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Knowledge.

Research.

Innovation.

AI and Player Risk Identification - Research Report Summary

Massachusetts Gaming Commission Meeting
November 6th, 2025

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Research Objectives

1. Identify use cases and ethical concerns of current and future applications of AI - **STUDY 1**.

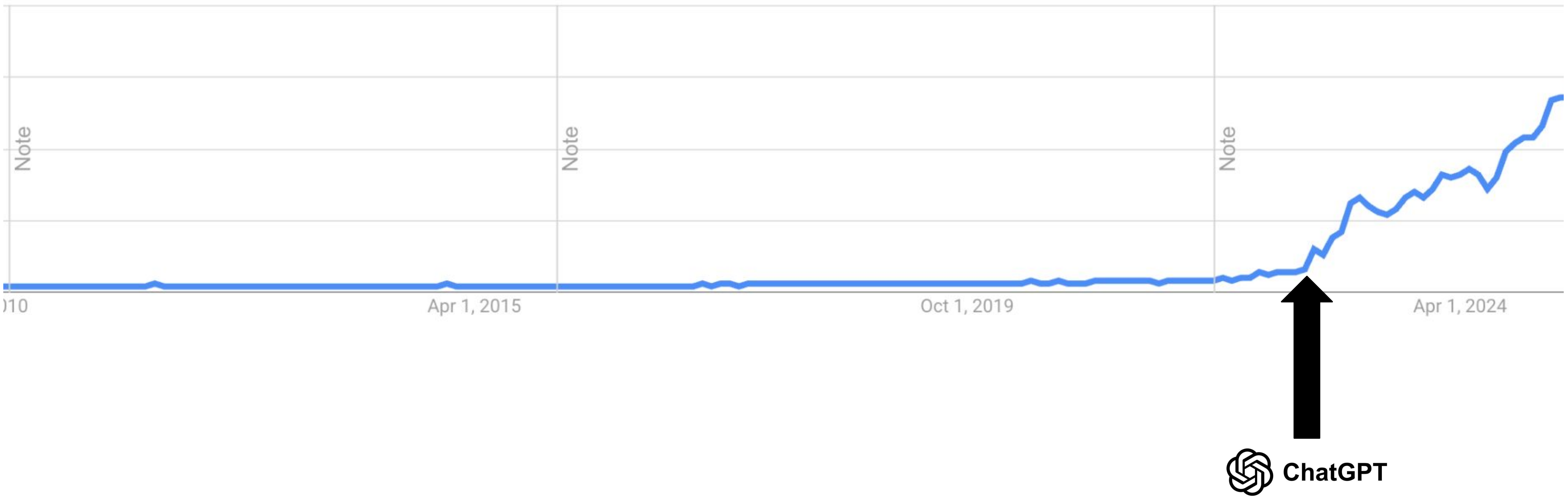
2. Understand the evidentiary support for behavioral markers of harm used for player risk detection - **STUDY 2**.

3. Obtain a targeted understanding of financial risk identification and the technology that exists to track players across operators and gaming modelaities - **STUDY 3**.

STUDY 1 - AI Use Cases


https://spectrum.ieee.org/dartmouth-ai-workshop

Interest over time for search term "ai"




Artificial Intelligence
Machine Learning
Deep Learning
Large Language Models
ChatGPT

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STUDY 1

Via focus groups…

1. How do participants define current uses of AI in the gambling industry?

2. What do participants believe are the possible future uses of AI in the gambling industry?

3. What do participants believe are the risks and ethical considerations of AI applications in the gambling industry?

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STUDY 1

Current AI Use Cases

Four main themes:

1. Operational Efficiency and Workforce Augmentation
2. Customer Relationship Management
3. Player Experience and Engagement
4. Compliance and Risk

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

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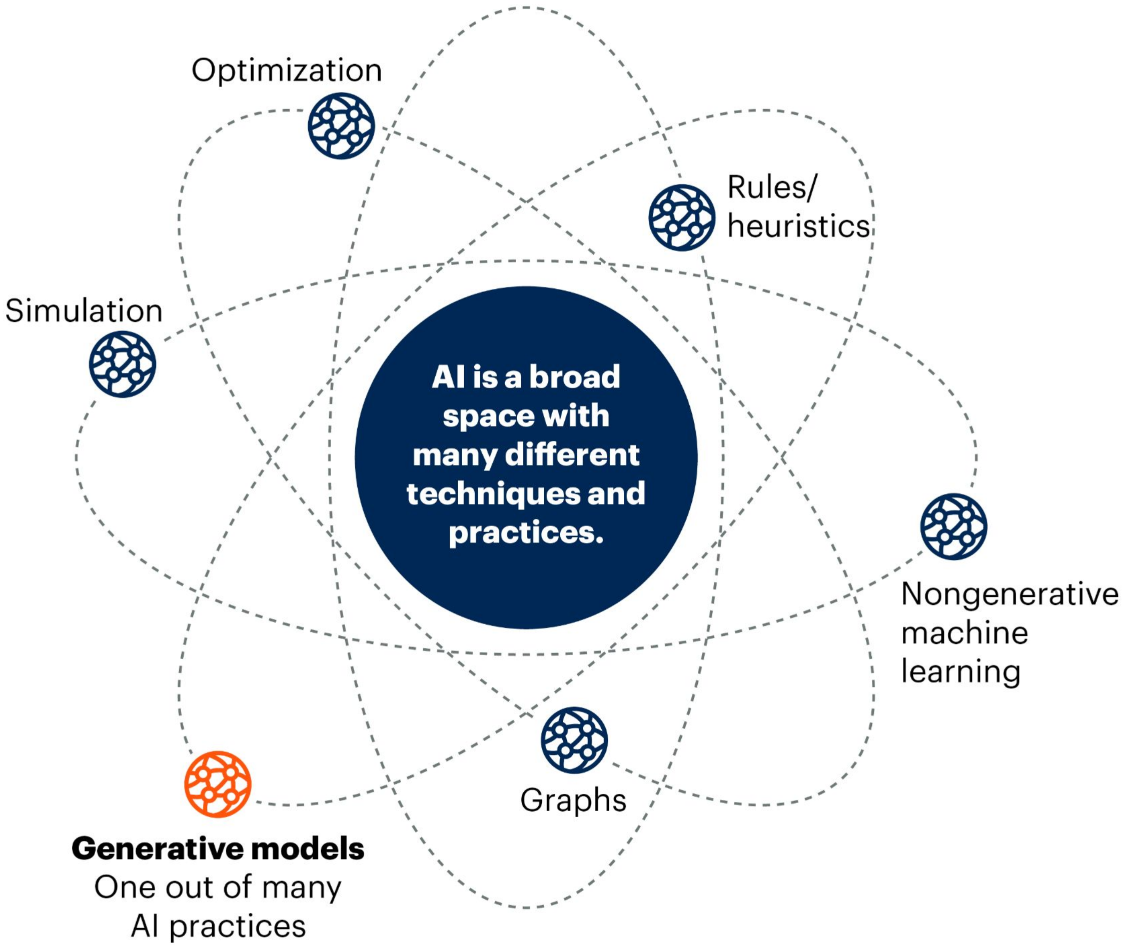
STUDY 1

Traditional AI

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

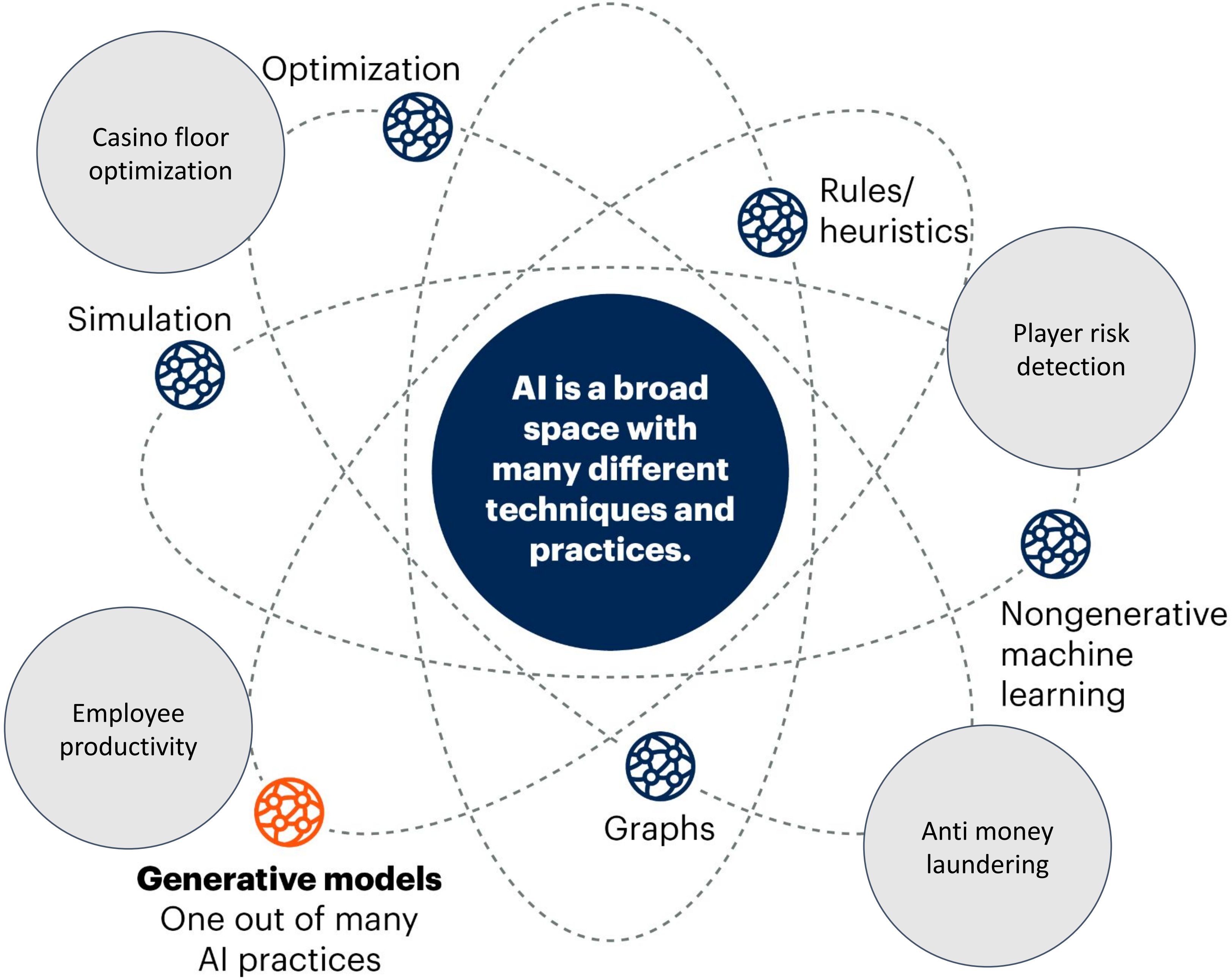
—*Gambling AI Expert*

AI Does Not Revolve Around GenAI



Source: Gartner

Gartner


AI is a broad space with many different techniques and practices.
Optimization
Casino floor optimization
Rules/ heuristics
Simulation
Player risk detection
Nongenerative machine learning
Employee productivity
Graphs
Anti money laundering
Generative models
One out of many AI practices

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GenAI = Speed and Scale

STUDY 1

"The pressures to get new content out at speed is huge. AI is perfect. Suddenly you've got a room full of developers."

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

"Scaling insights and best practices across the entire player database."

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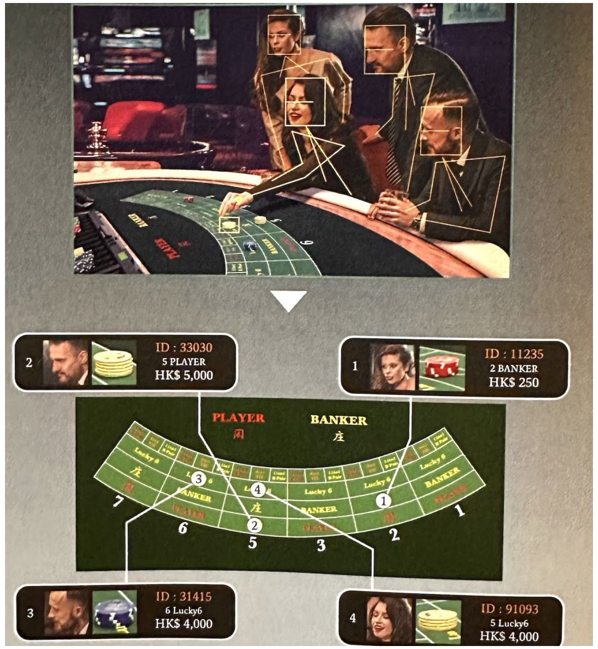
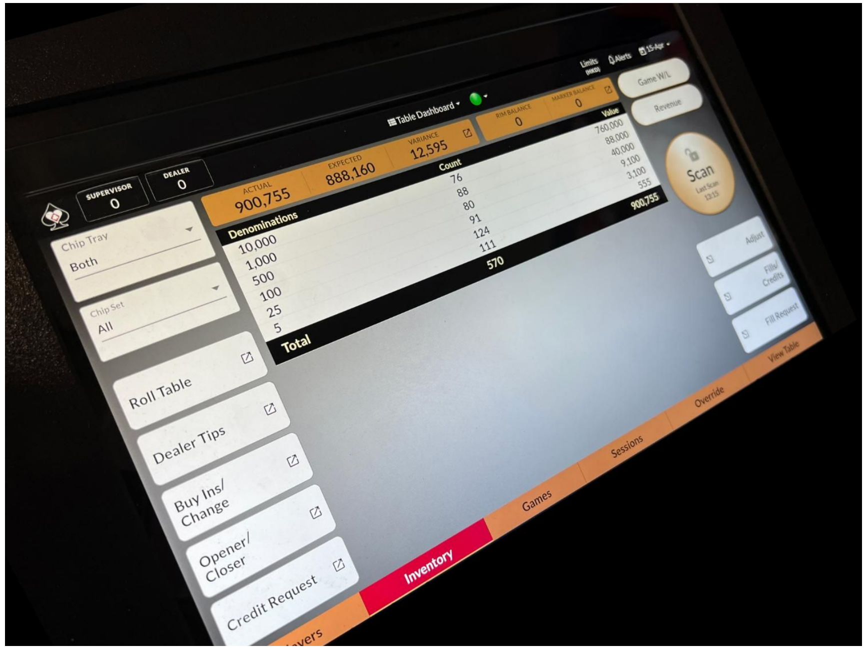
STUDY 1

Future AI Use Cases

- Novel data sources powering novel use cases





ANGEL

WDTS
WALKER DIGITAL TABLE SYSTEMS

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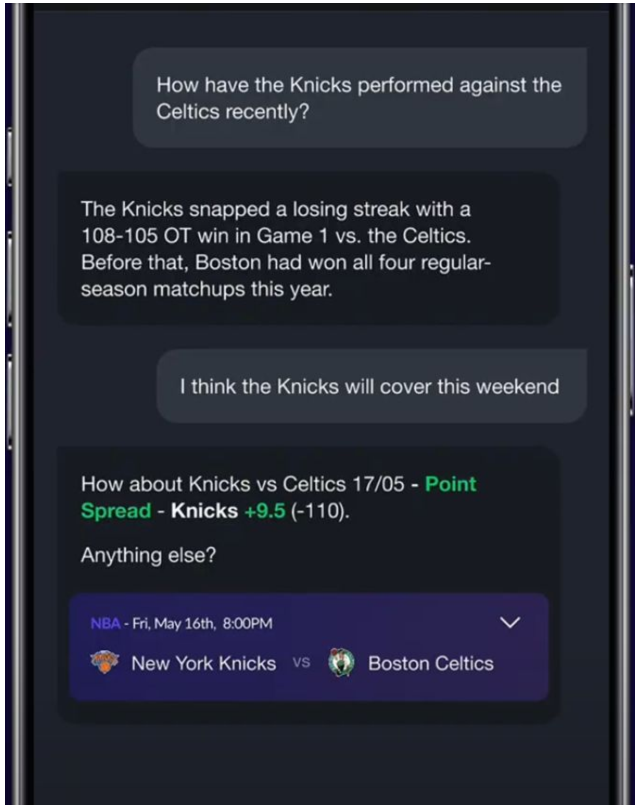
STUDY 1

Future AI Use Cases

- Agentic AI

"a category of AI systems capable of independently making decisions, interacting with their environment, and optimizing processes without direct human intervention"



promptbet.ai

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STUDY 1

Risks

- Hyper-personalization
- Human agency (agentic AI)
- Employee understanding and operational preparedness
    - LLMs (e.g., hallucinations, harmful outputs, abstaining)
- **Appropriate regulatory understanding and action**

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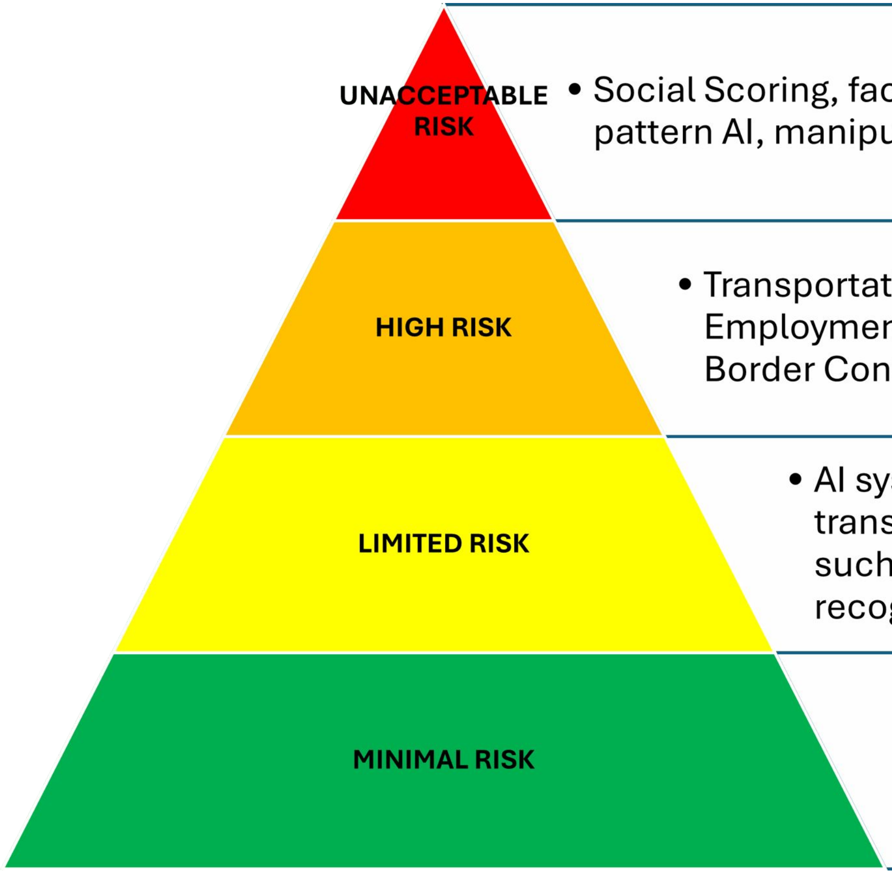
STUDY 1

The EU AI Act



- Social Scoring, facial recognition, dark pattern AI, manipulation
- Transportation systems, Safety, Employment, Education Access, Border Control, Justice Systems
- AI systems with specific transparency requirements such as chatbots, emotion recognition systems
- AI enabled Video games, spam filters

Prohibited AI Systems

AI systems:

- deploying **subliminal, manipulative, or deceptive techniques** to distort behaviour and impair informed decision-making, causing significant harm.
- **exploiting vulnerabilities** related to age, disability, or socio-economic circumstances to distort behaviour, causing significant harm.

https://artificialintelligenceact.eu/high-level-summary/

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

—*AI Lawyer*

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STUDY 1

Responsible AI in Gambling

- Using foundation language models as an example…

- If used in customer facing scenarios such as chatbots for account information or betting assistants:
  - What evaluation has been performed before implementation?
  - What ongoing evaluation procedures are in place?
  - Has it been evaluated for specific risks, e.g.:
    - information leakage
    - manipulation
    - persuasive nudging
    - advising on betting decisions

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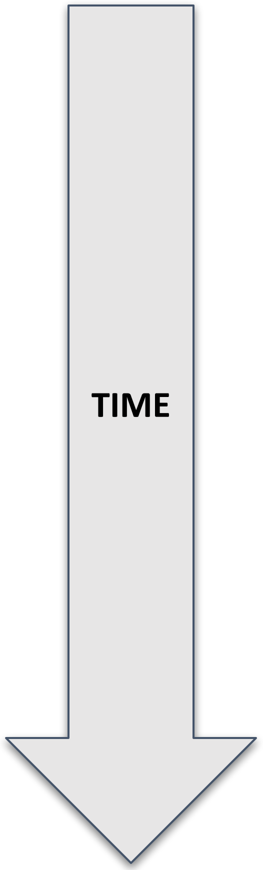
STUDY 1

Recommendations for Regulators

- Appoint an internal AI champion or task force
- Support industry training and internal governance
- Survey licensees' AI use cases
- Engage in cross-agency dialogue
- Develop sector specific AI-guidance



STUDY 2 - The BRIDGE Systematic Review

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STUDY 2

The BRIDGE Database

Behavioral **R**isk **I**ndicators **D**atabase of **G**ambling **E**vidence

- Evaluate the evidence that exists to support behavioral risk identification.
- Regulatory bodies are increasingly mandating the use of data-driven approaches to player risk detection.
- However, an ongoing challenge is providing guidance and determining which indicators are most effective for modeling risk.

A presentation at ICE London in February 2024 revealed nine key markers of harm: losses, changes in the use of responsible gambling tools, gambling product preferences, time spent gambling, customer-initiated contact, canceled withdrawals, depositing behavior, speed of play, and volume of stakes. October 2025 CEN voted to approve a draft framework on gambling harm markers, finalization by early 2026.

The UK Gambling Commission's list, includes: customer spend, patterns of spend, time spent gambling, gambling behavior indicators, customer-led contact, use of gambling management tools, and account indicators

The Ksa categorizes its indicators into five domains: intensity, loss of control, increase in gambling, operator behavior, and features of the games.

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STUDY 2

The BRIDGE Database

Behavioral **R**isk **I**ndicators **D**atabase of **G**ambling **E**vidence

- Development process around these current recommendations is unclear.
- Drawing strong inferences from existing research remains challenging.
- As noted in the Ksa report…

“some indicators have been studied extensively, while others have only been studied a few times,”

and

“even when indicators were studied multiple times, they were often operationalized in different ways and that makes comparisons difficult.”

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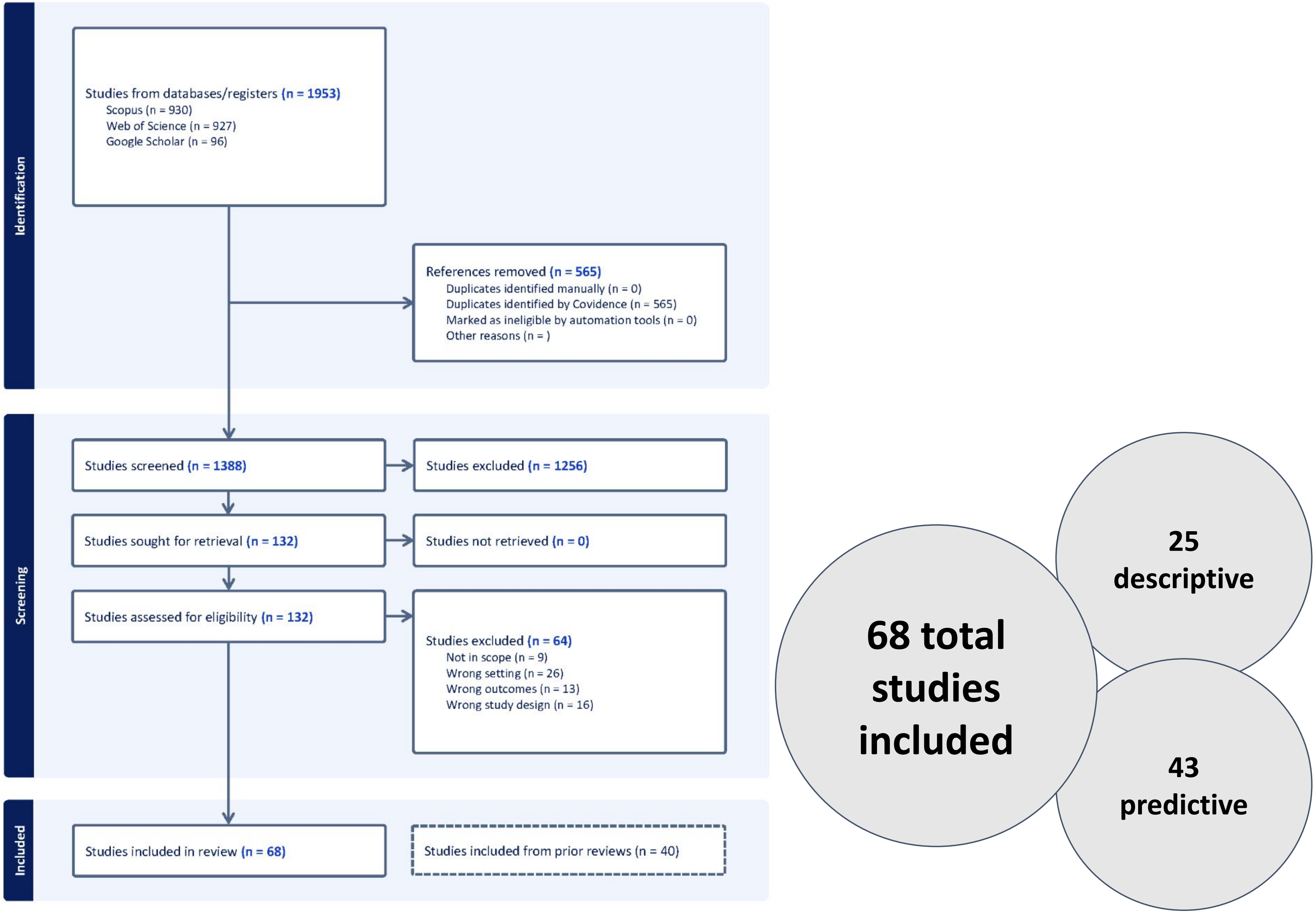
STUDY 2

The BRIDGE Database

Behavioral **R**isk **I**ndicators **D**atabase of **G**ambling **E**vidence

- We conducted a SYSTEMATIC LITERATURE REVIEW, specifically to understand the strength of evidence supports individual markers of harm.
- While several reviews are related to this topic, their scopes are broader.
- It has been acknowledged that the number and nature of predictors are often unclear or inconsistently reported.
- We set out to address this challenge…

What is the **LEVEL** and **QUALITY** of evidence for individual markers of harm?


Identification
Studies from databases/registers (n = 1953)
Scopus (n = 930)
Web of Science (n = 927)
Google Scholar (n = 96)
References removed (n = 565)
Duplicates identified manually (n = 0)
Duplicates identified by Covidence (n = 565)
Marked as ineligible by automation tools (n = 0)
Other reasons (n =)
Screening
Studies screened (n = 1388)
Studies excluded (n = 1256)
Studies sought for retrieval (n = 132)
Studies not retrieved (n = 0)
Studies assessed for eligibility (n = 132)
Studies excluded (n = 64)
Not in scope (n = 9)
Wrong setting (n = 26)
Wrong outcomes (n = 13)
Wrong study design (n = 16)
Included
Studies included in review (n = 68)
Studies included from prior reviews (n = 40)
68 total studies included
25 descriptive
43 predictive

Given the variability and inconsistency in indicator reporting we created a tiered categorization scheme:

65 low-level indicator categories…

Grouped into 5 high-level categories…

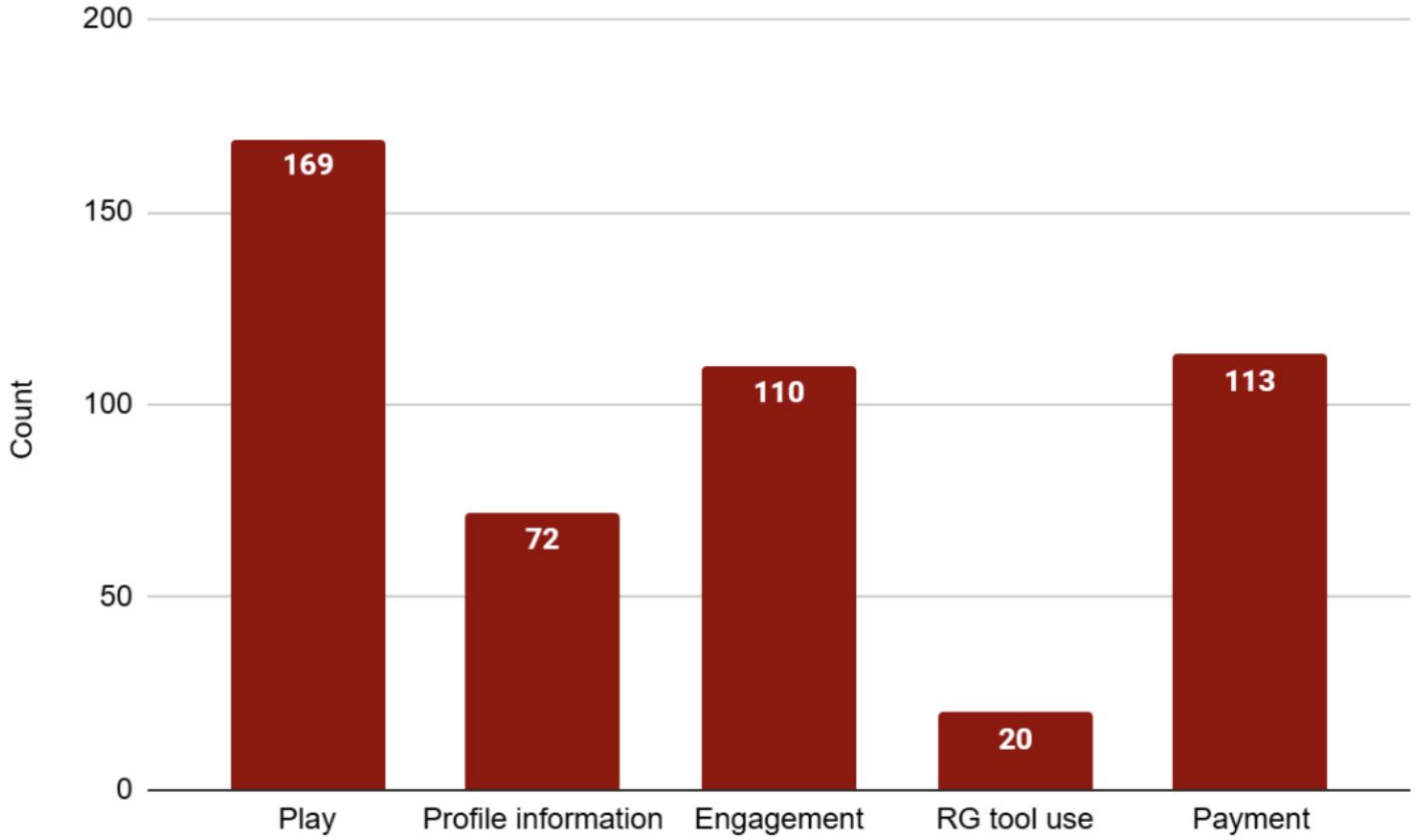
Indicator	Description
Play	Indicators related to betting/wagering behavior, such as bet frequency and size.
Profile information	Static account or demographic attributes, such as age, gender, or registration date.
Engagement	Indicators of when, how often, and how broadly a player interacts with games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

This allowed us to track usage of indicators across studies, i.e., the **LEVEL** of evidence.

Top 20 Indicators Across Predictive Studies According to Paper Appearances

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

Distribution of Indicators for Predictive Studies Across High-level Categories



We also constructed a scoring rubric.

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

This allowed us to track the **QUALITY** of evidence for each indicator.

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STUDY 2

The BRIDGE Score

We combined the level and quality of evidence to derive a "**BRIDGE SCORE**" for each indicator.

z-score calculated for each indicator and mapped onto a 0-10 scale, where 5.0 represents the average score across all indicators.

Scores above 5.0 reflect stronger or more consistently supported indicators, whereas scores below 5.0 reflect indicators that are either less common or backed by lower quality evidence

Top 10 Indicators according to the BRIDGE Score

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

Bottom 10 Indicators according to the BRIDGE Score

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

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STUDY 2

The BRIDGE Database

KEY FINDINGS

- Play indicators were the most commonly used category across all studies, but did not rank highest in evidentiary strength.

- The Payment category received the highest average BRIDGE Scores, with 5 of the top 10 indicators related to financial transactions. Indicators such as deposit amount and number consistently appeared in high-quality predictive studies and demonstrated strong methodological support.

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

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

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Recommendations

STUDY 2

- Guidelines should prioritize evidence-based indicators.
- There is a need for standardized reporting guidelines.
- There is a need for open data and code.
- Address transparency challenges and evaluation of commercial solutions.

STUDY 3 - Financial Risk Identification

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STUDY 3

In-depth expert interviews

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

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STUDY 3

Assessing Gambling Harm

Gambling Harm

Behavioral indicators from gambling activity

Vulnerability - life events, e.g., bankruptcy, job loss

Financial - broader spending patterns that signal stress

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STUDY 3

Key Findings

Conceptual Ambiguity: There is no universally agreed-upon definition of financial risk in gambling. Respondents indicated various approaches, ranging from simplistic loss-to-income ratios to more nuanced assessments of financial behaviors, highlighting ongoing challenges in operationalizing clear and effective risk criteria.

Technological Potential vs. Implementation Barriers: Advanced technologies such as open banking, credit reference agency data, and blockchain are currently available to support financial risk identification. However, practical challenges, including data classification difficulties, privacy concerns, consent issues, and uneven adoption rates, significantly constrain their current use.

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STUDY 3

Key Findings

Cross-Operator Data Sharing: Single-player tracking across multiple operators remains a major challenge, complicated by fragmented data infrastructures, privacy concerns, and competitive market dynamics. Existing solutions, such as GamProtect in the UK and centralized systems in state monopolies, demonstrate feasibility but are limited in widespread application.

Regulatory Barriers: Regulators face significant technical, financial, and capacity challenges in implementing comprehensive risk identification frameworks, which complicate efforts to standardize and enforce effective player protection measures.

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STUDY 3

Recommendations

- Establish a Clear Financial Risk Definition
- Explore Pilot Programs, e.g., UK Gambling Commission
- Facilitate Cross-Operator Tracking, e.g., UK's GamProtect
- Bolster Regulatory Data Infrastructure, e.g., ROGA data clearing house
- Assess Displacement Risks
- Explore Mandatory Carded-Play Systems

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