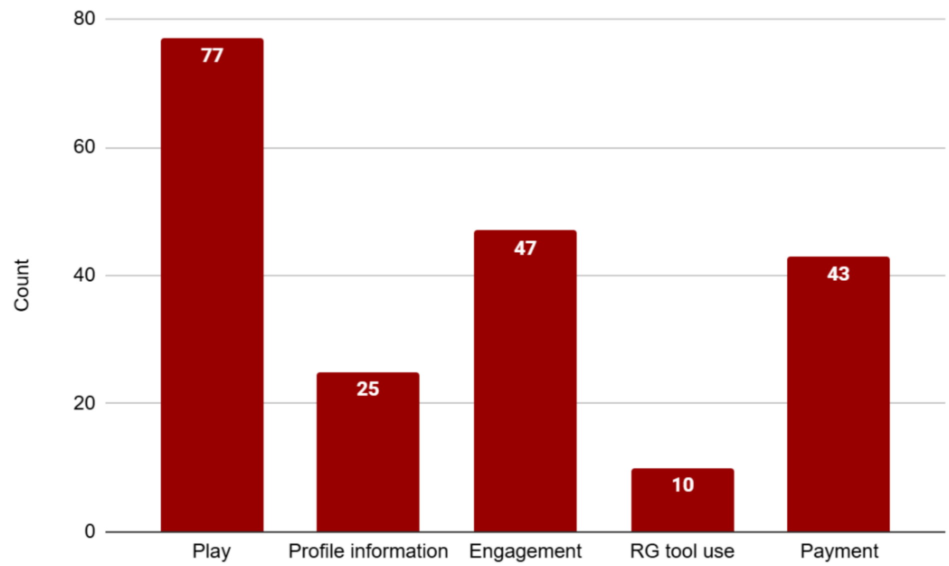



Table 6 – Top 20 indicators Across Descriptive Studies

| Indicator | High-level category | Appearances |
|---|---|---|
| Bet amount | Play | 18 |
| Active days number | Engagement | 17 |
| Bet number | Play | 10 |
| Net loss | Play | 9 |
| Bet intensity | Play | 9 |
| Duration | Engagement | 9 |
| Age | Profile information | 8 |
| Gender | Profile information | 8 |
| Breadth of involvement (e.g., games) | Engagement | 7 |
| Loss chasing | Play | 7 |
| Deposit number | Payment | 6 |
| Country or location of player | Profile information | 6 |
| Time of day | Engagement | 6 |
| Deposit declines | Payment | 6 |
| Losses | Play | 6 |
| Deposit amount | Payment | 4 |
| Wins amount | Play | 4 |
| Set limit | RG tool use | 4 |
| Deposit intensity | Payment | 4 |
| Deposit variability | Payment | 4 |

### *Cluster Analysis*

Studies employing cluster analysis (n = 12) – an unsupervised machine learning technique – aimed to identify subgroups of gamblers based on a combination of behavioral and, in some cases, demographic variables. The number of variables used in these analyses ranged from 3 to 14, with 7 of the 11 studies explicitly stating that variable selection was informed by prior literature. Most studies utilized the *k*-means clustering algorithm, while others applied latent class analysis (Perrot et al., 2018) or hidden Markov models (Bowman et al., year). One study also benchmarked multiple clustering algorithms to identify the most suitable method, offering a more objective approach to model selection (Ghaharian, et al., 2023).

Cluster analysis is a powerful exploratory technique, particularly suited to large behavioral datasets, as it groups individuals based on shared characteristics. However, a major limitation in the included studies was the lack of external validation. Most studies did not assess the resulting clusters against a validated outcome variable (e.g., self-reported harm or behavioral proxy).

For example, Ghaharian et al. (2023) used payment transaction data from 2,286 gamblers and identified three potentially “at-risk” groups. However, group interpretation relied solely on the relative differences in cluster variables within the sample, rather than comparison to an external outcome. Similarly, Wiley et al. (2020) clustered 11,130 DFS players and identified three distinct behavioral groups, but without validation against a known risk indicator. Despite these limitations, such exploratory studies offer valuable foundational insights, particularly when working with novel datasets (as in the cases of Ghaharian et al. and Wiley et al.) where outcome labels are unavailable.

A few studies did attempt some form of objective validation of clusters. For example, Dragicevic et al. (2011) applied the same algorithm and parameters as a prior study by Braverman and Shaffer (2012), which had access to an external outcome variable: account closure. Although Dragicevic et al. did not include an outcome variable of their own, the methodological alignment enabled a form of indirect validation through comparison.

Similarly, Ghaharian et al. (2024) replicated the clustering parameters and methods from their earlier study (Ghaharian et al., 2023) using a different dataset from another gambling operator. They also applied the prior cluster centroids to the new dataset to assign group membership, offering insight into the generalizability of the clustering solution. While these approaches support methodological consistency and transferability, they do not provide direct evidence that the resulting clusters correspond to “at-risk” or problem gamblers in the absence of an external outcome measure.

One study employed CHAID (Chi-square Automatic Interaction Detection), a decision tree algorithm used for segmentation based on a continuous dependent variable—in this case, the total amount of money spent (Chagas et al., 2022). The primary aim was to identify distinct player segments associated with higher spending and to examine the influence of product characteristics (e.g., lotto vs. scratch cards). While CHAID differs from cluster analysis (an unsupervised learning method) because it requires a predefined outcome variable, we include it in this category due to its shared objective of identifying meaningful player segments.

It is also worth noting that most of the literature using cluster analysis is cross-sectional or based on aggregated data, limiting its ability to capture behavioral change over time. An exception is Perrot et al. (2018), who used multilevel latent class analysis to track player behavior longitudinally, revealing monthly variations such as initial intense gambling followed by stabilization. Similarly, Bowman et al. applied hidden Markov models to identify dynamic “behavioral states” and transitions (e.g., moving from moderate winning to severe losing), offering a more nuanced view of behavioral progression.

### *Concentration Analysis*

Studies in this category (n = 6) aimed to describe overall gambling activity across full populations of users, typically using transactional data to identify subgroups of “highly involved” players. These subgroups were characterized by metrics such as high frequency of play, large bet volumes, or large losses, and consistently represented a small proportion of the total sample.

Rather than using clustering techniques, these studies relied on descriptive analyses to show how a minority of users account for a disproportionately large share of gambling activity (e.g., percentile plots). This approach is useful for understanding patterns of gambling involvement and industry reliance on a small subset of users. However, as with cluster analysis, these studies generally lacked outcome measures to validate whether the highly involved groups were experiencing gambling-related harm. High involvement alone cannot be equated with risk, limiting the ability to draw conclusions about player vulnerability or harm.

### *Statistical Analysis*

A smaller group of studies (n = 3) employed group comparison methods to assess differences in gambling behavior between predefined groups. Unlike cluster or concentration approaches, these studies incorporated outcome measures to identify patterns associated with higher risk. However, as they did not develop or test predictive models, they were not included in the predictive studies category.

LaBrie and Shaffer (2010) analyzed betting data from over 47,000 sports bettors, comparing those who closed their accounts due to gambling-related problems with those who closed for unrelated reasons. Their analysis revealed a subgroup of individuals with gambling-related problems who made larger bets, bet more frequently, and were more likely to exhibit intense betting soon after enrollment.

Two articles by Delfabbro et. al. (2023; 2024) took a different approach (from much of the literature contained in this report), focusing instead on which behavioral markers of harm might be useful to identify higher-risk gambling *products* rather than gambling participants.

Delfabbro et al. (2023) assessed whether behavioral markers could help differentiate the relative riskiness of online gambling products. Their analysis supported existing hypotheses that products with short event frequencies, continuous betting opportunities, and high availability (i.e., online slots, in-play betting, and micro-betting) were more strongly associated with harm markers. For example, bonus page visits and gambling at unusual times were most strongly linked to slots, live roulette, and other live table games, and in-session top-ups (i.e., loss chasing), were also prominent among slots, in-play combination sports bets, and live versions of blackjack and roulette. Conversely, they showed that changes to responsible gambling settings showed limited value in distinguishing risk between products.

In a follow up study, Delfabbro et al. (2024) further investigated product-risk associations using a larger, international sample that included self-reported PGSI data. People classified as having gambling problems were found to be more likely to gamble on a wider range of products and to gamble more frequently, particularly on casino games.

#### *Regression Analysis*

The included studies utilizing regression (n = 4) were classified as descriptive, as they lacked an outcome variable that was directly tied to player risk. For example, Edson et al. (2024) examined loss chasing as a defining marker and potential risk factor of problem gambling behavior, using a binary high/low approach for loss chasing dimensions. This study found that the 'high' groups consisted of diverse members, and only one variable (bet size) was positively predictive of mounting losses, but that none of the loss chasing groups were found to be statistically significant. Whiteford et al. (2022) employed regression to investigate the relationship between in-play betting behaviors (such as bet frequency, duration of play, and average stake); this study found the degree of involvement moderated the relationship between number of in-play bets and the remaining betting measures.

### Predictive Studies

Among the studies classified as predictive (n = 43), the majority employed supervised machine learning techniques to classify players based on a harm-related outcome. A smaller subset used unsupervised machine learning (n = 5) or statistical methods such as regression (n = 3). The overarching goal of these studies was to predict gambling-related harm using behavioral indicators derived from objective player tracking data.

Sample sizes ranged from 85 to 916,312 players, with observation periods spanning 1 month to 10 years. Of the 44 studies, 7 used data from players located outside of Europe. The gambling product verticals analyzed included casino games, sports betting, poker, lottery, daily fantasy sports (DFS), and electronic gaming machines (EGMs).

A range of outcome measures were used to define harm and serve as a target for models: account closure (n = 9), self-exclusion (n = 15), operator- or system-defined risk scores (n = 10), and validated screeners such as the PGSI (n = 9) and BBGS (n = 2). These outcomes fall into three general categories: validated screeners (n = 11), proxy measures of harm (n = 23), and operator-defined thresholds (n = 10).

The large majority of studies defined the outcome variable binarily. For example, when PGSI was used researchers commonly applied a cut-off score (typically 5+ or 8+) to classify individuals as either experiencing harm or not. Similarly, when harm proxies such as account closure or voluntary self-exclusion were used, models were developed to label users as either exhibiting the behavior or not.

The number of predictor variables varied considerably across studies, with one study including more than 150 behavioral indicators. The most common method for selecting candidate indicators prior to modeling was referencing prior literature (n = 20). However, in 15 studies, the selection process was either unclear, not stated, or appeared arbitrary.

During the modeling stage, most studies (n = 26) used a full model approach (i.e., retaining all candidate variables without elimination). Fourteen studies applied an objective method for variable selection, while 3 did not clearly describe their approach. One study used a subjective method for determining which variables to include.

The distribution of behavioral indicators across the five high-level categories is presented in Figure 4. The top 20 most frequently used indicators (according the low-level categorization scheme) are presented in Table 7[9].

Figure 4 – Distribution of Indicators for Predictive Studies Across High-level Categories

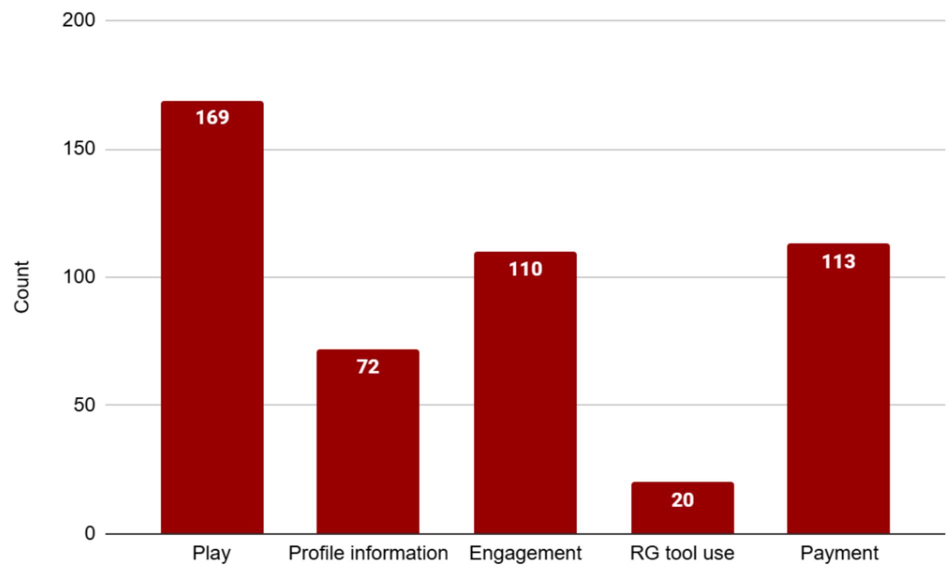



Table 7 – Top 20 indicators Across Predictive Studies

| Indicator | High-level category | Appearances |
|---|---|---|
| Bet amount | Play | 34 |
| Net loss | Play | 26 |
| Active days number | Engagement | 25 |
| Bet number | Play | 24 |
| Age | Profile information | 23 |
| Gender | Profile information | 21 |
| Breadth of involvement | Engagement | 20 |
| Deposit amount | Payment | 18 |
| Bet variability | Play | 17 |
| Session length | Engagement | 15 |
| Deposit number | Payment | 14 |
| Bet intensity | Play | 13 |
| Wins amount | Play | 12 |
| Withdrawal amount | Payment | 11 |
| Withdrawal number | Payment | 11 |
| Bet trajectory | Play | 10 |
| Country or location | Profile information | 10 |
| Set limit | RG tool use | 10 |
| Time of day | Engagement | 10 |
| Session number | Engagement | 9 |

[9] Raw count data for each indicator is available on Google Drive in the "BRIDGE Score Data" file.

*Evaluation Metrics – Coverage and Quality*

For each predictive study, we recorded how well the authors reported model performance using two criteria: metric coverage (i.e., the number of evaluation metrics reported) and metric quality (i.e., the actual performance of the model, such as accuracy or area under the curve [AUC]).

In terms of metric quality, we classified 14 studies as weak, 9 as moderate, and 20 as strong. A weak performance was defined, for example, as an AUC only slightly better than chance (i.e., 0.50–0.65), while a strong quality rating reflected more robust model performance (e.g., AUC > 0.75).

For metric coverage, 13 studies were rated as weak (e.g., reporting only 1-2 metrics when multiple are standard practice), 4 as moderate, and 26 as strong (e.g., a supervised ML model reporting accuracy, sensitivity, specificity, F1 score, and AUC).

Table 8 – Contingency Table

| **Metric Coverage →**<br>**Metric Quality ↓** | **Weak** | **Moderate** | **Strong** | **Total** |
|---|---|---|---|---|
| **Weak** | 8 | 2 | 4 | 14 |
| **Moderate** | 2 | 1 | 6 | 9 |
| **Strong** | 3 | 1 | 16 | 20 |
| **Total** | 13 | 4 | 26 | 44 |

## Overall Level of Support and Quality of Evidence

To summarize and compare the importance of different behavioral indicators across the literature (i.e., across both descriptive and predictive studies), we developed an intuitive 0–10 scoring system – the *BRIDGE Score*. This BRIDGE Score is based on two key components:

1. **Evidence Volume (Number of Papers):** For each indicator, we counted how frequently each indicator appeared across studies. Indicators mentioned in more papers were considered to have stronger empirical support.

2. **Evidence Strength (Paper Quality):** For each indicator, we calculated the average paper quality score based on ratings assigned during review (i.e., see Table 5 above). Indicators supported by higher-quality studies received higher scores. For predictive studies, quality ranged from 7 to 15.

To combine quality and quantity, we calculated a weighted z-score for each indicator (based on the combined average paper score), which reflects how far above or below average the indicator sits (adjusted for the number of supporting studies). We also adjusted the weight of the z-score to avoid over-penalizing indicators that had high levels of support from descriptive studies[10] (which only received baseline quality scores of 1). We then transformed this weighted z-score into a percentile and mapped it onto a 0–10 scale, where 5.0 represents the average score across all indicators. Thus, scores above 5.0 reflect stronger or more consistently supported indicators, whereas scores below 5.0 reflect indicators that are either less common or backed by lower quality evidence.

The full table of scores by indicator is available on Google Drive in the "BRIDGE Score Data" file. For each indicator, the file includes individual (i.e., descriptive and predictive) and combined data on study counts, average paper quality, z-scores, and weighted z-scores. Here, we present the top 10 and bottom 10 indicators in Tables 9 and 10, as well as provide a high level of summary by category in Table 11.

[10] We assigned each descriptive paper a weight of 0.089. This was derived from the average quality score of predictive studies (1 divided by 11.25).

Table 9 – Top 10 Indicators according to the BRIDGE Score

| Indicator | Category | Total Appearances | Average Study Quality | BRIDGE Score |
|---|---|---|---|---|
| Deposit max | Payment | 7 | 13.0 | 6.5 |
| Deposit amount | Payment | 22 | 11.8 | 6.5 |
| Deposit number | Payment | 20 | 11.8 | 6.4 |
| Withdrawal variability | Payment | 7 | 12.6 | 6.3 |
| Age | Profile information | 31 | 11.4 | 6.3 |
| Bonus amount | Play | 7 | 12.4 | 6.2 |
| Bet variability | Play | 20 | 11.5 | 6.1 |
| Withdrawal amount | Payment | 12 | 11.7 | 6.0 |
| Breadth of involvement | Engagement | 27 | 11.3 | 6.0 |
| Bonus number | Play | 10 | 11.7 | 6.0 |

Table 10 – Bottom 10 Indicators according to the BRIDGE Score

| Indicator | Category | Total Appearances | Average Study Quality | BRIDGE Score |
|---|---|---|---|---|
| Time of day | Engagement | 16 | 10.2 | 4.7 |
| Bet intensity | Play | 22 | 10.2 | 4.7 |
| Log in number | Engagement | 3 | 9.3 | 4.5 |
| Play break | RG tool use | 2 | 9.0 | 4.5 |
| Active days volatility | Engagement | 3 | 9.1 | 4.4 |
| Duration | Engagement | 16 | 9.8 | 4.4 |
| Losses | Play | 9 | 9.5 | 4.3 |
| Win rate | Play | 7 | 8.7 | 3.9 |
| Education | Profile information | 1 | 1.0 | 2.8 |
| Customer contact | Profile information | 1 | 1.0 | 2.8 |

Table 11 – BRIDGE Score Summary by Category

| Category | Indicator Count | Total Appearances | Average Study Quality | BRIDGE Score |
|---|---|---|---|---|
| Play | 16 | 247 | 10.7 | 5.3 |
| Profile information | 13 | 99 | 9.6 | 5.0 |
| Engagement | 14 | 156 | 10.7 | 5.1 |
| RG tool use | 4 | 30 | 7.9 | 4.2 |
| Payment | 18 | 154 | 11.2 | 5.5 |

# CONCLUSIONS AND RECOMMENDATIONS

This systematic review synthesized the current evidence base on behavioral indicators used to identify individuals at risk of gambling-related harm using objective tracking data. A total of 68 studies were included, with 25 classified as descriptive and 43 as predictive. Our central contribution is the creation of the Behavioral Risk Indicators Database of Gambling Evidence (BRIDGE)—a structured and living resource that catalogs indicators by both frequency of use and study quality.

## Key Findings

- **Play indicators were the most commonly used category across all studies** (n = 247), followed by Engagement (n = 156), Payment (n = 154), Profile information (n = 99), and RG tool use (n = 30). Despite their frequency, play indicators did not rank highest in evidentiary strength.
- **The Payment category received the highest average BRIDGE Scores**, with 5 of the top 10 indicators related to financial transactions. The top four highest-scoring indicators overall were all payment-related. Indicators such as deposit amount and number consistently appeared in high-quality predictive studies and demonstrated strong methodological support.

- **RG tool use was the least studied indicator category.** While many predictive studies used RG tools (e.g., self-exclusion) as *outcome variables*, few examined these tools as behavioral *predictors* of harm. This suggests a significant gap in the literature, particularly in evaluating how player interactions with RG tools (e.g., time-outs, limit-setting) might serve as early indicators of risk rather than simply endpoints of distress.

As highlighted in prior reviews and reports, the evidence base is difficult to compare and contrast, thus the BRIDGE Score provides a novel and intuitive method for assessing both the volume and quality of supporting evidence. It offers a more objective way to prioritize behavioral indicators than previously available, especially as industry and regulatory bodies seek to operationalize data-driven risk detection.

When comparing BRIDGE findings to recommendations from leading regulatory and industry bodies (e.g., UK Gambling Commission, Senet Group, Ksa, CEN), we observed both convergence and disconnects (see Table 12). Several recommended indicators were well-supported in the academic literature, while others – such as customer-led contact and RG tool use – were rarely studied or poorly reported. For example, although customer contact is a recommended indicator by both the UK Gambling Commission and CEN, only one study in our review included this variable. Similarly, RG tool use, despite being recommended, was the least represented category in our review.

Table 12 – BRIDGE Contrast with Extant Recommendations

| Group | Indicator | BRIDGE Indicator or *Category* | BRIDGE Appearances | BRIDGE Study Quality | BRIDGE Score |
|---|---|---|---|---|---|
| Senet | Spend from norm | Bet variability | 20 | 11.5 | 6.1 |
| Senet | Frequency of play | Bet number | 34 | 10.8 | 5.5 |
| Senet | Late-night play | Time of day | 16 | 10.2 | 4.7 |
| Senet | Deposit frequency | Deposit number | 20 | 11.8 | 6.4 |
| Senet | Failed deposits | Deposit declines | 13 | 10.4 | 5.0 |
| Senet | Withdrawal reversals | Withdrawal canceled | 9 | 10.7 | 5.2 |
| Senet | Multiple payment methods | Deposit method | 8 | 11.3 | 5.5 |
| Senet | Credit cards | Deposit method | 8 | 11.3 | 5.5 |
| UKGC | Customer spend | Bet amount | 52 | 10.8 | 5.6 |
| UKGC | Patterns of spend | Bet trajectory | 13 | 11.1 | 5.6 |
| UKGC | Time spent gambling | Session length | 18 | 11.1 | 5.6 |
| UKGC | Gambling behavior indicators | *Play* | *247* | *10.7* | *5.3* |
| UKGC | Customer-led contact | Customer contact | 1 | 1.0 | 2.8 |
| UKGC | Use of gambling management tools | *RG tool use* | *30* | *7.9* | *4.2* |
| UKGC | Account indicators | *Payment* | *154* | *11.2* | *5.5* |
| Ksa | Intensity (losses) | Losses | 9 | 9.5 | 4.3 |
| Ksa | Intensity (number of playing days) | Active days number | 42 | 11.0 | 5.9 |
| Ksa | Intensity (sum of stakes) | Bet amount | 52 | 10.8 | 5.6 |
| Ksa | Loss of control | Loss chasing | 13 | 11.3 | 5.7 |
| Ksa | Increase in gambling over time | Bet trajectory | 13 | 11.1 | 5.6 |
| Ksa | Game types | Breadth of involvement | 27 | 11.3 | 6.0 |
| CEN | Losses | Losses | 9 | 9.5 | 4.3 |
| CEN | Changes in the use of RG tools | *RG tool use* | *30* | *7.9* | *4.2* |
| CEN | Gambling product preferences | Breadth of involvement | 17 | 11.3 | 6.0 |
| CEN | Time spent gambling | Session length | 18 | 11.1 | 5.6 |
| CEN | Customer-initiated contact | Customer contact | 1 | 1.0 | 2.8 |
| CEN | Canceled withdrawals | Withdrawal canceled | 9 | 10.7 | 5.2 |
| CEN | Depositing behavior | *Payment* | *154 (3)* | *11.2* | *5.5* |
| CEN | Speed of play | Bet intensity | 22 | 10.2 | 4.7 |
| CEN | Volume of stakes | Bet amount | 52 | 10.8 | 5.6 |

Deposit related variables were particularly strong according to the BRIDGE database, and these are present in Table 12. However, more research may be needed surrounding payment methods and declined transactions to better understand the strength of those in determining at-risk players.

The disconnect between BRIDGE and current recommendations may reflect data availability constraints, as some data required for engineering specific indicators may not be accessible to independent researchers. But it may also reflect industry practice diverging from the academic evidence base.

### Limitations

Despite the strengths of this review, several limitations should be noted. While screening was conducted by multiple researchers to reduce bias, inclusion decisions may still reflect some subjectivity. The living nature of BRIDGE in the future will enable community-driven feedback, allowing others to submit studies or challenge current entries.

While our scoring system captures quantity and quality of evidence, it does not estimate the independent predictive value of each indicator. Most predictive models used in the reviewed studies were multivariate machine learning models, making it difficult to isolate the contribution of individual variables. As the field matures, more interpretable modeling techniques and sensitivity analyses should be encouraged.

The BRIDGE Score draws from established frameworks (e.g., TRIPOD-AI, CHARMS), but includes adapted elements and assumptions. It is intended as a practical tool – not a formal quality assessment instrument – and should be refined as the database evolves, particularly as new techniques and novel data source (e.g., text-based data) emerge. Ongoing refinement is also necessary to account for evolving indicator usage trends. For example, a recent focus on more measurable harms (e.g., financial) may lead to certain indicators having lower scores in the current evidence base.

The review excludes commercially available risk detection tools due to limited transparency. As highlighted in Marionneau et al. (2025), and confirmed in our supplemental scan of platforms such as Mindway[11], Future Anthem[12], BetBuddy[13], Crucial Compliance[14], and Sustainable Interaction[15], little information is publicly available on the indicators or methodologies used by these solutions. This lack of information does not make it possible to include these systems in the BRIDGE database. However, we would like to acknowledge that some authors of studies included in this review are affiliated with two commercial solutions: namely BetBuddy (e.g., Dragicevic et al., 2011; Percy et al., 2016; Sarkar et al., 2016) and Neccton[16] (e.g., Auer & Griffiths, 2023a, 2023b).

### Recommendations

As the Ksa noted in their markers of harm report, "it is reasonable to start with a set of indicators that are found to be relevant in the literature, but examining new indicators should be an ongoing process." We echo this sentiment. By establishing BRIDGE as a shared evidence base, we hope to support this ongoing process by improving algorithmic detection methods, guiding policy decisions, and ultimately contributing to harm prevention efforts. We offer the following recommendations:

1. **Prioritize evidence-based indicators.** As evidenced by this report, a plethora of behavioral indicators have been explored in the literature, and various regulatory bodies and other groups have made recommendations. While it is not possible to define a definitive list of indicators that must be used when implementing player risk detection solutions, a prioritization approach could be considered. Indicators with the strongest evidential support should be prioritized. For example, our BRIDGE findings suggest that payment-related indicators would take precedence based on the quality and level of evidentiary support. However, ongoing collection and assessment of the evidence is vital given the evolving nature of the field.

2. **Standardized reporting guidelines.** The current evidence base reveals significant inconsistency in how studies are conducted and, more importantly, reported. This variation makes it (1) difficult to compare findings across studies, and (2) often results in insufficient information to properly evaluate the effectiveness of behavioral indicators. We recommend the adoption of standardized reporting frameworks (similar to TRIPOD-AI) for studies developing or evaluating predictive models related to gambling harm.

[11] https://www.mindway.ai/
[12] https://www.futureanthem.com/
[13] https://www.playtech.com/products/betbuddy/
[14] https://www.crucialcompliance.gi/
[15] https://www.sustainableinteraction.se/
[16] https://www.neccton.com/

3. **Open data and code.** Very few studies share their underlying data or modeling code, making independent validation of findings nearly impossible. While we recognize that data may be proprietary or sensitive, there are workarounds. For example, Zendle and Newall (2024) created a simulated version of their dataset that allows others to (1) validate their results and (2) build upon their work to advance the field. We encourage similar approaches to promote transparency and replicability.

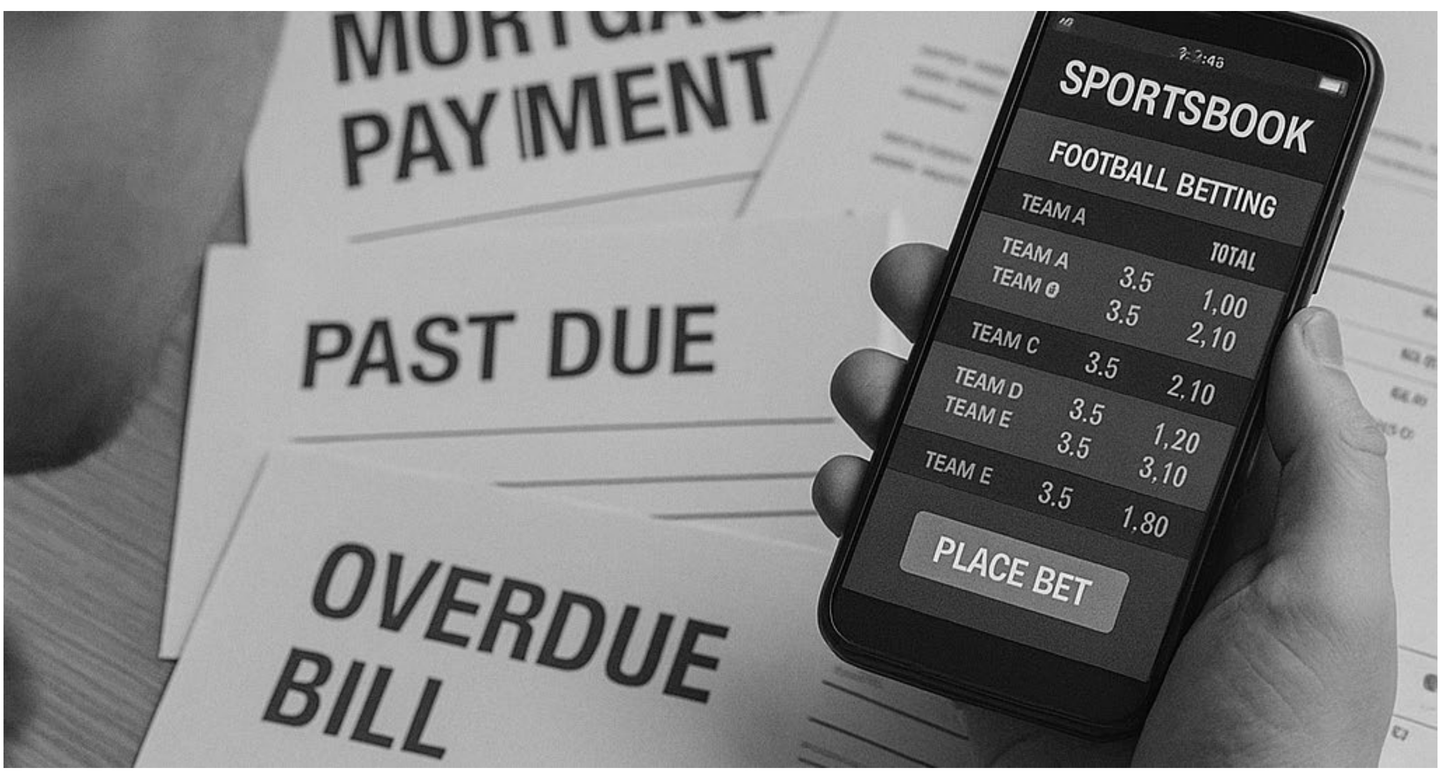
4. **Address transparency challenges and evaluation of commercial solutions.** At present, there is no standardized way to assess the efficacy of commercial harm detection systems. This lack of transparency poses challenges for regulators and operators alike, including questions around whether these systems are achieving their intended outcomes. The competitive nature of the market adds an additional layer of difficulty. We recommend that future work prioritizes the development of transparent evaluation frameworks for commercial tools used in harm detection. Furthermore, regulators may consider mandating error reporting and independent audits, as well as enforcing explainability standards for these systems.

# STUDY 3 – FINANCIAL RISK IDENTIFICATION

Financial risk identification within the gambling sector is an emerging area, it is also one that is neither well understood or defined. Despite widespread recognition of the significant and temporal role that financial harms play in the etiology and experience of gambling-related harms, our understanding of the financial behaviors and habits of gamblers remains notably limited. Thus, stakeholders are currently limited in their capacity to enact intervention efforts targeted at financial risk.

Financial harms from gambling are recognized as significant. Langham et al. (2016) introduced a comprehensive framework for gambling-related harm, comprised of seven dimensions, including relationship disruption, psychological distress, and criminal activity. Within this framework, financial harm presents as arguably the most influential dimension, as it often has an immediate impact on individuals and those around them. These harms also bear substantial temporal precedence, and can act as a trigger for subsequent harms. Furthermore, financial harms are relatively more tangible, via experiences of financial loss and observable changes in spending patterns. Given this significance, it is essential to understand how financial risk can be identified, and to evaluate the methods and technologies available to support effective detection and intervention.

We also currently lack a clear and widely accepted definition of what constitutes “financial risk,” though efforts to define it are emerging. For instance, the Dutch gambling regulator has suggested that individuals should not gamble more than 30% of their disposable income (Fletcher, 2024b). Similarly, the UK Gambling Commission has implemented financial risk checks based on specific thresholds, including “frictionless” checks for individuals who experience net gambling losses of £150 or more over any rolling 30-day period (Gambling Commission, 2022). But as with gambling harms more broadly, financial harms can manifest along a spectrum of severity: at the less severe end, individuals may lose the ability to make hedonic purchases (e.g., luxury goods, vacations), while at the more extreme end, they may struggle to meet essential obligations such as paying for food and housing (Langham et al., 2016). As such, gaining a clearer understanding of how “financial risk” is conceptualized and operationalized is essential to prevent financial harms from gambling.



## OBJECTIVES

The objective of this qualitative study was to capture the views and experiences of a group of industry experts on financial risk identification within the gaming industry. We sought to gain a targeted understanding of the technologies and practices used to monitor individual players across various gambling verticals (e.g., brick-and-mortar casinos, sports wagering, and horse racing). The insights gained from these interviews aim to provide foundational information for gaming regulators about potential strategies and the practical challenges associated with implementing strategies for financial risk identification.

## METHODS

This study was designed to address the limited availability of academic research on financial risk identification, particularly outside the scope of behavioral risk detection using operator data. As demonstrated in Study 2 of this report, most prior research on player risk has focused on behavioral tracking data from gambling platforms. One recent exception is Zendle and Newall (2024), which explored financial risk using open banking data and the PGSI – although this study did not appear in our initial literature search. Notwithstanding these limited examples, the broader evidence base remains scarce. This gap is further compounded by the lack of a clear definition of what constitutes "financial risk" in the context of gambling.

To address these gaps, we conducted eight in-depth, one-on-one interviews with industry experts who have domain expertise in financial technology (FinTech) and/or responsible gambling. This qualitative approach allowed us to gather rich, contextual insights into the current technologies, practices, and challenges involved in financial risk identification.

We employed a convenience and purposive sampling strategy to recruit individuals with relevant domain expertise. The UK was selected as the focal case study given its mature digital payments infrastructure and recent regulatory developments proposed by the UK Gambling Commission regarding financial risk checks (four participants were from this jurisdiction). Participants included stakeholders from across the financial risk ecosystem (see Table 13), including regulators, academics, and third-party financial technology providers.

| Participant | Country | Role |
|---|---|---|
| 1 | UK | CEO and founder, gambling-specific open banking service company. |
| 2 | USA | CEO and founder, global self-exclusion program. |
| 3 | USA | Technical Lead, single digital wallet solution for online and land-based gambling platforms. |
| 4 | UK | Head of Product, open banking service company. |
| 5 | Sweden | Postdoctoral researcher studying financial harms in gambling using transaction data. |
| 6 | UK | Consultant, consulting firm working with gambling operators. |
| 7 | USA | Assistant Professor, university laboratory that examines behavioral addictions. |
| 8 | UK | Postdoctoral data scientist working with bank transaction data. |

We created an interview questionnaire to guide the conversation, developed according to our specific research questions. The questions included:

- What is the current technology that exists to track individual players across different types of gaming (e.g., brick and mortar gaming, sports wagering, horse racing, etc.) and operators?
- What is the current technology that exists to perform financial risk identification and support player protection in the gambling sector?
    - How do you define financial risk?
- In which jurisdictions are these types of methodologies and technologies being used?
    - Why has adoption been early in these jurisdictions?
    - What are the challenges in these jurisdictions?
- What are the barriers to implementing these proposed methodologies and technologies in other jurisdictions?
    - Specifically, what are the barriers and challenges in the US market.

Two researchers were present for each interview - KG serving as the primary interviewer, MS as an observer and secondary questioner. Each interview lasted between 30 and 45 minutes and was conducted via video conferencing (i.e., Zoom). Audio recordings were transcribed using Zoom's built-in transcription functionality and manually verified by the research team.

Data analysis was performed by MS, who employed a descriptive approach to synthesize the data. First, repeated readings of all transcripts was performed to achieve data immersion. Then, rather than applying formal coding procedures, transcripts were summarized to identify key points, themes, and recurring patterns. This method was appropriate given the exploratory nature of the research and the relatively small number of interviews. To enhance the validity of the synthesis, MS shared and discussed the initial summaries and emerging themes with KG.

## FINDINGS

### Tracking Players Across Operators

Interviewees were first asked to describe current technologies that exist to track players across different types of gaming. This finding centers on opportunities and challenges of single-player tracking across operators from a harm prevention perspective. While new technologies have great potential to help achieve this goal, data sharing and tracking is a complex task, and gambling stakeholders may meet significant challenges.

When addressing the question of tracking players across operators, respondents' examples clustered around self-exclusion and harm prevention. Respondents emphasized that, although the technical capability now exists, data-sharing remains complex because each operator stores information differently and must first obtain customer consent. Centralized, single-wallet systems in state monopolies such as Norway illustrate what is possible in closed markets, but such a model may be challenging for competitive jurisdictions.

However, respondents explained that progress is being made in jurisdictions with competitive markets. In the UK the Betting and Gaming Council's GamProtect[17] initiative allows operators to share "risk flags" without exposing personal data. An interviewee stressed that, currently, GamProtect represents only a small part of the industry, but the number of affiliated operators is growing, and the interviewee foresees it becoming increasingly utilized. Interestingly, the participant proposed that the UK Gambling Commission should make GamProtect a condition for holding a license to increase adoption. And in the U.S., the Responsible Online Gaming Association (ROGA) is developing an independent clearing-house, while another interviewee described how, with players' consent, their company shares self-exclusion data across operators. This API-driven solution tokenizes self-excluded customers so other operators can recognize them without seeing identifiable details[18].

Reflecting on the challenges of data sharing across operators, another interviewee mentioned some alternative tools available to help prevent harm that do not require operator participation. For example, people who do not want to participate in gambling can use software like BetBlocker or GAMSTOP to block access to gambling websites.

Finally, one respondent highlighted the way certain omnichannel operators – Caesars was cited as an example – already link land-based loyalty cards to online accounts, demonstrating that end-to-end player tracking is technologically feasible. Additionally, another participant speculated on the potential of blockchain in this domain, suggesting it could be particularly useful in addressing data privacy and transparency concerns.

### Conceptualizing Financial Risk

After the topic of player tracking, discussion turned to definitions of financial risk. Here, interviewees attempted to define the term, focusing on both the strategies for measuring financial risk and the challenges posed by inflexible and deterministic definitions.

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[17] The GamProtect scheme (https://www.gamprotect.co.uk/) aims to solve the problem of providing consistent safer gambling protection across multiple platforms. It does this by allowing participating operators to compliantly and securely share information about customers who require support.

[18] API tokenization replaces a user's sensitive data with a cryptographically generated, non-identifiable token. This enables operators to securely verify a customer's self-exclusion status across platforms without needing to exchange or store their personal details.

Providing a UK perspective, a respondent explained how gambling harm appears to be framed through three complementary lenses. The first lens is behavioral: i.e., indicators that arise directly from gambling activity, such as rapid betting frequency or escalating stake sizes. The second is vulnerability, encompassing life events like bankruptcy or job loss that heighten susceptibility to harm. The third is financial, centered on whether a customer's broader spending patterns signal stress.

But most participants viewed financial risk, perhaps more simply, as a function of gambling losses relative to disposable income. Thus, financial risk may only be measurable by having a complete picture of players' financial situations. As a participant explained, if the ratio between sustained net losses and the individual's apparent disposable income over a given period approaches or equals one, the subject could be considered at-risk. However, some highlighted that the nature of these definitions is subjective and, therefore, they depend on individual perspectives and criteria. Reflecting on this, an interviewee mentioned existing research that leverages transaction data fused with PGSI data, which could be used to advance more objective assessment of financial risk amongst gamblers.

Other respondents also emphasized the need for clear risk indicators. For example, a respondent suggested that an efficient indicator could be comparing the cost of living for the physical address of players to assess whether the funds they are using exceed the parameters in their residing region. This entails generating an equation based on elements like monthly mortgage, cost of living, and gambling expenditure to understand the level of financial risk.

### *Challenges in defining financial risk*

Participants explained that obtaining a complete picture of players' financial situations is not an easy task, given that it comprises a series of elements, from salaries to inheritances. As such, a subject might be labeled as at-risk when they are not, and vice versa. Moreover, from the interviews it emerged that definitions of financial risk vary by country and culture, as do the measures to identify it. This is the case with jurisdictions such as the Nordic countries, which tend to prioritize public health approaches over founding policies on individual responsibility, as was viewed as the case in the U.S. For example, as highlighted by one interviewee, the Swedish Government has decided that players cannot spend more than 30% of their income on gambling. Another respondent declared that such measures would not be possible in the U.S. given the public's culture and attitudes around government interventions.

Additionally, a UK-based interviewee emphasized the need to distinguish between *financial risk* and *economic vulnerability*, with the latter having a clear regulatory definition (and being more in line with the three-lens framework above). Vulnerability can be defined via elements such as bankruptcy or CCJs[19] (County Court Judgements), which provide more objective indications that an individual has been facing significant financial issues. On the other hand, *financial risk* is more difficult to define and refers to typologies of financial distress that are less pronounced, such as changes in income, credit scores, and mortgage defaults. Some of this information can be obtained from credit reference agencies (CRAs), but is not publicly available. As such, the link between financial risk and gambling involvement is not clear. However, the interviewee explained that, as automated affordability checks are increasingly used in the UK gambling sector, there is an opportunity to grow that understanding.

## Technologies for Financial Risk Identification

### *Current FinTech Capabilities*

Participants described a range of technologies already deployed in payments and compliance that could be repurposed for player-protection. This includes protocols such as PCI DSS (Payment Card Industry Data Security Standard) requirements and penetration testing, while implementing AML (Anti-Money Laundering) and fraud prevention programs. As such, the participant explained that an important next step would be to leverage those tracking systems to detect at-risk players. However, executing such a strategy requires thorough reflection on how to file such reports while protecting customers' privacy and refraining from making direct accusations. Moreover, an interviewee explained a central role of FinTech companies should be creating risk mitigation tools, such as well-being apps that can offer services

[19] If an individual in the UK does not repay a debt, creditors can apply for a CCJ, which is a court order to pay the debt. A CCJ can make it difficult for individuals to get credit in the future.

like setting a budget limit for gambling. This is an important point, highlighting that the responsibility for mitigating financial risk should extend beyond gambling operators to include other stakeholders.

### *Deposit Limits*

One respondent mentioned that some European countries have been enacting global deposit limits as a way to address financial harms from gambling. In Spain, the Directorate General for the Regulation of Gambling has proposed an aggregate deposit limit for individual users across accounts held with multiple operators (Abogados, 2024). Similarly, in Germany, the Interstate Treaty on Gambling introduced a new rule that set a monthly limit of €1,000 across operators (Hofmann, 2024). However, these approaches may overlook important nuances in financial risk, such as differences in individual income levels, by applying a uniform deposit limit to all players. Additionally, implementing such measures requires a centralized system to track deposits and withdrawals something that, as noted above, may be difficult to achieve in more competitive gambling jurisdictions. However, one interviewee pointed to Sweden as an example, and we present this participant's perspective in Box 5.

**Box 5 – The Case of Sweden**

An interviewee explained that in Sweden, there is a centralized system run by the Gambling Authority that works as a national registry. If people want to gamble online, they must go through that system, which also offers self-exclusion tools. If they feel they are having gambling-related issues, they can ask their account to be paused, and they may not be able to log in to any operators in Sweden. The Swedish authorities are also attempting to utilize this system to verify whether a subject can afford to play, using a credit check. As the respondent pointed out, this represented a significant shift in the Swedish gambling realm since, historically, operators were the only entities tracking users. The participant emphasized that, in the Swedish context, the Gambling Authority is responsible for issuing licenses to operators and can therefore require them to develop action plans outlining how to fulfill this duty of care. However, 30% of operators in Sweden are unlicensed and are often served by FinTech companies. An issue here is that Swedish gambling authorities do not have direct control over Fintech companies, which fall under the financial inspection branch instead. This creates a situation where regulators have limited reach on FinTech companies unless there is a clear mandate from the government.

### *Banks*

Banks represent a clear, yet underutilized, avenue for identifying financial risk. Participants did emphasize the importance of reflecting on the role of financial institutions in preventing harm caused by gambling. However, most interviewees explained that banks are not typically required to undertake an active "policing" function. As such, unless regulators directly ask them, it is unlikely that banks will voluntarily undertake specific actions. Interviewees explained that banks are hesitant to conduct gambling-related checks mainly because, by sharing sensitive data, they could incur legal problems and significant fines. According to a respondent, steps in this sense could be taken if financial conduct authorities led the process, by guiding banks with specific approaches to preventing gambling harm.

However, concerns were also raised about unintended consequences. One interviewee warned that if banks gain access to detailed gambling transaction data, they could use it to make adverse decisions about customers—such as raising interest rates—based on gambling behavior. Moreover, gambling regulators already face significant challenges in getting banks and payment providers to comply with existing mandates, such as blocking transactions to unlicensed operators.

Although participants acknowledged the need for stronger collaboration between banks and regulators on financial risk detection, most expressed skepticism about the likelihood of meaningful progress in the near term.

### *Credit Reference Agencies*

Another avenue is credit reference agencies. An interviewee explained that the technologies used by credit reference agencies could be helpful to identify financial risk in gambling. According to them, the systems they already have in place to assess people's financial health and ability to afford, for example, mortgage and car loans, should be expanded to the gambling industry. However, it is necessary to reflect on how to incentivize relationships between these agencies and operators, which might not be motivated to do so. As such, the participants wondered whether regulators should compel gambling companies to leverage CRA data.

However, one participant underscored that, while this "passive" data has reasonable levels of accuracy, especially in tracking significant publicly available objective markers (CCJs, bankruptcy, etc.), it only detects individuals who are in high-risk situations. Thus, someone who is at moderate risk and has never had a bankruptcy issue may not be detected. On the other hand, more “active” data, as they described it, can now be shared with the user’s consent via *open banking*, providing direct access to detailed information, such as their bank statements. Thus, this detailed level of analysis represents a more efficient method for evaluating financial risk.

### *Open Banking*

Interviewees noted that open banking systems, which enable third-party providers to access banking transaction data with consumer consent, are assuming an increasingly prominent role in financial risk identification. Thus, they described opportunities and challenges in this regard, with particular reference to the UK, which they defined as one of the most innovative.

Open Banking is part of the European Union’s Payment Services Directive 2 (PSD2), which allows third-party payment service providers to access payment account information and initiate payments with customers’ consent. In the context of risk identification, the transaction-level bank statement data made available through open banking is particularly valuable. According to one respondent, the key strength of this system lies in its ability to support independent and objective analysis of detailed financial behavior. One example of its growing potential is the significant investment by CRAs in open banking companies, driven by the accuracy and reliability of the data they provide. Moreover, the UK Gambling Commission has identified open banking as a potential technology to support financial risk checks.

However, several participants also pointed to practical and ethical challenges. One participant explained that when the Commission first proposed the use of open banking for risk checks, it was met with concerns from both operators and players, particularly regarding transparency around how data would be used. In response, the Commission launched an industry consultation that ultimately led to a shift in approach—proposing the use of credit bureau data instead, as it does not require user consent. According to the participant, another reason for this shift may be that the more information operators hold about a player, the more accountable they become. For example, if an operator learns that a customer has a low-paid occupation, they may be obligated to intervene and could face increased regulatory scrutiny. This, the respondent suggested, disincentivizes operators from investing in proactive, technology-based tools—such as open banking—to detect at-risk players.

Another interviewee, who had conducted research on open banking for the UK Gambling Commission, underscored technical limitations in applying the technology to gambling-related harm prevention. While they had access to large datasets on users’ financial accounts, they faced significant challenges in classifying and identifying gambling transactions. They noted that transaction labels are often poor in quality, merchant category codes are frequently missing, and third-party tools used to classify merchants have yielded unsatisfactory results. Although legal gambling operators can be identified through the Gambling Commission's registers, the same is not true for illegal operators, making it difficult to assess the full scope of gambling-related harm. As the interviewee remarked, they were left wondering “whether absence of evidence is evidence of absence.”

Challenges also exist around consumer adoption. Open banking systems rely on users providing explicit consent to share their banking data. Interviewees highlighted generational divides in this regard: younger individuals, particularly those aged 20 to 35, are generally more comfortable using open banking apps and sharing data with third parties. Importantly, these demographics may also align with more engaged gamblers (Ghaharian et al., 2025). In contrast, older generations tend to be more skeptical of such tools, especially when it comes to data privacy.

Furthermore, open banking frameworks vary significantly across jurisdictions. Interviewees described the U.S. as having a comparatively immature open banking ecosystem. While similar services exist, they are typically based on “screen scraping” techniques, where user credentials are used to extract data from bank accounts, rather than more secure and standardized API protocols (as mandated in the UK and EU).

## Barriers to Implementing Financial Risk Identification

This final section outlines the various challenges gambling stakeholders may face when attempting to implement financial risk identification using emerging technologies. Participants discussed a range of issues, from outdated technological systems and weak data-sharing practices to privacy concerns and regulatory limitations. Below, we summarize the key barriers raised by interviewees.

*Obsolete technology*

A prominent issue identified by one interviewee is the continued reliance on outdated technology or methods. Current systems often use static thresholds, either government-mandated or internally defined, and rely on manual processes, such as requesting bank statements or conducting online searches about a player's employment when a red flag is triggered. These tools are rudimentary and, according to the participant, insufficient for the early detection of at-risk individuals.

*Lack of cross-operator data sharing*

While cross-operator tracking would be key in financial risk identification, an interviewee explained that, at present, it is challenging to achieve because collaboration among separate entities can be difficult. Thus, despite technical capabilities, data sharing among operators will not be accomplished in the short-term. One participant pointed out that, beyond legal and logistical hurdles, there is currently no third-party oversight of how operators handle customer data once acquired. Additionally, the ability to analyze behavior across operators is complicated by dual-channel offerings: many brands operate both online and land-based platforms, making it difficult to distinguish the precise context of transactions.

*Multiple apps and profiles*

Participants highlighted the fragmentation of user data as another key barrier. In many jurisdictions, land-based and online accounts are not integrated, meaning the same individual may appear as two distinct players in internal systems. Further, operators offering multiple apps, such as BetMGM in the U.S., have allowed users to register separately in different states or platforms, sometimes to exploit sign-up bonuses. This fragmentation severely limits operators' ability to monitor aggregate spending and undermines RG efforts.

*Data sharing between operators and regulators*

Among the many challenges to implementing financial risk identification systems, an interviewee explained that regulators are cautious when requesting data from operators, as it could be perceived as a sign of mistrust. Once regulators obtain such data, operators may fear they may lose control over its use, leading to reputational damage or punitive consequences. As such, participants stressed the importance of building systems that encourage transparent and secure data exchange.

*Operators discouraged from tracking players*

According to an interviewee, a pressing issue is that operators are discouraged from tracking at-risk players in the first place, as they drive the majority of casinos' revenue. Regarding this point, the same person explained that there might be a misconception that someone who gambles extensively is automatically considered at risk, and therefore, tracking their activities could lead to misleading results. This is particularly the case with operators not being willing to track the so-called high rollers, who bet large amounts of money but whose wealth can mitigate potential losses. These cases, however, are often not risk-free since, even if the financial risk is mitigated, there might be some psychological harm deriving from problematic gambling behaviors.

*CRA-related risks*

Some interviewees cautioned against using major credit reference agencies, such as TransUnion, to conduct risk assessments. While these companies offer detailed financial data, there are concerns around consumer discomfort with the depth and breadth of personal information collected—and particularly how that data is commercialized. As an alternative, one participant advocated for using firms that specialize in gambling-specific financial insights, rather than generalist data conglomerates.

*Privacy and consent*

Across interviews, privacy emerged as a central concern, especially in contexts where data sharing spans operators, regulators, and third parties. Participants noted that players are increasingly asking who has access to their personal information and for what purpose. Interviewees stressed the need for financial risk identification frameworks to uphold strong principles of data protection and transparency.

*Regulators' technical implementation challenges*
Regulators themselves face capacity challenges. One participant noted that implementing robust risk identification systems requires deep technical knowledge (particularly in data science and research design), which many regulatory bodies currently lack. The high cost of recruiting or upskilling staff creates an additional hurdle. For example, in the Netherlands, operators encountered issues when sharing data with regulators, due to both system limitations and weak data governance. As such, interviewees argued that regulators must prioritize investment in internal expertise and technical infrastructure, potentially by reallocating resources (e.g., through a levy on gross gaming revenues).

*Land-based vs. online casinos*
Interviewees consistently observed that tracking player behavior is far more difficult in land-based venues than in online settings. However, some jurisdictions are beginning to require carded play in physical venues, which may help bridge this gap and improve tracking capabilities in the future.

*Risk of displacement to unregulated markets*
Finally, several participants raised concerns about the unintended consequences of financial risk identification policies, such as those in the UK and the Netherlands. Financial risk checks that require sharing bank statements or detailed personal data may lead some consumers to disengage from regulated platforms altogether. In doing so, they may migrate to unregulated markets where privacy is less scrutinized but protections are also far weaker.

## CONCLUSIONS AND RECOMMENDATIONS

This study explored the emerging area of financial risk identification within the gambling sector, addressing current conceptualizations, available technologies, and practical implementation challenges. While stakeholders increasingly recognize the importance of financial harms, the absence of a shared definition of "financial risk," combined with fragmented data systems and weak cross-sector collaboration, continues to limit effective implementation. Jurisdictions such as the UK, Sweden, and the Netherlands are piloting approaches ranging from deposit limits to CRA- or open banking-enabled affordability checks, but adoption varies widely and raises questions about privacy, consent, and unintended consequences.

### Key Findings

- **Conceptual Ambiguity:** There is no universally agreed-upon definition of financial risk in gambling. Respondents indicated various approaches, ranging from simplistic loss-to-income ratios to more nuanced assessments of financial behaviors, highlighting ongoing challenges in operationalizing clear and effective risk criteria.
- **Technological Potential vs. Implementation Barriers:** Advanced technologies such as open banking, credit reference agency data, and blockchain are currently available to support financial risk identification. However, practical challenges, including data classification difficulties, privacy concerns, consent issues, and uneven adoption rates, significantly constrain their current use.
- **Cross-Operator Data Sharing:** Single-player tracking across multiple operators remains a major challenge, complicated by fragmented data infrastructures, privacy concerns, and competitive market dynamics. Existing solutions, such as GamProtect in the UK and centralized systems in state monopolies, demonstrate feasibility but are limited in widespread application.
- **Regulatory Barriers:** Regulators face significant technical, financial, and capacity challenges in implementing comprehensive risk identification frameworks, which complicate efforts to standardize and enforce effective player protection measures.

### Limitations
The study's exploratory nature and qualitative approach mean findings are context-dependent and based on a relatively small sample of industry experts primarily from the UK. The findings therefore reflect the views and perceptions of these participants at the time of the interviews and do not necessarily represent the full scope of existing practices or solutions in all jurisdictions.

Future research should broaden geographic scope and incorporate quantitative analyses to validate qualitative insights and further refine definitions and measurements of financial risk. For example, future research could explore how different definitions of financial risk perform in practice, through experimental or quantitative studies leveraging linked self-report, behavioral, and financial datasets. Additional studies examining consumer perspectives and attitudes toward privacy, consent, and data sharing would also further our understanding.

## Recommendations

Based on the findings, regulators exploring financial risk identification should consider the following actions:

1. **Establish a Clear Financial Risk Definition:** Benchmark against international practices and review relevant literature from gambling and related sectors.

2. **Explore Pilot Programs:** For example, such as the UK Gambling Commission's pilot on financial risk assessments (Gambling Commission, 2025c). Moreover, the exploration of novel technologies, such as open banking, should be conditional on first addressing key consumer issues, including privacy, consent, and representativeness challenges.

3. **Facilitate Cross-Operator Tracking:** Support industry-led initiatives, potentially through government collaboration. For example, the UK's GamProtect is supported by the Betting and Gaming Council (a trade association) and the Gambling Commission (the regulator).

4. **Bolster Regulatory Data Infrastructure:** Invest in robust data systems and technical expertise, either internally or via third-party services (e.g., as demonstrated by ROGA's recent RFP).

5. **Assess Displacement Risks:** Conduct targeted consumer research to better understand potential displacement to unregulated gambling markets.

6. **Explore Mandatory Carded-Play Systems:** Evaluate the feasibility of implementing mandatory carded-play tracking systems in land-based venues.

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# DISCLOSURES

During the last five years, International Gaming Institute (IGI) at University of Nevada, Las Vegas, has received funding for its research and programs from Action Gaming, American Gaming Association, Aristocrat Leisure Limited, Association of Gaming Equipment Manufacturers, Axes.ai, Bet Blocker, Clarion Gaming, DraftKings, Entain Foundation, ESPN, Evoke plc, Focal Research Consultants, Gaming Analytics, Global Payments, IGT, Kindbridge Behavioral Health, Las Vegas Sands Corporation, Massachusetts Gaming Commission, MGM Resorts International, Playtech plc, Responsible Online Gaming Association, Yuhaaviatam of San Manuel Nation, Sightline Payments, Sports Betting Alliance, State of Nevada Department of Health and Human Services, State of Nevada Knowledge Fund, Walker Digital Table Systems, and Wynn Resorts Ltd. Additionally, IGI organizes the triennial International Conference on Gambling and Risk Taking, a research-focused event supported by sponsors from industry, academia, and the legal/regulatory sectors; a full list of sponsors for the most recent conference can be found at https://www.unlv.edu/igi/conference/18th/sponsors.

IGI is home to an industry-focused advisory board (https://www.unlv.edu/igi/advisory-board), and specific programs, such as AiR Hub, have their own advisory panels. These advisory roles include resource support, and individual advisors are required to adhere to IGI policies. IGI maintains a strict research policy (https://www.unlv.edu/igi/research-policy), as well as a partnership and transparency framework (https://www.unlv.edu/igi/policies/partnership), to ensure appropriate firewalls exist between funding entities and IGI's research and programs.

Over the past five years, Kasra Ghaharian has either worked on projects funded by, or has personally received funding, honoraria, travel reimbursement, or consulting fees from the International Center for Responsible Gambling, the Nevada Department of Health and Human Services, the Nevada Governor's Office of Economic Development, the Massachusetts Gaming Commission, AXES.ai, Playtech, Evoke, Gaming Analytics, Walker Digital Table Systems, the Responsible Online Gaming Association, Videopoker.com, Kindbridge Behavioral Health, IGT, Differential Labs, Yaspa, Focal Research Consultants, Bet Blocker, Sports Betting Alliance, ESPN, Sightline, Global Payments, Telus, GP Consulting, the Responsible Gambling Council, the Illinois Council on Problem Gambling, the Alberta Gambling Research Institute, and Kindred Group. None of these entities had any role in the design, analysis, or interpretation of research conducted and imposed no constraints on its publication.

# APPENDIX

Table A1 – Low-Level Indicator Descriptions

| Indicator | Description |
|---|---|
| Accounts number | Number of betting accounts a player has. |
| Active days number | Count of number of days with a wager. |
| Active days trajectory | Some computation (e.g., slope, delta) of the change in active days over a time period. |
| Active days volatility | Some computation (e.g., standard deviation) of the count of active days. |
| Age | Age of the player. |
| Balance low | Indicators that represent when a player finishes a session with a low balance on their account. |
| Balance total | Similar to Net loss, but typically calculated at the wallet or account level. |
| Balance trajectory | Some computation (e.g., slope, delta) of the change in Balance total over a time period. |
| Bet amount | Some computation (e.g., total, average) of the monetary amount that has been wagered for bets. |
| Bet intensity | Some computation to reflect how many bets have been placed by a player in a specific time period (e.g., bets per session, bets per day). |
| Bet number | Count of bets made by a player. |
| Bet trajectory | Some computation (e.g., slope, delta) of the change in bets (e.g., amount, number) over a time period. |
| Bet variability | Some computation (e.g., standard deviation) of a player's betting behavior (e.g., amount, number). |
| Bonus amount | The monetary value of bets made with Bonus credits (i.e., not player's money). |
| Bonus number | The count of wagers made using Bonus credits. |
| Brand | Indicates whether a player is engaged across multiple brands (e.g., different operator or supplier online casino/sportsbook brands). |
| Breadth of involvement (e.g., games) | Indicators related to players' engagement across products and/or games (e.g., poker, sports betting, casino). |
| Canceled wager | Indicators related to when a player has changed their mind and canceled a wager that has been made. |
| Change personal info | When a player has made some change to their account information (e.g., name, contact information, etc.). |
| Country or location of player | The country or location of a player based on their account information. |
| Customer contact | A variable that indicates a player making contact with a gambling operator (e.g., bonus request). |
| Day of week | Indicators related to the day of week a player is engaged in betting activity. |
| Deposit amount | The monetary amount of deposits to a gambling account (i.e., from bank or other payment method). |
| Deposit approved | The count or amount of approved deposits. |
| Deposit declines | The count or amount of deposits that were declined. |
| Deposit intensity | Some computation to reflect how many deposits have been placed by a player in a specific time period (e.g., per session, per day). |
| Deposit max | Indicators related to the largest deposit amount (e.g., for a single deposit, within a time period). |
| Deposit method | Typically, the count of payment methods used and/or use of credit cards to make deposits to a gambling account. |
| Deposit number | Count of deposits made by a player. |
| Deposit variability | Some computation (e.g., standard deviation) of a player's depositing behavior (e.g., amount, number). |
| Duration | Calculation of a players amount of time spent gambling (e.g., number of days between earliest and last day gambling within a time period). |

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| Education | The education level of a player (e.g., high school, college, etc.). |
| Employment status | Employment status (e.g., employed, unemployed). |
| First deposit amount | The monetary amount of a player's first deposit. |
| Gender | Male, female, etc. |
| Income | Income of a player (e.g., annual salary). |
| Log in number | Count of the number of times a player has logged into a gambling platform. |
| Loss chasing | Indicators constructed to operationalize loss chasing behavior (e.g., across sessions, across days, correlations, increases in stake size). |
| Losses | Total monetary amount of lost bets. |
| Marital status | Married, single, etc. |
| Net loss | Calculation of a player's "position" over a specific time period (e.g., amount wagered minus amount won). |
| Platform (e.g., mobile) | Reflects a player's engagement across different technological platforms (e.g., mobile, desktop, etc.). |
| Play break | Indicators related to player's taking a break or pause from gambling. |
| Player value or VIP status | Indicators denoting the VIP status or value of the player to the operator. |
| Product risk | Indicators related to reflecting the "riskiness" of different games or wagers (e.g., choice of odds). |
| Recency | Indicators related to how "new" a player is (e.g., sign up date). |
| Removal of RG tools | A variable that reflects a player taking the action of removing RG settings (e.g., removing a limit). |
| Sawtooth pattern | Indicator computed to reflect steady increase in wagers with a sudden drop. |
| Season | Time of year of play. |
| Self-exclusion | Indicates use of self-exclusion tool by a player (e.g., count, binary). |
| Seniority | How long a player has had a relationship (account) with an operator. |
| Session intensity | Some computation to reflect how many sessions have been made by a player in a specific time period (e.g., sessions per day). |
| Session length | The length of time of a session (e.g., average, total). |
| Session number | Count of sessions made by a player. |
| Set limit | Indicates use of limit setting features by a player (e.g., number, binary). |
| Time of day | Typically used to indicate night play. |
| Win rate | Indicates how often a player experiences winning bets (e.g., number of days has a win, percentage of bets with a win). |
| Wins amount | Total monetary amount of all winning wagers. |
| Wins number | Count of winning wagers. |
| Withdrawal amount | The monetary amount of withdrawals to a gambling account (i.e., from bank or other payment method). |
| Withdrawal approved | The count or amount of approved withdrawals. |
| Withdrawal canceled | Indicates the occurrence of a player cancelling a withdrawal from gambling account to financial account (e.g., amount, number). |
| Withdrawal deposit ratio | A measure that compares the total amount of money withdrawn from gambling accounts to the total amount deposited. |
| Withdrawal number | Count of withdrawals made by a player. |
| Withdrawal variability | Some computation (e.g., standard deviation) of a player's withdrawal behavior (e.g., amount, number). |