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Deep technologies and safer gambling: A systematic review

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ABSTRACT

Deep technologies combine engineering innovation and scientific findings to solve complex problems and are becoming particularly relevant to the gambling industry. With the global rise of gambling practices and the subsequent increase of gambling-related problems and disorders, deep technologies have emerged as a way to create safer online gambling environments. However, there is still limited knowledge regarding their applicability and consequences. The present study systematically reviewed the existing literature on deep technologies in gambling environments, such as online casinos and betting platforms, and explored their potential benefits, risks, and effectiveness in promoting safer gambling experiences. This review followed the Preferred Reporting Items for Systematic Reviews and Meta-analysis (PRISMA) guidelines. Searches were conducted in *Web of Science, PubMed, Scopus, EBSCO,* and *IEEE* databases, and manually. A total of sixty-eight studies were included in the review. In general, four primary applications of deep technologies in online settings were found: (i) behavioural monitoring and feedback; (ii) predictive risk modelling; (iii) decision support and AI classifiers; and (iv) limit-setting/self-exclusion tools. They were primarily used to identify and classify problematic gambling, prompt individual action, regulate gambling behaviours, raise awareness of risk levels, promote responsible gambling practices, support research, interventions, and evaluate player protection initiatives. Together, the findings suggest that deep technologies offer ample opportunities to enhance gambler safety and reduce potential risks, although challenges may arise from their implementation, such as privacy and ethical concerns, malicious data use, misclassification of risk levels, and difficulties in large-scale application. Limitations and directions for future studies are discussed.

1. Introduction

Over the past decade, the technology industry has advanced significantly, driving greater digitalization and dependence on innovative solutions. Technology has become embedded in daily life, from household routines to professional and leisure domains (Paul et al., 2024; Polyakova et al., 2024). Likewise, the gambling market has also transitioned to the digital world, which offers users greater accessibility, a wider range of options, and a more personalized experience (e.g., Ghelfi et al., 2023).

Online gambling has become a popular digital recreational activity, captivating an estimated 224.1 million gamblers worldwide (Statista, n.d; Calado & Griffiths, 2016; Tran et al., 2024). Gambling platforms immerse users with a range of environmental stimuli, such as bright visuals, engaging sounds, and immediate rewards, which while enhancing user engagement can also reinforce harmful gambling

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behaviours (Dores et al., 2020; Johnson et al., 2023; Palmer et al., 2024). Conversely, problematic gambling has also increased, potentially driven by the use of online gambling products (Ghelfi et al., 2023; Kesaite et al., 2024; Tran et al., 2024).

Responses to mitigate gambling-related harm have mostly fallen within the responsible gambling paradigm, which emphasizes individual self-control and voluntary initiatives (e.g., self-exclusion, limit-setting, personalized feedback) rather than addressing the structural features of gambling environments (Wardle et al., 2024). However, this approach has been criticized by some as industry-friendly because it risks shifting responsibility from operators and regulators to individuals (Wardle et al., 2024). By contrast, a public health perspective highlights population-level strategies and mandatory safeguards, situating gambling harm prevention alongside other regulated domains such as alcohol and tobacco (Wardle et al., 2024). Within this context, deep technologies (henceforth referred to as 'deep tech') might play a central role in fostering safer environments by driving the rapid evolution of gambling platforms towards increasingly interactive, customisable, and potentially protective user experiences (TechWorks, n.d.; Peirce, 2022; Robinson et al., 2021).

1.1. Technological innovations and applications

Deep tech is a transversal, multidimensional concept that lacks a universally accepted definition within the scientific literature. Originating from the innovative start-up ecosystem, the term was initially used to describe ventures based on cutting-edge scientific discoveries and advanced engineering (Apodaca et al., 2023). Common examples include artificial intelligence, machine learning, natural language processing, predictive analytics, biometric systems, and other advanced inference techniques (TechWorks, n.d.; Robinson et al., 2021).

Currently, gambling companies tend to employ deep tech to maximize revenue, optimize product options, and enhance player engagement (Chao et al., 2021; Galekwa et al., 2024; Hassanniakalager & Newall, 2019; Tondello et al., 2017). For example, machine learning can help predict trends to develop more engaging games and tailor player profiles for targeted marketing campaigns (Hassanniakalager & Newall, 2019; Tondello et al., 2017). On the other hand, these technologies can support responsible gambling through real-time monitoring, identification of harm signs, and personalized interventions (Drosatos et al., 2018; Ghaharian, Binesh, et al., 2024; Van Baal et al., 2024).

1.2. Problematic gambling behaviours and responsible gambling

Problematic gambling denotes a spectrum of harmful gambling habits that negatively affect a person's life while not necessarily meeting the requirements for a clinical diagnosis (Neal et al., 2005). It characterizes the individual in terms of the severity of their gambling-related behaviours and the degree of their risk (Gambling Commission, 2020). These patterns emerge through an interplay of individual predispositions and platform characteristics designed to sustain engagement (Allami et al., 2021; Brand et al., 2019; Gainsbury, 2015; Strømme et al., 2021), such as near-wins (Dores et al., 2020), high event frequencies and speed of play (Harris & Griffiths, 2018), personalised notifications (Palmer et al., 2024), and gamified elements (Johansson et al., 2009). These features are oftentimes intentionally developed to provoke strong emotional reactions, such as excitement or relief (Johnson et al., 2023; Palmer et al., 2024). Moreover, cognitive distortions seem to potentiate the perpetuation of gambling behaviours and deter individuals from ceasing their playing, even after significant financial losses (Johansson et al., 2009; Wu & Clark, 2024). Common examples include erroneous perceptions, illusions of control, and the gambler's fallacy, in which beliefs about the probability of winning are influenced by previous outcomes (Barron & Leider, 2010; Palmer et al., 2024).

Over time, motivation may shift from reward-seeking to a more automatic and compensatory pattern, wherein gambling increasingly serves to alleviate negative emotional states, such as stress, anxiety, or guilt associated with previous losses (Brand et al., 2019). This gradual loss of control marks the transition from recreational to problematic gambling and may ultimately culminate in gambling disorder (Brand et al., 2019), which is clinically recognized as a behavioural addiction (American Psychiatric Association [APA], 2022; American Psychiatric Association [APA], 2023; World Health Organization [WHO], 2024).

Although addressing gambling disorder is crucial, harmful but subclinical gambling also warrants intervention (e.g., Harris & Griffiths, 2017; Sulkunen et al., 2021) given its impact on social relationships, financial stability, and mental health (Moreira et al., 2024; Office for Health, Improvement, & Disparities, 2023; WHO, 2024). To date, most preventive measures partly rely on voluntary actions, such as self-exclusion (Moreira et al., 2024), limit-setting, and cool-off periods (e.g., Andrade et al., 2023). However, these approaches often suffer from low uptake and a lack of long-term effectiveness (Bijker et al., 2023; Gainsbury, 2015; Kraus et al., 2024), particularly in online settings where anonymity undermines commitment and can facilitate relapse (Bijker et al., 2023; Håkansson & Komzia, 2023). Additionally, the inadequacy, unavailability, and lack of awareness of these tools hinders their effectiveness (Andrade et al., 2023; Håkansson & Komzia, 2023; Motka et al., 2018).

Preventive measures are therefore critical to mitigating progression from hazardous to disordered gambling, with responsible gambling initiatives seeking to promote safer practices through policies, tools, and guidelines (Blaszczynski et al., 2022). In the online setting, however, their success remains limited. This is particularly due to the overreliance on individual initiative for activating responsible gambling tools, the potentiation of harmful playing habits in this environment, and the exposure of users to targeted advertising that reinforces risk (Singer et al., 2024; Torrance et al., 2021). For this reason, it is crucial to develop mechanisms capable of proactively and effectively identifying and addressing risk factors (e.g., Marionneau et al., 2023).

1.3. The present study

Deep tech presents a promising opportunity to prevent, early detect, and intervene in problematic gambling behaviours. As online gambling platforms evolve and integrate new technological capabilities, safeguarding users becomes increasingly urgent and more complex. For instance, Andrade et al. (2023) conducted a content analysis of 40 cryptocurrency-based online gambling operators, highlighting significant gaps in consumer protection within technologically advanced and often poorly regulated gambling contexts.

As aforementioned, the ambivalence in the conceptualisation of deep tech leaves room for differing interpretations among the scientific community. In the present review, a pragmatic operational definition of deep tech was adopted, tailored to the gambling context. Here deep tech refers to computational approaches that integrate algorithmic modelling and/or intelligent automation within online gambling platforms to monitor, predict, or intervene in risk behaviours. This framing excludes purely descriptive or standard statistical analyses unless embedded within automated or real-time systems, thereby maintaining conceptual clarity while reflecting the technologies currently implemented in gambling environments.

Prior reviews have touched upon this subject by consolidating and assessing patterns, technologies, and intervention outcomes in gambling across multiple studies. These focused on summarizing existing data-driven science-based applications and models for predicting and identifying problematic gambling (Delfabbro and King, 2021; Delfabbro et al., 2023; Marionneau et al., 2025; Rodda, 2021; Škařupová et al., 2020), exploring the strategies implemented to promote responsible gambling practices (Ghaharian, Abarbanel, Phung, et al., 2023; Škařupová et al., 2020), and understanding how behavioural analysis can serve to develop gambling products with effective player protection tools (Chagas & Gomes, 2017). Although of relevance, these reviews leave unanswered questions about how diverse technological innovations intersect, how they align with both responsible gambling and public health approaches, and how they connect with emerging regulatory and ethical debates. Therefore, the present study extends this body of work by analysing the literature in a more comprehensive and up-to-date systematic review of deep tech in gambling, grounded in a broader conceptualisation of the term.

Overall, the present systematic review aimed to summarize the literature from the past decade in respect to the applications of deep tech in the context of gambling, particularly in preventing, detecting, and mitigating harm. The study was guided by one main research question: What are the current, potential, and key factors promoting the implementation of deep tech in gambling? While two other questions served as support for evaluating and exploring this topic: (i) What opportunities arise, and what are the risks associated with the use of deep tech in gambling?; and (ii) How effective and reliable is deep tech in preventing, detecting at-risk individuals, identifying problematic gambling behaviours, and designing and promoting interventions?.

2. Methods

The present systematic review was conducted in accordance with the Preferred Systematic Review and Meta-analysis (PRISMA 2020; Page et al., 2021) guidelines, and the research protocol was pre-registered in PROSPERO (CRD1049386) on February 24, 2025.

2.1. Eligibility criteria

The inclusion criteria encompassed peer-reviewed empirical studies that explicitly addressed deep tech implementation for identifying or mitigating risky gambling behaviours. To be considered, the applications had to be with participants aged 18 years or older and rely on technology-driven approaches that either: (i) relied on collected behavioural data from users (e.g., session tracking, wagers, frequency of play); (ii) employed advanced computational techniques (e.g., neural networks, decision tree models, clustering, logistic regression applied to large datasets); or (iii) implemented automated or real-time interventions (e.g., personalized messages triggered by risk classification). Additionally, studies must have been published in a peer-reviewed journal from January 2015 onward, in one of the following languages spoken by the research team: English, French, Italian, or Portuguese.

Studies were excluded if they were literature reviews, meta-analyses, or case studies, as well as non-research publications, including editorials, dissertations, commentaries, and book chapters. Also, purely informative/descriptive analysis, manual tools (such as general educational content), and clinical interventions not incorporating a technological interface, were not included in the review.

2.2. Information sources and search strategy

The search was conducted between December 10 and 17, 2024, using the following databases: *PubMed* (with the entire string and with MeSH terms only), *Web of Science, Scopus, EBSCO,* and *IEEE* (via b-on). Additionally, studies were identified through a manual search and by reviewing the reference lists of included studies, on January 11 and May 17, 2025.

The search string was structured around three main categories: (i) deep tech-related terms; (ii) gambling-related terminology; and (iii) intervention strategies. The search expression was used in titles and abstracts – (*"artificial intelligence" OR "AI" OR "deep tech*" OR "machine learning" OR "deep learning" OR biometrics OR "behavi?r* analy*" OR "behavi?r* tracking" OR "data analy*" OR* "log-data" *OR "account data" OR "account-based tracking data" OR "digital profiling" OR "user profiling" OR "pattern recognition" OR "predict* model*" OR "predict* analy*" OR "algorithm*" OR ANN OR "decision tree") AND (gambling OR gamblers OR betting OR casino) AND (prevention OR "early detection" OR "risk management" OR "harm prevention" OR "preventive measure*" OR "personali?ed intervention*" OR "personali?ed treatment*" OR "personali?ed feedback*" OR "intervention strateg*" OR "brief intervention" OR "responsible gambling" OR "limit setting" OR "pop-up message*" OR regulation* OR education OR protection) NOT ("emotion regulation" OR "drug use*" OR "substance use*" OR "substance abuse" OR "drug addiction" OR "alcohol*"*).

2.3. Selection process

The third and fourth authors independently screened the titles and abstracts of all selected articles. The selection of studies for full-text analysis was conducted by two independent reviewers, following the PRISMA recommendations (Lefebvre et al., 2024). Both reviewers applied inclusion and exclusion criteria to each record during the selection process. After completing their assessments, they compared their decisions and discussed discrepancies. If a consensus could not be reached, the second author was consulted for a final decision.

2.4. Data extraction

An Excel sheet was created with the information to be extracted from the included studies: (i) deep tech type, characteristics and purpose; (ii) study and sample information (research design, source and time of collection, data characteristics, statistical analysis); (iii) overall results and implications; and (iv) promoting factors, challenges, opportunities and risks of the deep tech.

2.5. Risk of bias assessment

The risk of bias was assessed using the Quality Appraisal for Diverse Studies (QuADS; Harrison et al., 2021) criteria, which serves to evaluate heterogeneous studies from various fields (e.g., psychology, health science). This tool comprises 13 topics, presenting a high inter-rater reliability ($k = 0.65$). The scoring is done in a 0-to-3-point system, where higher values represent higher methodological quality (maximum of 39 points). The first and second authors independently evaluated approximately half of the included studies, followed by an additional five studies assessed by the other author. The scores for the ten studies evaluated simultaneously were compared, and any differences were discussed by both researchers. The final scores were either identical or differed by only one point, and it was agreed that both researchers had evaluated the studies consistently.

3. Results

3.1. Study selection

Fig. 1 presents the full study selection process. The electronic search identified a total of 1229 records, from which 486 were duplicates. All articles were first screened by their title and abstract ($n = 743$) for inclusion, and the agreement between researchers was substantial ($k = 0.76$; Landis & Koch, 1977). From those, 67 articles were screened by their full text, leaving 43 eligible studies. The manual search resulted in the screening of 64 more articles, from which 25 were included. Therefore, data were extracted from a total of 68 studies.

3.2. Study characteristics

Most of the data of the included studies originated from European countries ($n = 34$, 50.00 %). Norway ($n = 11$, 16.18 %) was the major provider, followed by the United Kingdom and France (each, $n = 6$, 8.82 %), then by Canada and Finland (each, $n = 4$, 5.88 %), Sweden ($n = 3$, 4.41 %), Australia, the United States of America and the Netherlands (each, $n = 2$, 2.94 %), and finally by Switzerland, Germany, New

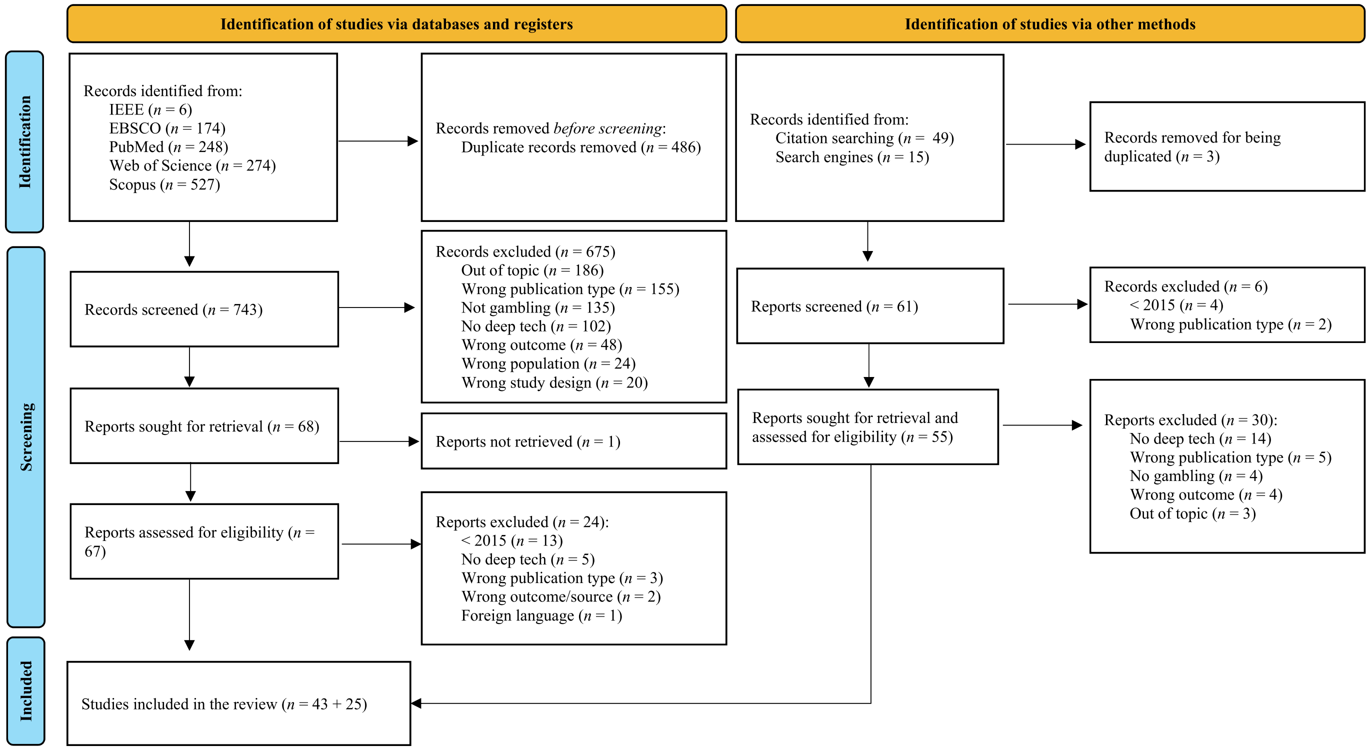

Fig. 1. PRISMA 2020 flow diagram for new systematic reviews which included searches of databases, registers and other sources. Source: Page MJ, et al. BMJ 2021;372:n71. doi: https://doi.org/10.1136/bmj.n71. This work is licensed under CC BY 4.0. To view a copy of this license, visit https://creativecommons.org/licenses/by/4.0/

Zealand and Japan (each, $n = 1$, 1.47 %). Ten of the included studies (14.71 %) analysed data from multiple countries, while 14 (20.59 %) did not report the country of origin.

The majority of the research ($n = 64$, 94.12 %) comprised behavioural data from individuals engaged in gambling activities. Participants were typically classified as average gamblers ($n = 53$, 77.94 %), and then as self-excluders ($n = 2$, 2.94 %), limit-setters ($n = 1$, 1.47 %) or actively seeking support/help for gambling-related issues ($n = 1$, 1.47 %). Seven studies (8.82 %) adopted experimental or comparative designs that explored contrasts between specific groups. These juxtaposed individuals who had self-excluded from gambling with non-problematic gamblers (Haefeli et al., 2015; Percy et al., 2016), and disordered gamblers with either university students (Cerasa et al., 2018) or individuals from the community (Takeuchi et al., 2022). Two studies specified the analysed data to gambling sessions (Auer & Griffiths, 2015a), or betting odds and results (Hassanniakalager & Newall, 2019), while the remaining only included university students who were not necessarily gamblers (Mueller et al., 2022).

Across the 64 studies analysing gamblers, data were collected from a total of 1,594,074 individuals (ranging between 30 and 175,818). Of these, 224,532 were females and 701,891 were males, yielding an approximate male-to-female ratio of 3:1. On average, each study had 15,952 males and 5222 females. The mean age of participants across studies was 40.13 years old ($SD = 14.23$). A detailed analysis of the included studies characteristics is presented in Table 1.

3.3. *Quality assessment*

In regard to the quality assessment of the included studies, their rating ranged from 22 to 39. The mean average score was 34.38 points, while the mode was 38.

3.4. *Main results*

The included studies were categorised in terms of their overall finality and/or employed technological and analytical approach into: (i) behavioural monitoring ($n = 8$, 10.29 %); (ii) decision support/AI classifiers ($n = 14$, 20.59 %); (iii) personalized messaging/alerts ($n = 10$, 14.71 %); (iv) predictive risk modelling ($n = 26$, 38.24 %); and (v) restriction and self-regulation features ($n = 11$, 16.18 %).

3.4.1. *Behavioural monitoring*

This category comprised studies examining systems that passively track gambling activity, such as time spent and money wagered. Two main types of tools were identified: behaviour/data analysis, and monitorization aimed at intervention. The first primarily focused on automatically collecting information on gambling behaviours in order to identify patterns and describe how individuals engage with gambling platforms (Leino et al., 2015; Sagoe et al., 2018; Scholten et al., 2020; Selin et al., 2024; Whiteford et al., 2022). The second type aimed to provide real-time feedback or interventions based on the collected behavioural data (Auer & Griffiths, 2018). These were used to quantify aspects of gambling, including bet sizes and frequency (Whiteford et al., 2022), identify gambling patterns (Scholten et al., 2020), analyse factors influencing user engagement (Leino et al., 2015; Sagoe et al., 2018), and examine responsible gambling tools (Heirene et al., 2021). While some studies combined personalised feedback with behavioural tracking data to examine cognitive distortions related to gambling (Auer & Griffiths, 2018), one study integrated behavioural data with geographical information to examine gambling-related patterns at the city level (Selin et al., 2024).

3.4.2. *Personalized messaging/alerts*

This category included intervention studies that delivered individualized messages to users, typically triggered by behavioural thresholds. Most studies evaluated interventions implemented via existing

Table 1
Characteristics of the included studies.

Authors	QuADS	Type of study	Source (Type gambling)	N [participants, sessions]	Time frame	Deep tech type/ name	Characteristics	Purpose	Pros	Counters
Behaviour monitoring										
Auer & Griffiths, 2018	35	Exploratory	Norsk Tipping (multiple games)	11,829 gamblers	April 2015	• Account/ Behavioural data tracking • Pop-messages	Behavioural tracking data includes theoretical loss (i.e., amount of money staked multiplied by the probability of winning). The system analyses the gambler's patterns and provides feedback, through pop-up messages, about their actual expenditures.	To track gambling behavioural patterns and provide users with personalized feedback that deals with possible cognitive dissonance.	• The approach combining personalized messages and analysis of behavioural data helped gamblers reduce their spending.	• The positive outcome of this approach depends on individual characteristics.
Heirene et al., 2021	29	Quantitative	x (sports and race betting)	39,853 gamblers	July 2018–June 2019	• Account/ Behavioural data tracking	These tools use account tracking data, which included age, gender, postcode, date of registration, use of deposit limits and/or temporary timeouts (short or long) and/or SE tools (temporary or permanent, start/end date and time, duration), amount [for limits], transaction details (date, time, amount for deposits and withdrawals), and bets placed (date, time, amount, sport, odds, and outcome).	How consumer protection tools, such as deposit limits, timeouts, and SE are implemented for safeguarding gamblers.	• These tools help to increase gamblers awareness for RG, and can be applied to everyone, without the need of problematic patterns – preventive potential. • Allied with personalize feedback, these tools help to make gamblers aware of their gambling patterns.	• These tools require the gambler's initiative and are changeable (their choice can be reverted). • There may be a lack of awareness of some tools. • Differences in the ease-of-access between gambling sites. • Highlight the need of regulation regarding these tools.
Leino et al., 2015	36	Quantitative	Norsk Tipping/ Multix (multiple games)	31,109 gamblers	January 2010	• Account/ Behavioural data tracking	Behavioural/Account tracking data included: total number of bets, payback percentage, average hit frequency, size of win and jackpot, availability of bonus features. Multilevel modelling of tracked data allows the analysis of influential structural game characteristics (e.g., reward features, betting options) in gambling behaviours (e.g., number of bets).	To monitor, track, analyse and register an individual's gambling behaviour and gambling history.	• Information, awareness, and modification regarding structural game characteristics may contribute to promote RG behaviours. • Behavioural tracking can be used unobtrusively, and can be used to supply or demand reductions	• These mechanisms do not have access to, nor account for, multiple-platforms gambling.
Sagoe et al., 2018	38	Quantitative	Norsk tipping (video lottery terminal)	93,034 gamblers	x	• Behavioural tracking data	Behavioural tracked data included: gambling sessions, time	To determine whether the number of electronic gambling	• This type of analysis allowed to understand how the	x

(*continued on next page*)

Table 1 (*continued*)

Authors	QuADS	Type of study	Source (Type gambling)	N [participants, sessions]	Time frame	Deep tech type/ name	Characteristics	Purpose	Pros	Counters
							spent, money spent, number of bets placed, and net outcome. Linear mixed model served to analyse variations of gambling behaviours across venues with different numbers of electronic gambling machines.	machines in a venue influenced the intensity and outcomes of gambling behaviour.	context of gambling motivates individuals to play. • Provides insights relevant for gambling regulations and harm reduction.	
Scholten et al., 2020	37	Quantitative	Ethereum blockchain (multiple games)	25,420 gamblers	Dice2.Win: 7th September 2018 – 9th March 2020 Etheroll.com: 4th August 2018 – 9th March 2020 FCK.com: 10th December 2018 – 2nd July 2019	• Account/ Behavioural data tracking	Behavioural tracking data included: duration (days), frequency, number of bets, mean bets per day and size, total wagered, and net and percentage loss.	To understand the spendings of gamblers in decentralize gambling applications and infer indicators of risk patterns.	• By analysing the gambling expenditures, it is possible to track problematic patterns.	• These applications are inherently anonymized, being necessary to account for possible non-human players. • There is a need to ascertain if these technologies enhance risky gambling.
Selin et al., 2024	35	Spatial analysis	Veikkaus (electronic gambling machines)	71,669 gamblers	2022	• Account/ Behavioural data tracking • Spatial analysis	Account tracking data included: stakes and losses, geographical location.	To determine the geographical distribution of gamblers across neighbourhoods.	• These analyses provide an overview of gambling patterns across multiple locations. • Regulators might use these tools to control and mitigate the negative effects of gambling across disadvantages neighbourhoods.	• The analysis was effectively applied to an urban region, but concerns are raised about the adequacy in a rural context.
Whiteford et al., 2022	37	Quantitative	Bwin Interactive Entertainment AG (sports betting)	24,781 gamblers	February – September 2005	• Account/ Behavioural data tracking	Behavioural tracking data included: bets (daily activity, number), stakes, winnings, and the duration, frequency, and other statistics related to bets and stakes.	Quantile analysis used to quantify how relationships between in-play betting behaviours vary across the spectrum of involvement.	• Similar and more automated analysis can detect at-risk gambling behaviours and reduce gambling related gambling.	• Gambler's behaviours across time should be incorporated. • Difficulty in recognizing gamblers with multiple gambling accounts.
Personalized Messaging / Alerts										
Auer & Griffiths, 2015a	30	Mixed (between and within) subjects	x (slots machines)	Group 1: 11,232 sessions Group 2: 11,787 sessions	June – November 2013	• Pop-up messages	Control of the number of games played, as well as the action of the player after the pop-message (ceased or continued playing).	To use personalized feedback to inform players about their behaviours, provide educational content (e. g., only few people play more than 1000 slot games), combat	• Pop-ups inform individuals of their gambling patterns • Feedback influences gambling behaviours of a small number of highly involved	• The reason behind ceasing playing was individually determined

(*continued on next page*)

Table 1 (*continued*)

Authors	QuADS	Type of study	Source (Type gambling)	N [participants, sessions]	Time frame	Deep tech type/ name	Characteristics	Purpose	Pros	Counters
								common misbeliefs among gamblers and give advice (e.g., do a break).	gamblers • Messages enhanced with psychological theory are more effective in reducing gambling than simple messages	
Auer & Griffiths, 2015b	26	Quasi-experimental (with matched pairs design)	(multiple games)	Mentor users: 1015 Non-users: 15,216	28-day period (pre- and post-opt-in)	• Account data tracking • Mentor	Opt-in feedback tool that provides gamblers with personalized visual, textual, and numerical summaries of their gambling behaviour, such as time spent playing, money won or lost, number of play days, and types of games played. It also shows trends over time and comparisons to similar players (lottery or casino). The feedback is given via a responsive dashboard on all devices and typically leads to a pause in gambling activity.	To monitor players' gambling behaviours and provide them with personalized, real-time feedback to facilitate self-awareness and informed decision-making.	• Reduces the gambling intensity • Non-judgmental and motivation presentation. • Helps gamblers to monitor, reflect upon and regulate their behaviours.	• Gamblers might not read the messages they received. • Doe does not account for multiplatform gambling.
Auer & Griffiths, 2016	38	Experimental: 2 (personalized information: present or no) x 2 (Recommendation: present vs. No) x2 (Normative feedback: present vs. no)	Norsk Tipping (multiple games)	17,442 gamblers	April 2015	• Personalized feedback • Account/ Behavioural tracking data	Gamblers are presented with personalized information about their gambling activity (in numbers and figures); recommendations (i.e., written information about using RG tools offered by the company); and/or normative feedback (in numbers and figures comparing their activity to the average active). Its effectiveness is based on time limit, money wagered, and gross gambling revenue.	To provide gamblers with personalized, real-time feedback to decrease their gambling bets.	• Personalized feedback decreases gamblers' behaviour • Both personalized and normative feedback had a stronger impact than a recommendation-only approach. • There was an immediate effect of these strategies	• Recommendations alone are not enough to have influence • Long-term effects were weaker (after 30 days), regardless of the type of information • The players are compared with average players, which might not be an accurate representation.
Auer et al., 2018	37	Quasi-experimental	Norsk Tipping (multiple games)	4692 gamblers with limit-setting	September 2015 – September 2017	• Personalized feedback	Players can choose to set a personal monthly loss limit. When they exceed 80 % of that limit, they receive a notification - via email,	Inform gamblers that they had reached 80 % of their loss limit.	• Personalized feedback showed a significant reduction in gambling behaviour in about 63 % of	• The intervention had little to no impact on the most intense players, who are often the most vulnerable. • Players who gamble

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Table 1 (*continued*)

Authors	QuADS	Type of study	Source (Type gambling)	N [participants, sessions]	Time frame	Deep tech type/ name	Characteristics	Purpose	Pros	Counters
							text, or pop-up messages - informing them of their spending status and providing a link to view their remaining available budget for the rest of the month		cases. • The system empowers and helps gamblers manage their spending with timely, data-driven reminders. • Pop-up messages or texts are low-cost, easy to automate, and can be widely implemented across digital platforms.	across multiple platforms may not be fully monitored, limiting the intervention's reach. • Only players who voluntarily set a loss limit were studied, which may exclude the highest-risk individuals who avoid setting such limits. • The 80 % threshold and messaging were uniform for all players, potentially reducing effectiveness across differing behavioural risks and profiles.
Auer & Griffiths, 2020	35	Quantitative	ComeOn Group (x)	7134 gamblers	14th July 2019 – 8th January 2020	• Behaviour monitoring • Mentor	The system monitors and tracks gambling behaviours, including money and time spent, failed deposit attempts, cancelled withdrawals, and deposit limit-setting. Using a combination of rule-based logic and ML, it delivers personalized messages via a pop-up window immediately after login, triggered by signs of risky or PG. These messages are based on the player's past six months of activity and may recommend actions (e.g., taking a break, setting deposit limits). Players can receive one message per week, and the same message cannot be repeated within three months. If a player does not log-in for three weeks, any pending message is deleted to maintain relevance.	To decrease gambling intensity through personalized pop-ups with information about past gambler's behaviours	• Personalized feedback reduced the amount of money gambled after a message was read. • The reduction in the amount of money gambled on the day and seven days after a message was read was significant regardless of the severity of the gambling patterns. • Players who had lost heavily showed a higher reduction in amount of money gambled than players who had recently won a large amount of money.	• High-risk players showed the lowest reduction in amount of money gambled.

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Authors	QuADS	Type of study	Source (Type gambling)	N [participants, sessions]	Time frame	Deep tech type/ name	Characteristics	Purpose	Pros	Counters
Auer & Griffiths, 2024b	38	Quasi-experimental, matched pairs design	x (casino games)	4362 gamblers	October 2022 & January 2023	• Account / Behavioural data • Mentor	The system monitors gamblers' behaviour and sends personalized messages based on specific risk-related patterns (e.g., deposit €500 or more in the past 30 days, withdrawn less than 20 % of that amount, gambled on at least five of the past seven days, and lost money the previous day). The messages are limited to one per week, with no repetition of the same message within three months and aim to encourage withdrawals. Instead of a pop-up, the message appears in a dedicated section of the gambling site, which the player must actively visit. The system tracks when the message is accessed, and behavioural data from the week prior is analysed to assess impact.	Personalized messages as an effective way of 'nudging' gamblers to withdraw money from their online gambling account.	• Behaviourally targeted messages can encourage safer practices (e.g., funds withdrawal), and their effectiveness is affected by timing and context (e.g., winning vs. losing). • Larger withdraws among message readers • Behaviour-specific targeting enhances relevance • Supports safer gambling without restricting access	• No long-term impact was assessed • Messages must be manually and voluntarily opened
Auer et al., 2024	37	Quantitative	Nederlandse Loterij (Multiple games)	639 gamblers	March 2021 – February 2023	• Behavioural monitoring • Mentor	Combines self-reported player assessments with actual behavioural tracking data (deposits, withdrawals, gambling days). Players estimate how much they deposited in the last 30 days and receive automated personalized feedback showing the actual amount deposited.	Assess accuracy of gamblers' self-estimates versus actual behaviour and provide feedback on estimation bias to reduce the dissonance	• Gamblers recall deposits easier than gambling losses, and those who underestimated had the highest actual deposits • Possible to have real-time automated personalize feedback • All players reduced deposits post-feedback, regardless of estimation accuracy	• Feedback had no added effect beyond general reduction • There is no causal proof, since feedback did not specifically drive changes vs. general trend
Forsström et al., 2020	36	Quantitative	Norsk Tipping (multiple games)	835 gamblers	14th January 2014 – 9th March 2015	• Playscan	The app intends to promote behavioural change, through: 1) risk assessment (based on the users' gambling history and different	To explore the effectiveness of this RG third-party app that is included in the gambling operators and	• Some clues support the idea that moderate and high-risk gamblers decrease their gambling	• These apps are unable to recognize if two or more people are using the same account. • It does not account

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Authors	QuADS	Type of study	Source (Type gambling)	N [participants, sessions]	Time frame	Deep tech type/ name	Characteristics	Purpose	Pros	Counters
							markers of excessive gambling) with three different risk levels (i.e., green, yellow, and red); 2) feedback on the risk assessment to the gambler, communicated via a messaging service built into the tool (if the person did not gamble during this period, she/he will not receive it); and 3) advice on how to limit their gambling (the users choose if they want the advice).	that intends to decrease PG for at-risk gamblers.	behaviours with the app. • The app is included in the gambling sites, which increases its accessibility and range.	for cross-platform or sites gambling. • Most people seek for these types of tools as self-test feature. • It seems insufficient to only inform gamblers about their risk level, as it does not always lead to decreased gambling • It depends on the individual's initiative and motivation (high dropouts).
Wohl et al., 2017	38	Quantitative	Ontario Lottery and Gaming (multiple games)	649 gamblers	29th May – 5th June 2015	• Win/Loss Tool	The Win/Loss tool provides accurate information about the financial outcome of the player on the EGMs, namely their winnings and losses over a specified period. The tool first asks them to give an estimation of their winnings and losses over a period and then provides the appropriate feedback.	Personalized behavioural feedback tool developed by Ontario Lottery and Gaming, that aims to inform participants about their gambling patterns.	• The tool seems to reduce risk associated with gambling and serve as intervention for those who gamble excessively by showing them their true behaviours and increasing their awareness about their gambling patterns and potentiating motivation to change.	• It is necessary to evaluate the program in long-term feedback. • Ethical concerns about gamblers privacy. • Expenditures seems to increase among those who were given a "green light" indicating that their gambling patterns were not problematic.
Wood & Wohl, 2015	37	Quasi-experimental in real life setting: 2 (group: BF x NBF) x 3 (Feedback: green x yellow x red)	Svenska Spel gambling (multiple games)	1558 gamblers	x	• Playscan (account data tracking)	Behavioural tracking data included: weekly deposits and wagers. Behaviour feedback encompassed an algorithm that calculates a risk score based on the intensity of play over a 10-week span, in which the colour given corresponds to the intensity of a gambler's past observed playing behaviours.	A personalize feedback tool built to inform gamblers, if they choose, about their gambling patterns. It works in a traffic light colour system indicating gambling intensity: green (low intensity or recreational play), yellow (moderately intense or risky play), and red (intense or risky play). If they did not play for 10 weeks the colour was grey.	• Determine risk scores across multiple games and inform about the games with most addictive potential. • Objectively assesses gambling habits and informs the player. • Tracks behaviour data and classifies players based on their gambling severity. • Positive impact on at-risk gamblers.	• Relies on gamblers initiative and motivation. • Not effective on problematic gamblers.
Decision support/ AI classifiers										
Auer & Griffiths, 2022a	23	Cross-sectional	European online casino (casino)	133,286 gamblers	1st January – 31st May 2020	• Mentor (account data tracking)	The behavioural tracking data analysis included: daily active	This tool tracks gambling behaviour in real-time and classifies	• The tool can recognize patterns and prevent the	• The tracked data can be result from multiple people

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Authors	QuADS	Type of study	Source (Type gambling)	N [participants, sessions]	Time frame	Deep tech type/ name	Characteristics	Purpose	Pros	Counters
							players, average daily bets, high/low gambling intensity trends. Based on these data, the application classifies the gamblers as presenting high, medium, or low risk.	the gambler based on their risk levels.	development of gambling disorders. • Relies on actual behavioural patterns, allowing for more objective evaluations.	gambling in the same account.
Auer & Griffiths, 2023c	30	Quantitative	European online casino (x)	2576 gamblers	November 2021 – March 2022	• Mentor (account data tracking)	The behavioural tracking data included: amount of money wagered, amount of money deposited, number of monetary deposits, amount of time spent gambling, and gambling frequency. Based on these data, the application classifies the gamblers as presenting high, medium, or low risk.	The tracked data enables the system to classify the daily risk of gamblers according to three categories: low-risk, medium-risk, high-risk. The authors evaluated the extent to which the contacts by email or telephone influenced their subsequent gambling behaviour.	• Behavioural tracking allows operators to identify PG • Receiving feedback from the operator about their risk lead problematic gamblers to reduce their harmful patterns • Operators may employ this RG tool to minimize harm and protect gamblers • Regulators and policymakers can recommend or enforce their use	• Results may not be generalizable, as they were derived from only one operator in one country) • There is no way of knowing if the person gambled in another operator or shared their account
Auer & Griffiths, 2024a	27	Quantitative	x	150,895 gamblers	January – June 2023	• Account/ Behavioural data tracking • Cluster analysis	The behavioural tracking data includes gambling frequency, deposits per session, total bets per session, and gaps between gambling periods. Using this data, excessive gambling can be classified through cluster analysis.	To use real-time tracking of gambling activities to classify binge gambling behaviours.	• Operators can use account data to detect and intervene on binge behaviours	• The tracking data used can result from multiple people using the same account.
Auer & Griffiths, 2024c	29	Quantitative	Norsk Tipping (multiple games)	37,986 gamblers	1st January – 20th April 2020	• Mentor (account data tracking)	The behavioural tracking data included: monetary deposit volume, frequency of deposits, gambling session length, amount of money lost, frequency of gambling, and gambling during the night.	This tool tracks gambling behaviour in real-time and classifies the players based on their risk levels.	• Potential prediction of future high-risk classification. • Operators can intervene in the identified high-risk players (e.g., suspension). • Relies on actual behavioural patterns, allowing for more objective evaluations.	• The tracking data used can result from multiple people using the same account.

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Authors	QuADS	Type of study	Source (Type gambling)	N [participants, sessions]	Time frame	Deep tech type/ name	Characteristics	Purpose	Pros	Counters
Catania & Griffiths, 2022	30	Quantitative	Kindred (multiple games)	982 gamblers	1st September – 31st December 2017	• Account/ Behavioural data tracking • Cluster analysis	The behavioural tracking data included: contacts with costumer services, gambling hours, active days, deposit amounts and frequency, cancelled withdrawals, third-party requests, registered credit cards, frequency of requesting bonuses through customer service, times an RG tool was removed by the gambler themselves.	Identification of profiles of gamblers based on both DSM-5 criteria and tracked data by using unsupervised learning models: Two-step cluster analysis	• Operators can help prevent disordered gambling by monitoring and analysing the whole of their users' behaviours, instead of using proxy measures (e.g., voluntary SE) • Objective data collected by tracking gambling patterns provides a more unbiased view of the gamblers risk, as it does not require self-reporting	• Dataset from only one operator, therefor results may not be generalizable • Operationalizing diagnosis clinical criteria in behaviours that can be tracked may be narrow
Ghaharian, Abarbanel, Kraus, et al., 2023	37	Quantitative	x (casino)	2286 gamblers	1st March 2019 – 29th February 2020	• Account/ Behavioural data tracking • Cluster analysis (k-means, partitioning around medoids, Gaussian mixture model, Single linkage hierarchical, Complete linkage hierarchical, and Average linkage hierarchical)	The behavioural tracking data included: transaction data of deposits and withdrawals between the gambler's funding account(s) and digital wallet or between their digital wallet and the gambling operator wagering account. Using cluster analysis, the authors classify a set of gamblers and understand different types of gambling (Occasional activity, Nighttime occasional activity, High deposit-to-withdrawal ratio, High activity, high intensity, and High volume, high variability).	Analyse gamblers payment behaviour with the goal of distinguished subgroups of gamblers.	• Subgroups of customers can help inform gambling payment providers' intervention and harm prevention measures. • This analysis is continuous, thus allowing for the observation of the gambler's evolution. • Two-way communication between payment providers and gambling operators might be useful to increase the efficacy of protection tools (control in multiple gambling provides).	• There is a need to increase the legislation and regulation.
Ghaharian, Abarbanel, et al., 2024	37	Quantitative	x (multiple games)	5580 gamblers	1st March 2019 – 29th February 2020	• Account/ Behavioural data tracking • Cluster analysis • RF	The behavioural tracking data included: transaction data of deposits and withdrawals between the gambler's funding account(s) and digital wallet or between their digital wallet and the gambling operator wagering account. Using cluster analysis	To analyse gamblers payment behaviour with the goal of distinguishing subgroups of gamblers (Replicates the study of Ghaharian et al., 2023, b).	• Gamblers' payment behaviours are representative of their gambling patterns and may reflect dynamics of certain gambling formats.	• For assuring both their optimization and adequacy, clusters should be tested in other realities.

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Authors	QuADS	Type of study	Source (Type gambling)	N [participants, sessions]	Time frame	Deep tech type/ name	Characteristics	Purpose	Pros	Counters
							and RF models it classifies gamblers by their type of gambling (Occasional activity, Nighttime occasional activity, High deposit-to-withdrawal ratio, High activity, high intensity, and High volume, high variability).			
Mosquera & Keselj, 2017	35	Exploratory	EGM (EGM multiple games (four slot-machine-type games and one poker game))	46,416 sessions	July 2010	• Account/ behavioural data tracking • K-means cluster analysis	Account/Behavioural tracking data included: sessions' duration and intensity, amount redeemed, and vouchers won, number of bets, net loss. Using cluster analysis, the authors classify gambling sessions, based on the intensity, duration and amount redeemed during the sessions.	To classify gamblers in terms of their risk and gambling patterns.	• The employed clustering method had a reliable performance in both specificity and sensitivity when classifying types of EGM gamblers. • The categorizations distinguished groups with differing gambling patterns, although differences in intensity and duration were not always significant. • Clusters of players showing non-PG patterns, moderate risk and higher risk were revealed.	• Involvement measures should be included to ascertain the type of decisions made during a session of EGM gambling. • The classification does not explain how gambling strategies are influenced by the outcome of a bet or the bonus round.
Murch et al., 2023	38	Quantitative	Loto-Québec (multiple games)	9145 gamblers	9th September – 10th November 2019	• ML supervised models	Behavioural tracking data included demographic information, indicators of online gambling behaviour and repeated engagement. ML models included logistic regression, decision trees, KNN, SVM, NN, and RFs. Algorithms like these would be used alongside with a limited number of personalized harm prevention initiatives, two binary dependent variables were used PGSI 8+ (high risk) and	To classify gamblers at-risk by means of ML algorithms and using tracked data of their activity in an online gambling website.	• ML models might be able to both detect at-risk gamblers and identify potential behavioural markers of harmful online gambling.	• Results might not be generalized to other contexts.

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Authors	QuADS	Type of study	Source (Type gambling)	N [participants, sessions]	Time frame	Deep tech type/ name	Characteristics	Purpose	Pros	Counters
							PGSI 5+ (moderate-to-high risk).			
Murch et al., 2024a	37	Quantitative	x (multiple games)	19,861 gamblers	9th September – 10th November 2019 (Murch et al., 2023) & February – March 2022	• RF algorithm	ML model based on RF considering binary dependent variables PGSI 8+ (high risk) and PGSI 5+ (moderate-to-high risk). The model uses 10 predictor variables including: financial and sociodemographic factors, and engagement with 'RG' features, indicators of utilization with specific gambling formats, and indicators of repeat engagement indicating potential loss changing.	To test AI-based PG detection systems that allocate harm reduction materials or referrals to PG treatment services.	• The models are useful tools to predict behaviour patterns and to help directing gamblers with PG to interventions.	• Issues arise in terms of the fairness of these systems as they might fail to detect at-risk gamblers from one or more sociodemographic groups.
Perrot et al., 2018	36	Quantitative	French operator (lottery and scratch)	10,000 gamblers	September 2015 – August 2016	• Account/ Behavioural tracking data • Multilevel LCA clustering	Behavioural tracking data included: sociodemographic (age, gander), account age, bets, money wagered, deposits, days gambled, variability of games played use of loyalty bonuses, chasing proxy. Using cluster analysis gamblers were classified in terms of their activity (i.e., monthly gambling behaviours) and of their characteristics (i. e., classes of gamblers).	To define typologies of gamblers that play online lottery or scratch games, using account-based gambling data to classify them in terms of their activity and characteristics.	• Account data paves the way for detecting specific behaviours in online gambling, enabling personalized intervention. • Multilevel LCA identified small, atypical behaviour groups, which might precisely correspond to at-risk gamblers. The classification model effectively differentiates both activity and classes of gamblers, aiding in the improvement of prevention strategies. • The variability of gambling activity over time is useful for early detection.	• The choice of the "best" model of clustering might be influenced by a misspecification of the factors' distributions, potentially leading to a less complex model or an overextraction of clusters. • Although pertinent behavioural factors for classifying problematic behaviours were used, these were not broad enough to guarantee a precise affirmation of PG (e. g., no contextual factors were included).
Suriadi et al., 2016	34	Exploratory	New Zealand Racing Board (multiple fixed-odds betting games)	91,405 gamblers	August 2013 – May 2014	• Account/ Behavioural tracking data. • Process mining • K-means cluster analysis • RF algorithm	Account/behavioural tracking data included: bet intervals, frequency of 9 gambling patterns, frequency of clawback behaviour activities, total sum of money won, number of times a	To identify and characterize various groups of gamblers, particularly problematic gamblers, directly from the data extracted, while using	• The two-level clustering analysis accurately classified gamblers based on their characteristics, distinguishing problematic gamblers from the	• The size and complexity of the data to be analysed requires adequate computational resources. • Narrowing down problematic gamblers

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Authors	QuADS	Type of study	Source (Type gambling)	N [participants, sessions]	Time frame	Deep tech type/ name	Characteristics	Purpose	Pros	Counters
						• Kruskal-Wallis and Dunn's tests	gambler won a bet. Using classification analysis, gamblers were categorized into various classes and groups of problem gamblers were identified. Accuracy was evaluated using RF algorithm and differences between clusters were assessed with the confirmatory statistics.	unsupervised learning techniques.	extract logs. • Patterns found suggested that players bet equal or less than their previous amount after winning or losing a bet. • Unsupervised clustering with confirmatory statistics is an automated, efficient, theoretically driven, and multi-faceted approach to process mining groups with high confidence. • Continuous evidence-based analysis of gamblers activity can be done automatically, thus allowing for early identification and intervention in problem gamblers.	from the total population poses a challenge when a single clustering method is used.
Takeuchi et al., 2022	39	Quantitative	x	71 gamblers with GD and 90 community controls	x	• ML	This implies functional magnetic resonance imaging together with advance ML pipeline (L1-regularized sparse canonical correlation analyses and sparse logistic regressions), and classifier output result of a weighted linear sum of selected brain connections. This provides a diagnostic score.	ML classifier for diagnosis of gambling disorder built from resting state measures of functional connections, from neuroimaging data.	• It offers a biomarker-based, objective tool, which can reduce bias and improve diagnostic accuracy. • The model performed well on data from a different site, which suggests it is not overfitted to a single dataset or scanner setup. • Non-invasive method with growing accessibility in clinical research	• The model was only test in males, so the model might not be adequate for females. • Requires access to high-quality fMRI scanners and processing expertise, which is not feasible to all players or settings. Also, it is a clinical approach instead of in-game one. • Less useful for real-time monitoring or treatment response.
Wiley et al., 2020	37	Exploratory	DraftKings (daily fantasy sports)	11,130 gamblers	1st August 2014 – 31st December 2016	• Account/ Behavioural tracking data • K-means cluster analysis	Account/Behavioural tracking data included: number of entries, active days, entry fees, net loss, percent lost, duration of engagement. Employing cluster	Use account tracking data to identify risk of PG in Daily Fantasy Sports.	• Natural grouping methods distinguish daily fantasy sports gamblers based on their engagement, performance, and risk profiles. • Identifies potential	• Cluster structures might change overtime as the gamblers style of play changes, and to be able to identify early risk of PG the classification should

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Authors	QuADS	Type of study	Source (Type gambling)	N [participants, sessions]	Time frame	Deep tech type/ name	Characteristics	Purpose	Pros	Counters
							analysis allied to the elbow test, the authors determine the optimal number of clusters to classify gamblers in terms of their risk scores and playing duration.		markers of risk: the continuation of gambling despite the negative outcomes and the large time involvement. • Operators can use and build upon this classification method to build sophisticated algorithms that identify risk of PG.	primarily focus on the first weeks or months of gambling. • Other factors relevant to distinguishing between groups were not included, such as sociodemographic and psychological data.
Restriction and self-regulation features										
Auer et al., 2019	37	Quasi-experimental (Matched-pairs design)	Norsk Tipping (Video lottery terminal)	7190 gamblers	January & March 2018	• Mandatory breaks	After a 60-min session gamblers are imposed a mandatory 90-s cold-off period. Three metrics are assessed: (i) time until the next session; (ii) next session's gambling intensity; and (iii) gambling intensity during the next 24-h.	To evaluate if intense gambling behaviours decreased after the mandatory play break.	• Mandatory play breaks show potential in mitigating PG, although they need to be improved to safeguard gamblers self-determination.	• Compared to those who voluntarily ended the session, mandatory breaks lead to shorter breaks before next session. • Gamblers staked more money in the session immediately after and 24-h after a forced termination (rebound effect), when compared to controls without this imposition.
Auer and Griffiths, 2020	38	Quantitative	Kindred (Multiple games)	49,560 gamblers	January & March 2017, that also played on January & March 2018	• Account data tracking • Voluntary deposits limits	Behavioural tracking data includes wager amount, frequency, intensity over time. Players set voluntary deposit limits (daily, weekly, monthly). Limits are enforced by the system: decreases are immediate, increases delayed by 7 days.	To reduce gambling intensity (measured via total amount wagered) and offer players control over their spending behaviour via voluntary limit-setting.	• Players in the top gambling intensity groups who set limits had significant reductions in their spending after 1 year without SE. • Limit-setters tended to be more loyal clientele after a year. • Limit-setting is voluntary, respecting player autonomy. • Enables operators to make informed decisions based on real gambling data.	• Only 1.3 % of players set a deposit limit; with many at-risk players not opting-in. • Limit-setters may be inherently more self-aware or cautious of their gambling. • Observational study, thus it cannot prove that limit-setting alone lead to reduced gambling. • Players in lower intensity groups showed no benefit, possibly because they already gamble within limits.
Auer et al., 2021	34	Qualitative	Kindred (multiple games)	175,818 gamblers, in which 14,581 had set a limit	January 2016 – May 2017	• Account data tracking • Voluntary loss or deposit limits	The behavioural tracking data included: daily bets, number of playing days, limit-	To ascertain the impact of voluntary limit-settings (daily, weekly, or monthly loss, or	• Overall, those who set voluntary limits were more loyal to the gambling	• Only few gamblers choose to impose limits to their games, and the probability of

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Authors	QuADS	Type of study	Source (Type gambling)	N [participants, sessions]	Time frame	Deep tech type/ name	Characteristics	Purpose	Pros	Counters
						• Predictive analysis	setting behaviours. The authors also made predictive analysis using simple statistic methods (regressions).	deposit limits) in the gamblers' loyalty to the operator.	operator over a year period. • Implementing these tools is favourable to gambling providers.	engage in these choices decrease with age.
Auer & Griffiths, 2022b	27	Quantitative	European online casino (casino)	70,789 gamblers	January – June 2017	• PlayScan • Account data tracking • ML model (logistic regression, linear discriminant analysis, RF, GBM, Naïves Bayes)	The behavioural tracking data included: bets, total losses per game type, age and gender, global monthly loss limit, whether they received feedback that they had reached 80 % of their personal global loss limit. Except for logistic regression, all models were trained with a fourfold cross-validation and with 75 % of the dataset.	To predict limit-setting behaviours based on gambling account data.	• Behavioural tracking data is useful for training models to identify PG markers. • ML models can predict future limit-setting, with GBM algorithms showing better performance. • Operators can encourage and personalize communication for early commitment to the usage of RG tools	• Data from only one jurisdiction, thus results are potentially not generalizable. • The operator imposes users to define a limit, which is an uncommon practice. • A percentage of gamblers that changed their limit, increased their gambling. Thus, the ML model predicts gamblers who are increasing their limits
Auer & Griffiths, 2023b	38	Quantitative	Skillonnet (Multiple games)	2201 gamblers	23rd July – 15th September 2021	• Behaviour monitoring • Mandatory break (60-min)	Tracks deposits, wagers, losses, and session times Implements automated 60-min forced play breaks after 10 deposits in a day. Analyses pre- and post-intervention behaviour using real-world operator data.	To ascertain if gambling intensity reduces after imposed cool-off periods.	• Short-term decrease in risky behaviour, with wagers dropping from 99.9 % to 55 %, and deposits dropping from 73 % to 32 % after the break. • Real-world large-scale data for valid insights. • Gambling activity did not increase in the day following the break, contrarily to prior fears. • Mandatory breaks potentially interrupt dissociative gambling states.	• No long-term impact, i.e., no significant reduction in gambling in the weeks following. • Gamblers may switch to less regulated sites. • No effect on next-day deposits. • The predictive model was exploratory and revealed that individual deposit behaviour after a break is complex and difficult to predict using behavioural data alone. • To improve predictive power, future models might need to include psychological or motivational factors.
Haefeli et al., 2015	36	Quantitative	x (multiple games)	300 gamblers	February 2007	• Automated text analysis (log-linear model)	Automated text analysis using dictionary-based datasets where words are linked to categories a priori. This analysis	To use automated text analysis to replace or supplement manual assessment processes and help to diagnose PG patterns.	• These analyses of gamblers text content can serve to redirect them to RG tools. • Can automatically	• There is a range of gamblers that do not adhere to RG tools, neither do they seek for help.

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							used linguistic scales relating to affect (positive emotion anxiety, anger, sadness), cognitive mechanisms (insight, causation, discrepancy, tentative, certainty, inhibition) and gambling-related problems (money, job, time, family)		process large sets of text with an almost endless availability of norm comparisons on the Internet. • Lower specificity approaches can be applied to trigger interventions (e.g., scheduled mailings or pop-ups informing or supporting self-appraisal of PG).	
Hawker et al., 2021	38	Longitudinal	not applied (multiple games)	30 Gamblers seeking for help	September 2019 – June 2020	• GamblingLess: Curb Your Urge	The app was available 24/7, and users can rate the intensity of the cravings immediately before and after the interventions. Assessments were randomly administered, via push notifications from the app, throughout the day, and measured: gambling episodes, gambling cravings and its characteristics, gambling self-efficacy, and craving self-efficacy. Momentary interventions consisted of either automatic recommendations or voluntary decision to use one of the 12 urge-curbing tips and activities.	Identifying gamblers experiencing cravings and providing them with strategies to manage their craving in real-time by using an app-delivered intervention, based on CBT and MI programs, and integrated in the MetricWire platform	• Smartphone apps can deliver dynamic interventions in real-time, which are easily accessible and self-directed. • User's feedback allows for developers to improve the app, therefore increasing engagement and satisfaction with the product.	• The cost-benefits (financial or efficacy) of using intervention apps are unknown. • Apps have to be programmed for an operating system, their correct functioning depends on the features and capacity of the smartphones, with the possibility of occurring technical errors. • The apps interventions and recommendations are constricted to the features inserted by the developer, not catering nor adapting to the user's evolving needs and characteristics.
Hopfgartner et al., 2022	38	Quantitative	Norsk Tipping (Multiple games)	21,129 gamblers	17th April & 21st May 2020	• Mandatory breaks	Players who received at least one play break were assigned to one of eight groups that had different mandatory break times (90 s, 5 min, or 15 min), personalized feedback based on their gambling activity (amount bet, won, and net result), and potential display of a	To assess how break length, feedback, and countdown visibility influenced gambling behaviour after a mandatory break.	• Longer breaks (especially 15-min) reduced short-term gambling patterns. • Breaks did not lead to a rebound effect nor to increased gambling. • All players bet less after the break, regardless of break length or feedback.	• Personalized feedback did not improve gambling outcomes, lengthened the pause between sessions nor reduce post-break betting in a statistically meaningful way. • Some minor findings (e.g., feedback 900's slightly better

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Authors	QuADS	Type of study	Source (Type gambling)	N [participants, sessions]	Time frame	Deep tech type/ name	Characteristics	Purpose	Pros	Counters
							countdown timer. All groups, except the control, had a logout button during the break. They assessed both the time to the next gambling session and the relative change in the amount bet within 60-min. After the break.			reduction in betting) were not statistically robust.
Hopfgartner, Auer, Santos, et al., 2024	38		Norsk Tipping (Multiple games)	23,234 gamblers	16th March 2020 & 31st July 2020	• Mandatory breaks	The study tested four mandatory cool-off periods triggered after 60 min of continuous gambling: a 90-s break (Control Group), a 90-s break with a "logout" button (Break 90 Group), a 300-s (5-min) break with a "logout" button (Break 300 Group), and a 900-s (15-min) break with a "logout" button (Break 900 Group).	To assess how break length, feedback, and countdown visibility influenced gambling behaviour after a mandatory break.	• Gamblers who used the "logout" button during the break had the longest time to the next gambling session. • The longer the break, the more gamblers logged out, suggesting increased self-awareness and recognition of their problem behaviours. • Gamblers continued gambling with the operator regardless of the break length, thus longer breaks (even up to 15 min.) seem acceptable and do not drive users away.	• Most behavioural changes caused by longer cool-off periods did not persist after the intervention ended. • Once players returned to the standard 90-s break, their gambling behaviour reverted to pre-experiment patterns. • The experiment took place during the pandemic, which could have influenced gambling behaviour in ways not typical of normal conditions.
Ivanova et al., 2019	36	Randomized controlled trial	x (online slots)	4323 gamblers	X	• Behaviour tracking data • Voluntary deposit limit-setting • Quantile regression analysis	Participants were randomly assigned into distinct groups varying in prompts' timing (at registration, pre- or post-deposit, no prompt/control). Behavioural tracked data included: changes in deposit limits (setting, increasing, decreasing, or removing) over time. Quantile regression analysis served to explore variations in gambling intensity	To assess the effectiveness of a voluntary, removable deposit limit prompt.	• Unprompted limit-setters tended to have higher intensity of gambling, suggesting they might be more aware of needing self-control, and changing limits (increasing or removing) could help identify high-risk gamblers.	• Voluntary and removable deposit limit-setting was not effective in reducing gambling intensity among online slot machine users, both in the overall group and the most involved 10 %.

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Authors	QuADS	Type of study	Source (Type gambling)	N [participants, sessions]	Time frame	Deep tech type/ name	Characteristics	Purpose	Pros	Counters
							across different percentiles of players, identifying subgroups with distinct gambling patterns. Odds ratios and group comparisons determined demographic (age, gender) and behaviour differences between limit-setters and non-setters, overtime.			
Walker et al., 2015	22	Experimental	x (slot machine)	900 gamblers	x	• Gambling tracking data • Simulated slot machine with various conditions for limit setting	Tracked data included: net payoff, earnings, wins and losses, time played. The simulations encompassed a different condition of limit settings, namely: (i) no win or loss limit - 5000 spins, 8.33 h of play; (ii) time limit of 1 h; (iii) $100 loss limit; (iv) $100 loss limit, $100 win limit; (v) $100 loss limit, $100 win "down"; (vii) $100 loss limit, $200 win limit; $100 win limit.	Test the effects of loss limit, time limits, and win limits on the gambler's behavioural patterns.	• Win limits seem to reduce both gains and losses for the average gamblers, while increasing the number of eventual winners (as they do not lose their gains back to the casino). • The definition of both a loss and win limit seems to assure better outcomes for the gambler and promote RG. • From limit-setting results a reduction in the amount of time gambling and less losses of money. • By defining win-limits the gambler can get accustomed to the difficult choice of stopping their behaviour and walking away, thus influencing their perceptions and self-management	• Limit-setting may not be a feasible RG strategy in games that do not provide feedback to the gambler. • The interpretation of the best outcome from the cumulative density functions depends on the point of view. For the gambler who prioritizes gains, the best strategy would be to define a win limit. RG promoters might advise the loss and win limit-setting (maybe the loss limit by itself) while opposing the no-or win only limit-setting • The impact of felf-imposed limits depend on the motivations and goals of the person that are stablishing them. • Gamblers might resist embracing win limits as they may be focused on chasing previous losses (problematic gamblers), their maximum gain is restricted and also their enjoyment, plus they might consider that wagering "house

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Authors	QuADS	Type of study	Source (Type gambling)	N [participants, sessions]	Time frame	Deep tech type/ name	Characteristics	Purpose	Pros	Counters
										money" is not irresponsible.
Wohl et al., 2024	38	Quasi- experimental (within subjects)	Ontario Lottery and Gaming (multiple games)	Hard lock: 61 gamblers Soft lock: 2387 gamblers Control: 311	March 2017 –September 2022 (Controls data was referent to 2018)	• Account data tracking • My PlaySmart (account data tracking)	The use of player tracking data collected included: data minutes played (time played and mean), coin-in. net win or loss, and jackpots for each visit prior to and after enrolling. The gamblers are notified when they reached 50 %, 90 % and 100 %.	Play management system that aims to strike a balance between voluntary and mandatory pre-commitment by giving players the option of managing the type of limit the set. Gamblers choose a hard (i.e., the player is not permitted to exceed their limit) or soft (i.e., the player is allowed to exceed their limit if they so desire) limit modality.	• Hard lock options are effective in decreasing gambling expenditures. • It increases the gamblers awareness for RG since they their patterns and limits. • Because it is a choice, it may enhance the gamblers adherence.	• Soft lock is ineffective as its flexibility allows gamblers to continue in gambling. • The choose of adhere to these mechanisms rely on gamblers own initiative. • There is no way to verify if the person starts to play to in order operator.
Predictive Risk Modelling										
Auer & Griffiths, 2023a	25	Quantitative	Kindred (multiple games)	16,771 gamblers	December 2021	• Mentor • multinomial regression	The real-time behavioural tracking data included: wagers, wins, deposits and withdrawals, balance before and after transactions, age, and gender. Based on this data, the monitoring application classifies the gamblers as presenting high, medium, or low risk.	Predictive analytics (multinomial regression) were used to assess risk scores, based on independent chasing losses variables computed from tracked data.	• Behavioural tracking allows for real-time detection of harmful patterns • Operators can use tracking data and predictive analysis to identify at-risk gamblers and introduce deposit restrictions or targeted interventions	• Need for a more advance AI-based detection model • Potential false positives from the classification of risk • Ethical and privacy concerns of data usage
Auer & Griffiths, 2023d	34	Quantitative	Nederlandse Loterij (multiple games)	43,731 gamblers	27th November 2020 & 15th April 2021	• Account data tracking • ML model (regression tree algorithms)	Tracked data included: metrics for each game (event frequency, return to player, hit frequency, continuity, and average bet and win), and metrics for each session (sessions and length, bets, wins and losses, return to player, hit frequency, and theoretical loss)	Examine the influence of structural game characteristics on gambling behaviour, using session tracking and ML to identify key structural game features related with betting patterns and model gambling intensity.	• Recognize and detect patterns in gambling behaviours, using game characteristics. • These measures can be associated with pop-up messages to inform gamblers of their behaviours.	• Some gambling characteristics enhance the risk of PG, which implies that the operators act to protect the consumer.
Auer & Griffiths, 2023e	28	Quantitative	x (multiple games)	945 gamblers	September 2021 & February 2022	• GBM • RF	The real-time behavioural tracking data included: wagers, wins, deposits and withdrawals, balance before and after transactions, age, and gender. Both prediction models used optimal	Prediction of self-reported problem gambling based on player tracking data, using ML algorithms: GBM, RF. Identification of profiles of gamblers and variables most related to PG using	• ML models can predict problem gambling from behavioural data, which are corroborated by self-reported PG • Both models showed good performance, with	• Need for regulations to operators regarding marketing practices, and enticing monetary deposits and limit

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Authors	QuADS	Type of study	Source (Type gambling)	N [participants, sessions]	Time frame	Deep tech type/ name	Characteristics	Purpose	Pros	Counters
							parameters and were trained with 80 % of the dataset. Cluster analysis included the variables with highest importance in the RF model. A z-score transformation was applied, and the number of clusters was determined using the elbow method.	unsupervised learning models: K-means cluster analysis.	RF being slightly more accurate • The most important variables predicting PG can be identified	
Cerasa et al., 2018	34	Between subjects	x	40 gamblers and 160 community controls	x	• ML models: SVM, CART binary decision tree	Both algorithms were trained using all personality features. CART's optimal parameter was obtained by evaluating the best performance over a 10-fold cross-validation approach repeated five times. SVM's optimal parameters were obtained by assessing several combinations of Kernel functions and tuning parameters values were tested, from which classifier selected Linear Kernel (Cost =1) for being the best performing.	Distinguishing of patients with GD and controls problem gambling based on personality data (i.e., NEO-PI-R)	• ML can aid early clinical diagnosis by analysing the data and identifying biomarkers related to PG • Clinicians may use ML algorithms as a complementary tool for intervention	• Only patients without other psychiatric disorders were included, therefore findings may not generalize to the population of gamblers presenting comorbidities
Challet-Bouju et al., 2020	37	Longitudinal	x (online lottery gambling)	1152 gamblers	September 2015 & February 2016	• Behaviour monitoring • LCA	Two-step approach, combining growth mixture modelling and LCA. The analysis was based upon behaviour indicators of gambling activity (money wagered and number of gambling days) and indicators of gambling problems (breadth of involvement and chasing). Profiles were described based upon the probabilities of following the trajectories that were identified for the four indicators, and upon several covariates (age,	To model early gambling trajectories and identify potential gambling problems among individuals who engage in online lottery gambling	• This analysis allows to identify types of gamblers and risk levels. • Growth mixture modelling allows to capture the complexity of the evolution of gambling practice over time.	• This type of analysis does not allow to evaluate the use of other gambling sites by gamblers.

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Authors	QuADS	Type of study	Source (Type gambling)	N [participants, sessions]	Time frame	Deep tech type/ name	Characteristics	Purpose	Pros	Counters
							gender, deposits, type of play, net losses, voluntary SE, and Playscan classification—a RG tool that provides each player with a risk assessment: green for low risk, orange for medium risk and red for high risk). Net losses, voluntary SE, and Playscan classification were used as external verification of problem gambling.			
Delfabbro et al., 2024	38	Quantitative	Unibet (Multiple games)	100,000 gamblers	January – June 2022	• Account/ Behaviour data tracking • series of negative binominal regressions	Behavioural tracking data included: active days, number of hours per session, bets made, total amount spent, number and frequency of deposits.	To determine the association between stablished markers of harm and the relative risk of different gambling products	• Behavioural risk markers stablished in literature (higher frequency of bonus seeking, repeat deposits, gambling at unusual hours, and declined deposits) seem to have value in assessing which products potentiate and encourage PG • Greater engagement in product features ilk shorter event frequencies, in-play sports betting and micro-betting is strongly associated with higher risk • Analysis of online behaviours offer an objective parameter for risk assessment, which might be valuable in regulatory work	• No standard assessment of risk or harm (e.g., PGSI scores) • It is not possible to determine if the differences between the potential products risk is derived from its' characteristics or if it is due to the type of gambler that gravitates towards those products
Finkenwirth et al., 2021	37	Quantitative	PlayNow (multiple games)	19,683 self-excluded gamblers	1st October 2014 – 30th September 2015	• Account data tracking • RF • logistic regression	Behavioural tracking data included: days and sessions gambled, bets amount and variability, losses, wins. Both models hyperparameters' were optimized by	Classification of SE status in online gambling, based on behavioural tracking data and enrolment in SE platform, by using a simple model and a ML algorithm: Logistic regression, and RF	• The predictive models were able to identify VSE status from the coarse behavioural tracked data inputted • Operators have access to more behavioural	• Results may not be generalizable to other platforms or types of gambling • Some self-excluders do not display evident gambling problems, and a significant proportion of

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Authors	QuADS	Type of study	Source (Type gambling)	N [participants, sessions]	Time frame	Deep tech type/ name	Characteristics	Purpose	Pros	Counters
							employing stratified 10-fold nested cross-validation.		information, which can strengthen the model and be used to identify at-risk users • Interventions can be made using the information gathered, such as providing feedback of their pattern or alerts pop-ups	problem gamblers do not self-exclude, raising the possibility that self-excluders may represent a specific subtype of problem gambler
Haeusler, 2016	35	Quantitative	bwin.com	2696 gamblers (n = 1348 self-excluders)	January 2015	• Behaviour tracking data • Stepwise logistic regression • ANN	Stepwise logistic regression served to identify predictors differentiating self-excluders from controls, using variables selected based on incremental validity. Logarithmic transformations to skewed payment-related data were used, as well as ANNs, selecting the optimal architecture using information criteria such as AIC and BIC to ensure model parsimony, validated it with cross-validation methods, and simulated saliency curves to interpret predictor contributions	To use payment data as source for predictors for the early detection of emerging gambling-related problems	• By tracking financial indicators, it is possible to identify at-risk individuals before escalating. The use of payment-related behaviours (e.g., deposits, withdrawals, reversed amounts) provides objective, quantifiable indicators that can predict SE and reflect loss of control. • ANNs can model complex, non-linear relationships, which traditional linear methods cannot capture, improving predictive power in some cases.	• SE is a rare event, which leads to a high rate of judgment errors, limiting the model's predictive validity. • ANNs are often seen as non-transparent and difficult to interpret, which can hinder practical use and acceptance. • Certain variables, like chargebacks or the number of payment methods, were found not to add predictive value, challenging some theoretical assumptions.
Hassanniakalager & Newall, 2019	34	Longitudinal	oddsportal.com (sports betting odds and results) football-data.co.uk (sports teams performances statistics)	X	2010–2018	• Behaviour tracking • ML mixed logistic regression models: multinominal and conditional	ML system based on mixed logistic regression models (multinomial and conditional). The model process historical betting data across four soccer bet types and simulates predictions using structured input variables: normalized bookmaker odds and recent team performance metrics (points earned, goals scored, goals	To analyse betting risks and prediction skill variation using ML, helping to uncover differences in product risk across soccer bet types. This with the aim of support RG by identifying where losses are highest and informing the design of more effective consumer warning labels.	• This type of ML system can be used to explore different types of bettors and help to define and develop better RG settings. • It can also be used to inform RG strategies to the gamblers (e.g., warning labels, informing about product features, and educate gamblers about observable features	• The timely communication of gamblers past losses could also help bookmakers who plan to increase their customer base by competing on price • Model accuracy may degrade over time if not regularly retrained with new data. • No real bettor data

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Authors	QuADS	Type of study	Source (Type gambling)	N [participants, sessions]	Time frame	Deep tech type/ name	Characteristics	Purpose	Pros	Counters
							conceded). It applies three predictive strategies (Most-skilled, Random, Least-skilled) and uses a rolling training-prediction approach across eight seasons of data. Model predictions are based on expected returns calculated from estimated outcome probabilities and potential payoffs.		that are correlated with these risks)	
Hopfgartner et al., 2023	32	Quantitative	x (multiple games)	25,720 gamblers (Austria: n = 7526; Germany: n = 10,822; Spain: n = 787; Poland: n = 4140; Sweeden: n = 877; Slovenia: n = 1532; and n = 414 future self-excluders)	1st November 2020 – 31st January 2021	• Account data tracking • Hierarchical logistic Regression Analysis • ML algorithms: AdaBoost, Decision trees, Extra-trees, GBM, RFs	Behavioural tracking data included: games played, deposits and withdrawals, and SE and voluntary limit-setting events. Stepwise backward elimination hierarchical logistic regressions, done for each country separately, served to determine the most important predictors from control (age, gender), behavioural, and monetary intensity variables. All ML models were trained with data from November and December to predict January SE. resulting from all but one country. They were trained five times, with data from all but one country. Optimal hyperparameters were determined with randomized cross-validation search, and a common parameter space was used.	Prediction of future SE based on player tracking data, by using ML algorithms.	• All models showed good performance in identifying future SEs • The overall best performing model was AdaBoost • Models trained with data from other countries are generalizable within multi-national operators • Operators can use ML models to identify and target potential problematic gamblers, increasing their awareness of RG tools	• Ethical considerations of the use of these ML are needed, as operators can misuse them to increase users' engagement and reinforce their problematic behaviours • SE is not an indubitable proxy of PG, and the reasons why the person SE are relevant to understand their risk level
Hopfgartner, Auer, Helic, & Griffiths, 2024	37	Quantitative	x (multiple games)	1743 gamblers	January 2022 – November 2023	• Account data tracking • Hierarchical logistic Regression	Self-reported data corresponded to the PGSI that was used to binarily categorize participants in two	Distinguishing between individuals with and without self-reported problem gambling, based on both self-	• Operators may utilize the identified behavioural markers of gambling harm to help	• Data characteristics influences the performance of a certain model; thus, they are not

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Authors	QuADS	Type of study	Source (Type gambling)	N [participants, sessions]	Time frame	Deep tech type/ name	Characteristics	Purpose	Pros	Counters
						Analysis • ML models: AdaBoost, Decision trees, Extra-trees (extremely randomized trees), GBM, and RF	subgroups, PGSI 5+ and PGSI 8 + . The behavioural tracking data included: bets, losses, withdraws, total deposits, number of deposits per session, and failed deposits. Stepwise backward elimination hierarchical logistic regressions, done for each country separately, served to determine the most important predictors from control (age, gender), behavioural, and monetary intensity variables. ML models were trained using two different approaches: 1) using data from two countries, and 2) adopting the standard approach of using of 70 % of the whole dataset for training. For comparison, a baseline model using only recent deposit totals was also included. The optimization of hyperparameters for each tree-based model was conducted through randomized cross-validation search, using a unified parameter space.	reported data and objective account-based tracking data.	identify users with PG or at-risk. • ML models trained with data from various countries seem to be capable of identifying problem gambling • ML models can capture the underlying patterns of harm, even when the training data is from another country. • Combining subjective (PGSI) responses with objective behavioural tracking provides a more comprehensive understanding of gambling behaviour and its consequences.	universally appropriate • PG has a multifaceted nature, thus models solely based on behavioural tracking data will not be able to fully capture the extent of the indicator of harm • Models trained in one country had weaker performance in others, suggesting that local context matters, and generalization is only partial. • Self-reported PGSI scores may not fully reflect gambling harm due to biases or underreporting.
Kainulainen, 2021	37	Quantitative	Fintoto Ltd. (now part of Veikkaus Ltd) (horse race betting)	9151 gamblers	August 1st – 30th, 2012	• Behavioural tracking data • Accelerated failure time survival log-logistic regression	Account/Behavioural tracking data included: number and time between betting days, wins and losses, sociodemographic characteristics (e.g., area of residency), volume of money wagered, net return.	To analyse gambling behaviours after a losing betting session and create a model that predicts the time until the next session	• The average gambler seems to temporarily abstain from gambling after a losing betting session • Past betting frequency strongly predicts their current betting frequency, and it is not influenced by large wins or losses	• Limited access to data (betting types and time-period) thus the estimations made are only related to the average bettor profile

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Authors	QuADS	Type of study	Source (Type gambling)	N [participants, sessions]	Time frame	Deep tech type/ name	Characteristics	Purpose	Pros	Counters
									• Loss-chasing is an unusual behaviour	
Kairouz et al., 2023	38	Quantitative	ARJEL / ANJ (multiple games)	9305 gamblers	15th December 2015 – 31st March 2016	• supervised ML models: Logistic regression, KNN, Decision trees, and SVMs	Self-reported data corresponded to the PGSI that was used to binarily categorize participants in two subgroups, PGSI 5+ and PGSI 8 + . The behavioural tracking data included: account-level information, usage of RG tools, financial transactions, betting information, winnings received, and detecting loss chasing. All models were trained using 70 % of the whole dataset, and both a LASSO penalty and 10-fold cross-validation were used.	Classifying online gamblers self-reported risk of experiencing gambling problems (i. e., PGSI 5+ or PGSI 8+) over 2 months, based on both self-reported data and objective account-based tracking data	• Both models showed excellent predictive performance in identifying gambler's risk • Identification of higher-risk gamblers outperform the identification of moderate-risk; thus, ML models appear to better distinguish the first from the population • Operators can proactively improve public health by monitoring and predicting problem gambling in their patrons	• SVMs are a non-linear ‘black box’ ML approach, thus it cannot be determined which are the most influential inputs • Results may not be generalizable • Optimal algorithmic approaches for different contexts (e. g., jurisdictions) need to be revisited over time • Autonomous decision-making systems can reinforce and amplify existing bias, deepening social inequity
Leino et al., 2016	34	Quantitative	Norsk-Tipping (Multix video terminal lottery) (Multiple games)	8636 gamblers	September 2015 – August 2016	• Behavioural tracking data • Mixed effects logistic model	Behavioural tracking data included: net outcomes and balance, stakes, wins and losses, games' payouts, bets, continuing betting session.	To explore if the gambler's continuity in betting during a session is impacted by the outcome of their previous bets	• The number of bets made during a gambling session seem to increase if the previous outcome was a win, but decrease if it was a loss • Losses disguised as wins are associated with higher persistence in betting compared to losses, although less than compared to wins • Understanding the effects of losses disguised as wins games can serve to inform changes to mitigate the development of gambling problems	• The mandatory loss limit imposed by the operator might be influencing the persistence of gamblers in their betting behaviours, thus these results can be different in platforms without this restriction
Louderback et al., 2021	38	Prospective longitudinal data	bwin.party (Multiple games)	New Subscriber Dataset: 1013 self-limiters, 312 self-excluders, and	2005–2011	• Behavioural tracking • receiver operating characteristic	Analysis of user-level behavioural data from gambling activity (e.g., spend, frequency, time).	To identify which gambling behaviour thresholds best predict risk indicators such as: voluntary SE, being	• Five new online limits were identified with acceptable sensitivity and	• However, the authors caution that these thresholds are not prescriptive limits but informative

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Authors	QuADS	Type of study	Source (Type gambling)	N [participants, sessions]	Time frame	Deep tech type/ name	Characteristics	Purpose	Pros	Counters
				680 account closers RG Dataset: 1845 RG-flagged individuals and 1762 matched controls BBGC Dataset: 1772		curve analysis • binary logistic regression	Use of logistic regression models to predict binary outcomes (e.g., whether a person exceeds a threshold or is flagged for harm). Use of ROC curves and AUC (Area Under Curve) to assess predictive accuracy. Application of Generalized Additive Models (GAMs) to explore nonlinear relationships between gambling behaviour and harm indicators. Data-driven, algorithmic threshold testing to define behavioural limits.	contacted by the RG team, account closure due to harm related to gambling. To evaluate predictive performance of these thresholds and models using AUC. To use GAMs to understand nonlinear risk patterns and identify behaviour associated with increased harm likelihood.	specificity: gambling on 11 or fewer days per month; wagering €167.97 or less per month, spending 6.713 % or less of annual income on gambling; losing €26.11 or less per month; variability in daily wagers of €35.14 or less. These new limits showed some validity for predicting PG and proxy indicators (self-limiting, SE, RG flags, account closure)	patterns, suggesting that risk increases gradually rather than abruptly beyond any single cutoff.
Luquiens et al., 2016	38	Quantitative	Winamax (online poker)	25,720 gamblers	13th November 2013 – 16th January 2014	• Account tracking data • Stepwise logistic regression	Self-reported data corresponded to the PGSI that was used to binarily categorize participants in two subgroups: non-problem gamblers (PGSI <5) and problem gamblers (PGSI ≥5). The second served as the outcome of the predictive model. Behavioural tracking data included: multi-tabling, deposits (compulsivity and total), losses (mean and total), total stakes, gambling sessions, active gambling days, time gambled, and sociodemographic data (age and gender) The model was trained with 70 % of the dataset.	Distinguishing problem gamblers from non-problem gamblers based on self-reported data and player tracking data, by using a ML algorithm: Stepwise logistic regression	• The model can discriminate with good performance between problematic and non-problematic gamblers • Feedback can be given to the user of their harmful classification, in accordance with this model • Operators can use this as a tool to determine at-risk users and promote public health by guiding them and complying with RG regulations	• Results may not be generalizable to other operators • Accounts may be used by other parties apart from the person who is legally allowed to • A percentage of users were misclassified, and the specificity was low, thus gamblers may receive false alarms of potential risk
Luquiens et al., 2018	33	Retrospective cohort	Winamax (multiple games)	1996 Self-excluded gamblers	June 2010 – October 2016	• Account data tracking • ML classification	Account-based data included: age and gender, deposits, betting activity, wins, session characteristics (duration, starting and	Describe the reported reasons for gamblers SE (i.e., addiction or commercial) and verify their veracity based on account-based data, by	• All SE, regardless of the given motive, were found to be heavy gamblers, thus potentially benefiting from	• Self-reported reasons for SE seem to be unreliable and inconsistent • Gamblers may SE from one platform

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Authors	QuADS	Type of study	Source (Type gambling)	N [participants, sessions]	Time frame	Deep tech type/ name	Characteristics	Purpose	Pros	Counters
							end date), date of SE and reason. All models had their parameters computed by form of a cross-validation method.	using ML classification models: Logistic regression, KNN, Decision trees, RFs.	further intervention. • Self-reported motives should not deter service providers from assessing risk and minimizing harm. • The SE's protective effect may be limited in time, thus those who SE should be offered referral for relapse prevention counselling	and continue gambling in another • Results may not be generalizable to all gamblers
McAuliffe et al., 2022	38	Quantitative	bwin.com (sports betting)	49,335 gamblers	1st March 2005 - 28th February 2007, & 1st March 2015 – 28th February 2017	• Account/ Behavioural data tracking • Linear regression	Behavioural tracking data included: spend from norm, frequency of play, increase in frequency of play, late-night play, deposit frequency, failed deposits, withdrawal reversals, multiple payment methods, account closure, voluntary deposit limit-settings, and exceeding deposit limits.	Use already stablish Markers of Harm risk (in intervention) that help to estimate at-risk sports gambler.	• The markers are positively associate with elevated gambling involvement and proxies of gambling-related harm.	It is still needed: • to recalibrate risk thresholds to increase the number of interventions. • to develop an aggregation procedure that optimizes the precision. • to add markers that tap underrepresented dimensions of risk.
Mueller et al., 2022	30	Experimental	x (lottery)	44 university students	23rd July 2018 – 8th August 2018	• Simple models: Logistic regression and Linear elastic net regression • ML models: SVM, Feed-forward ANN, RF, Tree-based GBM	Lottery design variables included: potential win and loss value, expected value, lottery trial, potential win being displayed, and accepting the displayed lottery by pressing an arrow. Socioeconomic characteristics included: subject-specific effects, highest education achieved, educational background, income level, age group, and gender. Past gambling behaviour included: interaction terms between lagged decisions, interaction terms between lagged decisions and positive	Prediction of risky gambling decisions, in an experimental setting, based on lottery design variables [L], socioeconomic characteristics [S], past gambling behaviours [G], and simple choice process metrics (SCPMs) derived from psychophysiological signals [P] and from eye movements as measures of visual attention [A]	• Lottery design were the main predictors of risky decisions • Physiological data provides useful insights, but do not effectively forecast gambling decisions • Physiological data provides useful insights, but do not effectively forecast gambling decisions.	• Privacy and ethical concerns related to monitoring of data and their potential misuse • Complex relationships difficult the isolation of effects attributable to individual SCPMs • The experimental setting lacks ecological validity, also habituation effects and cognitive biases can influence gambling behaviours.

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Authors	QuADS	Type of study	Source (Type gambling)	N [participants, sessions]	Time frame	Deep tech type/ name	Characteristics	Purpose	Pros	Counters
							outcome, and interaction terms between lagged decisions and negative outcome. Psychophysiological reactions included: skin conductance responses, blood volume pulse, chest breathing, respiration rate, heart rate, finger temperature, pupil size. Attention proxies included: time spent on fixing the win/loss box, looked first at left/win box, number of times switched between boxes. ML algorithms were trained using 80 % of the dataset, and hyperparameters were tuned via 10-fold stratified cross validation based on the training sample. Subject-specific dummy variables were included in each of the evaluated data sets (P, A, LSG, LSGPA) enabling the data-driven ML methods to capture potential differences in choice showing SCPM patterns across subjects			
Murch et al., 2024b	32	Quantitative	Loto-Québec (multiple games)	20,403 gamblers	17th February – 9th March 2022	• ML model: RF	The deep tech is a RF classification model, developed to detect gambling-related risk. It was selected for its strong predictive performance among several ML algorithms. It uses structured inputs derived from online gambling account data, including variables such as age, number and variability of weekly bets, amount wagered, frequency of	The model is designed to classify user into risk categories for gambling harm by analysing behavioural patterns in online gambling activity.	• If these systems continue to work well over time, these systems can improve the accurate detection and referral of at-risk online gamblers to relevant harm reduction materials and treatment services	• Although they represent an improvement over randomly guessing which users may be at-risk for harm, they are not precise enough to enable psychological treatments that may be contraindicated for different groups • It crucial to defined strategies to deal with a high number of people classify at-risk

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Authors	QuADS	Type of study	Source (Type gambling)	N [participants, sessions]	Time frame	Deep tech type/ name	Characteristics	Purpose	Pros	Counters
							rapid or repeated deposits, and indicators of risky re-engagement behaviour. The Population Stability Index (PSI) was used to detect changes in variable distributions over time, and to predict user risk levels (e.g., PGSI 5+ or 8+) by evaluating these inputs across multiple of decision thresholds, aggregating their outputs to generate a final risk score.			gambling. Otherwise, the systems will not be able to respond to severe cases.
Percy et al., 2016	34	Retrospective cohort	IGT (multiple games)	176 self-excluded gamblers and 669 community controls	SE: April 2009 & July 2011 (months leading up to their first exclusion) CG: January 2009 – 1st November 2010	• Account data tracking • ML models in WEKA: Logistic regression, Bayesian networks, NN, RF	Account-based data included: frequency of gambling, total and variability of the amount of money bet, intensity of the wager made, session time, gender, age, and country of residence. All models used default parameter values provided by WEKA software and applied ten-fold cross validation. SMOTE algorithm was also employed to balance the dataset to a 50:50 split.	Prediction of future SE based on player tracking data, by using ML algorithms: Logistic regression, Bayesian networks, NN, RF.	• Dataset balance by applying SMOTE or some other mechanism reduce specificity bias and allows the model to differentiate groups more accurately • All models could predict SE, with the highest performing model being RF, followed by Bayesian networks • Logistic regression was the worst performing • More flexible models better reflect the complex links in real-world settings.	• SE is not an indubitable proxy of problem gambling, and users may present non-harm-related motivations for SE • Factors driving the predictive results are not straightforward, raises practical, legal, and clinical concerns • Results may not be generalizable to other platforms.
Perrot et al., 2022	37	Quantitative	ARJEL / ANJ (multiple games)	12,438 gamblers	ARJEL: November 2015 & February 2016 FDJ: July 2019	• RFs, SVM, NN, or logistic regression	A ML system was created, consisting of three binary models based on PGSI thresholds (1, 5, and 8), each trained with one of four algorithms (RFs, SVM, NN, or logistic regression) selected based on Youden's Index and F1 score. Input features include behavioural indicators such as bet variability, deposit patterns, and re-engagement. The	Predict PG behaviours based on players' account data.	• The model was able to correctly identify problem gamblers and most non-problem gamblers. It can be used to personalize interventions to the gamblers, accordingly with their risk and gambling.	• Moderate-risk gamblers were often misclassified as problematic gamblers • It important to deal with false positives that is about 24 % in the present model • 2/3 of moderate-risk gamblers were classify as problematic gamblers, and ¼ of low-risk gamblers were not correctly classified.

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Table 1 (*continued*)

Authors	QuADS	Type of study	Source (Type gambling)	N [participants, sessions]	Time frame	Deep tech type/ name	Characteristics	Purpose	Pros	Counters
							three binary outputs are combined into a final four-class model that classifies users as non-problem, low-risk, moderate-risk, or problem gamblers.			
Sándor & Bakó, 2024	29	Longitudinal	Stoshidice (betting)	6486 gamblers	21-days periods starting: 2nd May 2012, 17th September 2012, 17th December 2012, 4th May 2013, 11th September 2013	• Cluster analysis • ML: feed-forward NN	Unsupervised clusters analysis was applied to behavioural data aggregated over a 7-day window, including data number of bets, bet sizes, active days, and games played. It was found two optimal clusters, one of which reflected “intensive” gambling behaviour. Using the clusters as targets, the deep learning model uses feedforward NN implemented within the H2O AutoML framework, and multiple hidden layers with ReLU activation function to capture complex patterns in user behaviour.	To predict early indicators of PG and user retention based on short-term user activity.	• The chosen behavioural descriptors can be applied to several types of gambling, allowing the assessment of problem gambling tendencies across different platforms. • It can contribute to implement proactive measures to prevent or reduce PG. • It can accurately predict players retention and gambling intensity based of identified key variables	• It is not able to recognize “true problematic gamblers” • Although promising, there is needed further replication and validation on other forms of gambling.
Stechschulte et al., 2024	32	Case study	Swiss online casino (casino)	x	1st March – 30th June 2021	• Account data tracking • Mutual information • linear and logistic regression	Indicators were extracted and generated from account-based data. They were evaluated in their adequacy to recognize PG through Mutual Information method and collinearity was checked to remove correlated indicators. The most informative and independent risk indicators included: total losses in the previous seven days, total deposits in the previous 15 days, total duration played in the previous seven days, stakes (amount bet per game) over the	Identification of detection features that indicate problem gambling at initial stages based on account-based data using a data-mining methodology	• New indicators of PG behaviour were identified • Absolute values of the indicators are more informative than relative or peak values • The linear combination of features uses indicators over a shorter period (e.g., 7 and 15 days), allowing for earlier detection • Operators can recognize problem gamblers at initial stages using the identified features and implement	x

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Table 1 (*continued*)

Authors	QuADS	Type of study	Source (Type gambling)	N [participants, sessions]	Time frame	Deep tech type/ name	Characteristics	Purpose	Pros	Counters
							previous seven days and making a deposit 12 h after a loss (chasing). Linear and logistic regression models were computed to determine the predictive performance of said features.		protective strategies timelier	
Ukhov et al., 2021	29	Quantitative	LeoVegas (multiple games)	10,000 gamblers	February 2019	• Account data tracking • GBM	Account-base data included: number of days since registration, active days, sessions characteristics (total, duration, variations, date, daytime), bets, wagers, winnings, deposits, withdrawals, age, gender, country. No threshold for decision rule separation was applied. Shapley values gave the contribution of each explanatory variable.	Prediction of problem-gambling-related SE based on account-based tracking data, by using a ML algorithm: Regularized GBM based on decision trees	• Objective assessment of gamblers behaviour patterns.	• Possible false positives. • The gamblers need to consent to receive feedback.

Note. AI = artificial intelligence; ANN = artificial neural networks; CART = classification and regression trees; CBT = cognitive behavioural therapy; DSM-5 = diagnostic and statistical manual of mental disorders 5; QuADS = quality appraisal for diverse studies tool; GBM = gradient boosting machines; KNN = k-nearest neighbour; LCA = latent class analysis; MI = motivational interviewing; ML = machine learning; NN = neural networks; PG = problematic gambling; PGSI = problem gambling severity index; RF = random forest; RG = responsible gambling; SE = self-exclusion; SMOTE = synthetic minority oversampling technique; SVM = support vector machines.

responsible gambling tools, such as *Mentor* (Auer et al., 2024; Auer & Griffiths, 2015b, 2020, 2024b), *PlayScan* (Forsström et al., 2020; Wood & Wohl, 2015), and the Win/Loss Tool (Wohl et al., 2017). These tools can be broadly grouped according to their primary functions. Behavioural monitoring and personalized feedback tools, like Mentor and PlayScan, continuously track players' gambling activity, including money and time spent, as well as failed deposit attempts, and deliver individualized feedback when behavioural thresholds or indicators of risky play are detected. Mentor provides personalized messages via pop-up windows immediately after login, based on patterns of play observed over the previous six months (Auer & Griffiths, 2020). PlayScan, in turn, classifies users into risk levels using a colour-coded system (green, yellow, red) informed by behavioural and self-reported data, and provides weekly feedback accompanied by personalized guidance (Forsström et al., 2020; Wood & Wohl, 2015). In contrast, information and self-awareness tools, such as the Win/Loss Tool, focus on increasing players' understanding of their gambling behaviour by providing objective data on cumulative outcomes, thereby enabling comparison between actual and perceived performance (Wohl et al., 2017).

3.4.3. *Restriction features*

This category comprised studies examining tools and measures aimed at promoting responsible gambling and protecting players from harm. Strategies included cool-off periods ($n = 4$), permanent exclusion ($n = 1$), a self-regulation app ($n = 1$), and limit-setting for deposits ($n = 3$), losses ($n = 1$), and time ($n = 1$). Measures were applied either mandatorily ($n = 3$), voluntarily ($n = 3$), or through a combination of both ($n = 2$). One study examined a self-management app providing real-time feedback and self-regulation strategies (Hawker et al., 2021).

3.4.4. *Decision support/AI classifiers*

This category includes studies that employed algorithmic systems or artificial intelligence tools to analyse gambling behaviour and classify user profiles. These were mainly used to describe individual differences and identify potentially problematic behaviour. Three analytical approaches were identified, where the first two depend on account-level or behavioural tracking focusing on: (i) risk classification (Auer & Griffiths, 2022a, 2023c, 2024c; Catania & Griffiths, 2022; Mosquera & Keselj, 2017; Murch et al., 2023; Murch et al., 2024a; Perrot et al., 2018; Suriadi et al., 2016; Wiley et al., 2020); or (ii) detection of binge gambling behaviours (Auer & Griffiths, 2024a; Ghaharian, Abarbanel, et al., 2024; Ghaharian, Abarbanel, Kraus, et al., 2023). A third, less frequent, line of research used biological data (namely, functional magnetic resonance imaging) to differentiate gambling disorder from non-clinical behaviours (Takeuchi et al., 2022). These studies applied analytical techniques including cluster analysis (e.g., Ghaharian, Abarbanel, Kraus, et al., 2023), machine learning models (e.g., Murch et al., 2023), and commercial tracking tools (e.g., Auer & Griffiths, 2024c).

3.4.5. *Predictive risk modelling*

This category comprised studies using data analytics or machine learning models to forecast and identify problematic gambling behaviours or markers of harm. Data collection periods varied, with most studies using recent behavioural tracking data (2015–2022: $n = 16$). The duration of data coverage ranged from one month (Auer & Griffiths, 2023a; Haeusler, 2016; Kainulainen, 2021; Ukhov et al., 2021) to over 48 months (Louderback et al., 2021; Luquiens et al., 2018; McAuliffe et al., 2022). Most studies used account or behavioural tracking data to train algorithms for detecting high-risk scores, harmful patterns, or self-exclusion, while some also included self-reports, clinical assessments, or physiological measures. Common analytical techniques included tree-based models, including random forest ($n = 10$), gradient boosting machines ($n = 6$), and decision trees ($n = 9$), as well as regression analyses (logistic $n = 14$; linear $n = 2$), support vector machines ($n = 4$), neural networks ($n = 5$), and other classification algorithms ($n = 7$). Some studies combined traditional statistical and machine learning approaches. Predictive models were trained using behavioural, financial, psychological, and restriction-related variables (e.g., Finkenwirth et al., 2021). Some studies incorporated personality features (Cerasa et al., 2018) or examined game design impacts (Mueller et al., 2022). Real-time tracking was used to monitor risk evolution over time and evaluate game features (Challet-Bouju et al., 2020; Delfabbro et al., 2024; Leino et al., 2016).

4. Discussion

The present review explored how deep tech is being employed to transform online gambling environments into safer and more responsible conscious spaces. The aspects considered were the factors promoting their implementation, the opportunities and risks they entail, and the evidence for their effectiveness in preventing, early detecting, and intervening in problematic gambling. Across the 68 studies reviewed, deep tech was applied in five interrelated functions: monitoring, informing, classifying, restricting, and predicting. These are primarily implemented by gambling operators as part of their responsible gambling and business practices, while researchers contribute to their development, validation, and improvement. Across all five functions a clear split was noted between active applications (direct platform-player interactions such as personalized messages and limit-setting) and passive systems (background behavioural monitoring, classifications, and predictive models). The reviewed evidence demonstrated technological progress: algorithms can detect behavioural patterns, platforms can deliver tailored interventions, and predictive models can stratify risk. Nevertheless, conceptual, methodological, and interpretive limitations constrain the extent to which algorithmic performance can be confidently translated into sustained reductions in gambling-related harm.

In this vein, the active applications identified largely correspond to what are commonly termed ‘responsible gambling tools’. Regulatory bodies have encouraged the development of such tools (e.g., Whiteford et al., 2022), and technological advances have further accelerated their deployment (e.g., Auer & Griffiths, 2015a, 2015b; Haefeli et al., 2015). However, these systems still place the decision-making burden primarily on players. For example, personalized feedback systems integrate normative comparisons, address cognitive distortions, and provide practical advice in real-time (Auer & Griffiths, 2015a, 2016, 2018), which have been shown to increase awareness of gambling patterns and risk when potentially harmful behaviours are present (Auer et al., 2024; Auer & Griffiths, 2015b, 2020, 2024b; Wohl et al., 2017; Wood & Wohl, 2015). Despite these benefits, positive effects are typically short-lived (Auer & Griffiths, 2016; Ivanova et al., 2019), with small impacts on high-intensity players (Auer et al., 2018, 2021) and potential misinterpretations of low-risk classification that can ultimately endorse and encourage increased gambling (Wohl et al., 2017). These limitations highlight the complexity of problematic gambling, where more intense gamblers experience stronger cravings and reinforcement cycles that increase their likelihood of seeking alternative ways to satisfy urges (Brand et al., 2019).

In addition to platform-embedded alert messages, one study evaluated a voluntary self-management smartphone app that provided real-time feedback and strategies to help reduce cravings (Hawker et al., 2021). Although promising, its heavy dependence on gamblers' motivation and awareness results in greater adherence among individuals already concerned about their gambling. This is in line with evidence showing that more conscious gamblers are more likely to use limit-setting tools (Auer, Hopfgartner, & Griffiths, 2020). Yet, users who opted for self-management frequently exhibited high levels of harmful behaviours, suggesting that such tools may capture individuals at later stages of risk. To enable earlier intervention, strategies such as raising awareness of responsible gambling tools (Hopfgartner et al., 2023; Wohl et al., 2024) and providing real-time behavioural feedback via pop-up messages (Haefeli et al., 2015) may help steer gamblers towards protective features before self-exclusion becomes necessary. These systems can also be advantageous for operators, as early identification of potential self-excluders allows the implementation of protective measures that may reduce escalation (Auer et al., 2021; Wohl et al., 2024). Nonetheless, ethical and privacy concerns persist, particularly regarding potential misuse of behavioural data (Hopfgartner et al., 2023).

To address the broader challenge of relying on player initiative, gambling platforms have also introduced obligatory restrictions, including mandatory breaks and compulsory limits on time, wagers, or games (e.g., Auer, Reiestad, & Griffiths, 2020). However, the reported effectiveness of these tools is mixed. On one side, there was no positive impact of this measure, with gamblers worsening their behaviours after mandatory breaks (Auer et al., 2019), having behavioural changes that did not persist over time (Hopfgartner et al, 2022), and switching to less regulated platforms (Auer & Griffiths, 2023b). On the other side, imposed breaks appeared to mitigate the perpetuation of gambling practices, while not causing rebound effects nor the abandonment of the operator (Hopfgartner et al, 2022).

Overall, active tools, whether feedback, voluntary self-management, or mandatory restrictions, highlight both the potential and the limitations of interventions that depend, to varying degrees, on the engagement and choices of gamblers themselves. This sets the stage for passive systems, which shift the emphasis away from player initiative towards continuous background monitoring and algorithmic inference. These systems mainly use the players' account and/or session data to analyse, classify and/or predict future behaviours. Although they serve as a base for active systems, they tend to align with the public health perspective more than the responsible gambling paradigm. This is due to passive systems' ability to adopt a more complex approach that can contribute to the prevention of harmful patterns by analysing a short amount of data and using it to classify risky gamblers and potential future problematic gamblers. Their strength lies in the capacity to analyse large volumes of objective data in real time, allowing momentary, longitudinal, and predictive evaluations of gambling behaviour and supporting personalised interventions across varying risk levels (e.g., binge, moderate, high-risk patterns; Chagas & Gomes, 2017; Ghaharian, Abarbanel, Phung, et al., 2023; Škařupová et al., 2020). Importantly, such systems also provide regulators with actionable insights into the distribution of gambling-related harm, particularly in disadvantaged neighbourhoods disproportionately affected by the industry (Selin et al., 2024).

Evidence shows that predictive and classification models tend to outperform traditional statistical methods, with complex algorithms such as random forest and gradient boosting being consistently identified as the best performers (Percy et al., 2016; Perrot et al., 2022). Systems such as Mentor illustrate how these tools can be implemented across multiple platforms and game types, offering adaptable and scalable solutions (Auer & Griffiths, 2022a, 2023c, 2024a, 2024c). Beyond accuracy, however, their reliability is challenged by methodological and conceptual issues. Difficulties in replicating outcomes from clustering studies (Ghaharian, Abarbanel, et al., 2024) and the narrowness of behavioural markers derived from diagnostic criteria (Catania & Griffiths, 2022) highlight the fragility of models when applied outside their original context.

The so-called “black box” nature of unsupervised machine learning models, which obscures how predictions are generated, is underlined as another key limitation (Kairouz et al., 2023). Their lack of interpretability restricts both academic scrutiny and regulatory trust. Moreover, findings regarding risk markers are inconsistent: while some studies found indicators such as self-exclusion or payment methods predictive of harm (Luquiens et al., 2018), others reported them as unreliable or context-dependent (Finkenwirth et al., 2021; Haeusler, 2016). Similarly, predictive models often struggle to identify moderate-risk gamblers, misclassifying and overlooking complex behavioural signals in multiplatform play (Auer & Griffiths, 2023a; Challet-Bouju et al., 2020; Ukhov et al., 2021). A related concern is the reliance on fixed thresholds to define problematic gambling, such as monetary or time-based cut-offs. These thresholds rarely capture the gradual and multifaceted nature of gambling-related harm, which emerges from a complex interplay of behavioural, psychological and contextual factors (Louderback et al., 2021).

In practice, platforms may also set thresholds too high, thereby overlooking individuals in intermediate stages of risk and only flagging the severer cases. Such practices undermine opportunities for early intervention, allowing harmful behaviours to escalate before protective measures are triggered. To appropriately address this, it might be required to integrate data from multiple sources (i.e., across platforms, gambling modalities, and relevant non-gambling contexts) to better understand the continuum of risk and improve precision of detection models. Building on this, future research should explore interoperable systems capable of integrating behavioural data across operators. Approaches such as federated learning or regulator-led data-sharing frameworks could reduce the fragmentation of risk detection, permit more comprehensive assessments while maintaining user privacy. In parallel, regulatory requirements for algorithmic transparency and periodic auditing would help ensure that predictive models are not only continuously updated but also interpretable and generalizable across jurisdictions. Such measures would strengthen the reliability of deep tech applications and prevent their commercial repurposing in ways that prioritise engagement over harm minimisation.

Despite these challenges, passive systems demonstrate considerable promise for early detection and intervention. Several studies emphasised their potential to enable targeted, personalised interventions and to assist operators in proactively safeguarding at-risk players (Auer & Griffiths, 2023a; Luquiens et al., 2016). However, this potential will only be realised if models are regularly updated, validated across diverse platforms and jurisdictions, and embedded within robust regulatory frameworks. Without such precautions, concerns about data privacy, ethical misuse, and the reinforcement of commercial interests remain central (Hassanniakalager & Newall, 2019; Mueller et al., 2022).

Overall, the reviewed evidence indicates that deep tech holds considerable promise for enhancing safer gambling practices. Active tools can raise awareness and reduce betting, but their effects are constrained by the reliance on user initiative, limited durability, and their weaker impact on high-intensity gamblers. Passive systems offer scalability and consistency, yet raise issues of interpretability, validity, and privacy. Both approaches can be used to increase individuals' engagement and to protect the gamblers. They share common challenges, including fragmentation across platforms, inconsistent thresholds, and risks of misuse. Their impact is maximised when combined with accurate detection, real-time feedback, and transparent, ethically guided regulation. In sum, deep tech can contribute meaningfully to gambling harm minimisation, but only if implemented within a clear, standardized, and public health–oriented framework. This finding, however, must be considered in light of some limitations that influence their interpretation.

4.1. Limitations and future studies

First, a notable proportion of included studies were identified by manually searching reference lists and prior reviews rather than through the database query. This is possibly due to the diversity of terminology used across publications. For example, concepts such as ‘player protection’, ‘behavioural tracking’, or ‘predictive analytics’ were sometimes described without direct reference to ‘responsible gambling’ or ‘deep tech’. This variation in language meant that some studies were not captured by the search string used. Still, the present study mitigated this limitation by complementing the database search with targeted manual scanning and citation chaining. This strategy allowed the identification of additional relevant studies which ensured a comprehensive coverage of the topic.

It should be noted that the date of publication does not always reflect the timeliness of the data used, as in the case of Whiteford et al. (2022), who based their analysis on data collected in 2005. This time discrepancy between the collection and publication dates raises important questions about the external validity of the results, especially in areas marked by rapid social, technological, or epidemiological changes. The use of outdated data can compromise the applicability of their conclusions to their current reality, reducing the practical usefulness of the evidence generated. Consequently, future studies should consider not only the date of publication but also the date of data collection as an inclusion criterion, to ensure greater temporal coherence and contextual relevance of the integrated evidence.

The uneven distribution across authors, countries, and industry collaborations is another important limitation of the current evidence base. A small group of researchers account for much of the literature, often with direct involvement in the tools under study. For instance, evidence on personalized feedback systems largely comes from Auer & Griffiths, 2015a, 2016, 2018, 2020, Auer & Griffiths, 2024a, 2024b, 2024c), who co-developed the commercial tool Mentor. Meanwhile research on PlayScan is concentrated among a few Swedish teams (e.g., Forsström et al., 2016; Jonsson et al., 2019). These contributions are valuable, but the dominance of a limited set of authors highlights the need to consider potential conflicts of interest and encourage replication by independent groups.

Geographically, most studies originated from countries where operators grant access to behavioural tracking or account data, leading to the underrepresentation of other regions (e.g., Asia, Africa, South America). This may be due to the illegality or heavy restriction of gambling in some countries (e.g., parts of Asia and the Middle East), limited research funding and infrastructure (e.g., Sub-Saharan Africa), or to an industry still in early development (e.g., Brazil). By contrast, countries with longer gambling traditions and mature markets (e.g., the UK, Norway, Sweden, Australia) are better positioned to generate large-scale datasets, offering useful lessons but also risking overgeneralization if relied on exclusively. Addressing these imbalances will require broader international collaboration, greater transparency about funding and conflicts of interest, and independent access to operator data.

In addition, only peer-reviewed published articles were included in the present review, which may have narrowed the range of strategies and technological applications identified as currently being implemented within the gambling industry. As such, future studies should also incorporate grey literature because it may provide valuable information and insights which were not captured in the present review (Ghaharian, Abarbanel, Phung et al., 2023). The methodological quality, although generally high, also varied across the included studies. While some were rigorous and transparent in their designs and analyses, others did not provide a full report of their procedures, data acquisition or analytic methods. This lack of detail undermines the reproducibility of the article and complicates cross-study comparison. Furthermore, author's affiliation with operators and the use of operator-provided datasets represents potential conflicts of interest that raise concerns about the extent to which findings can be independently verified. Importantly, the quality assessment tool employed explicitly considered these factors, which resulted in the lowering of the scores for some of the included studies.

The ambiguity surrounding the definition of deep tech also warrants attention. Notably, a consistent and widely accepted definition could not be identified, which required the adoption of a general, experience-based conceptualisation. As such, a working definition of deep tech was proposed, although future research is encouraged to assess its applicability and refine it further. Moreover, this arbitrary definition led to the inclusion of studies that engage with deep tech only indirectly, in particular those focused on data monitoring, where technologies are primarily employed within data processing workflows (e.g., Heirene et al., 2021; Leino et al., 2015; Selin et al., 2024). Nevertheless, the present review sought to include research that integrated elements of deep tech while also offering meaningful analyses and interpretations of the collected data. Accordingly, future research and stakeholders should evaluate the scalability of the present findings to gambling platforms. In line with this, relatively few studies have assessed the applications or data processing performed by gambling operators, which may reflect a broader lack of reporting and transparency concerning the underlying algorithms and systems used (for example, see Marionneau et al., 2025). Therefore, it is recommended that future research examines operator-developed apps and analytical tools to enhance transparency and the practical applicability of responsible gambling technologies.

4.2. Theoretical and practical implications

The present review contributes to both the theoretical and practical understanding of the gambling environment by summarising the potential applications of deep tech within the gambling sector. It adequately addresses the outlined objectives and highlights several implications for key stakeholders, including operators and regulatory bodies.

The study addressed specific features and tools that can enhance the safety and integrity of online gambling platforms. It underscores the necessity for a multifaceted approach to mitigate the negative consequences associated with gambling behaviour. While advanced gambling algorithms are capable of identifying risk patterns, their effectiveness is limited by a margin of error. This limitation could be mitigated by integrating self-reporting mechanisms, which complement algorithmic detection while offering insights into users' cognitive distortions that can be further examined using real gambling data (e.g., Chagas & Gomes, 2017).

Finally, the findings presented in the present review outline some features that regulatory authorities can actively mandate to more effectively oversee and control the gambling industry, such as geographic analysis of the gambling distribution. The proposed measures have the potential to enhance safer gambling practices and inform the development of more robust regulatory frameworks.

5. Conclusion

Online gambling is primarily a recreational activity designed to entertain. The integration of advanced technologies can enhance the viability of the gambling industry by promoting greater security and responsible use. From this perspective, the use of monitoring, predictive analytics, classification systems, and self-reporting tools demonstrates that it is possible to create a safer online gambling environment; one that prioritizes entertainment while minimizing potential harm. Nevertheless, responsibly ethical and sustainable implementation of these technologies depends on continuous independent research and robust regulatory frameworks that uphold transparency, accountability, and user protection.

CRediT authorship contribution statement

Leonor G. Cardoso: Writing – review & editing, Writing – original draft, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Beatriz C.R. Barroso:** Writing – review & editing, Writing – original draft, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Gloria Piccoli:** Investigation, Data curation, Conceptualization. **Miguel Peixoto:** Data curation. **Pedro Morgado:** Writing – review & editing, Validation. **António Marques:** Visualization. **Carla Rocha:** Project administration. **Mark D. Griffiths:** Writing – review & editing, Visualization, Validation. **Ricardo Queirós:** Writing – review & editing, Visualization, Validation, Project administration, Conceptualization. **Artemisa R. Dores:** Writing – review & editing, Visualization, Validation, Supervision, Project administration, Funding acquisition, Conceptualization.

Declaration of competing interest

The authors declare that there are no competing interests to declare.

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Data availability

Data will be made available on request.

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