Computers in Human Behavior Reports 18 (2025) 100644

Contents lists available at ScienceDirect

Computers in Human Behavior Reports

journal homepage: www.sciencedirect.com/journal/computers-in-human-behavior-reports

Duty of care, data science, and gambling harm: A scoping review of risk assessment models

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ARTICLE INFO

Keywords:
Gambling
Duty of care
Risk assessment
Data science
Harm detection
Harm prevention

ABSTRACT

Aims: Duty of care policies mandate gambling operators to identify problematic gambling behaviours amongst their customers. Online operators often employ risk detection algorithms to accomplish this task. This scoping review focuses on how such data science applications can perform from a duty of care perspective.

Methods: In line with the PRISMA guidelines for scoping reviews, we systematically retrieved academic studies, reports, and industry initiatives that used statistical methodologies to predict, model, or forecast gambling behaviour. The final sample consists of 31 academic studies published between 2015 and 2025, and 11 commercial solutions. Our analysis focuses on three critical stages of model development: 1) selection of estimation data; 2) decisions related to the model estimation process; and 3) assessment and interpretation of prediction model results.

Results: Models vary in terms of predictors, dependent variables, methodological approaches and assessment. Most models attempt to identify harm that has already occurred rather than forecasting future harm. Data are typically aggregated despite higher granularity in original datasets. Measures to assess the prediction ability of models are not optimal. Industry funding or involvement is prevalent in model development.

Conclusions: Currently, risk assessment algorithms do not function pre-emptively and are unlikely to capture the full extent of harm occurring in digital gambling. As such, their usability within the duty of care framework remains limited. Ways forward would entail openness and standardisation in terms of choice of variables, forecasting horizons, assessment of methods, and evaluation of results to improve models and regulatory oversight.

1. Introduction

Online gambling companies hold vast amounts of data on consumers and their interactions. Access to behavioural data allows gambling companies to employ data science and artificial intelligence (AI) to improve their operation. Data science refers to a range of data processing, statistical and computational methods. AI can be used to automate many aspects of data science, often using machine learning (ML) models that rely on algorithms that improve performance based on experience with data. Data-based applications have become increasingly prevalent in the gambling industry. Such applications include detection of anomalies related to fraudulent activities or crime (Dakalbab et al., 2022; Kim et al., 2024) and delivering personalised gambling content to consumers, including targeted marketing and behavioural nudges or sludges (Guillou-Landreat et al., 2021; Newall et al., 2019; Newall & Rockloff, 2022; Marionneau et al., 2023). Customer data can also be used to train algorithms to detect and flag potentially problematic gambling patterns or behaviours (Braverman & Shaffer, 2012; Philander, 2014; Auer & Griffiths, 2022; Ghaharian et al., 2022).

1.1. Customer data and duty of care

Harm detection solutions drawing on consumer data are already widespread in the gambling industry. In most jurisdictions, these models can form a part of voluntary corporate social responsibility (CSR) policies that companies can implement at their own discretion. However, in some European countries, harm detection can also be part of legally mandated ‘duty of care’ obligations. Duty of care refers to a legal

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https://doi.org/10.1016/j.chbr.2025.100644
Received 29 November 2024; Received in revised form 14 February 2025; Accepted 10 March 2025
Available online 11 March 2025

mandate on gambling operators to track customer behaviour and to intervene in cases where problematic behaviours are detected (Hancock et al., 2008). In land-based environments, duty of care focuses mainly on employee training. In online gambling, technological solutions are prevalent. At least 11 European countries (Austria, Denmark, France, Germany, Great Britain, Italy, Malta, The Netherlands, Norway, Spain, Sweden) have legal provisions or principles on duty of care, although these vary in breadth and scope (Meerkerk, 2022).

Regulators therefore rely heavily on operators to design and implement these duty of care models (Ukhova et al., 2024). As a rule, policies oblige licensed operators to detect problematic or risky gambling behaviour but concrete measures to fulfil this duty are usually left to the license holder to determine (Meerkerk, 2022). For example, in Sweden, duty of care entails that operators should safeguard customers from harmful gambling by monitoring gambling patterns and by contacting customers that show signs of excessive gambling (Samuelsson & Cisneros Örnberg, 2022). In Austria, the monopoly provider is obliged to monitor gambling behaviour and to conduct an affordability check in case of suspicion of excessive gambling. Germany requires licensed operators to have algorithm-based systems to identify potential gambling problems (Meerkerk, 2022). In Great Britain, a recent high court decision ruled that companies, in fact, do not owe a duty of care to customers despite the licensing conditions suggesting this (Cooley, 2024).

In online gambling, gambling operators often employ AI models trained to analyse behavioural patterns in player tracking data (Meerkerk, 2022). AI-based tracking tools use a variety of 'markers of harm' such as repeat deposits, use patterns of gambling management tools (e.g., limit-setting), frequency of gambling, or night-time gambling (Delfabbro et al., 2023; Catania & Griffiths, 2022; McAuliffe et al., 2022). The British Gambling Commission (2024) has recommended seven categories of harm indicators for operators to monitor. These include patterns of spend, customer spend, time indicators, behaviours, customer-led contacts, use of gambling management tools, and account indicators. The French Regulator ANJ (2024) has recommended that operators use behavioural indicators such as financial transactions and time spent, indicators related to limit-setting and help-seeking, and attitude-related indicators. In the Netherlands, the gambling authority Kansspelautoriteit (2024) has produced a list of signals that operators need to monitor, including using credit cards or e-wallets for deposits, gambling for more than 6 h in a 24-h period, insufficient funds on bank account during transfer, and maximum monthly net deposits. When reaching a predetermined threshold, these tools can prompt interventions, ranging from automated messages to contacts or even involuntary exclusion (Meerkerk, 2022; VixioGambling Compliance, 2024).

Little research has investigated the effectiveness of duty of care policies. However, one evaluation of markers of harm in two samples of sports bettors found that less than one percent of bettors ever exceeded any risk score thresholds (McAuliffe et al., 2022). This suggests that harm thresholds may be unreasonably elevated or that markers may be ill-adapted, as global estimates of problematic or at-risk gambling, particularly online, are significantly higher (Tran et al., 2024). Furthermore, qualitative evidence from individuals experiencing gambling-related problems has shown that duty of care models may not function optimally, with individuals being allowed to continue gambling without interventions despite clearly excessive gambling (Samuelsson & Cisneros Örnberg, 2022). Suggested reasons for lacking effectiveness have included insufficient enforcement and poor regulatory guidelines. Furthermore, as most models are industry-developed, competing profit objectives of gambling operators may influence resourcing or even development of models (Meerkerk, 2022; Samuelsson & Cisneros Örnberg, 2022).

1.2. Development of risk assessment models

Most models that enable gambling operators to monitor customers for duty of care purposes, are commercial products. However, an emerging body of academic research also uses customer data to identify, analyse and predict potentially harmful gambling behaviours. To our knowledge, four prior reviews have looked at existing data science applications in the gambling research field (Ghaharian et al., 2022; Chagas & Gomes, 2017; Mak et al., 2019; Deng et al., 2019). Mak et al. (2019) systematically map and compare machine learning applications in addiction psychiatry but not in harm detection. Ghaharian et al. (2022), Deng et al. (2019), and Chagas and Gomes (2017) map the state of data science applications in gambling research. None of these reviews have focused on the use of data science applications for duty of care. Furthermore, no prior reviews have charted existing industry initiatives and models in the field.

Data science is a vast field, and different methodological choices throughout the development and implementation of risk detection models have significant impacts on how well they perform their task. To evaluate the potential of data science to contribute to duty of care, it is therefore important to understand how and based on what kind of methodologies existing duty of care models are built. In particular, to properly evaluate the performance of these models, we need a better understanding of three crucial stages of model development.

First, the selection of estimation data and variables influences what is predicted and how. Variable selection includes the choice of markers of harm but also dependent variables – including whether models predict survey-based measures or other actions, and at what thresholds harm is flagged. In addition, timepoint aggregation influences the granularity of data, i.e., at what time intervals data are summarised. Lower data frequencies can lead to a loss of some significant findings. It is also relevant to consider the kinds of training sets used for models. Training sets are example data that are used to train ML models.

Second, decisions related to the model estimation process influence how a model is built and fitted, and what kind of factors it considers. Models can use a variety of methods, including different supervised and unsupervised ML models. In a field with little standardisation, it is particularly important to consider and compare different algorithms (also Ghaharian et al., 2022). In addition, model fitting includes hyperparameter tuning. ML algorithms have hyperparameters that are fixed before estimating a model with training data. The optimal hyperparameter values are selected as the ones that provide the best prediction performance for a separate validation dataset that was not used to estimate the actual model. The values of these fixed hyperparameters can have a substantial effect on the prediction and generalisability of the estimated model, and changing a single hyperparameter value can therefore affect results significantly.

Third, model assessment and interpretation can differ based on the kind of evaluation metrics that are used. In data science, the ROC curve is typically used to plot the true positive rate (TPR) (share of correctly classified individuals with gambling problems) against the false positive rate (FPR) (share of individuals without problematic gambling, incorrectly classified as having gambling problems). The AUC is a summary measure of classification performance across these threshold combinations, making it a convenient tool when the dataset is balanced (i.e., the number of individuals experiencing problems is approximately the same as that of individuals not experiencing problems) and the model specific preferences regarding TPR and FPR are not known. AUC values range from 0.5 (no classification ability) to 1 (perfect classification ability). However, when the dataset is highly imbalanced, which is almost always the case when the task is to identify problematic gambling, other methods of testing the model performance should be considered.

1.3. The current study

This paper presents the results of a scoping review of data science-based risk assessment models from a duty of care perspective. A scoping review methodology is appropriate due to lack of standardisation in the field. As also identified in a previous review (Ghaharian et al., 2022), there has been a critical need for data science applications to inform policy and practice in the gambling field. The identification and prediction of harmful gambling from a duty of care perspective can be a valuable policy tool (Newall & Swanton, 2024), but this necessitates a more thorough translation of theory into practice (Ghaharian et al., 2024). In the current scoping review, we focus on the three critical stages of model development outlined above: 1) selection of estimation data; 2) decisions related to the model estimation process; and 3) assessment and interpretation of prediction model results.

2. Methods

In line with the scoping review methodology (Tricco et al., 2018; Grant & Booth, 2009), we systematically retrieved academic studies, reports, and industry initiatives that used statistical methodologies to predict, model, or forecast gambling-related harm. The main aim was to map what kind of data-driven methodologies are used to predict problematic gambling behaviour, with what data, and how well these models are estimated to perform.

2.1. Study selection

First, we identified relevant studies by conducting a systematic literature search in scientific databases (Scopus, Ebscohost, and Google Scholar). As databases differ in their search algorithms, we adjusted our search parameters accordingly. For Scopus, we included all references that featured our search terms in the title, abstract, or keywords. In Ebscohost, we included all references across all databases. In Google scholar, we included the first 50 hits per search term. This cut-off was based on an initial screening of results, confirming that no relevant results appeared after the 50 most relevant results.

We also searched for additional resources based on the lists of references of identified studies, by scoping for grey literature on Google, and by using the database of Vixio Gambling Compliance. Vixio is an intelligence and data service specialising in industry and regulatory developments in the gambling field. It has a search function that enables searching for news and regulatory updates using keywords. The Vixio database is available under license.

The search terms used across the databases were: ‘Gambling AND forecast OR machine learning OR predictive modelling OR account data OR artificial intelligence OR data science’. We also tried other search terms, including ‘duty of care’, ‘algorithm’, ‘risk detection’ and ‘prediction’. However, these searches did not yield additional results. ‘Algorithm’ and ‘prediction’ are widely used terms in any research paper and resulted in hundreds or thousands of irrelevant hits. Using ‘duty of care’ as a search term did not yield results related to the use of data science to detect gambling harms. Instead, literature on duty of care focused on policy and legal commentaries. We did not limit our searches to online gambling because similar models could be used in identified land-based gambling.

To capture privately developed models or approaches taken by the gambling industry, we also extended our search on google to include prominent gambling provider names and the term ’responsible gambling software’. The searches in the academic databases were conducted in English, but with no restrictions on the language of results. However, all included sources were in English. The grey literature searches on Google were conducted in English, French, German, Italian, Swedish, Norwegian, and Finnish. Collectively, the research team was able to read these languages.

We included all results published between January 2015 and February 2025. The search was originally conducted in March 2024, but later updated in February 2025. The updated search was conducted on Scopus and Ebscohost. The updated search resulted in the inclusion of three additional studies. The choice to limit results to articles published after 2015 was motivated by the fast developments in the field and our aim to scope only recent approaches. As data science methods evolve rapidly, we expected that studies published over 10 years ago would be unlikely to have additional information value with regard to current applications in the duty of care field.

The second phase of our review consisted of the identification, screening, and inclusion of studies, described in Fig. 1, based on PRISMA 2020 guidelines adapted for scoping reviews (Tricco et al., 2018). Our search yielded a total of 1088 records. Based on the titles of references, we first removed duplicates (N = 293) and unrelated hits (N = 647). We screened the remaining 148 records for their relevance based on their abstracts, resulting in the exclusion of a further 99 papers. Two papers could not be retrieved. The remaining 47 papers or reports were read in full. At this stage we excluded eight papers but included an additional three papers after the updated searches in 2025.

At all review stages, two members of the research team read and evaluated the papers independently. We then compared results. Any disagreements were discussed in the full group to reach consensus on the final decision to include or exclude. The final sample consists of 42 papers or reports, of which 31 are academic papers and 11 are models produced by gambling companies or other private actors. The list of commercial or company models is unlikely to be comprehensive due to wide variety in how these are promoted online and our inability to conduct google searches in all languages. However, these 11 models provide a sample of existing approaches and their methodological detail.

During the abstract screening and full report reading phase, we applied the following exclusion criteria: We excluded (1) non-empirical discussion papers that did not include original data; (2) prior reviews; (3) reports that did not use data science methods to model problematic gambling or harmful gambling behaviour; (4) theses produced by students; (5) papers focusing on video gaming instead of gambling. For company models, we excluded software designed to ensure conformity with self-exclusion registries, limit-setting or compliance reporting, only, as these models were not used to track and identify harmful gambling behaviours.

2.2. Analysis methods

The analysis focuses on assessing models that identify or predict problematic gambling. We focused on three crucial stages of model development: 1) data used for estimations; 2) decisions made during the model estimation process; and 3) assessment of the prediction power and interpretation of model results. The choice to focus on these stages was based on our on-going work investigating the development of a regulator-led (rather than industry-led) prediction model for duty of care purposes. The results of this work will be reported separately.

For each included study, we systematically noted the reference, data-related variables (size and data frequency), method-related variables (dependent variable used, predictor set, forecasting horizon), modelling-related variables (purpose of model, model estimation (including hyperparameter tuning), model assessment, possible model comparison, possible discussion on type I and II error preference), details on interpretation and reporting, source of funding, and whether data, code, or the model were openly available. All data were double checked by at least two authors.

3. Results

3.1. Company models

Our review included 31 academic studies (see Table 1) and 11 commercial or company-built software solutions to track and identify potentially harmful gambling indicators using data science methods.

It was not possible to systematically assess the commercial models due to overall lack of information on their data, method, or modelling-

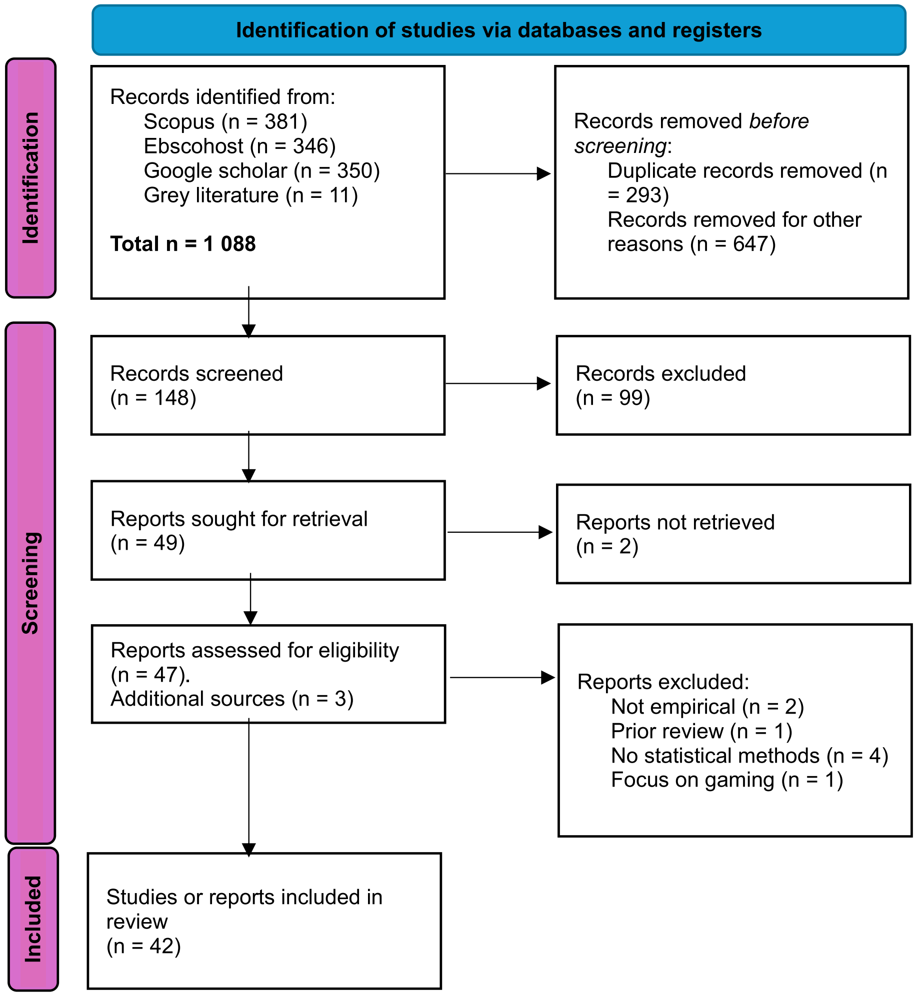

Fig. 1. Prisma flow diagram.

related metrics. Available data extracted from the descriptions of these models is described in appendix A. Overall, our search captured six in-house models of gambling companies (Entain Group; Gaming1; Kindred; Sisal; Spel; Veikkaus) and five commercial models (Buddy, Databricks, Mindway, Openbet, Xuvi). Openly available descriptions of the models contained general level details or promotional material highlighting the use of AI and prediction ability. One model provided sample code (Databricks). Most models described predicting some form of risk level or profile. Predictors included behavioural indicators such as consumption and betting patterns, payments, browsing time or logins, subscribing to marketing, visiting bonus pages, or changes in the use of gambling management tools. Further details on methodological choices were not described for any model on their publicly available website.

Some commercial models advertised the possibility to customise behavioural indicators or dependent variables in accordance with what clients wish to consider as problematic on their platforms (Xuvi). Others proposed a full-service platform solution where the same data-driven consumer segmentation algorithm can be used for targeted interventions, personalisation, promotions, as well as churn detection and prevention (Bet Buddy).

3.2. Descriptive results of academic literature

Table 1 provides a summary of the included 31 academic studies.

Included academic studies employed similar methodologies to predict gambling harm as described in commercial models. Some of the commercial models (Kindred, Openbet) also reference peer-reviewed literature included in our review as proof of their scientific model development (Auer & Griffiths, 2022, 2023a, 2023b, 2023c, 2023d, 2023e; Catania & Griffiths, 2022; Hopfgartner et al., 2023).

Twelve included studies employed survey-derived measures (such as the Problem Gambling Severity Index, PGSI) as the dependent variable (Auer & Griffiths, 2023c, 2023d; Hing et al., 2019; Hopfhgartner et al., 2024; Kairouz et al., 2023; Louderback, LaPlante, Currie, & Nelson, 2021; Luquiens et al., 2016; Murch et al., 2023, 2024a, 2024b; Perrot et al., 2022; Seo et al., 2020). Five studies predicted voluntary self-exclusions (Finkenwirth et al., 2021; Hopfgartner et al., 2023; Percy et al., 2016, 2020, Ukhov et al., 2021).

Predictors included a variety of behavioural indicators, typically variables related to time and money spent, gambling frequency, transactions, or use of gambling management tools. In addition, studies included some demographic characteristics, most commonly gender, age, or country of residence. One study (Auer & Griffiths, 2023d) also included variables related to gambling motives. The number of predictors ranged from less than ten to over a hundred across studies. In many cases, the number of predictors differed across models, or the final number of the predictions used was not clearly described.

Most studies used a dependent variable that corresponded to the same period as the behavioural predictors (e.g., the same month). This meant that models identified harms that have already occurred. 13 studies forecast some form of future gambling problems or current problem gambling status with retrospective data. These types of studies were mostly conducted in the most recent years included in the review (2023–2024) (Auer & Griffiths, 2022; Auer & Griffiths, 2023b, 2023c,

Table 1
Studies included in the review.

Reference	Dependent variable	Reported data size (Players, N)	Predictors	Forecasting horizon	Funder	Open access
Auer and Griffiths (2022)	Loss limit change	70,789	Gambling behavioural variables	Following 3 months	Industry	No
Auer and Griffiths (2023a)	Cluster analysis	150,895	Gambling behavioural variables	Comparison of two time periods	None declared	No
Auer and Griffiths (2023b)	Daily risk categorisation	37,986	Gambling behavioural variables; demographics	Following day/ period	None declared	No
Auer and Griffiths (2023c)	PGSI category	945	Gambling behavioural variables; demographics	Following day/ period	None declared	No
Auer and Griffiths (2023d)	Survey on reasons for gambling	3627	Gambling behavioural variables; motivational variables; demographics	Following day/ period	Industry	No
Auer and Griffiths (2023e)	Cluster analysis	150,895	Gambling behavioural variables; demographics	Cross-sectional	None declared	No
Catania and Griffiths (2022)	Cluster analysis	982	Gambling behaviour variables	Cross-sectional	None declared	No
Chagas et al. (2022)	Cluster analysis	154,585	Gambling behavioural variables, demographics	Cross-sectional	None declared	No
Challet-Bouju et al. (2020)	Cluster analysis	1152	Gambling behavioural indicators	Cross-sectional	Academic	No
Delfabbro et al. (2023)	Gambling behavioural indicators (markers of harm)	100,000	Participation in different gambling products	Cross-sectional	Industry	No
Finkenwirth et al. (2021)	Self-exclusion	19,683	Betting behavioural variables	Cross-sectional	Academic	No
Ghaharian et al. (2023a)	Cluster analysis comparison	5580	Transaction variables	Cross-sectional	None declared	Yes (data and scripts)
Ghaharian et al. (2023b)	Cluster analysis	2286	Variables related to transactions	Cross-sectional	None declared	Yes (data)
Hing et al. (2019)	PGSI category	722	Survey-based gambling behavioural variables	Cross-sectional	Government	No
Hopfgartner et al. (2023)	Self-exclusion	25,720	Gambling behavioural variables; demographics	Following month	None declared	No
Hopfgartner et al. (2024)	PGSI category	1742	Gambling behavioural variables; account variables; demographics	Following day/ period	None declared	No
Kairouz et al. (2023)	PGSI category	9306	Gambling behavioural and account variables	Following period	Academic	No
Lajcinová et al. (2023)	Gambling anomalies	22,000	Gambling behavioural variables	Cross-sectional	Academic	No
Louderback, LaPlante, Currie, & Nelson, 2021	BBGS, use of RG tools	48,114 (2066 RG; 2244 BBGS)	Gambling behavioural variables	Cross-sectional	Industry	No
Luquiens et al. (2016)	PGSI	14,261	Gambling behavioural variables; demographics	Following period	Industry	No
Murch et al. (2023)	PGSI category	9145	Gambling behavioural and account variables	Following period	Academic	Yes (scripts)
Murch et al. (2024a)	PGSI category	9145 & 11,258	Gambling behavioural variables; demographics	Following day/ period	Academic	Yes (scripts)
Murch et al. (2024b)	PGSI category	9145 & 10,716	Financial activity; demographics	Following day/ period	Academic	Yes (scripts)
Percy et al. (2016)	Self-exclusion	22,500	Gambling behavioural variables; demographics	Cross-sectional	Academic	No
Percy et al. (2020)	Self-exclusion (gender bias)	22,500	Gambling behavioural variables; gender	Cross-sectional	None declared	No
Peres et al. (2021)	Cluster analysis	15,083	Gambling behavioural variables	Cross-sectional	Academic	No
Perrot et al. (2018)	Cluster analysis	10,000	Gambling behavioural variables; demographics	Cross-sectional	Academic	No
Perrot et al. (2022)	PGSI category	12,438	Gambling behavioural and account variables	Following period	Academic	No
Sándor and Bakó (2024)	Cluster analysis	2263 (445)	Transaction variables	Following 7-day period	Academic	Yes (data and scripts)
Seo et al. (2020)	GPSS, degree of PG	5045	Gambling behaviour; demographics	Cross-sectional	Academic	Yes (data)
Ukhov et al. (2021)	Self-exclusion, gambling type	10,000 (2500 per category)	Gambling behaviour; demographics	Cross sectional	None declared	No

2023d; Hopfgartner et al., 2023, 2024; Kairouz et al., 2023; Luquiens et al., 2016; Murch et al., 2023, 2024a; 2024b; Perrot et al., 2022; Sándor & Bakó, 2024). However, the forecast horizon was very short (usually the following day) and the model fitting and forecasting were performed with only a single period per individual. Furthermore, models that predicted or forecast problematic behaviour using survey-based dependent variables used the same period for self-evaluation and model fitting. Rather than pure forecasting, this method therefore tests how individuals self-assess their own past gambling behaviour.

Almost half of the included studies were funded via academic or governmental sources. Five studies declared direct funding from the industry. 12 studies did not disclose any funding but reported industry connections or affiliations in their conflict-of-interest statements. Four studies provided open access to their data, and five studies provided open access to scripts used (see Table 1). Many studies were unable to provide open access to data due to lack of permission from a gambling company due to proprietary considerations.

In the following, we focus on the data, decisions in model estimation, assessment of prediction power, and interpretation of included studies in more detail.

3.3. *Data used in estimations*

Included studies differed in terms of data size, ranging from less than 1000 to over 150,000 individuals. However, across studies, final datasets used to fit the models were aggregated to lower frequencies. Original datasets were typically at stake, session, or daily levels but aggregated to 1-12-month periods. This reduced the frequency and information-value of the data and limited analytical power and possibilities to include time dimensions in analyses. While such a practice can be appropriate from a research perspective, it does not permit instantaneous reactions from a duty of care perspective.

The training sets used to build models varied in length. Four studies used training sets that spanned over at least a year (Chagas et al., 2022; Lajcinová et al., 2023; Louderback, LaPlante, Currie, & Nelson, 2021; Percy et al., 2016). 21 studies used periods ranging from one month to less than a year (Auer & Griffiths, 2022, Catania & Griffiths, 2022; Auer & Griffiths, 2023a; Auer & Griffiths, 2023c; Auer & Griffiths, 2023e; Challet-Bouju et al., 2020; Delfabbro et al., 2023; Finkenwirth et al., 2021; Ghaharian et al., 2023a; Ghaharian et al., 2023b; Hopfgartner et al., 2023, 2024, Kairouz et al., 2023; Luquiens et al., 2016; Murch et al., 2023, 2024a, 2024b, Peres et al., 2021; Perrot et al., 2018; Perrot et al., 2022; Seo et al., 2020). The remainder of studies used training sets that were shorten than a month. Two studies did not specify the training set period (Percy et al., 2020; Ukhov et al., 2021). Five studies included more than one training set time periods (Auer & Griffiths, 2023e; Lajcinová et al., 2023; Percy et al., 2016; Peres et al., 2021; Perrot et al., 2022).

3.4. Model estimation

Most studies used supervised machine learning (ML) algorithms and/or traditional regression methods to predict problematic gambling. Traditional regression models often assume a linear relationship between predictors and the response variable while machine learning typically estimate functional forms between variables that are highly nonlinear. The selection of the type of ML modelling framework or algorithm varied (e.g., neural network, random forest, etc.).

Ten studies used unsupervised machine learning (k-means, hidden Markov model, dynamic time warping etc.) or other algorithms to cluster gamblers into different groups based on behavioural and other characteristics (Auer & Griffiths, 2023a, 2023c, 2023d; Catania & Griffiths, 2022; Challet-Bouju et al., 2020; Ghaharian et al., 2023a, 2023b; Peres et al., 2021; Perrot et al., 2018; Seo et al., 2020). In these studies, modelling consisted of choosing variables and running a clustering algorithm with different numbers of clusters. The optimal number of clusters is chosen based on the evaluation of different measures. The algorithm attempts to form distinct groups based on the values of initially chosen variables. When the clusters are estimated, specific characteristics of each group were analysed by showing mean values (and other measures such as standard deviation) of each behavioural variable distribution separately for different groups. Groups were then used to separate those who could be classified as having a problem with gambling.

17 studies compared different ML algorithms (Auer & Griffiths, 2022; Auer & Griffiths, 2023b; Auer & Griffiths, 2023c; Auer & Griffiths, 2023e; Finkenwirth et al., 2021; Ghaharian et al., 2023a; Ghaharian et al., 2023b; Hopfgartner et al., 2023, 2024; Kairouz et al., 2023; Lajcinová et al., 2023; Murch et al., 2023, 2024a; Percy et al., 2016; Perrot et al., 2022; Sándor et al., 2024; Seo et al., 2020). ML algorithms can differ in terms of their ability to learn relationships between specific gambling behaviour variables and a chosen measures for problematic gambling. In addition to the choice of model, internal hyperparameter tuning can have an important effect on results.

Most studies using ML algorithms discussed hyperparameter tuning, although to varying levels of detail (Auer & Griffiths, 2022; Auer & Griffiths, 2023a; Auer & Griffiths, 2023c; Auer & Griffiths, 2023d; Catania & Griffiths, 2022; Challet-Bouju et al., 2020; Finkenwirth et al., 2021; Ghaharian et al., 2023a; Ghaharian et al., 2023b; Hopfgartner et al., 2023, 2024; Kairouz et al., 2023; Lajcinová et al., 2023; Louderback, LaPlante, Currie, & Nelson, 2021; Murch, 2023, 2024b; Percy et al., 2016; Peres et al., 2021; Perrot et al., 2018; Perrot et al., 2022; Sándor et al., 2024; Seo et al., 2020).

3.5. Model assessment

Most studies used the Area Under the curve (AUC) of Receiver Operating Characteristics (ROC) to assess the performance of models in terms of identifying those with problems from those without problems. The AUC measure may be misleading in situations where data are imbalanced, as in most studies with far fewer individuals with problematic gambling in comparison to without problematic gambling. Most included studies had highly unbalanced datasets, with the proportion of individuals with identified gambling problems ranging from 20 % to less than 1 %. Six studies mitigated the imbalance either by over-sampling the minority class (individuals with problems) or by under-sampling the majority class (individuals without problems) for the estimation dataset (Finkenwirth et al., 2021; Kairouz et al., 2023; Murch et al., 2023, 2024a, Percy et al., 2016; Seo et al., 2020). One further study discussed the imbalance although data balancing procedures were not used (Perrot et al., 2022).

Only three studies employed Precision-Recall AUC (PRAUC) to evaluate the prediction ability of the models (Murch et al., 2023; 2024a, Perrot et al., 2022). The PRAUC provides a more accurate reflection of model performance in unbalanced datasets by using precision (proportion of correctly classified individuals with problems amongst all individuals classified as having problems) and recall (proportion of correctly classified individuals with problems among all individuals with problems). Achieving a high PRAUC requires models to accurately identify most individuals with problems without too much incorrect categorisation.

3.6. Summary of results

Table 2 provides an overview of the results as proportions. Data underlying this table are available in appendix B. The table shows how many studies used specific methodological tools and procedures of all studies concerned with those choices. Overall, results show variety

Table 2
Summary of main results.

	N studies	N studies relevant	Share of studies for which relevant (%)
Funding from industry/ private sector	10	31	37 %
Open access to data	4	31	15 %
Open access to code	5	31	16 %
Dependent variable from survey responses	12	22	55 %
Dependent variable self-exclusion	4	22	18 %
Forecasting future gambling harm	13	31	42 %
Aggregation of initial dataset	31	31	100 %
Training set one year or more	4	31	13 %
More than one training set period	5	31	16 %
Used unsupervised ML/ clustering methods	10	31	32 %
Multiple ML algorithms compared	17	27	63 %
Hyperparameter tuning is discussed	21	27	78 %
Unbalanced nature of data discussed	9	18	50 %
Use of data balancing procedures	6	18	33 %
Use of area under the precision-recall curve	3	18	17 %

Note: details underlying this table are available in Appendix B.

across studies in terms of data and methods used. Percentual results show a significant lack of standardisation in the field.

4. Discussion

This scoping review has focused on 11 commercial or company models and 31 academic papers using data science-based risk assessment models to predict or identify harmful gambling. Some of the commercial models included in our review referenced some of the included academic studies as part of their model development. Academic literature is therefore likely to be a good proxy for the current state of development also in the commercial field. Overall, our results have shown important variety in terms of predictors, dependent variables, methodological approaches to estimations, and assessment, as also identified in a prior review (Ghaharian et al., 2022). Methodological variety has a profound effect on how well models can be compared or evaluated. This, in turn, impacts their ability to respond to duty of care mandates.

From a duty of care perspective, it appears that models are still developing and require work to effectively accomplish their task of identifying or forecasting problematic gambling behaviours. While many European countries now rely on data science-based models as a tool for harm reduction or even harm prevention (Meerkerk, 2022), it is unlikely that current models can accomplish this task. Furthermore, as only a small minority of individuals are identified by these models (cf. McAuliffe et al., 2022), particularly in comparison to the prevalence of problematic gambling amongst those who gamble online (Tran et al., 2024), a large part of harms goes unnoticed. To respond to the duty of care mandate, the development of models predicting harm needs to be rigorous, effective, trustworthy, and open so that they can be overseen and evaluated by regulators.

Based on our results, we propose five avenues forward towards a more standardised data science approach for duty of care purposes.

First, applications need to be more open. The industry-developed software solutions included in our review were not openly available, with little information on the model, modelling procedure, code, or data used to build them. This is not surprising due to intellectual property issues. In research papers, methods were described more thoroughly. Yet, even in academic research, few provided open access to data or code. In most cases, this was due to confidentiality agreements with gambling companies that had provided access to their data for the study. In other fields, such as psychology and economics, there has been an identified replication crisis of academic results (Baker, 2016; Hou et al., 2020; Maniadis et al., 2017; Open Science Collaboration, 2015). This is partly due to lack of publicly available data and code. To avoid a similar situation in gambling research and regulatory oversight of duty of care policies, it would be important to develop avenues for open access to data from gambling companies. This would also allow independent evaluation and comparison of existing models.

Second, variables need to be more thoroughly investigated and designed. Almost half of the studies in our review used a survey-derived measure such as the PGSI to identify individuals with problematic gambling. The PGSI is a standardised instrument that has become the gold standard in estimating the prevalence of problem gambling (Currie et al., 2013; Dowling et al., 2018; Williams & Volberg, 2014). The use of the PGSI as a dependent variable is therefore justified from a research perspective (also Murch et al., 2024a). Yet, any survey-based measure can be biased and prone to measurement errors (Williams et al., 2012). A survey-based measure can also disregard harmful behaviours amongst those who would not be classified as ‘problem gamblers’ or whose behaviours have important temporal variations (cf. Browne & Rockloff, 2018). This may lead to some problems going unrecognised. From a duty of care perspective, focusing on PGSI categories can also sustain discourses of small minorities harmed by gambling rather than allowing effective detection and intervention when or before harms occur.

While survey-based measures can be helpful in developing models, an effective duty of care implementation would need to strive to detect harmful gambling behaviour from measurable actions rather than from survey responses, only. Some studies use voluntary self-exclusion as a measure of gambling problems, but self-exclusion is also unlikely to be an optimal measure. Only a small minority of individuals with gambling-related problems opt to self-exclude (Williams et al., 2007; Australian Productivity Commission, 2010; Håkansson & Henzel, 2020) and individuals who self-exclude may also do so for other reasons than experienced harm (Auer & Griffiths, 2016).

It is unlikely that a single measure can capture all harm, and markers of harm can also differ across individuals and jurisdictions. However, some best practices can be identified. One way forward could be to have multiple separate measures that can be related to problematic gambling. These can include different variables related to the amount of time and money spent gambling. Previous research also shows that gambling spending is a good indicator of gambling problems (Fiedler et al., 2019). Money and time spent should be tracked in absolute terms, but additional indicators could also track these relative to affordability or a baseline level. To set reasonable thresholds for indicators, model development could be informed by evidence-based research, such as the lower risk gambling guidelines (Hodgins et al., 2023).

Third, and related to the second point, the forecasting horizon of models needs to be more forward-looking. Most existing models only identify harms once these have already occurred. Even in cases where some form of forecasting of future harm took place, this was only for the very near future (i.e., next day). For studies that used self-exclusion as the dependent variable, the focus was on behaviour associated with self-exclusion at one time point. In the case of survey-based models, the dependent variables (survey responses based on e.g., past three-month gambling behaviour) were concurrent with the model fitting data and period. Use of survey data also necessitated aggregating other data to similar levels. Company data can be available at session-levels, but studies model gambling harm with lower frequency data such as monthly aggregations.

Aggregated data can be justified as gambling harms are more wide spanning than microlevel behaviours. However, aggregation also results in the loss of crucial information. Daily or session-level data may allow better detection of both current and future trends toward harm. Computational resources have increased significantly and are unlikely to pose barriers to analysing more granular data. This is particularly true of commercial models used for duty of care purposes: constantly updated datasets are needed to identify harms in real-time. Real-time data can also contribute to constant optimisation of the model to become more forward-looking. From a public health and duty of care perspective, it would be essential to identify harms already before they occur. Predicting harmful gambling beforehand would allow targeting consumer-specific interventions or nudges to prevent these harms (also Marionneau et al., 2023).

Fourth, methodologies need to be better assessed and compared. Models employing clustering and unsupervised machine learning rely on differences across groups. The justifications given to different thresholds varied across studies as there are no empirically defined limits to distinguish groups. Thresholds for groups would therefore require evidence-based and theory-driven analysis (Chagas et al., 2022; Challet-Bouju et al., 2020). Several studies in our review compared different statistical or ML models. One study compared six different ML models (Ghaharian et al., 2023b). A previous review (Ghaharian et al., 2022) also found that the number of identified groups varied across studies employing clustering methods. In addition to model choice, different hyperparameters within the model affect results. Hyperparameters can affect conclusions related to the prediction power of the algorithm and the importance of predictors.

Fifth, and finally, the unbalanced nature of datasets needs to be better addressed. As they stand, AUC values (related to ROC curves) can provide a misleading impression of model performance in samples with a high imbalance. For example, in a sample of 1000 with only 10 experiencing problematic gambling, an AUC of 0.9 might suggest excellent performance. However, this could occur if the model correctly classifies 9 out of 10 individuals with problems, but also incorrectly classifies many individuals without problems as having problems with their gambling (e.g., 100 out of 990). While the TPR and TNR (true negative rate) may appear similar, the absolute number of misclassified individuals without problematic gambling vastly exceeds that of the misclassified individuals with problems, leading to potential overestimation of utility. A more widespread use of area under the precision recall curve (PRAUC) would be a good way forward. Oversampling does not provide the same advantages as PRAUC, as oversampling the minority class may increase the risk of overfitting while under-sampling the majority may lead to losing valuable information.

Overall, our results have shown that while duty of care-based models are developing, they are not yet sufficient to prevent or significantly reduce gambling harms. Harm prevention requires multilevel solutions where universal and selective harm prevention are needed to target non-gamblers and those gambling at low-risk levels, and indicated measures are needed to help those with an increased risk of harm (Fiskaali et al., 2023). Duty of care models can provide one tool within this wider prevention portfolio, but, at least in their current form, duty of care models cannot be relied on as the only measure.

To bring the field forward, regulators would need to take a stronger role in defining and implementing duty of care policies and guidelines. Gambling business models depend on high spenders who are usually also experiencing problems (Wardle et al., 2023). Effective prevention of harms is therefore directly associated with reduced revenue (Livingstone & Rintoul, 2020). As in any sector, profit objectives can be a threat to effective implementation of duty of care or other social responsibility goals. From a harm prevention perspective, the best option could be a centralised, cross-provider duty of care system maintained by an independent authority. If this cannot be achieved, it is crucial to at least define what companies should be measure, at what thresholds, and how compliance is ensured. The responsibility for identifying those at-risk should not be assigned to gambling operators if effective research-based models and guidelines have not been first developed by regulators or independent scholars.

The current lack of guidance to operators in implementing duty of care (Meerkerk, 2022) has created a situation in which operators are merely mandated to measure something. This something can easily become a black box strategy or a form of AI-washing (cf. Seele & Schultz, 2022) where regulators see companies as a necessary part of the solution. If companies hold the power over model development, they can freely choose how these models are developed and what these models detect. This leaves regulators with little power or oversight in evaluating if models, in fact, respond to the duty of care mandate.

4.1. Limitations and further studies

This study has some limitations. We were not able to systematically assess commercial and company-developed harm detection algorithms due to lack of openly accessible data. The list of company models is also unlikely to be complete due to high variety in how these are called and described in the public space. This limited us to investigate data science applications in research papers. While some commercial models were based on the research literature reviewed, most were not. Further studies could attempt to analyse company models in more detail by, for example, making data requests to developers directly. In addition, differing methodologies and approaches taken in the included studies did not allow us to conduct a meta-analysis. Finally, our analysis focused on the detection or forecasting of gambling-related problems, and not the full range of duty of care activities, such as contacting identified individuals. As such, our review only gives a partial image of the implementation of duty of care mandates.

Further studies should give attention to the full duty of care process, starting with precise definition of what kind of harm is identified, at what threshold, how contact is initiated with flagged individuals, how adequate protective measures are selected, and how long-term implications are tracked. It would be particularly important to compare how duty of care policies are implemented across countries, if company models take different requirements into account, and how this can affect performance. This type of comparison was not possible in the current study due to lacking information on commercial models. Further studies are also needed to develop better methodologies into prospective forecasting of harms (cf. Murch, 2023) and looking into different markers and their ability to predict and forecast harm.

4.2. Conclusion

Several European countries mandate gambling providers to perform active duty of care by monitoring and intervening with harmful gambling behaviours. In many cases, this mandate involves the use of risk detection models using artificial intelligence. Our results have shown that these types of models vary in terms of predictors, dependent variables, methodological approaches and assessment. Most models only recognise harm that has already occurred but cannot predict or prevent future harms or escalations of gambling behaviour.

Data-driven models for duty of care purposes have promise, but also methodological challenges that can result in them identifying only a small minority of individuals experiencing gambling problems, and only once these harms have occurred. Existing models perform well in predicting who are the ‘one percent’ experiencing severe pathological gambling. However, they are unlikely to recognise at-risk individuals with lower severity of problematic gambling. More rigorous methodological development, methodological openness, and comparison across different models is needed to drive the field forward. Duty of care can be an important addition to gambling harm reduction and prevention, but only if it is properly defined and overseen.

CRediT authorship contribution statement

Virve Marionneau: Writing – review & editing, Writing – original draft, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Kim Ristolainen:** Writing – review & editing, Validation, Investigation, Formal analysis, Data curation, Conceptualization. **Tomi Roukka:** Writing – review & editing, Investigation, Formal analysis, Data curation, Conceptualization.

Primary funding

VM, KR, and TR received funding for this paper from the Finnish Ministry of Social Affairs and Health based on the provisions of section 52 of the Finnish Lotteries Act. Open access funded by Helsinki University Library

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgements

We are thankful for comments from and discussions with the expert members of the Gambling Harms Evaluation Group under the Finnish Ministry of Social Affairs and Health. We also thank Elli Luoma for her help with the references.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.chbr.2025.100644.

Data availability

Links to research articles are provided in the manuscript.

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