Multimodal Generative AI and Foundation Models for Behavioural Health in Online Gambling

Konrad Samsel[a,*], Mohammad Noaeen[a,*], Neil Seeman[a,b], Karim Keshavjee[a], Li-Jia Li[c] and Zahra Shakeri[a,d,e,**]

[a]*Institute of Health Policy, Management and Evaluation, Dalla Lana School of Public Health, University of Toronto, Toronto, Ontario, Canada*

[b]*Massey College, University of Toronto, Toronto, Ontario, Canada*

[c]*LiveX AI, San Francisco California, United States*

[d]*Schwartz Reisman Institute, University of Toronto, Toronto, Ontario, Canada*

[e]*Faculty of Information, University of Toronto, Toronto, Ontario, Canada*

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ABSTRACT

Online gambling platforms have transformed the gambling landscape, offering unprecedented accessibility and personalized experiences. However, these same characteristics have increased the risk of gambling-related harm, affecting individuals, families, and communities. Structural factors, including targeted marketing, shifting social norms, and gaps in regulation, further complicate the challenge. This narrative review examines how artificial intelligence, particularly multimodal generative models and foundation technologies, can address these issues by supporting prevention, early identification, and harm-reduction efforts. We detail applications such as synthetic data generation to overcome research barriers, customized interventions to guide safer behaviors, gamified tools to support recovery, and scenario modeling to inform effective policies. Throughout, we emphasize the importance of safeguarding privacy and ensuring that technological advances are responsibly aligned with public health objectives.

1. Introduction

The advent of in-person electronic gambling machines (EGMs) introduced immersive experiences for players, allowing wagers to be placed as rapidly as once every 2.5 seconds (Dowling, Smith and Thomas, 2005). These principles now extend to online gambling, where fast-paced digital platforms heighten the risk of behavioral addiction and related harms (Gainsbury, 2015). This escalation is facilitated by the unprecedented accessibility and personalized interfaces of many gambling sites, factors that can further exacerbate public health challenges tied to disordered gambling (Gainsbury, 2015).

Online gambling has become a major global concern, propelled by rapid technological growth and evolving social norms. In 2023, the worldwide online gambling market was valued at $92.9 billion and is projected to grow at a compound annual rate of 11.7% to reach $145.6 billion by 2028 (Market Research Report, 2023). Younger populations appear especially drawn to digital platforms, with reports indicating that nearly 50% of gamblers aged 18–34 prefer online options over traditional venues (National Gambling Association, 2022). This surge has an escalating public health toll, as an estimated 1–3% of adults worldwide experience disordered gambling, affecting tens of millions of individuals (World Health Organization, 2019). The wider societal costs are likewise striking. In the United States, gambling-related problems are estimated to cost $6 billion per year in healthcare, criminal justice, and lost productivity

(Smith and Doe, 2022), while the United Kingdom, where 0.7% of adults are classified as problem gamblers, sees a related societal expense exceeding £1.2 billion annually (Gambling Commission, 2021).

Growth in online gambling stems not only from technological advances but also from changes in social norms and regulatory environments, creating novel challenges for public health practitioners. While online offerings parallel in-person betting in terms of game types and prizes, they possess distinctive features argued to amplify their appeal (Hubert and Griffiths, 2018). Surveys point to constant accessibility, anonymity, and mobile integration as influential drivers of engagement (Hubert and Griffiths, 2018; Columb and O'Gara, 2018), while user-friendly financial transactions and immersive interfaces may further intensify addictive tendencies (Gainsbury, 2015). Gambling behaviors can span a continuum from recreational to at-risk to problematic (Latvala, Lintonen and Konu, 2019), suggesting a need for proactive interventions, such as user feedback, limit-setting, self-exclusion measures, and mental health support, to mitigate escalation (Rodda, 2022).

Data analytics and artificial intelligence (AI) present innovative avenues for tackling these issues. Past research has examined AI-driven methods for detecting risky behaviors (Auer and Griffiths, 2023b) and supporting in-game limit-setting (Auer and Griffiths, 2022). Lessons from AI applications in patient care, such as psychiatric referral management (Habicht, Viswanathan, Carrington, Hauser, Harper and Rollwage, 2024) and personalized treatment (D'Alfonso, 2020), indicate how similar frameworks might be adapted to address online gambling addictions. Nonetheless, AI can also aggravate negative outcomes if misapplied. Operators

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*These authors contributed equally to this work.

**Corresponding author

ORCID(s):

increasingly leverage advanced data analytics and risk management solutions to make platforms appear more rewarding, which can inadvertently deepen gambling-related harm (Tyler, Akerlof, Allegra, Arnold, Canino, Doornenbal, Goldstein, Budtz Pedersen and Sutherland, 2023). The unchecked personalization behind these immersive environments risks creating cycles of overexposure and escalating problematic behaviors.

Multimodal Generative AI and foundation models offer a new frontier for addressing these multifaceted challenges. Through real-time analytics, personalized interventions, and comprehensive policy simulations, these emerging technologies hold potential for improving early detection and harm reduction in online gambling. However, their responsible deployment requires robust governance to avoid exacerbating existing harms or introducing new risks to vulnerable populations. In this narrative review, we synthesize the contexts under which gambling-related addictive behaviors arise and discuss how advanced AI technologies may strengthen primary prevention, early screening, and addiction management in online gambling. We also highlight ethical considerations and oversight mechanisms needed to ensure these innovations align with public health goals. Finally, we propose concrete strategies for achieving a paradigm shift in AI-driven harm reduction and detail a set of potentially high-impact applications enabled by multimodal generative AI, while underscoring the core challenges, ethical, technical, and organizational, that must be addressed to realize their full promise.

2. Understanding Problem Gambling

Problem gambling, also referred to as pathological gambling or gambling disorder, is a behavioural addiction characterized by '*frequent, repeated episodes of gambling that dominate the patient's life to the detriment of social, occupational, material, and family values and commitments*' (World Health Organization, 2016). Though standardized diagnostic criteria are available, the condition is often underdiagnosed due to the low proportion of individuals experiencing harmful effects who are willing to seek support (Lupo, Vitale, Carriero, Calabrò, Imperiale, Ercolani, Filippini, Santoro, Carvello, Rizzo et al., 2023). It has been estimated that around 71% of those with problematic gambling have never sought treatment for their condition (Suurvali, Hodgins, Toneatto and Cunningham, 2008). Problematic gambling behaviour, if left untreated, can be associated with harms including bankruptcy, housing instability, and worsening mental health (Latvala et al., 2019). In some cases, problem gambling can also impair judgment and decision-making abilities, leading to more impulsive and risky behaviours (Vestergaard, Ulrichsen, Dahl, Marcussen and Christiansen, 2023). Importantly, the negative impacts associated with this condition can extend beyond individuals, often also affecting those around them (Tulloch, Hing, Browne, Rockloff and Hilbrecht, 2021). These wider harms can include increased

household financial strain, relationship breakdowns, emotional distress among affected family members, and an overall decrease in one's quality of life (Latvala et al., 2019).

Recently, Internet gaming disorder (IGD) and problematic Internet use have been identified as conditions associated with problematic gambling (Karlsson, Broman and Håkansson, 2019). While it has been proposed that these behavioural addictions may share similar risk factors, further work is needed to determine whether any causal associations exist between them (Karlsson et al., 2019). The distinction between gaming and gambling is becoming increasingly blurred, with some games incorporating gambling-like elements, and gambling sites increasingly 'gamifying' core features of their platforms (Wu, Sescousse, Yu, Clark and Li, 2018; Raneri, Montag, Rozgonjuk, Satel and Pontes, 2022). The recent classification of IGD in the Fifth Edition of The Diagnostic and Statistical Manual of Mental Illnesses (DSM-V) has helped in establishing several distinctions between disordered gambling and gaming (Darvesh, Radhakrishnan, Lachance, Nincic, Sharpe, Ghassemi, Straus and Tricco, 2020). Differentiating between these behavioural addictions can also assist in the development of tailored approaches to mitigating their severity and impact. While problematic gamblers tend to experience more financial-related harms, IGD is more often characterized by physical and health-related harms associated with recurrent gaming behaviour (Delfabbro, King and Carey, 2021).

Approaches to aid in the screening of problem gambling have previously been proposed, and serve as tools to identify individuals requiring further intervention or diagnostic assessment. These criteria typically consist of readily quantifiable factors such as the frequency and duration of gambling activities and the amount of money spent on gambling (Gooding, 2023; Turner, Elton-Marshall, Shi, Wiebe, Boak, van der Maas and Mann, 2018; Williams, Shaw, Belanger, Christensen, el Guebaly, Hodgins, McGrath and Stevens, 2023; Auer and Griffiths, 2023b). One example of a screening tool is the Problem and Pathological Gambling Measure (PPGM-R), a 15-item self-reported assessment for classifying the risk of gambling disorder (Gooding, 2023). In tandem with these screening tools, knowledge of high-risk demographics, gender-based differences, and other behavioural factors may be effective in informing public health approaches to screening and early management.

2.1. Demographic Risk Factors

The risk of engaging in gambling behaviour has previously been associated with demographic factors including age, initial age of gambling, and gender. These factors are situated within a larger scope of social, behavioural, and environmental determinants (Figure 1). Understanding risk factors associated with problem gambling is essential for designing effective interventions and prevention strategies tailored to specific populations.

Adolescents and younger adults represent a particularly vulnerable population, being prone to engaging in risky gambling behaviours during their formative years (Bastiani,
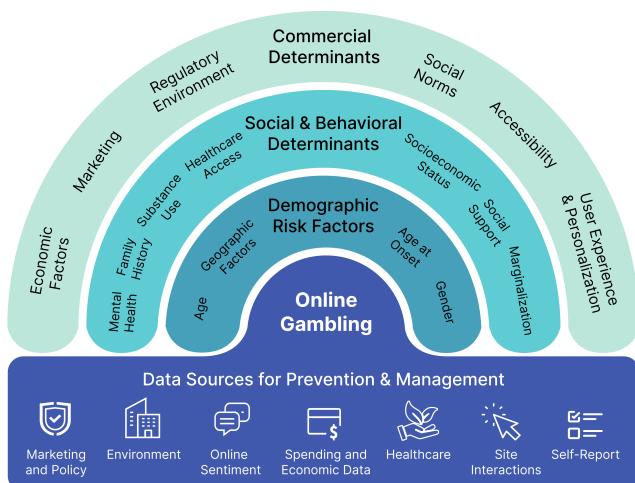
Figure 1: Environmental determinants of online gambling and associated data sources for research and prevention. The determinants are classified into accessibility, socioeconomic factors, regulatory environments, and commercial influences. These determinants interact to shape online gambling behaviors and outcomes. The figure also maps relevant data sources, including demographic surveys, public health records, and behavioral datasets, to support research on these influences and inform interventions aimed at reducing gambling-related harms.

Russell and Newall, 2023; Rizzo, La Rosa, Commodari, Alparone, Crescenzo, Yıldırım and Chirico, 2023). Adolescents' developing cognitive control systems may hinder effective decision-making in these contexts, making them more susceptible to developing problematic gambling behaviours (Emond and Griffiths, 2020). The age at which adolescents begin to engage in these activities has been suggested as a risk factor, with one cross-sectional study finding severe gamblers were more likely to have started gambling at an earlier age (Sharman, Murphy, Turner and Roberts, 2019). The growing inclusion of gambling-related elements in adolescent games, such as virtual wagers and loot boxes, underscores the need for research into the impacts of these early exposures to gambling tendencies in later life. Among other demographic factors, the prevalence of problem gambling has historically been higher in males (Williams, Leonard, Belanger, Christensen, El-Guebaly, Hodgins, McGrath, Nicoll, Smith and Stevens, 2021; Turner et al., 2018; Claesdotter-Knutsson and Håkansson, 2021). Online gambling, specifically, carries a similar demographic risk profile, with males and younger adults more likely to engage with these platforms (Hing, Russell and Browne, 2017).

2.2. Social, Behavioural, and Health Determinants

The co-occurrence of alcohol and substance use with gambling behaviours significantly increases the risk of developing gambling addiction (Hilbrecht, Baxter, Abbott, Binde, Clark, Hodgins, Manitowabi, Quilty, SpÅngberg, Volberg, Walker and Williams, 2020). Prior research has suggested that individuals who engage in excessive alcohol consumption or substance use are more likely to exhibit impulsive behaviours, including problem gambling (Yau and Potenza, 2015). The link between gambling and substance use may stem from similar neurobiological and psychological factors underlying these conditions (Pettorruso, Testa, Granero, Martinotti, d'Andrea, di Giannantonio, Fernández-Aranda, Mena-Moreno, Gómez-Peña, Moragas et al., 2021). The combination of alcohol or substance use with gambling may lead to a cycle of addictive behaviours, exacerbating the development and severity of gambling addictions (Yau and Potenza, 2015). The underlying mechanisms of addiction, including neurobiological (Potenza, Sofuoglu, Carroll and Rounsaville, 2011), emotional (Jauregui, Estévez and Urbiola, 2016), and structural factors (Barnes, Welte, Tidwell and Hoffman, 2015), can predispose individuals to engage in multiple addictive behaviours, including gambling. Additionally, individuals with addiction to other substances may turn to gambling as an alternative or complementary form of seeking pleasure or relief (Potenza et al., 2011), increasing the likelihood of experiencing gambling-related problems (Armoon, Griffiths, Fleury, Mohammadi and Bayat, 2023; Barnes et al., 2015).

Problematic gambling has also been noted to co-occur with mental health diagnoses such as depression, anxiety disorders, and personality disorders (Hilbrecht et al., 2020). The co-occurrence of mental health disorders and problem gambling presents complex challenges for diagnosis and treatment, emphasizing the importance of integrated approaches that address both gambling behaviours and underlying mental health conditions. In tandem, lower socioeconomic status (SES) is known to be associated with the overall incidence of problem gambling (Williams et al., 2021, 2023), mental health and substance use (Lasserre, Imtiaz, Roerecke, Heilig, Probst and Rehm, 2022). Interestingly, an opposite association has been observed in some studies of online gambling, where those with higher incomes and educational levels may be more likely to partake in betting activities and exhibit problematic behavioural tendencies (Gainsbury, 2015). It has also been argued that these differences between online and offline offerings may become less pronounced as online gambling platforms become more well-known and easier to access (Gainsbury, 2015). By extension, social mobility and changes in SES, predictive of mental health (Barakat and Konstantinidis, 2023), present an interesting domain that may benefit from investigation in an online gambling context.

Other determinants suggested for their relationship with problematic gambling include financial literacy, family history of gambling, and access to health services. A previous investigation found financial literacy to be associated with gambling, with lower levels of financial literacy corresponding to an elevated risk of unhealthy gambling behaviours (Wang, Yang and Xin, 2023a). Moreover, family history of gambling has been proposed as an additional predictive factor of addictive gambling behaviour (Williams et al., 2023; Gooding, 2023). Former investigations have found

that individuals self-reporting perceived problematic gambling behaviours were more likely to have a family history of gambling compared to those not reporting such behaviours (Gooding, H., Williams and Williams, 2023). Structural barriers to accessing relevant health services and a lack of social support networks can also serve as risk factors for the progression of this behavioural addiction (Dąbrowska, Moskalewicz and Wieczorek, 2017).

2.3. Commercial Determinants

Commercial determinants of health present an interesting aspect of study in the context of gambling promotion and severity. Reflecting aspects such as the broad commercial landscape (Reith and Wardle, 2022), regulatory environments (Engebø, Torsheim and Pallesen, 2021; Turner, Sinclair and Matheson, 2023), accessibility (Russell, Browne, Hing, Rockloff, Newall, Dowling, Merkouris, King, Stevens, Salonen, Breen, Greer, Thorne, Visintin, Rawat and Woo, 2023), product design (McAuliffe, Edson, Louderback, LaRaja and LaPlante, 2021), and broader economic conditions (Olason, Hayer, Meyer and Brosowski, 2017), these determinants are increasingly being recognized as important drivers of gambling behaviour. Marketing strategies, which serve to increase awareness and positively shape perceptions on gambling, can be argued to influence social norms and help normalize engagement in these platforms (Guillou-Landreat, Gallopel-Morvan, Lever, Le Goff and Le Reste, 2021). Recent attention has also focused on the role of celebrities and social media influencers in the appeal of these platforms (Pitt, McCarthy, Randle, Daube and Thomas, 2024). With this marketing often occurring on digital social media platforms, the risk of adolescents and youth being exposed to gambling messaging is also heightened (Guillou-Landreat et al., 2021).

3. Online Gambling Characteristics

Developments in gambling offerings have introduced novel methods of participation, such as in-person EGMs and internet-based games. As a 'continuous' form of gambling (Williams et al., 2021), EGMs are characterized by their repetitive nature, which translates to a shorter recovery period in between gambling engagement and reward (Harris, Gous, de Wet and Griffiths, 2021). Moreover, the increased prominence of auditory and visual stimuli commonly found in these machines further promotes continued user engagement (Shao, Read, Behrens and Rogers, 2013). Recently, a natural policy experiment from Australia highlighted the effects of EGM access restrictions on the prevalence of gambling-related harms (Russell et al., 2023). Lower levels of harm were associated with access restrictions (Russell et al., 2023), highlighting the contributions of accessibility in gambling prevention and management. Unfortunately, the ease of access to gambling activities has tended to increase due to the emergence and worldwide growth of online gambling.

The gambling landscape has undergone significant transformations in recent years, with the proliferation of online gambling platforms contributing to shifts in gambling behaviour and overall prevalence rates of problematic gambling behaviours (Marionneau, Ruohio and Karlsson, 2023; Emond and Griffiths, 2020; Elton-Marshall, Leatherdale and Turner, 2016; Miles, Rothschild, Åkesson and A., 2023; Langham, Thorne, Browne, Donaldson, Rose and Rockloff, 2016). There is growing evidence that online gamblers are at a greater risk of experiencing problem gambling compared to those who engage in offline gambling (Scholes-Balog and Hemphill, 2012; Griffiths, Wardle, Orford, Sproston and Erens, 2021). Overall, the popularity, lack of restrictions, and personalization among online offerings are among the factors proposed to increase the likelihood of problem gambling.

Increasing Popularity of Online Gambling. Online gambling offerings, including online wager platforms, sports gambling apps, and virtual slot machines, have witnessed an increase in popularity, particularly among adolescents (Emond and Griffiths, 2020; Gainsbury, 2015). According to a 2016 cross-sectional survey of 10,035 Canadian adolescents, 41.6% of respondents reported engaging in gambling activities within the prior three months (Elton-Marshall et al., 2016). Moreover, based on survey data collected using the Canadian Adolescent Gambling Inventory (CAGI), it was estimated that 17.4% and 18.2% of those who had self-reported engaging in online gambling activities were classified at a 'high' and 'low to moderate' level of gambling severity, respectively (Elton-Marshall et al., 2016). Comparable estimates for youth who reported engaging in offline gambling yielded estimates of 1.2% for 'high' and 7.2% for 'low to moderate' severity (Elton-Marshall et al., 2016). Online sports betting emerged as the most popular form of online gambling among adolescents (Elton-Marshall et al., 2016). From this same survey, simulated gambling such as free online poker and gambling games on social media were also prevalent among Canadian youth, with approximately 9% of respondents reporting past engagement in these platforms (Elton-Marshall et al., 2016).

Ease of Access. Online gambling platforms have shaped the gambling experience by providing unparalleled accessibility to users (Ghelfi, Scattola, Giudici and Velasco, 2023; Emond and Griffiths, 2020; Marionneau et al., 2023). In contrast to traditional brick-and-mortar casinos, which include age restrictions and have limitations based on operating hours and physical proximity, online platforms allow individuals to participate in gambling activities from the comfort of their own homes or while on-the-go via mobile devices (Hilbrecht et al., 2020; Favieri, Forte, Casagrande, Dalpiaz, Riglioni and Langher, 2023; Allami, Williams, Hodgins, Stevens, Shaw, el Guebaly, Christensen, McGrath and Belanger, 2003). Consequently, individuals may find themselves more inclined to participate in these activities due to the accessibility afforded by online platforms (Marionneau et al., 2023).

Lack of Sufficient Age Restrictions. One concerning aspect of online gambling platforms is the lack of stringent

age verification measures compared to traditional brick-and-mortar casinos. While physical casinos typically enforce strict age restrictions and require identification verification to prevent underage gambling, online platforms may have less robust age verification mechanisms in place (Bastiani et al., 2023). This lax enforcement increases the risk of underage individuals engaging in gambling activities, as they may circumvent age restrictions and access online gambling platforms without adequate age verification checks (Elton-Marshall et al., 2016).

Personalization of Gambling Experience. Online gambling platforms leverage sophisticated and personalized data analytics to tailor gambling experiences to individual preferences (Tyler et al., 2023). By analyzing user data and behavioural patterns, these platforms can customize the presentation of games, offers, and incentives to align with each user's interests and preferences (Marionneau et al., 2023; Miles et al., 2023). This personalized approach may enhance user engagement and immersion in the gambling experience. Moreover, integrating personalized features, such as targeted advertisements (Nixon, 2022) and recommendations (Sahota, 2024) based on past behaviour, may further incentivize individuals to continue gambling and increase their participation in gambling activities, particularly when presented with tailored incentives and stimuli that resonate with their preferences.

Increased Intensity. Online gambling platforms facilitate a higher intensity, frequency, and prevalence of gambling activities compared to traditional venue-based gambling (Marionneau et al., 2023). Features such as unlimited pay-to-play options, minimal wait times between bets, and the availability of multiple gambling options may contribute to the heightened intensity and frequency of online gambling experiences. The absence of physical and frequency constraints, and the seamless transition between different gambling activities, enable individuals to engage in continuous and uninterrupted sessions, leading to increased intensity and frequency of problematic gambling behaviours (Allami, Hodgins, Young, Brunelle, Currie, Dufour, Flores-Pajot and Nadeau, 2021; Ghelfi et al., 2023). Compared to other gambling forms, the amount of time between bet placement and outcomes is much shorter, which may influence an individual's ability to manage impulsive tendencies (Ghelfi et al., 2023; Hilbrecht et al., 2020; Calado and Griffiths, 2016).

Online gambling has evolved into a dynamic and highly engaging ecosystem, designed to captivate and retain users. For vulnerable groups such as adolescents, the combination of instant accessibility and hyper-personalization is not merely appealing, it is dangerous. Addressing these challenges requires more than regulation; it necessitates a comprehensive understanding of the psychological drivers and structural factors underpinning this digital phenomenon, laying the groundwork for innovative and effective public health interventions.

4. Artificial Intelligence Addressing Problem Gambling

Artificial Intelligence holds significant promise for addressing the complex issue of problem gambling, but it also raises key ethical questions regarding fairness and transparency. This section draws on a diverse body of research across several key areas—*Detection and Prediction*, *Behavioral Analysis and Risk Factors*, *AI for Intervention and Prevention*, *Ethical and Fairness Considerations*, *Preventive Strategies*, and *Limitations in AI for Problem Gambling*—to provide a broad synthesis of current knowledge and challenges in this evolving field.

4.1. Core Applications of AI in Problem Gambling

Detection and Prediction. A substantial portion of AI research in problem gambling focuses on developing predictive models that flag at-risk individuals early. Studies have explored diverse machine learning approaches, including logistic regression, random forests, and artificial neural networks, to analyze betting transactions, session durations, and user correspondence with customer service (Murch, Kairouz and French, 2024b; Smith, Peters and Reiter, 2024; Jach, Probierz, Kozak, Stefański, Dziczkowski, Hrabia, Juszczuk, Głowania, Wołek, Sznapka et al., 2024; Murch, Kairouz, Dauphinais, Picard, Costes and French, 2023; Murch, Kairouz and French, 2024a; Kairouz, Costes, Murch, Doray-Demers, Carrier and Eroukmanoff, 2023; Percy, d'Avila Garcez, Dragičević, França, Slabaugh and Weyde, 2016b; Percy, França, Dragičević and d'Avila Garcez, 2016a; Finkenwirth, MacDonald, Deng, Lesch and Clark, 2021; Percy, Garcez, Dragicevic and Sarkar, 2020; Auer and Griffiths, 2023b). Some of these models have shown lasting stability over months, with only minor threshold adjustments required to maintain accuracy (Murch et al., 2024a,b). In parallel, AI chatbots have been trialed to deliver cognitive behavioral therapies, offering a scalable way to connect individuals experiencing gambling problems to early support (Murch et al., 2024b). This trend toward automated detection and screening suggests a broader move from reactive to proactive healthcare strategies.

Behavioral Analysis and Risk Factors. Complementing predictive algorithms, a growing body of research is dedicated to understanding *which behaviors* best indicate risk. Studies highlight that problem gamblers typically deposit more frequently, lose more money per session, and exhibit wider fluctuations in betting stakes (Emond and Griffiths, 2020; Auer and Griffiths, 2023b; Ghaharian, Binesh, Soligo, Golab and Abarbanel, 2024). Further, analyses of online forum posts and chat data suggest a correlation between high community engagement and heightened problem gambling behaviors (Smith et al., 2024). However, these findings often remain correlational rather than strictly causal, reflecting the multifaceted nature of gambling harm (Deng, Lesch and Clark, 2019; Ghaharian, Abarbanel, Phung, Puranik, Kraus, Feldman and Bernhard, 2023). Detecting behavioral

patterns, such as sudden increases in deposit amounts, enables researchers and operators to improve machine learning models and create more accurate methods for identifying individuals at risk.

AI for Intervention AI is also being leveraged for *intervention and monitoring* efforts, extending beyond detection to deliver personalized harm-reduction materials. Systems can recommend contacting local helplines or provide immediate feedback that contextualizes a user's actual gambling behaviors in real-time (Murch et al., 2024b; Kairouz et al., 2023; Sándor and Bakó, 2024; Kim, Park and Lee, 2024; Peres, Fallacara, Manzoni, Castelli, Popovič, Rodrigues and Estevens, 2021). Some platforms employ nudges to encourage self-imposed deposit limits, while others focus on more specialized use cases, such as detecting match-fixing in sports (Kim et al., 2024). These interventions align with a broader push toward public health models that proactively support vulnerable individuals. Incorporating short 'motivational check-ins', tailored to a user's recent betting trajectory, may strengthen engagement and steer players toward safer gambling habits.

Ethical and Fairness Considerations. Despite these advances, the ethical dimensions of AI in problem gambling remain complex. Concerns include the potential for algorithms to perpetuate existing inequalities if, for instance, they perform poorly for specific demographic groups (Murch et al., 2024a; Percy et al., 2020; Ghaharian et al., 2024). Debates around fairness (equality vs. equity) further complicate how limited resources, such as free counseling sessions, are offered to different user segments (Murch et al., 2024a). Moreover, critiques exist that AI interventions may serve as 'power mechanisms' shaping individuals into 'responsible gamblers' according to industry-driven norms, rather than addressing deeper structural factors (Ghaharian et al., 2024). Transparent communication about algorithmic limitations and an inclusive approach to model validation are crucial to mitigate such risks.

Despite these challenges and limitations in current AI applications for problem gambling, advancements in **generative AI and foundation models** offer a promising new direction. By enabling more adaptive, scalable, and context-aware solutions, these technologies can address gaps in data quality, fairness, and personalized interventions. In the following section, we illustrate how Generative AI and foundation models can push beyond traditional approaches, enhancing research, prevention, and treatment strategies while maintaining robust ethical safeguards.

4.2. Prevention Strategies Enabled by AI

AI-based methods show potential for reducing the public health burden of problem gambling via a structured prevention framework, mirroring general public health models (Figure 2).

Primary Prevention. Primary prevention addresses root causes and broad risk factors before problems arise (Kisling and Das, 2023). In online gambling, this includes regulating commercial determinants and raising public awareness (Petry, Zajac, Ginley, Lemmens, Rumpf, Ko and Rehbein, 2018). Multimodal foundation models can analyze text, images, and videos to evaluate marketing tactics—such as how prominently responsible gambling messages appear on advertisements or if certain imagery targets underage audiences. These AI-driven audits foster accountability in advertising, promote clear disclosures, and facilitate more informed public dialogue. Automated sentiment analysis on social media can further capture public perceptions, fueling data-driven efforts to refine prevention campaigns (Olawade, Wada, David-Olawade, Kunonga, Abaire and Ling, 2023; Lim and Schmälzle, 2023).

Secondary Prevention. Secondary prevention aims to identify and support individuals or communities at higher risk (Kisling and Das, 2023). Existing work leverages AI-based analyses of user engagement, demographic data, and environmental exposures to pinpoint groups susceptible to developing problem gambling (Booth, Dowling, Landon, Lubman, Merkouris and Rodda, 2021; Monreal-Bartolomé, Barceló-Soler, García-Campayo, Bartolomé-Moreno, Cortés-Montávez, Acon, Huertes, Lacasa, Crespo, Lloret-Irles et al., 2023). Additional data sources, including social media sentiment on online gambling and demographic trends in site visits, betting frequencies, and wager amounts, may help identify emerging patterns and inform tailored community prevention efforts.

Tertiary Prevention. For individuals already exhibiting harmful gambling behavior, tertiary prevention focuses on limiting further damage and fostering recovery (Kisling and Das, 2023). Screening tools combining machine learning and user engagement metrics (e.g., deposit variability, multiple visits) can predict self-exclusion or problematic gambling with moderate-to-high accuracy (Finkenwirth et al., 2021; Auer and Griffiths, 2023b; Murch et al., 2023). For example, one Canadian study (Finkenwirth et al., 2021) employed 20 betting variables related to gambling frequency, intensity, and variability to develop predictive models for self-exclusion, reporting area under the curve (AUC) values ranging from 0.65 to 0.76. Another Canadian investigation (Murch et al., 2023) combined user engagement and demographic data, achieving AUC values as high as 0.84 when predicting high-risk behaviors. Such findings have prompted platforms to consider offering personalized feedback, deposit-limit reminders, or prompts to seek help (Auer and Griffiths, 2023a). Meanwhile, AI-enabled chatbots or telehealth tools can deliver ongoing monitoring and individualized guidance, further reducing barriers to care.

4.3. Limitations in AI for Problem Gambling

Many studies still rely on self-reported data, such as the Problem Gambling Severity Index (PGSI), which is susceptible to recall and social desirability biases (Murch et al., 2024b). In addition, results based on a single online gambling platform may not capture a user's broader gambling behaviors, including land-based activities (Hopfgartner, Auer,
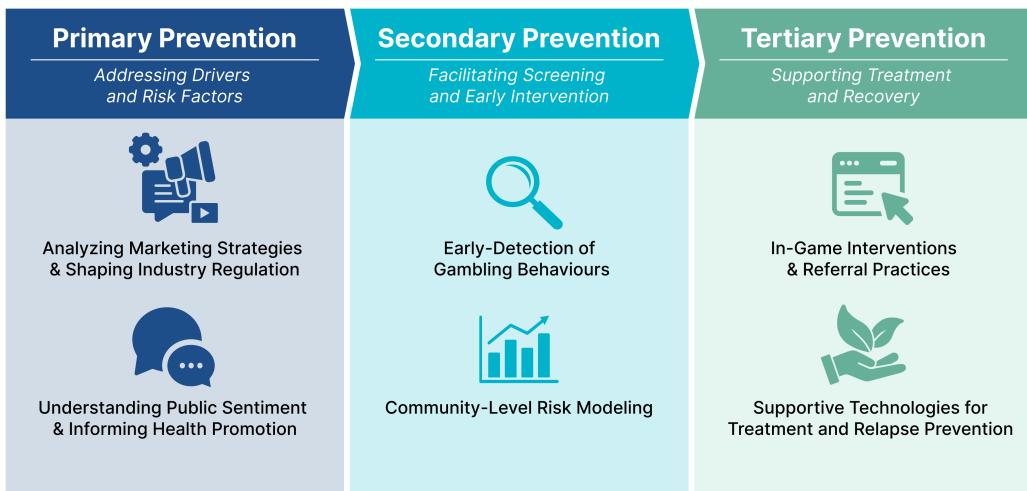
Figure 2: Technological interventions in online gambling prevention. This figure highlights a population health approach with three tiers: primary prevention focuses on risk factor analysis and public health promotion; secondary prevention includes early detection of gambling behaviors and risk modeling; and tertiary prevention addresses treatment and recovery with in-game interventions and relapse prevention technologies.
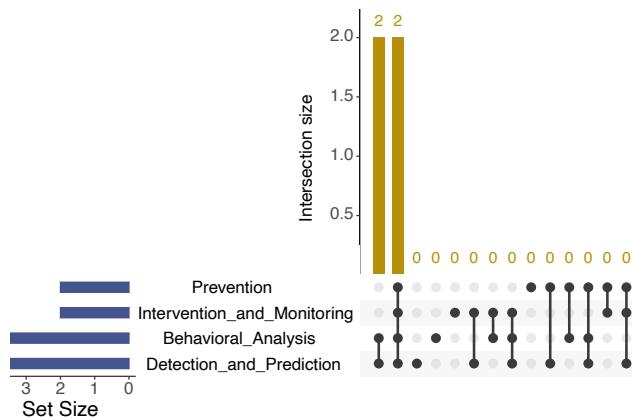

Figure 3: UpSet plot illustrating the intersections of requirement vectors across AI application categories. The vectors are defined as follows: *Detection and Prediction* ($V_{\mathrm{DP}} = \{1, 0, 1, 0, 0, 1, 0, 1\}$), *Behavioral Analysis* ($V_{\mathrm{BA}} = \{1, 0, 1, 0, 0, 1, 0, 1\}$), *Intervention and Monitoring* ($V_{\mathrm{IM}} = \{1, 0, 1, 0, 0, 0, 0, 0\}$), and *Prevention* ($V_{\mathrm{P}} = \{1, 0, 1, 0, 0, 0, 0, 0\}$). A size of two for intersections indicates that two requirements co-occur across two categories. A size of zero means that no category combination includes those specific requirements simultaneously. The plot highlights the consistent inclusion of demographic (r_1) and behavioral determinants (r_3), while systemic factors like policy engagement (r_7) and fairness (r_8) are underrepresented, particularly in *Intervention and Monitoring* and *Prevention*.

Helic and Griffiths, 2024). Sample sizes vary greatly, as does the granularity of available data, leading to heterogeneous reporting standards and difficulties in comparing results across different operators or jurisdictions. Evaluation metrics also lack uniform definitions, with area under the curve (AUC), accuracy, precision, and recall frequently used

but differently interpreted (Murch et al., 2024a). Furthermore, co-morbid conditions (e.g., mental health issues) and personal financial factors often remain unaccounted for, creating gaps in the contextual understanding of gambling harm. As AI tools become more prevalent, the sector must address these limitations through larger, more representative datasets, cross-platform validation, and consensus on robust evaluation protocols. Only then can AI fulfill its potential to guide ethical, data-driven strategies for mitigating gambling harm.

Moreover, to provide a broad synthesis of current knowledge and challenges in this evolving field, we propose a structured evaluation of the extent to which key requirements are addressed by various AI application categories in online gambling. Let $R = \{r_1, r_2, \dots, r_8\}$ denote the set of eight requirements identified from the literature, comprising:

1. r_1: Demographic Risk Factors
2. r_2: Social Determinants
3. r_3: Behavioral Determinants
4. r_4: Health Determinants
5. r_5: Commercial Determinants
6. r_6: Real-world Player Data Access
7. r_7: Policy Engagement
8. r_8: Algorithmic Fairness and Bias

Each AI application category—*Detection and Prediction*, *Behavioral Analysis*, *Intervention and Monitoring*, and *Prevention*—is represented by a binary vector $V_A = \{v_1, v_2, \dots, v_8\}$, where $v_i = 1$ indicates that the requirement r_i is addressed by the existing literature that focused on this specific application, and $v_i = 0$ indicates it is not. For instance, the vector for *Detection and Prediction* is

$$V_{\mathrm{DP}} = \{\, 1,\ 0,\ 1,\ 0,\ 0,\ 1,\ 0,\ 1 \,\},$$

reflecting its emphasis on demographic, behavioral, data access, and fairness-oriented components, while placing less

priority on social and health determinants. Using these representations, an UpSet plot (Figure 3) visualizes the intersections of requirements across these categories. The analysis reveals consistent attention to demographic and behavioral determinants across all application categories, highlighting their foundational role in addressing gambling-related harm. However, systemic considerations like Policy Engagement (r_7) and Algorithmic Fairness and Bias (r_8) are underrepresented, particularly in *Intervention and Monitoring* and *Prevention*.

The requirement mapping highlights critical patterns across AI applications in online gambling. Demographic (r_1) and behavioral (r_3) determinants are consistently prioritized, reflecting their central role in identifying and addressing problem gambling. However, systemic factors such as policy engagement (r_7) and algorithmic fairness (r_8) are often overlooked, despite their importance for ensuring ethical and regulatory compliance. Moreover, while data access (r_6) is essential for *Detection and Prediction* and *Behavioral Analysis*, its limited presence in *Intervention and Monitoring* and *Prevention* presents challenges in acquiring granular, real-time data. Connecting application categories with their requirement vectors exposes these gaps and enables targeted, ethically grounded advancements. The following section elaborates on how *Generative AI and Foundation Models* can tackle these challenges and redefine harm-reduction strategies.

5. The Potential of Generative AI in Problem Gambling

This section presents six use cases illustrating how Generative AI and Foundation Models provide integrative and innovative solutions that bridge gaps across disciplines. While previous AI efforts have made strides in addressing these challenges, the advanced capabilities of these models enable more adaptive, scalable, and precise approaches, offering transformative potential for behavioral health and gambling studies.

5.1. Synthetic Player Profiles

Real-world datasets for online gambling research are notoriously difficult to access due to privacy, legal, and proprietary constraints (Perrot, Hardouin, Thiabaud, Saillard, Grall-Bronnec and Challet-Bouju, 2022; Jach et al., 2024; Drosatos, Nalbadis, Arden-Close, Baines, Bolat, Vuillier, Kostoulas, Wasowska, Bonello, Palles et al., 2018; Hopfgartner et al., 2024; Gainsbury, 2015). As a result, researchers and practitioners frequently lack the scope to develop robust harm-reduction strategies. By employing large-scale foundation models and modern generative AI, it is now possible to craft *Synthetic Player Profiles* that authentically mirror real gambling behaviors without revealing any individual's identity (Harris, Parke and Griffiths, 2018).

Instead of relying on extensive real-world datasets, which are often scarce or inaccessible, we propose using a small anonymized or aggregated collection $\{\mathbf{V}_1, \dots, \mathbf{V}_m\}$ to

calibrate a foundation model M with parameters Θ. Through a suitable loss function (e.g., negative log-likelihood), M approximates $p(\mathbf{V})$ by learning $q_\Theta(\mathbf{V})$ over key behavioral features—such as deposit amounts, session durations, chat text, and self-exclusion flags (Shanahan, McDonell and Reynolds, 2023; Wang, Peng, Que, Liu, Zhou, Wu, Guo, Gan, Ni, Yang et al., 2023b; Park, Goldstein, O'Gara, Chen and Hendrycks, 2024). Once trained, M produces synthetic profiles $\mathbf{V}^* \sim q_{\Theta^*}(\mathbf{V})$, capturing realistic correlations while preserving anonymity. Privacy mechanisms (e.g., k-anonymity, differential privacy) and a rigorous validation pipeline ensure that these synthetic records remain secure and reliable. Thus, even with limited or partial real data, researchers and operators can generate lifelike player trajectories for testing new interventions, policy changes, or predictive models without exposing actual user information.

Transformer-based models, Generative Adversarial Networks (GAN) variants (Goodfellow, Pouget-Abadie, Mirza, Xu, Warde-Farley, Ozair, Courville and Bengio, 2014), and diffusion-based techniques (Yang, Zhang, Song, Hong, Xu, Zhao, Zhang, Cui and Yang, 2023) can further integrate text logs, biometric signals, or mobile data, creating multifaceted synthetic records. Similar methods have been used in healthcare (e.g., blending clinical notes and diagnostic images) (Moor, Banerjee, Abad, Krumholz, Leskovec, Topol and Rajpurkar, 2023; Giuffrè and Shung, 2023) and finance (e.g., simulating trader actions) (Zuo, Jiang and Zhou, 2024), enabling research free of confidentiality breaches. By aligning generation strategies with the unique traits of regional betting cultures, researchers can reveal subtle risk patterns that standardized models might miss, opening opportunities for more focused and relevant interventions.

Still, careful audits are vital to avoid biases or loss of minority patterns (Perrot et al., 2022; Gainsbury, 2015). Fairness checks and federated learning can guard original datasets and validate that the synthetic data genuinely reflects real-world distributions (Drosatos et al., 2018). Meanwhile, cognitive architectures like CoALA (Sumers, Yao, Narasimhan and Griffiths, 2023) and multi-agent simulations (Park, O'Brien, Cai, Morris, Liang and Bernstein, 2023) allow these synthetic actors to 'bet', respond to outcomes, and deploy responsible gambling tools, all with memory-driven and adaptive behavior. Researchers can even simulate real-time chat threads or forum interactions (Ghaharian et al., 2023; Moor et al., 2023) to capture conversational nuances, including emojis or full natural language. By providing a safe yet realistic testing ground, Synthetic Player Profiles pave the way for large-scale experimentation in online gambling studies.

5.2. Responsible Marketing

The gambling industry increasingly deploys sophisticated, AI-driven marketing strategies to attract and retain customers, raising significant concerns about potential harms as a commercial determinant of health (Kshetri,
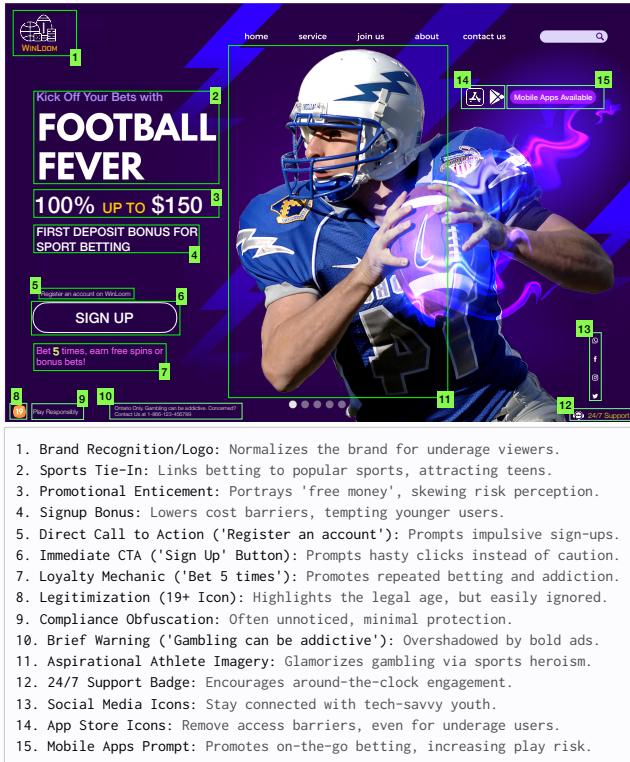
1. Brand Recognition/Logo: Normalizes the brand for underage viewers.
2. Sports Tie-In: Links betting to popular sports, attracting teens.
3. Promotional Enticement: Portrays 'free money', skewing risk perception.
4. Signup Bonus: Lowers cost barriers, tempting younger users.
5. Direct Call to Action ('Register an account'): Prompts impulsive sign-ups.
6. Immediate CTA ('Sign Up' Button): Prompts hasty clicks instead of caution.
7. Loyalty Mechanic ('Bet 5 times'): Promotes repeated betting and addiction.
8. Legitimization (19+ Icon): Highlights the legal age, but easily ignored.
9. Compliance Obfuscation: Often unnoticed, minimal protection.
10. Brief Warning ('Gambling can be addictive'): Overshadowed by bold ads.
11. Aspirational Athlete Imagery: Glamorizes gambling via sports heroism.
12. 24/7 Support Badge: Encourages around-the-clock engagement.
13. Social Media Icons: Stay connected with tech-savvy youth.
14. App Store Icons: Remove access barriers, even for underage users.
15. Mobile Apps Prompt: Promotes on-the-go betting, increasing play risk.

Figure 4: Generative AI-Driven Analysis of Marketing Strategies in Online Gambling Advertisement. An online sports-betting advertisement analyzed using generative AI (GPT-4o). Marketing strategies were detected from visual and textual elements, annotated numerically, and listed below. Model parameters: temperature = 0.2, max tokens = 950, top-p = 0.9, frequency penalty = 0.2, presence penalty = 0.0.

Dwivedi, Davenport and Panteli, 2024; Singer, Wöhr and Otterbach, 2024; Dunlop and Ballantyne, 2021). These strategies leverage targeted advertising, personalized content, and persuasive messaging via digital channels (e.g., social media, email, in-app notifications), often normalizing gambling as both accessible and glamorous (Pettorruso et al., 2021; Baek, 2023; Rodgers, 2021). Such aggressive tactics, including gamified promotions and immersive content, can disproportionately expose underage and vulnerable individuals, exacerbating public health challenges.

Multimodal AI and foundation models, including generative AI and vision-language models (VLMs) (Zhu, Chen, Shen, Li and Elhoseiny, 2023), offer a powerful means of transforming these practices. They can synthesize and analyze text, images, and videos to detect child-directed language or visuals in ads, allowing regulators to enforce stricter compliance standards (Campbell, Plangger, Sands and Kietzmann, 2022; Bjørseth, Simensen, Bjørnethun, Griffiths, Erevik, Leino and Pallesen, 2021). One promising application involves scrutinizing influencer content on social platforms (Kim, Jiang, Nakada, Han and Wang, 2020), flagging gambling promotions lacking proper disclosure (Pitt et al., 2024; Warraich, Tazbaz and Califf, 2024). Similarly, tools used for misinformation detection in political campaigns (Chen and Shu, 2024; Kuznetsova, Makhortykh,

Vziatysheva, Stolze, Baghumyan and Urman, 2025; Kumar and Taylor, 2024) could be adapted to evaluate the factual accuracy and ethical framing of gambling advertisements. In line with broader advertising insights (Grewal, Satornino, Davenport and Guha, 2024; Zhang, Shen, Zhang, Xu, Li, Yao and Yu, 2021), AI-based audits can also uncover manipulative or stereotype-reinforcing elements (Shumanov, Cooper and Ewing, 2022; Liu-Thompkins, Okazaki and Li, 2022), ensuring that marketing does not glorify gambling as a fast path to financial security.

To illustrate these concepts more concretely, we define an AI-driven function $f_\Theta : (\mathcal{M}, \mathcal{U}) \rightarrow \mathcal{R}$ that assigns a risk or relevance score $r \in \mathcal{R}$ to marketing materials aimed at specific user groups. Let $\mathcal{M} = \{m_1, \ldots, m_k\}$ be marketing items (e.g., text, images, videos) and let $\mathcal{U} = \{u_1, \ldots, u_n\}$ denote user segments defined by demographics, behaviors, and social ties. In practice, f_Θ combines VLMs to process multimodal content (Zhu et al., 2023) and graph neural networks (GNNs) to account for relational data (Wu, Pan, Chen, Long, Zhang and Philip, 2020; Bhadra, Khanna and Beuno, 2023). Once trained on labeled examples (e.g., ads deemed high-risk), f_Θ flags harmful content and recommends interventions (e.g., restricting ad distribution, altering imagery, or providing disclaimers). This pipeline can incorporate privacy safeguards (e.g., data anonymization) and continuous validation (e.g., adherence to ethical marketing guidelines) to ensure transparency and social responsibility.

As shown in Figure 4, generative AI can annotate suspicious elements ranging from exaggerated reward claims to youth-targeted graphics, thereby illustrating how f_Θ might assign higher risk scores to unethical or misleading promotions. Another emerging technique features GNNs that model intricate relationships among users, behaviors, and content (Bhadra et al., 2023). By mapping how a promotion spreads through a user's social network, these models can forecast cascading effects and dynamically adjust campaigns to reduce harm. When enhanced with emotion recognition layers, they can further detect ads that exploit anxiety or overconfidence, proactively flagging them for immediate review.

5.3. Personalized Behavioral Interventions

Generative AI heralds a paradigm shift in delivering personalized behavioral interventions for online gambling, moving from static approaches to dynamic, adaptive strategies (Baig, Hobson, GholamHosseini, Ullah and Afifi, 2024; Yang, Khatibi, Nagesh, Abbasian, Azimi, Jain and Rahmani, 2024; Geng, Liu, Fu, Ge and Zhang, 2022). Large Language Models (LLMs) and other generative methods enable real-time customization of prompts, nudges, and supportive messages based on user data such as spending habits, session durations, and even emotional tone (Aggarwal, Tam, Wu, Li and Qiao, 2023; An, Shen, Wang and Yang, 2024; Nie, Shao, Fan, Shao, You, Preindl and Jiang, 2024). This mirrors personalized marketing, yet applied to health and well-being (Lee, Lee, Jeong and Kim, 2024), allowing interventions to be generated *on the fly* at critical moments

and potentially halting escalation into problematic gambling behaviors. Let $\mathcal{D} = \{d_1, \ldots, d_m\}$ represent key data streams (e.g., betting amounts, session timestamps, chat logs), and let $\mathcal{I} = \{i_1, \ldots, i_k\}$ be a set of intervention strategies (e.g., nudges, cooldown reminders, self-reflection prompts). We define an AI-driven mapping $g_\Theta : \mathcal{D} \to \mathcal{I}$, where the generative model's parameters Θ are calibrated using real or *synthetic data* to ensure diverse scenarios while preserving privacy. Once trained on historical gambling patterns and labeled intervention outcomes, g_Θ delivers personalized, context-aware content in real time, with safeguards like data anonymization and ethical review boards mitigating potential misuse.

The personalization deepens when sentiment analysis and contextual data are integrated, allowing the system to react differently to frustration, overconfidence, or distress (Nepal, Pillai, Campbell, Massachi, Heinz, Kunwar, Choi, Xu, Kuc, Huckins et al., 2024; An et al., 2024; Maher, Davis, Curtis, Short and Murphy, 2020; Subramanian, Yang, Azimi and Rahmani, 2024). For instance, a user on a losing streak might receive empathetic messages encouraging a break, while a winning user might see reminders about responsible wagering limits. This Generative AI-based adaptability parallels advancements in mental health apps, where contextual prompts foster self-reflection (Kirk, Vidgen, Röttger and Hale, 2024; Moor et al., 2023). One promising extension is to use digital 'micro-rewards', which gently incentivize players to follow recommended limits or take breaks, reinforcing positive behaviors without relying on intrusive tactics. Over time, this targeted personalization fosters a supportive environment in which users feel guided and motivated to make healthier gambling choices.

5.4. Gamified Recovery Tools

Generative AI offers powerful new possibilities for developing interactive, gamified recovery tools tailored for individuals addressing problem gambling (Stade, Stirman, Ungar, Boland, Schwartz, Yaden, Sedoc, DeRubeis, Willer and Eichstaedt, 2024; Obradovich, Khalsa, Khan, Suh, Perlis, Ajilore and Paulus, 2024). These tools move beyond traditional approaches by providing engaging, personalized experiences that tackle the unique challenges of gambling addiction (Cheng and Ebrahimi, 2023). For example, AI-generated simulations can mimic real-life gambling scenarios within a safe, controlled digital environment, enabling users to practice impulse control and decision-making skills under realistic triggers (Sezgin and McKay, 2024). This strategy parallels the use of serious games in education and health, where immersive learning environments reinforce critical competencies.

In addition to simulations, generative AI can develop gamified exercises that reward positive behaviors linked to recovery, such as adhering to self-exclusion programs or attending therapy sessions (Cheng and Ebrahimi, 2023). These elements boost motivation and adherence, both vital for maintaining progress. Moreover, AI can produce tailored

narratives and videos that highlight others' recovery stories, instilling a sense of community, hope, and relatable success (Sezgin and McKay, 2024; Arenas, Viduani and Araujo, 2022; Nye, Delgadillo and Barkham, 2023). Let $\mathcal{S} = \{s_1, \ldots, s_n\}$ represent a user's state (e.g., emotional cues, triggers, progress metrics), and let $\mathcal{M} = \{m_1, \ldots, m_k\}$ denote gamified modules (e.g., simulations, reward systems, narrative exercises). We define a generative mapping $h_\Theta : \mathcal{S} \to \mathcal{M}$, where the parameters Θ are learned from real or *synthetic data* (see Section 5.1) to preserve privacy. Once trained, h_Θ personalizes each module in real time, adjusting difficulty or content based on user feedback (Sezgin and McKay, 2024; Nye et al., 2023). Incorporating wearable-sensor data (e.g., heart rate) into $\mathcal{S}$ could enhance early detection of emotional distress, prompting instant delivery of coping strategies.

Generative AI has already been leveraged in mental health to create personalized images for emotional management (Sezgin and McKay, 2024), and similar logic applies to gambling recovery: dynamic content and adaptive reward systems can drive sustained engagement (Li, Zhang, Lee, Kraut and Mohr, 2023; Obradovich et al., 2024). AI chatbots can further complement these modules, offering guidance and real-time interventions between human therapy sessions. The integration of simulations, gamified exercises, and on-demand support delivers a comprehensive and data-driven approach to achieving lasting recovery.

5.5. AI-Driven Counselor Training and Decision Support

The rising complexities of online gambling demand innovative approaches to counselor training and decision support, and multimodal AI coupled with foundation models offers a transformative solution (Shen, Li, Yang, Ni, Tao, Yu, Zheng, Xu and Hu, 2024; Li et al., 2023). One particularly promising use case is the creation of AI-driven training platforms that simulate realistic counseling scenarios for diverse behavioral health issues (Shen et al., 2024; Steenstra, Nouraei, Arjmand and Bickmore, 2024). For instance, a virtual client could present with the intertwined challenges of financial distress, strained relationships, and comorbid mental health conditions, incorporating voice tone, facial expressions, and text-based interactions to capture the nuance of real sessions (Stade et al., 2024; Magill, Mastroleo and Martino, 2022). This mirrors systems in addiction counseling (e.g., substance abuse (Steenstra et al., 2024)) and mental health (e.g., depression or anxiety (Stade et al., 2024)), where trainees practice techniques like Cognitive Behavioral Therapy (CBT) or motivational interviewing and receive instant, targeted feedback.

Beyond training, AI provides vital clinical decision support across multiple domains. By analyzing gambling transactions, online behaviors, and communication data, clinicians gain a holistic view of client patterns (Shen et al., 2024; Maslej, Kloiber, Ghassemi, Yu and Hill, 2023). Similar analytics have been applied to eating disorders (e.g., tracking food logs, mood trends) (Li et al., 2023) and chronic pain
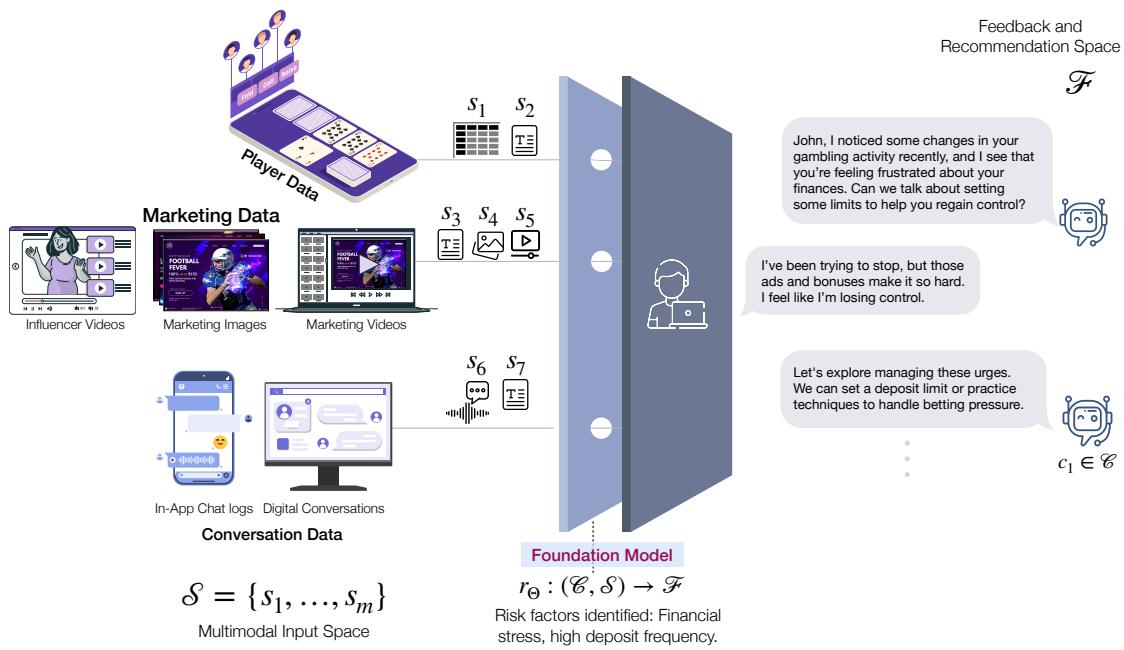
Figure 5: Multimodal Foundation Model for Problem Gambling Counseling. This figure illustrates the integration of multimodal data ($S = \{s_1, \ldots, s_m\}$), including player behaviors, marketing influences, and conversational cues, into a foundation model (r_Θ). The model processes these inputs to generate actionable insights ($\mathcal{F}$) that guide counselors ($\mathcal{C}$) in providing tailored interventions. The counselor ($c_1 \in \mathcal{C}$) interacts with the model's recommendations to address specific client concerns, such as identifying risk factors (e.g., financial stress, high deposit frequency) and proposing strategies like deposit limits or behavioral exercises.

management (e.g., monitoring activity levels, medication use) (Abedi, Colella, Pakosh and Khan, 2024), all with the goal of enabling informed, personalized interventions (Stade et al., 2024). AI-powered conversational agents can also serve as virtual peer counselors, helping practitioners process complex cases or manage emotional stress (Stade et al., 2024; Shen et al., 2024; Xi, Chen, Guo, He, Ding, Hong, Zhang, Wang, Jin, Zhou et al., 2023). This mirrors trauma or family therapy settings, where virtual peers offer real-time guidance on handling sensitive topics (Xi et al., 2023; Abedi et al., 2024). Let $\mathcal{C} = \{c_1, \ldots, c_p\}$ be counselor trainees or practicing clinicians, and let $S = \{s_1, \ldots, s_m\}$ represent multimodal simulation elements (e.g., text dialogues, vocal tones, facial cues, or virtual environments). We define a generative mapping $r_\Theta : (\mathcal{C}, S) \to \mathcal{F}$, where $\mathcal{F}$ is a feedback or recommendation space (e.g., performance metrics, evidence-based treatment steps). Parameters Θ are learned from real or *synthetic data* that reflect various behavioral health scenarios. Once trained, r_Θ dynamically adapts each simulation to individual counselor needs, suggesting tailored techniques (e.g., CBT vs. motivational interviewing) or even highlighting relevant ethical considerations (Figure 5).

Hyper-realistic virtual environments further expand these capabilities by recreating specific situations such as online casinos (Magill et al., 2022), helping counselors grasp the triggers and temptations their clients face. Comparable setups apply to social anxiety, where users virtually encounter stress-inducing social scenarios. While these technologies offer substantial promise, it remains essential to

balance innovation with ethics (Althoff, Clark and Leskovec, 2016; Xi et al., 2023), ensuring user safety, fairness, and respect for privacy. Augmenting rather than replacing human expertise, AI-driven counselor training and decision support have the potential to transform the quality and accessibility of behavioral health services.

5.6. Scenario Modeling for Policy Development

Generative AI enables a proactive and data-driven approach to policy-making by creating detailed scenario models and simulations (Cao, Zhuang and He, 2024; Barnett, Kieslich and Diakopoulos, 2024). Rather than merely reacting to existing issues, policymakers can explore 'what-if' scenarios in gambling regulation, such as changing advertising standards, adjusting self-exclusion rules, or altering tax structures, and instantly gauge their effects on addiction rates, economic outcomes, and social dynamics (Barnett et al., 2024; Tyler et al., 2023). Similar modeling applies to broader public policy contexts like environmental measures or public health, where AI can integrate large datasets (e.g., demographics, economic indicators) to provide intuitive visual reports and interactive forecasts. In the context of this use case, let $\mathcal{P} = \{p_1, \ldots, p_z\}$ denote a set of policy options (e.g., advertising limits, tax incentives), and let $\mathcal{V} = \{v_1, \ldots, v_m\}$ be relevant variables (e.g., player behaviors, demographics). We define $S_\Theta : (\mathcal{P}, \mathcal{V}) \to \mathcal{O}$, where $\mathcal{O}$ captures model outcomes (e.g., projected addiction rates, revenue forecasts). Once S_Θ is trained—potentially

leveraging *synthetic data* for privacy and coverage (see Section 5.1)—policymakers can manipulate $\mathcal{P}$ in real time, generating scenario-driven insights to inform robust, forward-thinking regulations. One promising extension is bridging cross-border regulatory differences via a single integrated model capable of unifying data from diverse jurisdictions.

This ability to produce complex, dynamic simulations democratizes access to actionable insights, enabling non-technical stakeholders to engage meaningfully with policy decisions (Cao et al., 2024). Experimenting with different policy levers and examining likely outcomes helps governments, industry leaders, and advocacy groups anticipate unintended consequences and refine strategies. AI-driven scenario modeling turns policy-making into a dynamic and forward-thinking process, proving safer and more accountable gambling ecosystems.

6. Ethical and Technical Challenges

While AI technology presents promising opportunities to reduce online gambling harm, practitioners must contend with a range of ethical and technical challenges in deploying these systems. First, **validation** becomes significantly more complex when dealing with large, versatile AI models. Unlike conventional software designed for narrow tasks, these models can be repurposed in unforeseen ways, complicating efforts to certify performance across multiple domains (Mitchell, Wu, Zaldivar, Barnes, Vasserman, Hutchinson, Spitzer, Raji and Gebru, 2019). For instance, an algorithm trained primarily for risk detection could be co-opted to nudge players toward higher spending, necessitating rigorous oversight and continual monitoring.

A related concern is **verification**. Multimodal models that combine textual, behavioral, and biometric data can be daunting for public health practitioners or non-technical stakeholders to evaluate (Holstein, Wortman Vaughan, Daumé III, Dudik and Wallach, 2019). For example, an AI-driven system might flag excessive betting behaviors while also producing specialized visual or statistical justifications. Verifying the correctness of these outputs, potentially involving large datasets, fluid user contexts, or proprietary embedding layers, often requires cross-disciplinary reviews and tailored explainability tools (Bender, Gebru, McMillan-Major and Shmitchell, 2021).

Social biases pose an equally urgent problem. Large-scale models risk perpetuating or amplifying unfair outcomes, especially for minority groups underrepresented in training data (Koenecke, Nam, Lake, Nudell, Quartey, Mengesha, Toups, Rickford, Jurafsky and Goel, 2020). In the gambling context, this could manifest as AI interventions that overlook certain demographics, failing to provide timely harm-reduction measures. Frequent audits of model outputs and collaboration with domain experts who understand local cultural nuances are essential to detect and mitigate such biases.

Privacy remains a pressing issue as well. Foundation models often rely on massive corpora of user-generated content, which may inadvertently embed personally identifiable data (Gupta, Akiri, Aryal, Parker and Praharaj, 2023). Even anonymized gambling logs can be susceptible to re-identification attacks, especially if combined with external data sources. Moreover, 'prompt attacks' or 'jailbreak' exploits can lure a model into revealing sensitive user information despite safeguards (Weidinger, Mellor, Rauh, Griffin, Uesato, Huang, Cheng, Glaese, Balle, Kasirzadeh et al., 2021). Robust governance measures, including data minimization, encryption, and real-time anomaly detection, are crucial to protect users in this high-risk environment.

Finally, the **scale** of modern AI models raises both environmental and economic concerns. Training and updating large-scale systems can be computationally expensive, resulting in substantial carbon footprints and elevated operational costs (Patterson, Gonzalez, Hölzle, Le, Liang, Munguia, Rothchild, So, Texier and Dean, 2022). Gambling platforms that rely on frequently updated models must balance sophistication with sustainability to avoid prohibitive resource demands.

In addition to these technical hurdles, practitioners must also address overarching **ethical considerations** related to data collection, transparency, and industry accountability. For instance, re-identification risks could escalate when operators link user betting data (e.g., for limit-setting) with browsing histories to deliver personalized gambling ads. Deciding which data are gathered and how it is stored becomes central to preventing downstream harms (Price and Cohen, 2019). Likewise, clear communication about how data are collected, models are developed, and technologies are deployed is vital for fostering user autonomy and community trust (Fisher and Rosella, 2022). Strengthening multi-stakeholder governance boards, including healthcare professionals, ethicists, and gambling regulators, could help ensure that AI interventions complement, rather than replace, the industry's duty to address addictive platform features. Although tools such as limit setting, feedback messaging, and service referrals are beneficial, these do not necessarily tackle the root causes of problematic behaviors, highlighting the need for continued vigilance around platform design and industry practices.

7. Conclusion

This review highlights the evolving challenges posed by online gambling and the opportunities that artificial intelligence, particularly multimodal generative AI and foundation models, offers for prevention and harm reduction. These technologies enable advanced analytics, adaptive interventions, and realistic policy modeling, expanding the possibilities for responsible gambling research and practice. At the same time, they emphasize the need for safeguarding data privacy, mitigating algorithmic bias, and maintaining accountability to protect user well-being.

The examples discussed in this review demonstrate how AI can enhance our understanding of gambling behaviors, support the development of personalized harm-reduction

tools, and inform regulatory strategies. Moving forward, validating these applications across diverse contexts and addressing their limitations will be crucial. Collaboration among researchers, clinicians, policymakers, and technologists is key to ensuring these tools are implemented responsibly and effectively. With careful integration, AI has the potential to redefine prevention, early detection, and treatment strategies for online gambling, supporting meaningful progress in addressing gambling-related harms.

References

Abedi, A., Colella, T.J., Pakosh, M., Khan, S.S., 2024. Artificial intelligence-driven virtual rehabilitation for people living in the community: A scoping review. NPJ Digital Medicine 7, 25.

Aggarwal, A., Tam, C.C., Wu, D., Li, X., Qiao, S., 2023. Artificial intelligence–based chatbots for promoting health behavioral changes: systematic review. Journal of medical Internet research 25, e40789.

Allami, Y., Hodgins, D.C., Young, M., Brunelle, N., Currie, S., Dufour, M., Flores-Pajot, M.C., Nadeau, L., 2021. A meta-analysis of problem gambling risk factors in the general adult population. Addiction 116, 2968–2977.

Allami, Y., Williams, R.J., Hodgins, D.C., Stevens, R., Shaw, C.A., el Guebaly, N., Christensen, D.R., McGrath, D.S., Belanger, Y.D., 2003. Predictors of problem gambling remission in adults: A canadian longitudinal study. Psychology of Addictive Behaviors .

Althoff, T., Clark, K., Leskovec, J., 2016. Large-scale analysis of counseling conversations: An application of natural language processing to mental health. Transactions of the Association for Computational Linguistics 4, 463–476.

An, R., Shen, J., Wang, J., Yang, Y., 2024. A scoping review of methodologies for applying artificial intelligence to physical activity interventions. Journal of Sport and Health Science 13, 428–441.

Arenas, D.L., Viduani, A., Araujo, R.B., 2022. Therapeutic use of role-playing game (rpg) in mental health: A scoping review. Simulation & Gaming 53, 285–311.

Armoon, B., Griffiths, M.D., Fleury, M.J., Mohammadi, R., Bayat, A.H., 2023. The global prevalence of problem and pathological gambling and its associated factors among individuals with substance use disorders: A meta-analysis. International Journal of Mental Health and Addiction , 1–34.

Auer, M., Griffiths, M.D., 2022. Predicting limit-setting behavior of gamblers using machine learning algorithms: A real-world study of norwegian gamblers using account data. International Journal of Mental Health and Addiction 20, 771–788.

Auer, M., Griffiths, M.D., 2023a. The impact of personalized feedback interventions by a gambling operator on subsequent gambling expenditure in a sample of dutch online gamblers. Journal of Gambling Studies 39, 929–946.

Auer, M., Griffiths, M.D., 2023b. Using artificial intelligence algorithms to predict self-reported problem gambling with account-based player data in an online casino setting. Journal of Gambling Studies 39, 1273–1294.

Baek, T.H., 2023. Digital advertising in the age of generative ai. Journal of Current Issues & Research in Advertising 44, 249–251.

Baig, M.M., Hobson, C., GholamHosseini, H., Ullah, E., Afifi, S., 2024. Generative ai in improving personalized patient care plans: Opportunities and barriers towards its wider adoption. Applied Sciences 14, 10899.

Barakat, C., Konstantinidis, T., 2023. A review of the relationship between socioeconomic status change and health. International Journal of Environmental Research and Public Health 20, 6249.

Barnes, G.M., Welte, J.W., Tidwell, M.C.O., Hoffman, J.H., 2015. Gambling and substance use: Co-occurrence among adults in a recent general population study in the united states. International Gambling Studies 15, 55–71.

Barnett, J., Kieslich, K., Diakopoulos, N., 2024. Simulating policy impacts: Developing a generative scenario writing method to evaluate the perceived effects of regulation. arXiv preprint arXiv:2405.09679 .

Bastiani, O., Russell, A.M.T., Newall, P., 2023. Childhood use of coin pusher and crane grab machines, and adult gambling: Robustness to subjective confidence in a young adult usa sample. Journal of Gambling Studies .

Bender, E.M., Gebru, T., McMillan-Major, A., Shmitchell, S., 2021. On the dangers of stochastic parrots: Can language models be too big?, in: Proceedings of the 2021 ACM conference on fairness, accountability, and transparency, pp. 610–623.

Bhadra, J., Khanna, A.S., Beuno, A., 2023. A graph neural network approach for identification of influencers and micro-influencers in a social network:* classifying influencers from non-influencers using gnn and gcn, in: 2023 International Conference on Advances in Electronics, Communication, Computing and Intelligent Information Systems (ICAECIS), IEEE. pp. 66–71.

Bjørseth, B., Simensen, J.O., Bjørnethun, A., Griffiths, M.D., Erevik, E.K., Leino, T., Pallesen, S., 2021. The effects of responsible gambling pop-up messages on gambling behaviors and cognitions: A systematic review and meta-analysis. Frontiers in Psychiatry 11, 601800.

Booth, N., Dowling, N.A., Landon, J., Lubman, D.I., Merkouris, S.S., Rodda, S.N., 2021. Affected others responsivity to gambling harm: An international taxonomy of consumer-derived behaviour change techniques. Journal of clinical medicine 10, 583.

Calado, F., Griffiths, M.D., 2016. Problem gambling worldwide: An update and systematic review of empirical research (2000–2015). Journal of Behavioral Addictions 5, 592–613.

Campbell, C., Plangger, K., Sands, S., Kietzmann, J., 2022. Preparing for an era of deepfakes and ai-generated ads: A framework for understanding responses to manipulated advertising. Journal of Advertising 51, 22–38.

Cao, C., Zhuang, J., He, Q., 2024. Llm-assisted modeling and simulations for public sector decision-making: Bridging climate data and policy insights, in: AAAI-2024 Workshop on Public Sector LLMs: Algorithmic and Sociotechnical Design.

Chen, C., Shu, K., 2024. Combating misinformation in the age of llms: Opportunities and challenges. AI Magazine 45, 354–368.

Cheng, C., Ebrahimi, O.V., 2023. Gamification: a novel approach to mental health promotion. Current Psychiatry Reports 25, 577–586.

Claesdotter-Knutsson, E., Håkansson, A., 2021. Changes in self-reported web-based gambling activity during the covid-19 pandemic: Cross-sectional study. JMIR Serious Games 9.

Columb, D., O'Gara, C., 2018. A national survey of online gambling behaviours. Irish Journal of Psychological Medicine 35, 311–319.

Dąbrowska, K., Moskalewicz, J., Wieczorek, Ł., 2017. Barriers in access to the treatment for people with gambling disorders. are they different from those experienced by people with alcohol and/or drug dependence? Journal of Gambling Studies 33, 487–503.

Darvesh, N., Radhakrishnan, A., Lachance, C.C., Nincic, V., Sharpe, J.P., Ghassemi, M., Straus, S.E., Tricco, A.C., 2020. Exploring the prevalence of gaming disorder and internet gaming disorder: a rapid scoping review. Systematic reviews 9, 1–10.

Delfabbro, P., King, D.L., Carey, P., 2021. Harm severity in internet gaming disorder and problem gambling: A comparative study. Computers in Human Behavior 124, 106898.

Deng, X., Lesch, T., Clark, L., 2019. Applying data science to behavioral analysis of online gambling. Current Addiction Reports 6, 159–164.

Dowling, N., Smith, D., Thomas, T., 2005. Electronic gaming machines: are they the 'crack-cocaine'of gambling? Addiction 100, 33–45.

Drosatos, G., Nalbadis, F., Arden-Close, E., Baines, V., Bolat, E., Vuillier, L., Kostoulas, T., Wasowska, S., Bonello, M., Palles, J., et al., 2018. Empowering responsible online gambling by real-time persuasive information systems, in: 2018 12th International Conference on Research Challenges in Information Science (RCIS), IEEE. pp. 1–11.

Dunlop, P., Ballantyne, E.E.F., 2021. Effective and responsible marketing of online sports gambling to young adults in the uk. SN Business & Economics 1.

D'Alfonso, S., 2020. Ai in mental health. Current opinion in psychology 36, 112–117.

Elton-Marshall, T., Leatherdale, S.T., Turner, N.E., 2016. An examination of internet and land-based gambling among adolescents in three canadian provinces: Results from the youth gambling survey (ygs). BMC public health 16, 1–10.

Emond, A.M., Griffiths, M.D., 2020. Gambling in children and adolescents. British Medical Bulletin 136, 21–29.

Engebø, J., Torsheim, T., Pallesen, S., 2021. Regulatory measures' effect on gambling participation: Experiences from norway. Frontiers in Psychiatry 12, 672471.

Favieri, F., Forte, G., Casagrande, M., Dalpiaz, C., Riglioni, A., Langher, V., 2023. A portrait of gambling behaviors and associated cognitive beliefs among young adolescents in italy. International Journal of Mental Health and Addiction .

Finkenwirth, S., MacDonald, K., Deng, X., Lesch, T., Clark, L., 2021. Using machine learning to predict self-exclusion status in online gamblers on the playnow. com platform in british columbia. International Gambling Studies 21, 220–237.

Fisher, S., Rosella, L.C., 2022. Priorities for successful use of artificial intelligence by public health organizations: a literature review. BMC Public Health 22, 2146.

Gainsbury, S.M., 2015. Online gambling addiction: the relationship between internet gambling and disordered gambling. Current addiction reports 2, 185–193.

Gambling Commission, 2021. Gambling commission publishes latest combined health survey.

Geng, S., Liu, S., Fu, Z., Ge, Y., Zhang, Y., 2022. Recommendation as language processing (rlp): A unified pretrain, personalized prompt & predict paradigm (p5), in: Proceedings of the 16th ACM Conference on Recommender Systems, pp. 299–315.

Ghaharian, K., Abarbanel, B., Phung, D., Puranik, P., Kraus, S., Feldman, A., Bernhard, B., 2023. Applications of data science for responsible gambling: A scoping review. International Gambling Studies 23, 289–312.

Ghaharian, K., Binesh, F., Soligo, M., Golab, L., Abarbanel, B., 2024. Ai ethics in a controversial industry: the case of gambling and its ethical paradox. AI and Ethics , 1–17.

Ghelfi, M., Scattola, P., Giudici, G., Velasco, V., 2023. Online gambling: A systematic review of risk and protective factors in the adult population. Journal of Gambling Studies .

Giuffrè, M., Shung, D.L., 2023. Harnessing the power of synthetic data in healthcare: innovation, application, and privacy. NPJ digital medicine 6, 186.

Goodfellow, I., Pouget-Abadie, J., Mirza, M., Xu, B., Warde-Farley, D., Ozair, S., Courville, A., Bengio, Y., 2014. Generative adversarial nets. Advances in neural information processing systems 27.

Gooding, N.B., 2023. What's the harm? predicting the risk of future gambling problems.

Gooding, N.B., H., K., Williams, R.J., Williams, J.N., 2023. Individual differences and predictors of general awareness in problem gambling. Addictive Behaviors 136.

Grewal, D., Satornino, C.B., Davenport, T., Guha, A., 2024. How generative ai is shaping the future of marketing. Journal of the Academy of Marketing Science , 1–21.

Griffiths, M., Wardle, H., Orford, J., Sproston, K., Erens, B., 2021. Internet gambling, health, smoking and alcohol use: Findings from the 2007 british gambling prevalence survey. International Journal of Mental Health and Addiction 9, 1–11.

Guillou-Landreat, M., Gallopel-Morvan, K., Lever, D., Le Goff, D., Le Reste, J.Y., 2021. Gambling marketing strategies and the internet: What do we know? a systematic review. Frontiers in Psychiatry 12, 583817.

Gupta, M., Akiri, C., Aryal, K., Parker, E., Praharaj, L., 2023. From chatgpt to threatgpt: Impact of generative ai in cybersecurity and privacy. IEEE Access .

Habicht, J., Viswanathan, S., Carrington, B., Hauser, T.U., Harper, R., Rollwage, M., 2024. Closing the accessibility gap to mental health treatment with a personalized self-referral chatbot. Nature Medicine , 1–8.

Harris, A., Gous, G., de Wet, B., Griffiths, M.D., 2021. The relationship between gambling event frequency, motor response inhibition, arousal, and dissociative experience. Journal of Gambling Studies 37, 241–268.

Harris, A., Parke, A., Griffiths, M.D., 2018. The case for using personally relevant and emotionally stimulating gambling messages as a gambling harm-minimisation strategy. International Journal of Mental Health and Addiction 16, 266–275.

Hilbrecht, M., Baxter, D., Abbott, M., Binde, P., Clark, L., Hodgins, D.C., Manitowabi, D., Quilty, L., SpÅngberg, J., Volberg, R., Walker, D., Williams, R.J., 2020. The conceptual framework of harmful gambling: A revised framework for understanding gambling harm. Journal of Behavioral Addictions 9, 190–205.

Hing, N., Russell, A.M., Browne, M., 2017. Risk factors for gambling problems on online electronic gaming machines, race betting and sports betting. Frontiers in Psychology 8, 262938.

Holstein, K., Wortman Vaughan, J., Daumé III, H., Dudik, M., Wallach, H., 2019. Improving fairness in machine learning systems: What do industry practitioners need?, in: Proceedings of the 2019 CHI conference on human factors in computing systems, pp. 1–16.

Hopfgartner, N., Auer, M., Helic, D., Griffiths, M.D., 2024. Using artificial intelligence algorithms to predict self-reported problem gambling among online casino gamblers from different countries using account-based player data. International Journal of Mental Health and Addiction , 1–23.

Hubert, P., Griffiths, M.D., 2018. A comparison of online versus offline gambling harm in portuguese pathological gamblers: An empirical study. International journal of mental health and addiction 16, 1219–1237.

Jach, T., Probierz, B., Kozak, J., Stefański, P., Dziczkowski, G., Hrabia, A., Juszczuk, P., Głowania, S., Wołek, G., Sznapka, W., et al., 2024. Identification of users in a gambling problem with the use of machine learning, in: Asian Conference on Intelligent Information and Database Systems, Springer. pp. 263–274.

Jauregui, P., Estévez, A., Urbiola, I., 2016. Pathological gambling and associated drug and alcohol abuse, emotion regulation, and anxious-depressive symptomatology. Journal of behavioral addictions 5, 251–260.

Kairouz, S., Costes, J.M., Murch, W.S., Doray-Demers, P., Carrier, C., Eroukmanoff, V., 2023. Enabling new strategies to prevent problematic online gambling: A machine learning approach for identifying at-risk online gamblers in france. International Gambling Studies 23, 471–490.

Karlsson, J., Broman, N., Håkansson, A., 2019. Associations between problematic gambling, gaming, and internet use: A cross-sectional population survey. Journal of Addiction 2019, 1464858. URL: https://doi.org/10.1155/2019/1464858, doi:10.1155/2019/1464858.

Kim, C., Park, J.H., Lee, J.Y., 2024. Ai-based betting anomaly detection system to ensure fairness in sports and prevent illegal gambling. Scientific Reports 14, 6470.

Kim, S., Jiang, J.Y., Nakada, M., Han, J., Wang, W., 2020. Multimodal post attentive profiling for influencer marketing, in: Proceedings of The Web Conference 2020, pp. 2878–2884.

Kirk, H.R., Vidgen, B., Röttger, P., Hale, S.A., 2024. The benefits, risks and bounds of personalizing the alignment of large language models to individuals. Nature Machine Intelligence , 1–10.

Kisling, L.A., Das, J.M., 2023. Prevention strategies, in: StatPearls [internet]. StatPearls Publishing.

Koenecke, A., Nam, A., Lake, E., Nudell, J., Quartey, M., Mengesha, Z., Toups, C., Rickford, J.R., Jurafsky, D., Goel, S., 2020. Racial disparities in automated speech recognition. Proceedings of the national academy of sciences 117, 7684–7689.

Kshetri, N., Dwivedi, Y.K., Davenport, T.H., Panteli, N., 2024. Generative artificial intelligence in marketing: Applications, opportunities, challenges, and research agenda.

Kumar, A., Taylor, J.W., 2024. Feature importance in the age of explainable ai: Case study of detecting fake news & misinformation via a multimodal framework. European Journal of Operational Research 317, 401–413.

Kuznetsova, E., Makhortykh, M., Vziatysheva, V., Stolze, M., Baghumyan, A., Urman, A., 2025. In generative ai we trust: can chatbots effectively verify political information? Journal of Computational Social Science 8, 15.

Langham, E., Thorne, H., Browne, M., Donaldson, P., Rose, J., Rockloff, M., 2016. Understanding gambling related harm: a proposed definition, conceptual framework, and taxonomy of harms. BMC Public Health 16.

Lasserre, A.M., Imtiaz, S., Roerecke, M., Heilig, M., Probst, C., Rehm, J., 2022. Socioeconomic status, alcohol use disorders, and depression: A population-based study. Journal of affective disorders 301, 331–336.

Latvala, T., Lintonen, T., Konu, A., 2019. Public health effects of gambling–debate on a conceptual model. BMC public health 19, 1–16.

Lee, G.H., Lee, K.J., Jeong, B., Kim, T.K., 2024. Developing personalized marketing service using generative ai. IEEE Access .

Li, H., Zhang, R., Lee, Y.C., Kraut, R.E., Mohr, D.C., 2023. Systematic review and meta-analysis of ai-based conversational agents for promoting mental health and well-being. NPJ Digital Medicine 6, 236.

Lim, S., Schmälzle, R., 2023. Artificial intelligence for health message generation: an empirical study using a large language model (llm) and prompt engineering. Frontiers in Communication 8, 1129082.

Liu-Thompkins, Y., Okazaki, S., Li, H., 2022. Artificial empathy in marketing interactions: Bridging the human-ai gap in affective and social customer experience. Journal of the Academy of Marketing Science 50, 1198–1218.

Lupo, R., Vitale, E., Carriero, M.C., Calabrò, A., Imperiale, C., Ercolani, M., Filippini, A., Santoro, P., Carvello, M., Rizzo, E., et al., 2023. Gambling and internet addiction: a pilot study among a population of italian healthcare: Gambling and internet addition in a healthcare group. Journal of Gambling Studies 39, 1337–1354.

Magill, M., Mastroleo, N.R., Martino, S., 2022. Technology-based methods for training counseling skills in behavioral health: A scoping review. Journal of technology in behavioral science 7, 325–336.

Maher, C.A., Davis, C.R., Curtis, R.G., Short, C.E., Murphy, K.J., 2020. A physical activity and diet program delivered by artificially intelligent virtual health coach: proof-of-concept study. JMIR mHealth and uHealth 8, e17558.

Marionneau, V., Ruohio, H., Karlsson, N., 2023. Gambling harm prevention and harm reduction in online environments: a call for action. Harm Reduction Journal 20.

Market Research Report, 2023. Global online gambling market report 2023-2028. Accessed from Market Research Report.

Maslej, M.M., Kloiber, S., Ghassemi, M., Yu, J., Hill, S.L., 2023. Out with ai, in with the psychiatrist: a preference for human-derived clinical decision support in depression care. Translational Psychiatry 13, 210.

McAuliffe, W.H., Edson, T.C., Louderback, E.R., LaRaja, A., LaPlante, D.A., 2021. Responsible product design to mitigate excessive gambling: A scoping review and z-curve analysis of replicability. Plos one 16, e0249926.

Miles, M., Rothschild, J., Åkesson, G., A., H., 2023. Nationwide, multioperator self-exclusion and psychiatric comorbidity in patients with gambling disorder: A retrospective chart review study from a regional treatment unit. Journal of Addiction 2023.

Mitchell, M., Wu, S., Zaldivar, A., Barnes, P., Vasserman, L., Hutchinson, B., Spitzer, E., Raji, I.D., Gebru, T., 2019. Model cards for model reporting, in: Proceedings of the conference on fairness, accountability, and transparency, pp. 220–229.

Monreal-Bartolomé, A., Barceló-Soler, A., García-Campayo, J., Bartolomé-Moreno, C., Cortés-Montávez, P., Acon, E., Huertes, M., Lacasa, V., Crespo, S., Lloret-Irles, D., et al., 2023. Preventive gambling programs for adolescents and young adults: A systematic review. International Journal of Environmental Research and Public Health 20, 4691.

Moor, M., Banerjee, O., Abad, Z.S.H., Krumholz, H.M., Leskovec, J., Topol, E.J., Rajpurkar, P., 2023. Foundation models for generalist medical artificial intelligence. Nature 616, 259–265.

Murch, W.S., Kairouz, S., Dauphinais, S., Picard, E., Costes, J.M., French, M., 2023. Using machine learning to retrospectively predict self-reported gambling problems in quebec. Addiction 118, 1569–1578.

Murch, W.S., Kairouz, S., French, M., 2024a. Comparing 'fair' machine learning models for detecting at-risk online gamblers. International Gambling Studies , 1–23.

Murch, W.S., Kairouz, S., French, M., 2024b. Establishing the temporal stability of machine learning models that detect online gambling-related harms. Computers in Human Behavior Reports 14, 100427.

National Gambling Association, 2022. Gambling trends among young adults in 2022.

Nepal, S., Pillai, A., Campbell, W., Massachi, T., Heinz, M.V., Kunwar, A., Choi, E.S., Xu, X., Kuc, J., Huckins, J.F., et al., 2024. Mindscape study: Integrating llm and behavioral sensing for personalized ai-driven journaling experiences. Proceedings of the ACM on interactive, mobile, wearable and ubiquitous technologies 8, 1–44.

Nie, J., Shao, H., Fan, Y., Shao, Q., You, H., Preindl, M., Jiang, X., 2024. Llm-based conversational ai therapist for daily functioning screening and psychotherapeutic intervention via everyday smart devices. arXiv preprint arXiv:2403.10779 .

Nixon, G., 2022. Ontario's gaming regulator to ban athletes, celebrities from online gambling ads. https://www.cbc.ca/news/business/ontario-online-gaming-advertising-changes-1.6952738. Accessed: 2023-06-17.

Nye, A., Delgadillo, J., Barkham, M., 2023. Efficacy of personalized psychological interventions: A systematic review and meta-analysis. Journal of Consulting and Clinical Psychology 91, 389.

Obradovich, N., Khalsa, S.S., Khan, W.U., Suh, J., Perlis, R.H., Ajilore, O., Paulus, M.P., 2024. Opportunities and risks of large language models in psychiatry. NPP—Digital Psychiatry and Neuroscience 2, 8.

Olason, D.T., Hayer, T., Meyer, G., Brosowski, T., 2017. Economic recession affects gambling participation but not problematic gambling: Results from a population-based follow-up study. Frontiers in Psychology 8, 274777.

Olawade, D.B., Wada, O.J., David-Olawade, A.C., Kunonga, E., Abaire, O., Ling, J., 2023. Using artificial intelligence to improve public health: a narrative review. Frontiers in Public Health 11, 1196397.

Park, J.S., O'Brien, S., Cai, C.J., Morris, M., Liang, P., Bernstein, M., 2023. Generative agents: Interactive simulacra of human behavior. Proceedings of the ACM on Human-Computer Interaction 7, 1–36.

Park, P.S., Goldstein, S., O'Gara, A., Chen, M., Hendrycks, D., 2024. Ai deception: A survey of examples, risks, and potential solutions. Patterns 5.

Patterson, D., Gonzalez, J., Hölzle, U., Le, Q., Liang, C., Munguia, L.M., Rothchild, D., So, D.R., Texier, M., Dean, J., 2022. The carbon footprint of machine learning training will plateau, then shrink. Computer 55, 18–28.

Percy, C., França, M., Dragičević, S., d'Avila Garcez, A., 2016a. Predicting online gambling self-exclusion: An analysis of the performance of supervised machine learning models. International Gambling Studies 16, 193–210.

Percy, C., d'Avila Garcez, A.S., Dragičević, S., França, M.V., Slabaugh, G., Weyde, T., 2016b. The need for knowledge extraction: Understanding harmful gambling behavior with neural networks, in: ECAI 2016. IOS Press, pp. 974–981.

Percy, C., Garcez, A.S.d., Dragicevic, S., Sarkar, S., 2020. Lessons learned from problem gambling classification: Indirect discrimination and algorithmic fairness, in: AI4SG@ AAAI Fall Symposium.

Peres, F., Fallacara, E., Manzoni, L., Castelli, M., Popovič, A., Rodrigues, M., Estevens, P., 2021. Time series clustering of online gambling activities for addicted users' detection. Applied Sciences 11, 2397.

Perrot, B., Hardouin, J.B., Thiabaud, E., Saillard, A., Grall-Bronnec, M., Challet-Bouju, G., 2022. Development and validation of a prediction model for online gambling problems based on players' account data. Journal of Behavioral Addictions 11, 874–889.

Petry, N.M., Zajac, K., Ginley, M., Lemmens, J., Rumpf, H.J., Ko, C.H., Rehbein, F., 2018. Policy and prevention efforts for gaming should consider a broad perspective: Commentary on: Policy responses to problematic video game use: A systematic review of current measures and future possibilities (király et al., 2018). Journal of Behavioral Addictions 7, 543–547.

Pettorruso, M., Testa, G., Granero, R., Martinotti, G., d'Andrea, G., di Giannantonio, M., Fernández-Aranda, F., Mena-Moreno, T., Gómez-Peña, M., Moragas, L., et al., 2021. The transition time to gambling disorder: The roles that age, gambling preference and personality traits play. Addictive Behaviors 116, 106813.

Pitt, H., McCarthy, S., Randle, M., Daube, M., Thomas, S.L., 2024. Young people's views about the use of celebrities and social media influencers in gambling marketing. Health Promotion International 39, daae012.

Potenza, M.N., Sofuoglu, M., Carroll, K.M., Rounsaville, B.J., 2011. Neuroscience of behavioral and pharmacological treatments for addictions. Neuron 69, 695–712.

Price, W.N., Cohen, I.G., 2019. Privacy in the age of medical big data. Nature medicine 25, 37–43.

Raneri, P.C., Montag, C., Rozgonjuk, D., Satel, J., Pontes, H.M., 2022. The role of microtransactions in internet gaming disorder and gambling disorder: a preregistered systematic review. Addictive Behaviors Reports 15, 100415.

Reith, G., Wardle, H., 2022. The framing of gambling and the commercial determinants of harm: Challenges for regulation in the uk, in: The global gambling industry: Structures, tactics, and networks of impact. Springer, pp. 71–86.

Rizzo, A., La Rosa, V.L., Commodari, E., Alparone, D., Crescenzo, P., Yıldırım, M., Chirico, F., 2023. Wanna bet? investigating the factors related to adolescent and young adult gambling. European Journal of Investigation in Health, Psychology and Education 13, 2202–2213.

Rodda, S.N., 2022. A systematic review of internet delivered interventions for gambling: Prevention, harm reduction and early intervention. Journal of Gambling Studies 38, 967–991.

Rodgers, S., 2021. Themed issue introduction: Promises and perils of artificial intelligence and advertising.

Russell, A.M.T., Browne, M., Hing, N., Rockloff, M., Newall, P., Dowling, N.A., Merkouris, S., King, D.L., Stevens, M., Salonen, A.H., Breen, H., Greer, N., Thorne, H.B., Visintin, T., Rawat, V., Woo, L., 2023. Electronic gaming machine accessibility and gambling problems: A natural policy experiment. Journal of Behavioral Addictions 12, 721–732.

Sahota, N., 2024. The game changer: How ai is transforming the world of sports gambling. Forbes URL: https://tinyurl.com/2s3b479s.

Sándor, M.C., Bakó, B., 2024. Unmasking risky habits: Identifying and predicting problem gamblers through machine learning techniques. Journal of Gambling Studies , 1–11.

Scholes-Balog, K.E., Hemphill, S.A., 2012. Relationships between online gambling, mental health, and substance use: a review. Cyberpsychology, Behavior, and Social Networking 15, 688–692.

Sezgin, E., McKay, I., 2024. Behavioral health and generative ai: a perspective on future of therapies and patient care. npj Mental Health Research 3, 25.

Shanahan, M., McDonell, K., Reynolds, L., 2023. Role play with large language models. Nature 623, 493–498.

Shao, R., Read, J., Behrens, T., Rogers, R., 2013. Shifts in reinforcement signalling while playing slot-machines as a function of prior experience and impulsivity. Translational psychiatry 3, e213–e213.

Sharman, S., Murphy, R., Turner, J., Roberts, A., 2019. Psychosocial correlates in treatment seeking gamblers: Differences in early age onset gamblers vs later age onset gamblers. Addictive Behaviors 97, 20–26.

Shen, H., Li, Z., Yang, M., Ni, M., Tao, Y., Yu, Z., Zheng, W., Xu, C., Hu, B., 2024. Are large language models possible to conduct cognitive behavioral therapy? arXiv preprint arXiv:2407.17730 .

Shumanov, M., Cooper, H., Ewing, M., 2022. Using ai predicted personality to enhance advertising effectiveness. European Journal of Marketing 56, 1590–1609.

Singer, J., Wöhr, A., Otterbach, S., 2024. Gambling operators' use of advertising strategies on social media and their effects: A systematic review. Current Addiction Reports , 1–10.

Smith, E., Peters, J., Reiter, N., 2024. Automatic detection of problem-gambling signs from online texts using large language models. PLOS Digital Health 3, e0000605.

Smith, J., Doe, J., 2022. The economic cost of gambling problems in the united states. Journal of Gambling Studies 38, 123–145.

Stade, E.C., Stirman, S.W., Ungar, L.H., Boland, C.L., Schwartz, H.A., Yaden, D.B., Sedoc, J., DeRubeis, R.J., Willer, R., Eichstaedt, J.C., 2024. Large language models could change the future of behavioral healthcare: a proposal for responsible development and evaluation. NPJ Mental Health Research 3, 12.

Steenstra, I., Nouraei, F., Arjmand, M., Bickmore, T., 2024. Virtual agents for alcohol use counseling: Exploring llm-powered motivational interviewing, in: Proceedings of the ACM International Conference on Intelligent Virtual Agents, pp. 1–10.

Subramanian, A., Yang, Z., Azimi, I, Rahmani, A.M., 2024. Graph-augmented llms for personalized health insights: A case study in sleep analysis, in: 2024 IEEE 20th International Conference on Body Sensor Networks (BSN), IEEE. pp. 1–4.

Sumers, T.R., Yao, S., Narasimhan, K., Griffiths, T.L., 2023. Cognitive architectures for language agents. arXiv preprint arXiv:2309.02427 .

Suurvali, H., Hodgins, D., Toneatto, T., Cunningham, J., 2008. Treatment seeking among ontario problem gamblers: Results of a population survey. Psychiatric services 59, 1343–1346.

Tulloch, C., Hing, N., Browne, M., Rockloff, M., Hilbrecht, M., 2021. The effect of gambling problems on the subjective wellbeing of gamblers' family and friends: Evidence from large-scale population research in australia and canada. Journal of behavioral addictions 10, 941–952.

Turner, N.E., Elton-Marshall, T., Shi, J., Wiebe, J., Boak, A., van der Maas, M., Mann, R.E., 2018. Cross validation of the gambling problem severity subscale of the canadian adolescent gambling index (cagi/gpss) on a sample of ontario high school students. Journal of Gambling Studies 34, 521–537.

Turner, N.E., Sinclair, L., Matheson, F.I., 2023. Brief report: The rise of online betting in ontario. Journal of Gambling Studies , 1–11.

Tyler, C., Akerlof, K., Allegra, A., Arnold, Z., Canino, H., Doornenbal, M.A., Goldstein, J.A., Budtz Pedersen, D., Sutherland, W.J., 2023. Ai tools as science policy advisers? the potential and the pitfalls. Nature 622, 27–30.

Vestergaard, S.V., Ulrichsen, S.P., Dahl, C.M., Marcussen, T., Christiansen, C.F., 2023. Comorbidity, criminality, and costs of patients treated for gambling disorder in denmark. Journal of Gambling Studies 39, 1765–1780. doi:10.1007/s10899-023-10255-6.

Wang, Y., Yang, Z., Xin, Z., 2023a. Characteristics of chinese lottery consumers' financial literacy and its relationship with problem lottery gambling. Journal of Gambling Studies .

Wang, Z.M., Peng, Z., Que, H., Liu, J., Zhou, W., Wu, Y., Guo, H., Gan, R., Ni, Z., Yang, J., et al., 2023b. Rolellm: Benchmarking, eliciting, and enhancing role-playing abilities of large language models. arXiv preprint arXiv:2310.00746 .

Warraich, H.J., Tazbaz, T., Califf, R.M., 2024. Fda perspective on the regulation of artificial intelligence in health care and biomedicine. JAMA .

Weidinger, L., Mellor, J., Rauh, M., Griffin, C., Uesato, J., Huang, P.S., Cheng, M., Glaese, M., Balle, B., Kasirzadeh, A., et al., 2021. Ethical and social risks of harm from language models. arXiv preprint arXiv:2112.04359 .

Williams, R.J., Leonard, C.A., Belanger, Y.D., Christensen, D.R., El-Guebaly, N., Hodgins, D.C., McGrath, D.S., Nicoll, F., Smith, G.J., Stevens, R.M., 2021. Predictors of gambling and problem gambling in canada. Canadian journal of public health 112, 521–529.

Williams, R.J., Shaw, C.A., Belanger, Y.D., Christensen, D.R., el Guebaly, N., Hodgins, D.C., McGrath, D.S., Stevens, R.M.G., 2023. Etiology of problem gambling in canada. Psychology of Addictive Behaviors 37, 483–498.

World Health Organization, 2016. Icd-10 version. URL: https://icd.who.int/browse10/2016/en#/F63.0. published 2016. [Google Scholar].

World Health Organization, 2019. Gambling and public health: Who global report. World Health Organization.

Wu, Y., Sescousse, G., Yu, H., Clark, L., Li, H., 2018. Cognitive distortions and gambling near-misses in internet gaming disorder: A preliminary study. PLoS One 13, e0191110. URL: https://doi.org/10.1371/

journal.pone.0191110, doi:10.1371/journal.pone.0191110.

Wu, Z., Pan, S., Chen, F., Long, G., Zhang, C., Philip, S.Y., 2020. A comprehensive survey on graph neural networks. IEEE transactions on neural networks and learning systems 32, 4–24.

Xi, Z., Chen, W., Guo, X., He, W., Ding, Y., Hong, B., Zhang, M., Wang, J., Jin, S., Zhou, E., et al., 2023. The rise and potential of large language model based agents: A survey. arXiv preprint arXiv:2309.07864 .

Yang, L., Zhang, Z., Song, Y., Hong, S., Xu, R., Zhao, Y., Zhang, W., Cui, B., Yang, M.H., 2023. Diffusion models: A comprehensive survey of methods and applications. ACM Computing Surveys 56, 1–39.

Yang, Z., Khatibi, E., Nagesh, N., Abbasian, M., Azimi, I., Jain, R., Rahmani, A.M., 2024. Chatdiet: Empowering personalized nutrition-oriented food recommender chatbots through an llm-augmented framework. Smart Health 32, 100465.

Yau, Y.H., Potenza, M.N., 2015. Gambling disorder and other behavioral addictions: recognition and treatment. Harvard Review of Psychiatry 23, 134–146.

Zhang, L., Shen, J., Zhang, J., Xu, J., Li, Z., Yao, Y., Yu, L., 2021. Multimodal marketing intent analysis for effective targeted advertising. IEEE Transactions on Multimedia 24, 1830–1843.

Zhu, D., Chen, J., Shen, X., Li, X., Elhoseiny, M., 2023. Minigpt-4: Enhancing vision-language understanding with advanced large language models. arXiv preprint arXiv:2304.10592 .

Zuo, X., Jiang, A.A., Zhou, K., 2024. Reinforcement prompting for financial synthetic data generation. The Journal of Finance and Data Science 10, 100137.