Gambling Advertising on Social Media

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"The Medium is the Message"
(Marshall McLuhan)

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Stuttgart, in July 2025 Johannes Singer

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List of Abbreviations

API	Application Programming Interface
ARD	Working Group of the Public Broadcasting Authorities of the Federal Republic of Germany
BERT	Bidirectional Encoder Representations from Transformers
CorEx	Correlation Explanation
LDA	Latent Dirichlet Allocation
LLM	Large Language Model
MOA	Model of Addiction
NLP	Natural Language Processing
UK	United Kingdom
URL	Uniform Resource Locator
ZDF	Second German Television

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1 General Introduction

Digitalisation has made social media available worldwide. Internet and mobile devices have reduced access barriers, making it easier to engage with social platforms. Consequently, social media now connects people worldwide, facilitating nearly limitless communication anytime, anywhere. Currently, 5.24 billion people worldwide use social media services (We Are Social et al., 2025a). In Germany, 60% of the population engages in social media on a weekly basis (Müller, 2024). Among the most active users were children and young people, with 92% using social networks weekly and 62% of those aged 14 to 29 doing so daily (Müller, 2024). This trend indicates that social media is becoming an integral part of users' daily lives. It is no longer solely for entertainment but is also a key source of information and interaction. The intensive use of social platforms blurs the lines between public and private spheres. As a result, social media entered users' private lives, influencing their behaviour and perceptions. Owing to this functional dynamic, social media has established itself as an attractive advertising platform (Torrance et al., 2021).

In addition to social media, digitalisation has also contributed to the growth of the gambling industry worldwide (Wardle et al., 2024). The global accessibility of gambling, especially through various online platforms, has led to greater acceptance by the industry. Currently, gambling is legal in over 80% of countries, including Germany (Wardle et al., 2024). In response to these dynamic developments in a rapidly changing media landscape, the State Treaty on Gambling has legalised online gambling in Germany since 2021 (Glücksspielstaatsvertrag 2021 - GlüStV 2021, 2020). One of the main objectives of the State Treaty on Gambling is to encourage individuals interested in gambling and existing gamblers to engage with the legal gambling market. Unlike illegal gambling, the legal gambling market is monitored by the gambling supervisory authority, and legal providers must comply with binding regulations. The aim of this is to protect the population, particularly vulnerable groups, from gambling-related harm.

While advertising aims to direct interested individuals towards the legal gambling market, it also poses significant risks. Research indicates a causal link between exposure to gambling advertising and attitudes towards gambling, the intention to gamble, and gambling behaviour (McGrane et al., 2023). Increased exposure is associated with a dose–response effect, i.e., the more individuals are exposed to gambling advertising, the more likely they

are to develop positive attitudes towards gambling, want to try it, or intensify their gambling activity if they are already engaged in it. These risks especially impact vulnerable groups, such as children, young people, and individuals with gambling-related disorders (McGrane et al., 2023). The latter are at a risk of escalating their gambling activity or relapsing if they are already abstinent (Syvertsen et al., 2022). These risks clearly contradict the State Treaty on Gambling's aim of protecting the population from gambling-related harm, specifically the goals of preventing gambling and betting addiction, creating conditions for effectively combating addiction, and ensuring the protection of young people and gamblers.

Social media plays a particularly important role in the advertising tension between steering people into the legal gambling market and health risks, especially for vulnerable groups. With the advancement of digitalisation, social media has emerged as an attractive advertising platform for gambling providers (Torrance et al., 2021). These platforms offer the opportunity to promote products within a global network and engage directly with users, unrestricted by location or time. By leveraging social networks, advertising content can swiftly reach a vast audience since users themselves disseminate content (Torrance et al., 2021). Ultimately, social media allows gambling providers to connect with potential customers and retain existing customers (Bradley & James, 2019), thereby enhancing brand awareness and fostering brand loyalty (Barreda et al., 2015).

In this context, gambling advertising on social media poses a significant risk to children and young people (McGrane et al., 2023). International studies have revealed that gambling advertisements are prevalent on social networks (Guillou-Landreat et al., 2021; James & Bradley, 2021; Newall et al., 2019; Rossi & Nairn, 2022; Torrance et al., 2021). Furthermore, gambling providers' accounts are particularly popular among this demographic (Rossi & Nairn, 2022; Rossi et al., 2021). As a result, it can be inferred that children and young people are heavily exposed to gambling advertisements on social media. This exposure can lead to the normalisation of gambling (Gainsbury, King, Abarbanel et al., 2015) and foster unrealistic expectations of winning along with positive impulses (Rossi & Nairn, 2022). Furthermore, advertising content rarely includes warning messages or age restrictions (Bradley & James, 2019; Houghton et al., 2019; Killick & Griffiths, 2020; Rossi et al., 2021). Recent studies have highlighted content marketing as a

major form of advertising (Rossi & Nairn, 2022, 2024a, 2024b; Rossi et al., 2021). Providers are increasingly focusing on entertaining seemingly innocuous content to maximise their reach. However, this form of advertising is particularly appealing to children and young people (Rossi & Nairn, 2024b), who often fail to recognise it as advertising (Rossi & Nairn, 2024a). This can foster positive attitudes towards and potentially encourage gambling (Rossi & Nairn, 2022).

To safeguard particularly vulnerable groups such as children and young people from the dangers of gambling advertising, the State Treaty on Gambling establishes specific advertising guidelines (Glücksspielstaatsvertrag 2021 - GlüStV 2021, 2020). These guidelines prohibit excessive advertising and the targeting of minors and other similarly vulnerable groups. Furthermore, efforts should be made to exclude minors as advertising recipients. These guidelines aim to ensure that the content and scope of advertising do not undermine the fundamental objective of the State Treaty on Gambling, which is to protect the population from gambling-related harm. A recent survey on gambling behaviour in Germany revealed that about a third (36.5%) of the population had engaged in gambling activities within the last 12 months (Buth et al., 2024). Of these respondents, 2.4% were found to be suffering from gambling-related disorders. Young people are particularly affected, with 4.9% of 18-to 25-year-olds suffering from these disorders. Although gambling in Germany requires a minimum age of 18 years, 0.4% of 16-to 17-year-olds already suffer from the consequences of gambling (Buth et al., 2024). Despite existing advertising guidelines focusing on protecting vulnerable groups, it is evident that children and young people in Germany are most affected by gambling-related issues. As children and young people are the most active social media users in Germany (Müller, 2024), they are likely to be exposed to a high level of gambling advertising on these platforms. Against this background, this dissertation analyses gambling advertising on social media in Germany for the first time.

In response to the evolving research landscape and ongoing regulatory changes, there is a need to collect the latest findings in the field of gambling advertising. Chapter 2 provides a systematic review of the research literature on the advertising strategies used by gambling providers and their impact on social media. To achieve this, three scientific databases were searched, focusing on international journal articles in English published

from 2021 onwards. Beyond providing an overview, this systematic review addresses the following questions: (i) What are the characteristics of gambling advertising on social media in terms of frequency, content, and user engagement? (ii) What are the effects of gambling advertising and advertising strategies on users' attitudes and behaviours? Furthermore, (iii) what safety measures are implemented to protect individuals, particularly vulnerable groups, from gambling-related harm? Finally, (iv) what are the current research gaps in the area of gambling advertising?

Chapter 3 broadens the scope of international research and addresses some research gaps by examining gambling advertising on social media (i) with a particular focus on German gambling operators. Furthermore, (ii) it compares various sectors including sports betting, state lotteries, social lotteries, commercial lotteries, and casinos. The analysis draws on data from tweets posted by selected accounts on the microblogging platform X (formerly Twitter), accessed via the platform's API. (iii) This chapter employs an exploratory mixed-methods approach that integrates a qualitative summative content analysis with semi-supervised guided topic modelling to examine the number of followers and interactions, as well as the frequency and content of tweets.

The stigmatisation and self-stigmatisation of gamblers are significant barriers to seeking help and treatment (Brown & Russell, 2020; Hing, Holdsworth et al., 2014; Hing, Nuske, Gainsbury, & Russell, 2016; Hing, Nuske, Gainsbury, Russell, & Breen, 2016; Hing & Russell, 2017a; Miller & Thomas, 2017). Strategies to reduce the stigmatisation of gambling addiction can be developed by understanding prevailing stereotypes. As gambling-related disorders particularly affect young people in Germany, who also represent the most active user group on social media, Chapter 4 examines whether gambling addiction is stigmatised on the social network YouTube in Germany and how the corresponding stereotypes are constructed in everyday language. Comments from two selected videos were collected using the YouTube’s API. These were analysed using a deep learning approach combining guided topic modelling and qualitative summative content analysis.

2 Gambling Operators' Use of Advertising Strategies on Social Media and Their Effects: A Systematic Review

by Johannes Singer, Andrea Wöhr and Steffen Otterbach

Abstract

Purpose of Review Social media offer gambling operators an attractive channel for connecting with gamblers and promoting their products. The aim of the present study is to review the recent literature to summarise the latest findings on marketing strategies of gambling operators, and their effects, with particular focus on social media.

Recent Findings A systematic review on gambling advertising in social media has been conducted, taking into account English-language journal articles from 2021 onwards, which include primary data collection. Searching three data bases, a total number of 12 studies from peer-reviewed journals were identified. Gambling advertising has an enormous reach, including esports sponsorship and a surge in popularity on streaming platforms, which raises concerns about the protection of gamblers in general and of vulnerable groups in particular. The studies identify individual advertising strategies and investigate the influence of incentives and tips on gambling behaviour. Gaps in the current literature include evidence from certain regions or countries, research into communication strategies on individual social media platforms, and questions about the effectiveness of regulatory measures regarding gambling advertising.

Summary Gambling operators flexibly adapt their advertising strategies to the surrounding conditions. This appears to be problematic, as the intensity and complexity of gambling advertising increases at the same time as the boundaries between advertising and seemingly neutral content blur. Vulnerable groups, especially children and adolescents, are at special risk, because advertising on social media is particularly attractive for them, while protection mechanisms such as age limits are often missing or being ignored.

Keywords Gambling advertising · Gambling promotion · Social media · Marketing · Public Health · Consumer protection

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2.1 Introduction

Advertising for gambling on social media is one of the most pressing topics that gambling regulators need to address. Social media are highly attractive for gambling companies as a low-cost alternative or supplement to "traditional" advertising (Guillou-Landreat et al., 2021). The immediacy, entertaining qualities and especially the possibilities for interaction account for the special appeal of social media (Torrance et al., 2021). These characteristics pose high demands on regulators as they need to create a level playing field for advertising in different channels, thus preventing companies from moving to new and less regulated platforms (Guillou-Landreat et al., 2021). As regulators often lag behind actual industry developments, they fall short of user expectations who presume a comprehensive protection through regulation (Thomas et al., 2017). Additionally, wording in legislation documentation is often very general (e.g. "advertising must not be excessive",[1] "advertising for public gambling that makes gambling appear to be a commodity of everyday life is not permitted"[2]), which might be useful when addressing constantly changing marketing strategies and features, but complicates practical application. On the other hand, the scientific evidence that regulation should be based on is also fragmentary.

Another difficulty lies in the subject itself: Gambling advertising is not always evident as such, especially on social media. Whereas banners or pop-ups are fairly easy to identify, the borders start to blur in the case of affiliates, influencers and brand ambassadors, and are almost or completely unrecognizable when advertising appears in the shape of user-generated content. The "opacity of commercial peer-to-peer advertising" has been acknowledged to be a particularly sensitive issue (together with "unethical placement of targeted advertising through online profiling" (Hörnle et al., 2019)). These less obtrusive forms of marketing seem to be particularly effective: Content marketing (i.e. content not necessarily related to the product or brand) has been shown to be especially appealing to 11-to-24-year olds (Rossi & Nairn, 2022). This is in line with the finding that advertising has higher effects on vulnerable groups, e.g. on persons with gambling disorder (Binde & Romild, 2019). Consequently, these forms of advertising need major attention.

[1] German State Treaty on Gambling 2021, https://www.gluecksspiel-behoerde.de/images/pdf/201029_Gluecksspielstaatsvertrag_2021.pdf

[2] Examples of content and auxiliary terms and conditions for virtual slot machines and online poker, https://www.gluecksspiel-behoerde.de/images/pdf/Musternebenbestimmungen_virtuelle_automatenspiele_online_poker.pdf

2.1.1 Aim of the study

A rapidly changing landscape as well as ongoing regulatory adjustments make it necessary to continuously examine the latest findings on gambling advertising, social media marketing strategies and their effects. To the authors of the present article, five previous reviews were known, among them three systematic (Guillou-Landreat et al., 2021; James & Bradley, 2021; Newall et al., 2019), one rapid (Torrance et al., 2021) and one narrative review (Rossi & Nairn, 2022). These reviews suggest that gambling advertising on social media is heavily centred around sports (Guillou-Landreat et al., 2021; Newall et al., 2019; Torrance et al., 2021). Such a close association is likely to contribute to the normalisation of gambling (Guillou-Landreat et al., 2021; Rossi & Nairn, 2022). Young people (Guillou-Landreat et al., 2021; James & Bradley, 2021) and particularly children (Newall et al., 2019; Rossi & Nairn, 2022) could be at particular risk of harm, as well as people with gambling disorder (Newall et al., 2019). An area that the authors would like to see analysed more closely includes digital marketing strategies and their effects (Guillou-Landreat et al., 2021; James & Bradley, 2021; Torrance et al., 2021), preferably without relying solely on self-report data (Newall et al., 2019; Torrance et al., 2021). Also, evidence from countries other than the UK or Australia could contribute to a better understanding (Torrance et al., 2021).

Starting from this basis, the present review puts particular focus on the following research questions:

i. What are the attributes of gambling advertising on social media platforms in terms of their frequency, content, and user involvement? Are there differences between individual jurisdictions?
ii. What are the effects of gambling advertising and gambling operators' marketing strategies on users' attitudes and behaviour?
iii. What safeguards are being put in place to protect people, especially vulnerable groups such as children, adolescents or people with a gambling disorder, from gambling harm?
iv. What are the current research gaps in the area of gambling advertising, taking into account methodological and content-related aspects, and what should be prioritised in future studies?

2.2 Methods

Following PRISMA guidelines (Page et al., 2021), a systematic review was conducted. The search strategy consisted in a combination of terms for social media (including social networks such as Facebook, Instagram, TikTok, Twitter, Twitch, YouTube, Weibo, and WeChat) with terms for gambling advertising and gambling marketing (see Appendix Figure 7.1). The * operator was used to include all variations of the initial terms. Synonyms of the initial terms were also included in the search string, as in the previous reviews. In addition, the proper names of social networks were explicitly included to identify studies that did not use generic terms in their title or abstract, in order to identify the widest possible range of literature. The final string used the Boolean operators (AND/ OR). The terms were searched for in the title, abstract, and keywords. Three databases were searched: Business Source Premiere, Scopus and PubMed. All searches were conducted on August 22nd, 2023, yielding a total number of 1,735 record (see Figure 2.1).

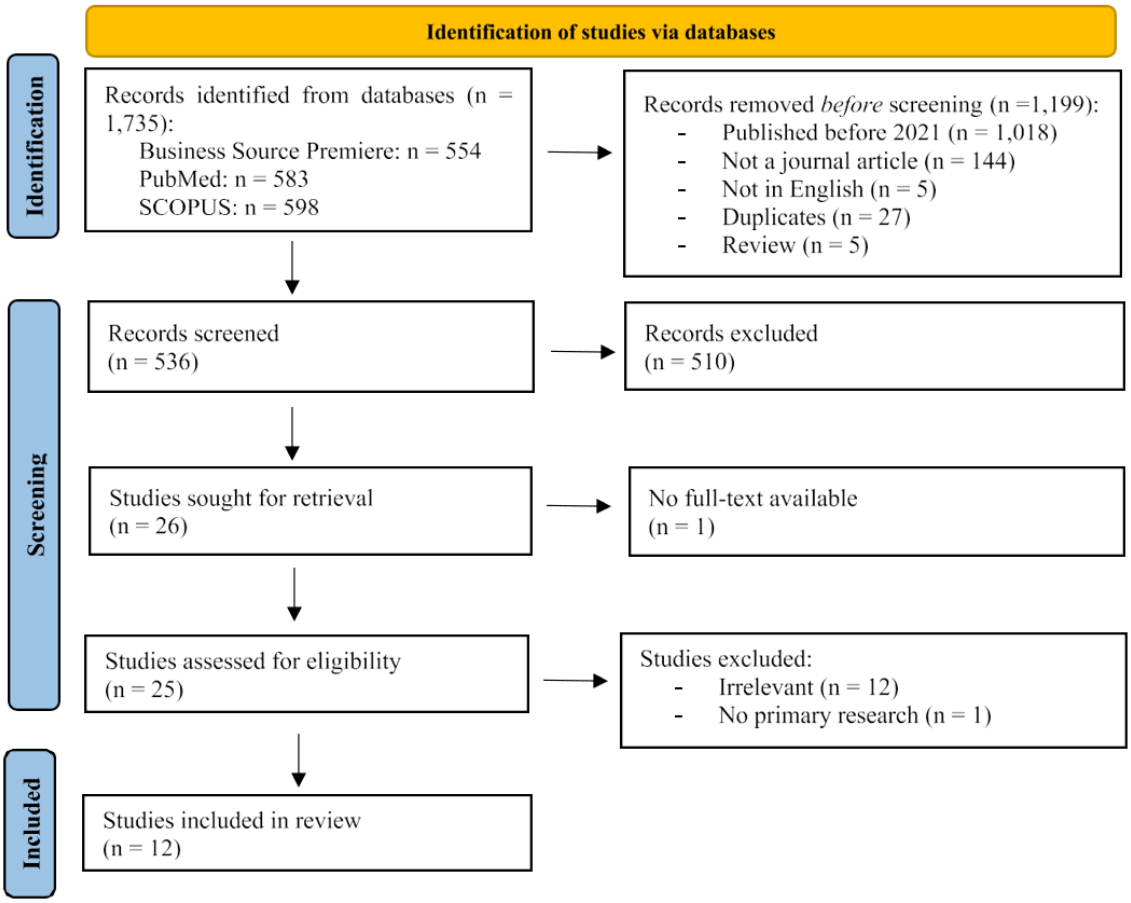

Figure 2.1 PRISMA flow chart. Own representation based on PRSIMA flow chart (Page et al. 2021)

2.2.1 Inclusion and Exclusion Criteria

Only publications from the beginning of 2021 onwards were considered to avoid overlapping with results from previous reviews (Guillou-Landreat et al., 2021; James & Bradley, 2021; Newall et al., 2019; Rossi & Nairn, 2022; Torrance et al., 2021). The records needed to contain some form of primary data collection to ensure that the current state of research on gambling advertising on social media was reflected. Records that were not journal articles, such as commentaries, or reviews were not included. Papers written in languages other than English and duplicates were also excluded. The inclusion and exclusion criteria are summarized in Table 2.1.

Table 2.1 Inclusion and exclusion criteria

Inclusion criteria	Exclusion criteria
Topic	
Gambling	Not related to gambling
Advertising	Not related to advertising
Social media	Not related to social media, for example related to traditional media
Study design	
Primary data collection	No primary data collection
Journal article	No journal article or review
Other criteria	
Records from the year 2021 onwards	Records before the year 2021
Languages in English	Other languages

2.2.2 Identification and Screening

As a first step, records on the topic of gambling advertising on social media were identified using the search string shown in the appendix. Using the filter functions of the databases, of the 1,735 records found, 1,199 publications were removed because they did not meet the inclusion criteria (see Figure 2.1), mostly because of their early publication date (n = 1,018). One hundred forty-four records were rejected because the document type did not meet the requirement of being classified as journal article. Another five records were discarded because they were in languages other than English. Bibliographic information of the records was extracted from the databases and stored in lists. Furthermore, 27 duplicates resulting from the three different data bases were excluded based on congruent

author and title of the record. Finally, the previous reviews ($n = 5$) were excluded, leaving 536 publications for screening.

The titles and (where necessary) abstracts of the records were screened by two reviewers (AW and JS). The reviewers met regularly to discuss their individual decisions. Discrepancies were resolved through discussion and consensus among the reviewers, and together with the third author (SO). In this process, another 510 records were excluded for being off-topic or not containing primary research. Of the remaining 26 records, one publication was not available. Consequently, 25 records were retrieved for full text screening. Twelve more publications were found to be off-topic and one publication lacked primary data.

2.2.3 Search Results

A final set of 12 studies met the eligibility criteria and were included in the analysis. As shown in Table 2.2, six studies used web scraping to analyse data from social networks (Biggar et al., 2023; Hellman et al., 2023; Hernández-Ruiz & Gutiérrez, 2021; Lindeman et al., 2023; Russell et al., 2023; Singer et al., 2023), of which one study looked at the collected data descriptively (Biggar et al., 2023). In addition, three studies conducted qualitative analysis (Hellman et al., 2023; Lindeman et al., 2023; Russell et al., 2023), and one study used natural language processing (NLP) methods to analyse the collected data (Hernández-Ruiz & Gutiérrez, 2021). One study used a combination of mixed-methods and NLP (Singer et al., 2023). Furthermore, two studies used an observational design (Balem et al., 2022; Critchlow et al., 2023), with one study combining this with a survey (Balem et al., 2022). There are also three studies that use surveys (Gonzálvez-Vallés et al., 2021; Noble et al., 2022; Wardle et al., 2022). In addition, one study conducted an online experiment (Newall et al., 2022). The studies were conducted in 7 different jurisdictions, namely the UK ($n = 4$) (Biggar et al., 2023; Critchlow et al., 2023; Newall et al., 2022; Wardle et al., 2022), Spain ($n = 2$) (Gonzálvez-Vallés et al., 2021; Hernández-Ruiz & Gutiérrez, 2021), Australia ($n = 2$) (Noble et al., 2022; Russell et al., 2023), Germany ($n = 1$) (Singer et al., 2023), France ($n = 1$) (Balem et al., 2022) and simultaneously in Finland and Sweden ($n = 2$) (Hellman et al., 2023; Lindeman et al., 2023). The included studies can be grouped into three overarching themes according to the research objectives of the systematic review: (1) advertising strategies of gambling operators on social media (n = 6)

(Biggar et al., 2023; Critchlow et al., 2023; Hellman et al., 2023; Hernández-Ruiz & Gutiérrez, 2021; Lindeman et al., 2023; Singer et al., 2023); (2) effects of gambling advertising on social media (n =5) (Balem et al., 2022; Gonzálvez-Vallés et al., 2021; Noble et al., 2022; Russell et al., 2023; Wardle et al., 2022); and (3) effects of responsible gambling messages (n = 1) (Newall et al., 2022).

Table 2.2 Studies included in the systematic review

Paper	Jurisdiction	Methodology	Key findings	Overarching Theme
Balem et al. (2022)	France	Longitudinal observational study & online survey	The use of wagering inducements was associated with increased gambling intensity, frequency and at-risk behaviours, especially for at-risk gamblers.	Effects of gambling advertising on social media
Biggar et al. (2023)	UK	Webscraping (data from 3 esports titles & 62 esports teams)	Gambling operators have used sponsorship agreements with the esports market to attract potential customers.	Advertising strategies of gambling operators on social media
Critchlow et al. (2023)	UK	Observational study of weekly expenditure on gambling advertising	In the UK, spending on gambling advertising declined during the first COVID-19 lockdown, but increased again in subsequent lockdowns. Decreased expenditure correlates with reported reductions in overall gambling.	Advertising strategies of gambling operators on social media
Gonzálvez-Vallés et al. (2021)	Spain	Online survey (n=1.032 students including 613 regular bettors)	Young people perceive the influence of tipsters as a factor that can promote addiction.	Effects of gambling advertising on social media
Hellman et al. (2023)	Finland / Sweden	Webscraping (qualitative analysis of 13,241 posts from Finnish and Swedish accounts on four social media platforms)	Gambling operators use social responsibility communication to create a positive image of their brand and to normalise gambling.	Advertising strategies of gambling operators on social media
Hernández-Ruiz & Gutiérrez (2021)	Spain	Webscraping (60,259 tweets/retweets from 8 operators) & NLP (sentiment analysis with GPLSI)	The communication of gambling providers on Twitter is characterised by positive messages; surprise is the dominant emotion associated.	Advertising strategies of gambling operators on social media

Table continued

Table 2.2 continued

Lindeman et al. (2023)	Finland / Sweden	Webscraping (qualitative analysis of posts from 28 operators & 72 accounts & 4 social media platforms)	"A substantial number" of posts did not present gambling or games straightforward; especially in Finland, posts were associated with social responsibility and "doing good".	Advertising strategies of gambling operators on social media
Newall et al. (2022)	UK	Randomised online experiment (n=506 participants)	No evidence for the protective effect of the message "when the fun stops, stop" was found.	Effects of responsible gambling message
Noble et al. (2022)	Australia	Survey (n=6,377 students)	Exposure to online gambling ads was associated with gambling and being classified an at risk or problem gambler.	Effects of gambling advertising on social media
Russell et al. (2023)	Australia	Webscraping (qualitative analysis of 53,000 tweets from 4 wagering operators)	Gambling operators have switched their advertising to products available during the Australian lockdowns, with content being replaced rather than reduced. The switch in advertising was accompanied by a switch in usage towards available products.	Effects of gambling advertising on social media
Singer et al. (2023)	Germany	Webscraping (qualitative analysis of 34,151 tweets from 13 operators), NLP (qualitative analysis & semi-supervised topic model with CorEx)	Twitter plays a smaller role in Germany than e.g. in the UK. Informative content is frequently combined with less neutral content. Responsible gambling messages are rarely used.	Advertising strategies of gambling operators on social media
Wardle et al. (2022)	UK	Two surveys (survey 1: n=1,496 emerging adults; survey 2: 2,980 adult regular sports bettors)	Almost a third of current gamblers reported that marketing had prompted unplanned spendings.	Effects of gambling advertising on social media

Own illustration based on the studies used

2.3 Results

Twelve publications matching the above outlined criteria were found (see Table 2.2). Given the short period of time covered by the search, this is a substantial leap in number—previous reviews had identified between 21 (Guillou-Landreat et al., 2021) and 46 (Newall et al., 2019) publications, although covering much longer periods of time (between five years (Torrance et al., 2021) and no time limit (James & Bradley, 2021)).

2.3.1 Gambling Advertising on Social Media: Frequency, Content and User Involvement

Several publications examine the volume and frequency of gambling advertising on social media. Studies on gambling advertising on YouTube, Twitter, Facebook, Instagram in Finland and Sweden (Lindeman et al., 2023) and on Twitter in Germany (Singer et al., 2023) and in Spain (Hernández-Ruiz & Gutiérrez, 2021) show a high volume of messages, although at much lower levels than e.g. in the UK.

To attract new customers, gambling companies seem to regard esports events as an attractive advertising opportunity. Biggar et al. (2023) examined the sponsorship agreements of popular esports titles during the *League of Legends World Championship* in 2021. The sponsorship deals enabled gambling companies to reach at least tens of millions of followers on Twitter, Instagram and Facebook.[3] Due to the high share of young men, these followers are particularly interesting as potential future gamblers.

With respect to content, advertising is often linked to seemingly neutral information. Indeed, the most common way of addressing followers on Twitter seems to be by content marketing, as it was found to account for the largest part of the messages. 44 percent of the Finnish and 58 percent of the Swedish posts investigated by Lindeman et al. (2023) were found to be free of "actual references or visual portrayals of gambling activities" (p. 47–48). In their content analysis, Singer et al. (2023) coded a third of the Twitter messages as "news", i.e. messages informing on sports-related "facts" rather than gambling-related issues.

[3] As it is unknown how many followers are registered on more than one channel, the exact number cannot be determined. The approximate figure given here refers to the minimum number.

Although interactive features have been identified as one of the key features of digital marketing, they do not yet seem to play such an important role, or at least not in all jurisdictions. Reactions or comments to posts and likes were rare in Finland, Sweden and Germany (Lindeman et al., 2023; Singer et al., 2023) with the exception of very few posts that attracted tens of thousands of reactions (in Finland and Sweden). In Sweden, operators' efforts to make users react by polls or by answering a question rose to more than 50% of all posts in 2020 but played minor roles in Finland or Germany. Only the use of hashtags was widespread, as they could be found in most Finnish and Swedish messages. The hashtags used in German tweets related mostly to "factual" information other than the gambling companies themselves or their offers (Singer et al., 2023).

Although responsible gambling messages played a minor role in terms of frequency Guillou-Landreat et al. (2021), their use was found to assist in the creation of a positive corporate image. In this way, gambling companies were able to portray themselves as responsible and reliable entities, and present gambling as a recreational activity like any other. Such image cultivation could be particularly important in state monopolies, owing to the need to justify and defend market limitations, which is difficult to achieve without public support (Hellman et al., 2023).[4] In addition, responsible gambling messages can contribute to the sheer volume of messages when there are no other messages at hand, as shown by the case of an Australian operator who sent messages about responsible gambling only during the lockdown period (Russell et al., 2023).

2.3.2 Effects of Gambling Advertising on Social Media

Several studies address the question of advertising efficiency. A coincidence between the expenditures for advertising and gambling activities was found by Critchlow et al. (2023): Reduced spendings on advertising in the UK during the first lockdown corresponded with self-reported reduction in gambling during the same time period; although the reasons might be ambiguous due to the special circumstances during the pandemic.

[4] An example for such a close interlocking can be seen in Germany, where the drawing of the lottery numbers forms part of the daily news program.

Noble et al. (2022) found a significant association between the exposure to online gambling ads and gambling among Australian students. In their study, no other advertising type could be associated with gambling behaviours. Moreover, increased exposure to online gambling ads coincided with a higher probability of at-risk or problem gambling.

Gambling advertising could also induce gamblers to spend more money than planned. Combining data from two British non-probability online surveys, Wardle et al. (2022) found that about 30 percent of current gamblers reported unplanned gambling expenditures after having seen a gambling advert, promotion or sponsorship (Wardle et al., 2022). The association appeared after having received a single form of direct marketing or following a sole gambling brand on social media, and was stronger for persons with gambling problems.

While most studies rely on self-report data, Balem et al. (2022) use tracking data provided by the French national gambling authority and the national lottery to investigate the effects of wagering inducements. Frequent use of these inducements, the authors found, was associated with increased gambling frequency and intensity. Again, the effect was stronger for at-risk gamblers.

The online survey undertaken by Gonzálvez-Vallés et al. (2021) found tipsters to be particularly influential. The authors identified a *very strong* correlation between bets placed owing to the advice of tipsters and the amount of money wagered. Their student respondents also saw a connection between gambling disorder and the influence of tipsters.

2.3.3 Effects of Responsible Gambling Messages

Several studies have looked at whether gambling operators on social media are also promoting the dangers of gambling as part of their advertising strategies. It is shown that responsible gambling content hardly plays a role for communication on Twitter in Spain (Hernández-Ruiz & Gutiérrez, 2021), Germany (Singer et al., 2023) and once more for Australia (Russell et al., 2023). Apparently, its frequency of use is connected to the regulation in force, which is shown by the sudden leap of posts in Sweden after a change in law whereas during the same time period, the volume remained stable for the Finnish monopolist *Veikkaus* (Lindeman et al., 2023). The use of responsible gambling messages

seems to have dual benefit for gambling operators: Besides compliance with the laws, they assist in the creation of a positive corporate image (Hellman et al., 2023) and contribute to the sheer volume of messages when there are no other messages at hand (Russell et al., 2023).

On the other hand, one study even questions the efficacy of responsible gambling messages (Newall et al., 2022): UK's most common safer gambling message "when the fun stops, stop", which is said to have "helped over 5 m adults approaching gambling more responsible" by the company who developed the campaign,[5] is not found to have any protective effects on the participants in a randomised experiment.

2.3.4 Research Gaps

In addition to the research findings, the literature reviewed also provides an analysis of current research gaps, with various recommendations for future research. For example, there is a lack of work on sponsorship and the development of brand partnerships by gambling operators in the esports sector (Biggar et al., 2023). Despite initial findings, there is a need for long-term research into the relationship between gambling and esports, and for as many esports titles as possible to be analysed as comprehensively as possible.

Due to the established selection criteria, most of the studies were conducted during the global COVID-19 pandemic. Some studies point to this fact and indicate that the findings should be understood in the light of this situation (Critchlow et al., 2023; Hellman et al., 2023; Lindeman et al., 2023; Russell et al., 2023; Singer et al., 2023; Wardle et al., 2022). A study from Australia points to the possibility that future research could compare the analysed data between the different lockdown phases (Critchlow et al., 2023). This could determine the extent to which there is a correlation between increased advertising expenditure and an increase in gambling. In addition, three studies that have looked at the advertising strategies of gambling providers on social media (Hernández-Ruiz & Gutiérrez, 2021; Lindeman et al., 2023; Singer et al., 2023) emphasise the need to examine both the extent of this content and the effects on vulnerable people, especially children, young people and gamblers with a gambling disorder, more closely and in the long term.

[5] https://www.creativebrief.com/agency/corner/case-studies/the-senet-group-when-the-fun-stops-stop

With regard to the effects of gambling advertising, further differentiation is needed as to exactly which products or incentives lead to more problem gambling (Balem et al., 2022; Gonzálvez-Vallés et al., 2021). The same applies to the time of betting or the amount of the bet (Gonzálvez-Vallés et al., 2021). The environment could also be analysed to determine the impact of gambling advertising (Balem et al., 2022) and the involvement of different age groups or generations (Gonzálvez-Vallés et al., 2021). It is also proposed to analyse the impact of the COVID-19 pandemic on the impact of gambling advertising (Russell et al., 2023).

Two studies explicitly address the methodological perspective and suggest that future studies should use longitudinal research designs to investigate the long-term effects of gambling advertising (Noble et al., 2022; Wardle et al., 2022). This would, in turn, allow comparisons to be made between the closure phases and the post-pandemic period (Wardle et al., 2022). Also conclusions could be drawn as to whether a reduction in terrestrial gambling has an impact on the number of people with a gambling disorder and could possibly be classified as a harm-reduction measure. As some studies use self-report data (Newall et al., 2022), the authors generally point out that other research designs, such as longitudinal designs, are needed to overcome the known limitations (Newall et al., 2022).

2.4 Discussion

2.4.1 Gambling Advertising on Social Media: Frequency, Content and User Involvement

For gambling operators, social media are an attractive advertising platform to reach users directly, regardless of place and time, all around the globe and at comparatively low cost (Torrance et al., 2021). Their aim is to attract potential customers and retain existing ones (Bradley & James, 2019). Biggar et al. (2023) show how gambling companies access potential client groups—young, male, with gambling affinity—through the sponsorship of esports titles, which might also assist in the convergence of gaming and gambling (Gainsbury, King, Abarbanel et al., 2015; Johnson & Brock, 2019) as well as contribute to the normalisation of gambling (Clemens et al., 2017; Gainsbury, Delfabbro et al., 2016). Visibility is increased even further whenever the teams' athletes appear on

livestreaming platforms such as Twitch. Twitch has been criticised for not having any age restrictions or other protective measures in their streaming service (Koncz et al., 2023).

Both the wide use of content marketing and the employment of responsible gambling messages as an image-enhancing strategy make the boundaries between advertising and "factual" information blur, giving cause for concern about the protection of vulnerable groups. Content marketing is often seen as humorous and harmless and therefore especially appealing to children and young adults, who are not yet able to effectively identify advertising contents (Rossi & Nairn, 2022), and thus contributes to the normalisation of gambling (Gainsbury, Delfabbro et al., 2016). Additionally, the use of positive emotions and sentiment as well as humorous content have been shown to be of particular appeal to children and young people (Rossi & Nairn, 2022). As vulnerable groups are at specific risk from gambling advertising (McGrane et al., 2023), future research should explore the extent to which children and young people are exposed to gambling advertising on social media. Alternative research designs can help overcome the limitations regarding self-reporting without breaching ethical conventions (e.g. (Smith et al., 2020)).

2.4.2 Effects of Gambling Advertising on Social Media

The studies identified in this review contribute substantially to the growing body of research on the effect of gambling advertising, both in terms of the general effects of gambling advertising and the effects of individual advertising strategies. These findings could contribute to a taxonomy of advertising strategies and their effects, which is needed all the more because harm for consumers could manifest quickly (Kolandai-Matchett & Wenden Abbott, 2022). Such a taxonomy could form an adequate basis for legislative bodies and authorities to react and take appropriate action.

2.4.3 Effects of Responsible Gambling Messages

Studies from Spain (Hernández-Ruiz & Gutiérrez, 2021), Germany (Singer et al., 2023), and Australia (Russell et al., 2023) show that responsible gambling messages play only a minor role in the communication of gambling operators on social media. The use of such messages is often based on the regulation in force (Lindeman et al., 2023), although

this can be problematic if the legislation is imprecise. For example, in Germany, the legislator states that "advertising must not be excessive",[6] but this is not further defined. Shortcomings in the protection of minors were also identified (Lindeman et al., 2023; Singer et al., 2023), as the marketing of gambling services in all three countries observed (Finland, Germany and Sweden) was accessible to persons under the age of 18. These findings are remarkably alarming as children and young people are particularly vulnerable to gambling and, as the example of sports betting operators in the UK shows (Rossi & Nairn, 2022), find this content particularly appealing.

Even when responsible gambling messages are used in operators' communications, their purpose tends to be to create a positive corporate image (Hellman et al., 2023) or simply to increase the number of posts in order to attract more attention in the social networks (Russell et al., 2023). Moreover, the effectiveness of these responsible gambling messages is questionable (Auer & Griffiths, 2020), as the example of "when the fun stops, stop" messages confirms (Newall et al., 2022). As responsible gambling messages are one of the few safeguards used by gambling and social media companies (James & Bradley, 2021), these results are exceptionally worrying.

2.4.4 Research Gaps

The 12 studies reviewed have filled some existing research gaps, such as the lack of studies from countries other than Australia and the UK (Newall et al., 2019; Torrance et al., 2021). Several studies focusing on the advertising strategies of gambling operators used on Twitter, Instagram, Facebook and YouTube now feature Germany (Singer et al., 2023), Spain (Hernández-Ruiz & Gutiérrez, 2021) and Finland and Sweden (Hellman et al., 2023; Lindeman et al., 2023) (besides Australia and the UK).

But there is still a need for more research in this area, as vulnerable groups are at particular risk from gambling advertising (McGrane et al., 2023). Future research should explore the extent to which children and young people are exposed to gambling advertising on social media. Alternative research designs can help to overcome the limitations of self-report, for example longitudinal observational study designs combined with the use of

[6] German State Treaty on Gambling 2021, https://www.gluecksspiel-behoerde.de/images/pdf/201029_Gluecksspielstaatsvertrag_2021.pdf

tracking data, as shown in a study from France (Balem et al., 2022). Longitudinal research approaches in different countries can serve as a useful extension of existing evidence, investigating which groups of people are particularly affected by gambling advertising and which forms of advertising have the strongest impact. In addition, longitudinal study designs also provide an opportunity to identify long-term marketing trends and advertising strategies.

Machine learning methods offer a further possibility for future research, as the studies from Spain (Hernández-Ruiz & Gutiérrez, 2021) and Germany (Singer et al., 2023) have shown. Appropriate models can be used to analyse not only large amounts of text, but also images, sounds and videos, which, alongside text, are the central content in social networks for conveying content and information (James & Bradley, 2021), especially on Instagram or (more recently) TikTok.

A common challenge in analysing data from social networks is the lack of precise data on who is actually consuming the content. This makes it particularly difficult to monitor personalised marketing, as content changes depending on who is being targeted (James & Bradley, 2021).

Finally, future research should place a stronger focus on the connection between gambling and esports (Biggar et al., 2023), explicitly on the convergence of gaming and gambling (Kolandai-Matchett & Wenden Abbott, 2022). A more comprehensive picture is needed because harm for consumers could manifest quickly. One such topic could be the role of online communities (Sirola et al., 2021), as these form an inherent part of the lifestyle of younger generations.

2.5 Conclusions

The present study illustrates the growing importance of social media in the advertising strategies of gambling operators. Operators flexibly adapt how to approach customers according to the respective circumstances. This is particularly problematic as the intensity and complexity of gambling advertising increases, and the boundaries between advertising and neutral content blur. Vulnerable groups, especially children and young people, are at increased risk, as the current forms of advertising have been shown to be of particular

appeal to them. Moreover, the rapid developments imply that regulators will have a hard time keeping up.

Further research is needed to gain a deeper understanding of the specific characteristics of gambling advertising on different social networks and to investigate the extent to which children and adolescents are exposed. Longitudinal research approaches or forms of machine learning can be useful complements to existing research methods, providing more robust evidence for regulators, who need to minimise potential harm, especially for vulnerable groups.

2.6 Limitations

The present review has several limitations. First, only articles in English language were considered; therefore, global representativeness cannot be claimed. Besides, grey literature or texts from official bodies which could provide insight on how regulators respond to the constant changes are also missing. Owing to the fact that the publication date of the latest review on this subject was used as a starting point for the search, the period of the investigation was relatively short; however, due to the rapidly changing nature of the review's subject, 12 relevant and up to date publications could be identified. Given that each study has its own focus and mirrors the conditions of the country investigated, the results remain necessarily fragmentary and cannot give a comprehensive picture of the overall situation.

3 How do Gambling Providers Use the Social Network Twitter in Germany? An Explorative Mixed-Methods Topic Modelling Approach[7]

by Johannes Singer, Vadim Kufenko, Andrea Wöhr, Marius Wuketich and Steffen Otterbach[8]

Abstract

This study examines the social media activities of gambling providers in Germany, focusing on the platform Twitter. A collection of 34.151 tweets from 13 Twitter accounts was made, representing casinos, sports betting, state lotteries, social lotteries and lottery brokers. We apply an explorative mixed-methods approach, integrating a summative content analysis together with a semi-supervised guided topic modelling approach, to analyse frequency, number of followers, interaction and content of Twitter messages, and work out differences among the individual providers. The results show that Twitter does not seem to be particularly important for gambling providers who are active in Germany. Regarding outreach, frequency of tweets and interaction, Twitter plays a much smaller role than, for example, in the UK. The potential for Twitter to be an advertising, marketing and interaction channel has not yet been fully exploited, which would make it a perfect moment for developing an appropriate regulatory framework. Overall, the results of semi-supervised topic modelling show that providers most often use informative content (*news*) and combine it with other, usually less neutral content. It is alarming that many providers make little or no use of *Responsible Gambling* messages. Even though the activities are presently on a low level, they contribute to the normalisation of gambling, setting incentives for increasing gambling participation. Children and youth form a large segment of Twitter users. Potential harm can arise especially for this group because of the lack of enforcement of any age limit.

[7] To maintain consistency, the article's original American spelling was converted to British English, and the spelling of "modelling" was standardised to align with the rest of the dissertation.

[8] Further support was provided by Lorenz Weißenberg, who assisted in coding the categories and ensured interrater reliability. The authors would like to thank Thomas Krause for valuable comments and discussions. The idea for the project has been presented in two symposia (International Gambling Research Colloquium—Meeting of early career researchers, February 18th, 2021; Symposium Glücksspiel, Gambling Research Center at the University of Hohenheim, March 17th, 2021).

Keywords Advertising · Gambling · Marketing · Social media · Semi-supervised topic modelling · Twitter

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3.1 Introduction

The activities of gambling providers in the social media, to our knowledge, have only been researched in Australia and the UK (Bradley & James, 2019; Gainsbury, Delfabbro et al., 2016; Houghton et al., 2019; Killick & Griffiths, 2020). However, the question regarding how social media are used as advertising platforms is also relevant for Germany, particularly as the new State Treaty on Gambling (Glücksspielstaatsvertrag 2021 - GlüStV 2021, 2020), entered into force on the first of July 2021 legalises forms of online gambling that have been prohibited or, during the last months before the State Treaty came into force, tolerated. Providers of online casinos, online poker, virtual slot machine games and sports betting will be permitted from July 2021 onwards (Koch, 2021), assuming that they hold a corresponding license. The social media activities of gambling providers in a semi-legal environment, to our knowledge, have not yet been examined.

Legalisation of online gambling is seen critically by addiction experts, as the internet offers an almost endless number of opportunities for gambling and facilitates access to it (Griffiths & Barnes, 2008). Gambling providers on the other hand welcome the new opportunities. Many providers already use social media to market and advertise their brands and products, maintaining several accounts on different social networks in order to reach as many users as possible (Gainsbury, Delfabbro et al., 2016). Not only can they advertise their products in a global network at low cost and get in direct contact with current and potential future customers (Parke et al., 2015), they also use social media to build brand awareness (Barreda et al., 2015).

Despite this situation, research on social media advertising for gambling is scarce (Torrance et al., 2021), and, to our knowledge, non-existing for Germany. This research gap may be partly related to methodological difficulties in quantifying the influence of such advertising strategies on gambling behaviour (Binde, 2014). Barely any attempts of a

quantitative analysis using unsupervised and semi-supervised machine learning methods have been made in order to analyse the advertisement activities of the German gambling providers. However, no one will deny that marketing and advertising on social media are gaining importance and must, therefore, be duly investigated.

Over the past decade, the use of social media has grown and this trend is expected to continue (Duggan et al., 2016). New offers and applications such as TikTok or Clubhouse frequently appear online. This growth also applies to the "big players", as can be seen from the example of Twitter. The social network recorded a 20% increase in daily monetisable users worldwide compared to the previous year, reaching 199 million in Q1 2021 (Twitter, 2021). In Germany, 31% of the population uses social media daily; among 14- to 29-year-olds, the rate is as high as 66%. Alongside Facebook and Instagram, Twitter is used by 2% of the population; among those under the age of 30, also 2% use the microblogging social media platform daily (Beisch & Koch, 2021).

Although Twitter enjoys great popularity among gambling operators (Gainsbury, King, Hing, & Delfabbro, 2015), the advertising strategies can be seen as problematic in that, for example, warnings and notices are very rarely included (Bradley & James, 2019; Gainsbury, King et al., 2016; Houghton et al., 2019; Killick & Griffiths, 2020; Sproston et al., 2015; Thomas et al., 2015). With the help of positive framing, gambling is portrayed as a social and leisure activity like any other (Binde, 2014; Bradley & James, 2019; Gainsbury, Delfabbro et al., 2016; Gainsbury, King et al., 2016; Sproston et al., 2015; Tisdall, 2019). Different types of sports, especially football, are inextricably connected to gambling offers (Cassidy & Ovenden, 2017; Houghton et al., 2019; Lopez-Gonzalez & Griffiths, 2018). Vulnerable individuals, particularly young people, are exposed to enormous amounts of advertising, especially since registration on Twitter requires a minimum age of only 13 (Twitter, 2020), and this restriction is rarely checked. This is an alarming situation since young people are more likely to be influenced by gambling advertisements (Hanss et al., 2015). Besides, advertising aims to increase the number of gamblers and may therefore increase gambling-related harm (Parke et al., 2015). People with gambling disorder are likely to intensify their gambling behaviour (Hing, Cherney et al., 2014; Hing, Lamont et al., 2015), gambling more often and more riskily (Hing et al., 2018).

From a researcher's point of view, investigating the communication via Twitter is attractive because of the breadth and depth of the data on the exchange between gambling providers and their target audiences, available for quantitative analysis. The well-established Twitter Application Programming Interface (API) allows to extract Twitter-objects with rich metadata, which can be used for further analysis. Although analysing short text corpora can be challenging, a number of works has recently emerged (Berger et al., 2020; Liu et al., 2017; Steuber et al., 2022) paving the way to further studies on text analysis of Twitter accounts of different firms.

The growing complexity and availability of gambling (Lawn et al., 2020; Winters & Smith, 2019) is reflected in an increase in the prevalence, diversity and intensity of advertising (Browne et al., 2019; Newall, 2017). Thus, contemporary gambling marketing represents a multi-layered mix of mass media promotion, consumer marketing and subtle marketing, in which advertising is a key component (Newall et al., 2019). Given this fact and the multitude of possible concerns, it is almost negligent that policy makers have paid little attention to social media advertising, for example, by suggesting guidelines or forms of legal regulation.

In the following study, the advertising practices of various gambling providers on Twitter will be examined to get a picture of the situation in Germany. Since there is no freely accessible information on paid advertising, the analysis is limited purely to the activity of the corresponding accounts. First, the frequency of the tweets and interactions with the tweets, i.e., likes and retweets, are described. Second, the contents of the tweets are analysed. Strategies and mechanisms used, such as URLs, hashtags and replies, are considered. Based on a summative content analysis of a random sample, a topic modelling approach is applied to determine the distribution of topics for the complete corpus. The limitations of previous research approaches are taken into account and the novelty of our work is related to i) the choice of the mixed-methods approach, thus applying both qualitative and quantitative methods of empirical social research; ii) analysis of the situation in Germany and iii) consideration of providers from different sectors (Torrance et al., 2021).

3.2 Data and Methodology

3.2.1 Identification of Twitter Accounts

Based on the report from the gambling supervisory authorities of the federal states of Germany (Whitelist), various sectors and providers were identified: casinos, slot machines, social lotteries, sports betting, state lotteries, and lottery brokers, resulting in a total of 126 possible gambling providers. Following the recommendations given in Bradley & James (2019), only Twitter accounts were selected that met the following criteria: (1) the Twitter account had to be in German; (2) there had to be a certain level of activity (i.e., at least one tweet per week) and (3) the two Twitter accounts with the largest number of followers per sector were included.

In the case of sports betting providers, an exception from the third criterion was made in that accounts from six providers were chosen (instead of two). Thus, a broader data base was obtained, making the results more readily comparable with previous research, which primarily focuses on sports betting providers in Australia and the United Kingdom (Bradley & James, 2019; Gainsbury, King, Hing, & Delfabbro, 2015; Houghton et al., 2019; Killick & Griffiths, 2020).

The situation with the Twitter accounts of casinos and slot machine providers was different: these do not tend to actively use Twitter and some accounts were inactive or had not been updated for a long time. Therefore, only one account from the casino sector and none from the slot machine sector met the criteria. In total, 13 accounts were included in the study.

3.2.2 Sample

Table 3.1 gives an overview of the data collected: 34,151 tweets from 13 accounts were collected on April 8, 2021. Account holders were the sports betting providers *ADMIRALBET, bet-at-home, bwin Sportwetten, mybet, Tipico and Unibet Sportwetten*[9]; the state lotteries *Lotto BW* and *LOTTO Bayern*; the social lotteries *Aktion Mensch e.V.* and *Sportlotterie*; the lottery brokers *LOTTO24.de* and *Lottoland.com* and the casino provider

[9] *Unibet Sportwetten* offers sports betting, online slots and poker. On the company ‘s Twitter account, the sectors online slots and poker do not play a role during the observation period.

Spielbanken Bayern[10]. The gambling providers generated 32,861 tweets (96.22%); 1,290 tweets (3.78%) were retweets. The average number of shared tweets varied from 15.19 (*bwin Sportwetten*) to 0.42 (*Spielbanken Bayern*).

Table 3.1 Twitter account information by provider

Gambling provider	Account starting date	Followers	Number of tweets		
			Total since start	Per day	Collected via API
State lotteries					
Lotto BW	2014–09-22	1735	8781	3.67	3200
LOTTO Bayern	2015–06-11	1452	3907	1.84	3198
Social lotteries					
Aktion Mensch e.V	2009–06-29	78,105	31,254	7.27	3199
Sportlotterie	2014–02-03	1149	1911	0.73	1909
Lottery brokers					
Lottoland.com	2012–02-02	1225	3283	0.98	3198
LOTTO24.de	2012–11-14	2478	5804	1.89	3199
Casino					
Spielbanken Bayern	2013–01-02	132	1258	0.42	1258
Sports betting					
ADMIRALBET	2010–01-19	1713	4851	1.18	3200
bet-at-home	2011–08-01	1813	11,314	3.20	3198
bwin Sportwetten	2013–05-23	2938	43,692	15.19	3200
mybet	2019–03-27	20	434	0.58	434
Tipico	2016–04-13	3799	2493	1.37	2488
Unibet Sportwetten	2018–02-15	4521	2497	2.18	2470

The provider whose account registration dated back the longest was the social lottery *Aktion Mensch e.V.*, whereas the sports betting provider *mybet* held the most recent account. Since registration, *bwin Sportwetten* had posted the largest number of tweets (43,692) and *mybet* the fewest (434). *Aktion Mensch e.V.* had the highest number of followers with 78,105, *mybet* the fewest (20).

[10] Of the two lottery brokers, *LOTTO24.de* holds a license for Germany, *Lottoland.com* does not.

The observation period starts with the registration of the most recent account (03/27/2019) and ends about two years later (04/08/2021). Thus, a consistent time period in which all accounts were active is ensured, allowing for a meaningful comparison of frequency, interaction and content.

3.2.3 Methods

In this study, we use an exploratory mixed methods approach, where an initial qualitative phase of data collection an analysis is followed by a phase of quantitative data collection and analysis. Thus, we address the limitations of previous studies that rely on a single method (Bradley & James, 2019; Houghton et al., 2019; Killick & Griffiths, 2020). The methods can be categorised into the ones related to data acquisition, qualitative analysis, preprocessing, quantitative analysis and evaluation.

In the first part of our analysis dedicated to data aquisition, we use the statistics program R and the package rtweet (Kearney, 2019) to collect the most recent tweets within the observation period for each provider. A maximum of 3200 tweets (excluding retweets) could be collected per account. This requires a Twitter developer account and a personalised access key to the Twitter API. This data gives insight into the frequency of tweets, number of followers and interaction with the tweets. In all, 18,051 tweets were collected for the observation period.

In the second part of our analysis, we carry out a qualitative summative content analysis (Hsieh & Shannon, 2005) to examine the content of the tweets. In a first step, we randomly select 10 tweets per provider, resulting in 130 tweets, which serve as a basis for the development of a coding scheme. Using an inductive approach, we assign the content of the tweets to specific codes. Code identification provides a way to capture content, detect and classify messages into interpretable topics. This qualitative classification is based on the domain knowledge about the gambling market and products specific to Germany. The results of this qualitative classification are valuable per se, yet they relate to the selected subsample of tweets. In order to test whether the given distribution of topics can be generalised for the complete sample of tweets, a semi-supervised guided topic modelling approach is applied. The results of the qualitative analysis are used to initialise the topics and guide the algorithm.

Next, we summarise and condense the codes. Eight categories can be identified, some of which have already been described in previous studies (Houghton et al., 2019; Killick & Griffiths, 2020; Thomas et al., 2015), namely, *additional information*, *interaction*, *marketing*, *news*, *product advertising*, *Responsible Gambling*, *results*, and *other*. These categories are then applied to a random sample of 50 tweets per provider, resulting in 650 tweets. The number of 50 was chosen due to the difference in activity between the providers, with *Aktion Mensch e.V.* posting 3.194 tweets and *Sportlotterie* only 66 tweets during the observation period. The above-mentioned categories and the related words are used as seeds, or guides, for the semi-supervised topic modelling.

For the quantitative analysis we use the Python programming language in order to preprocess the tweets,[11] assemble the corpus and conduct semi-supervised topic modelling. This allows us to apply the findings of the summative content analysis to all 18,051 tweets of the observation period and evaluate the generalisation of our analysis. A diligent preprocessing of tweets was necessary in order to proceed to the quantitative analysis. The preprocessing routines involved global ones,[12] including but not limited to capitalisation of text to lowercase, converting German diacritics into their non-diacritic character combinations, removal of German stop words and extraction of text from images,[13] actively used by the providers to visualise their messages. Lemmatisation of the words was carried out using a special tagger,[14] tailored for German language (Wartena, 2019). Since usually pre-processing involves removal of special characters and numbers, local or provider-specific pre-processing involved translating certain frequently observed objects, like the hotline telephone numbers for prevention, certain symbols and icons or specific product names containing numbers, into interpretable words.

Regarding the semi-supervised topic modelling a number of methods has been considered. As Steuber et al. (2022) demonstrated, guided or seeded Latent Dirichlet Allocation (LDA as in (Blei et al., 2001)) can be successfully applied to Twitter data. However, Gallagher et al. (2017) noted that LDA is based on a number of generative assumptions on

[11] During the work on the given paper the following version of Python had been used: 3.7.13.
[12] In addition, several functions from packages Gensim (Rehurek and Sojka 2011), NLTK (Bird et al. 2009), NumPy (Harris et al. 2020) and Pandas (McKinney 2010) were used.
[13] For this purpose, the well-established "pytesseract PyPI" library available at https://pypi.org/project/pytesseract/ has been applied. With only a few exceptions "pytesseract" successfully extracted short messages embedded into images (Hoffstaetter 2022).
[14] In our context the lemmatizer demonstrated better results compared to conventional stemmers.

the distribution of topics over words, which are often unrealistic and result in rather narrow topic definitions. Therefore, we have decided to apply the Correlation Explanation (CorEx) topic model, treating topics as latent factors. The CorEx model is relatively new and to our knowledge this is a first time that this model is used on German Twitter data. There are different ways of guiding the algorithms. In Steuber et al. (2022) the topic distribution and related words were identified using clustering analysis, which yielded rather dispersed results for some topics. Although such approaches can be fruitful, our mixed methods strategy has a decisive advantage: we use the qualitative analysis to feed the extensive domain knowledge into the seeds of the topic modelling algorithm.

The codes from the summative content analysis act as a guide for the CorEx model. The specification of anchor words enables the topic modelling procedure to assign certain keywords to the different content categories. To evaluate whether the initial topic distribution and classification of tweets from the qualitative analysis can be generalised to a larger corpus, we use an inter-rater reliability and agreement approach resembling the one used in Goh et al. (2020): For the qualitative coding of the 650 randomly selected tweets we compare the corresponding results from the CorEx classification using Fleiss' (1971) κ from the pyirr package (Rick de Klerk, 2022).

3.3 Results

3.3.1 Descriptive Analysis

The first steps in our analysis are of a descriptive nature and represent frequencies and descriptive statistics on the Twitter messages for a general overview. Below we summarise the main descriptive findings from the tables, which can be found in the Appendix.

Frequency of the Tweets

The activity of the providers varied considerably (see "Appendix, Table 7.1"). *bwin Sportwetten* (3197) and *Aktion Mensch* e.V. (3191) posted the most tweets in the observation period, *Sportlotterie* the fewest (66). The highest number of tweets per day came from *bwin Sportwetten* (4.30) and *Aktion Mensch e.V.* (4.29), the fewest from *Sportlotterie* (0.09).

Interaction with the Tweets

Actions such as retweeting, commenting or liking a tweet, and the use of hashtags create additional content and visibility to a wider audience. Consequently, both number of followers and level of interaction are assessed to evaluate the activities of the individual providers. The number of retweets and likes is shown in Table 7.2 (see "Appendix").

It is of note that gambling providers sometimes retweet the content of other accounts. This is especially common among sports betting providers, who, for example, often retweet the messages of major football clubs such as FC Bayern Munich. These retweets (*n* = 694) are excluded from the analysis so that we can exclusively examine the content created by the gambling providers themselves.

Content of the Tweets

Finally, we examine the number of images and URLs included, as well as the providers' responses to user comments (see "Appendix, Table 7.3"). Images were used in varying frequencies. Whereas *Spielbanken Bayern* used images in almost every tweet (94.04%), *ADMIRALBET* almost never did (4.00%). Most providers added one or several URLs to their tweets, linking their websites or other content. Even *LOTTO24.de*, the provider with the lowest number of URLs, used a URL in one third of its tweets (33.97%). In contrast, replies to tweets were rare, with the exception of *LOTTO24.de,* who responded to user questions or comments in 40.38% of all cases.

Next, we look at hashtags. Hashtags enable providers to relate their brand and products to certain topics. Frequent hashtags are displayed on the start screen of the users, increasing visibility. Table 7.4 (see "Appendix") presents the most frequent hashtags. First was *lotto6aus49* (number lottery), followed by *bundesliga* (German term for *national league*) and *jackpot*.

Table 7.5 (see "Appendix") shows the top 5 hashtags for each provider. Providers from the same sector mostly used identical or similar hashtags. Sports betting providers, for example, addressed sports teams, sporting events, (betting) odds and facts about sports events. The social lottery *Aktion Mensch e.V.* addressed primarily social issues, with hashtags such as *inclusion*, *disability*, *accessibility* and *participation*. In contrast, the social lottery *Sportlotterie* exclusively referred to their own company and brand.

Hashtags could clearly be assigned to certain sectors; the only intersection appeared between lotteries and lottery brokers, whose product interests are closely related: the state lotteries *Lotto BW* and *LOTTO Bayern* and the lottery brokers *Lottoland.com* and *LOTTO24.de* referred to their products (e.g., *lottozahlen* and *lotto6aus49*) and advertised high chances of winning (e.g., *jackpot* and *eurojackpot*).

The majority of the hashtags are related to the contents. Only few hashtags describe characteristics or qualities of the provider using them. Several sports betting providers stress the high quality of their offer (*quotenboost*, *topquoten*, *bonus*), sometimes in combination with their own brand name (*tipicotopfakt*, *mybetmeister*). The state lottery *LOTTO Bayern* emphasises its legal status (*legalbeimoriginal*) and proximity (*bayern*). The hashtag *glücklichmacher* used by the lottery broker *LOTTO24.de,* suggests that by using the company's products, the users will be made "happier".

3.3.2 Qualitative and Quantitative Content Analysis

In the first step, 50 randomly selected tweets per provider are categorised to develop a coding scheme based on associated codes and keywords for the entire dataset. After the 650 tweets were coded by the first researcher, a second researcher applied the categories to 40% of the data. We calculate Cohen's (1960) κ as a measure of inter-rater reliability. Table 3.2 shows consistently high inter-rater reliability with κ values larger 0.84 for seven out of eight categories. On average the Cohen's κ was around 0.77 with only one outlier.[15]

[15] The only substantial deviation in κ was noted for the category *interaction*. Since 15 Twitter messages fall into this category, despite a high expected agreement rate of 90.72, minor mismatches between the two raters may explain the low κ value of 0.46. Another potential explanation could be the well-known paradox of the chance-correction ratio, which may result in a low κ value even under high agreement (see Feinstein and Cicchetti (1990)).

Table 3.2 Content categories of the 650 randomly selected tweets (50 per provider)

Category	Qualitative analysis (n^a = 1,115)			CorEx (n = 793)	
	n	%	Cohen's κ^b	n	%
1. Product advertising	165	15	0.9300	167	21
2. Additional information	159	14	0.9385	157	20
3. Results	89	8	0.8710	91	11
4. Marketing	190	17	0.8438	148	19
5. Interaction	15	1	0.4611	17	2
6. Responsible Gambling	98	9	0.9593	54	7
7. News	350	31	0.8924	123	16
8. Other	49	4	0.9168	36	5

The analysis is based on 650 randomly selected tweets (50 tweets per provider) during the observation period from 2019-03-27 to 2021-04-08

[a] *n* means the number of identified content categories for all 13 providers. The number of content categories is higher than the number of tweets, as a tweet can be classified in several categories

[b] The values for Cohen's κ refer to the agreement of the two researchers regarding the qualitative coding of 650 randomly selected tweets. The comparison of the agreement between the qualitative content analysis and the semi-supervised topic modelling regarding the 650 randomly selected tweets is shown in Table 7.6 (see "Appendix")

The eight identified topics and the associated codes and keywords from the summative content analysis serve as a guide for the semi-supervised CorEx topic model (Gallagher et al., 2017). It is important to note that associated codes and keywords are identified on a provider-specific basis, as providers operate in different gambling sectors and therefore use different jargon, house style and wording in their Twitter messages. Also with regard to the eight categories, it should be mentioned that (i) not every provider takes up all eight categories and (ii) individual messages can be assigned to more than one category. By specifying provider-specific anchor words, the topic modelling procedure is able to capture the specific characteristics of each provider as accurately as possible and optimise pre-processing for the entire dataset.

Given the provider-specific anchor words, we perform the CorEx topic modelling for each provider and compare the match with the qualitative summative content analysis. Table 3.2 shows the level of correspondence for the 650 randomly selected and previously qualitatively classified Twitter messages. With the exception of the categories *news* and

Responsible Gambling, a relatively high level of matching can be seen. While the qualitative content analysis assigns 165 of the 650 messages to the category *product advertising*, the CorEx topic modelling assigns 167. A similar result can be seen in the categories *additional information* (159 vs. 157) and *results* (89 vs. 91). It is noteworthy that in the qualitative categorisation tweets are much more frequently assigned to more than one category, i.e. 650 tweets are assigned to a total of 1,115 categories, while in the CorEx topic modelling it is 793. The relatively poor match for the *Responsible Gambling* category can be explained by the fact that images and symbols are often used for this. *Bet-at-home*, for example, uses only an emoticon-sized symbol to indicate the age restriction. *Sportlotterie* also often uses images to indicate *Responsible Gambling*.

In the next step, we further examine the correspondence of the qualitative and quantitative topic analysis by calculating Fleiss κ for each provider and category (see Table 7.6). Given that not every provider´s Twitter messages cover all eight categories, 67 categories are identified for comparison.[16] The inter-rater reliability shows substantial agreement on 58 categories (87%) having a positive κ, and 50 categories (75%) additionally having a *p*-value below 5%, indicating that the agreement between the qualitative and the quantitative analysis is significantly different from a chance agreement (Table 3.3). CorEx yielded relatively high coherence values,[17] calculated as in Syed and Spruit (Syed & Spruit, 2017), between 0.45 and 0.63 (see "Appendix", Table 7.7).

[16] Theoretically, there would be 13 providers × 8 categories = max 104 categories to compare.

[17] The decisions on the number of topics are based on the qualitative analysis. Although the coherence does not play a central role in our approach, we have decided to report it in order to show that the choice of topics is overall coherent with the corpus. The total correlation indicator, native to the CorEx method, was also relatively high in almost all cases, yet this indicator is not standardized and is not as intuitive as the coherence score (C_V), which we use for the reporting purposes.

Table 3.3 Inter-rater reliability of the 67[a] content categories of all 13 providers based on the 650 randomly selected tweets (50 per provider)

Value	n	%
κ (+)	58	87
p-value (< 0.05)	55	82
κ (+) & p-value (< 0.05)	50	75
κ (-) & p-value (< 0.05)	5	7

[a] In total, 67 content categories can be identified for all 13 gambling providers. The provider whose content can be classified into the fewest categories (3) is Aktion Mensch e.V. The largest number of content categories (7) can be found at several providers (e.g. Lotto BW)

Finally, we apply the semi-supervised CorEx topic model to the entire dataset containing 18,051 tweets. Again, a single tweet can be assigned to one or more categories which is the reason why the aggregate number of content exceeds the total number of tweets. The quantitative results of CorEx topic classification are presented in Table 3.4 (all providers) and Table 3.5 (grouped by provider).

Table 3.4 Content of the complete dataset (18,051 tweets) translated into English

Category (corresponding content in bold type)	Associated codes	Number of content (%)
1. News *Example: "**3 defeats in a row conceded the #SGE last. To make matters worse, they have a poor record against #HerthaBSC: No goal in the last 3 duels.** Will #SGEBSC score something today? The bets for the game:* http://po.st/jcv4E*"* *(bwin Sportwetten, 2019-12-06)*	**sporting events,** match results, team line-ups, competitions, athletes, social projects, explanations on gambling	7224 (33%)
2. Product advertising *"Here we go! Will #BVB take the lead before the break like in the first leg? 1.60 – Dortmund score the 1st goal of the 1st half #BVBSLA live betting* 👉 http://po.st/rEelqM*"* *(bwin Sportwetten, 2019-12-10)*	drawing of lottery numbers, **sports betting events,** other lotteries, **URLs to specific offers**	4466 (21%)
3. Additional information *Example:* *"**Around € 45 million in today's #LOTTO6aus49 jackpot – closing time 7 p.m.** http://lotto-bayern.de/losgehts #LegalbeimOriginal #6aus49"* *(LOTTO Bayern, 2020-11-28)*	odds, **prize amount**, **time and date of the gamble,** winning numbers	3802 (18%)
4. Marketing *"Today we have something outstanding for you! **Win an online meet and greet with FC Red Bull Salzburg!** How can you win this? Comment on this post, tell us which player you would like to meet virtually. We wish you good luck with the Tipico sweets!"* *(Tipico, 2020-11-13)*	brand promotion, engagement, celebrity endorsement, company information, **raffles**	2333 (11%)
5. Results *Example: "**The #lotto numbers 6aus49 of 20.11.2019: 2,7,10,18,31,42 SZ: 0.** Did you win the 1 million euros? Check here: https://t.co/Q0VaZbnpxy"* *(Lottoland.com, 2019-11-20)*	winning totals, successful betting slips, **winning numbers**	1637 (8%)
6. Responsible Gambling *Example:* *"On Friday there is € 10 million in the #Eurojackpot jackpot* 🍀👍😎 *Chance of winning 1:95 million //* http://lotto-bw.de ***From 18. Addictive. Help at* http://bzga.de***"*** *(Lotto BW, 2019-11-25)*	responsible gambling and **harm-reductive content, age restrictions** (often pictured as symbols)	1179 (5%)

7. Other *Example: **"@Weedogonzales[a] Check with our support in live chat** ")* *(Tipico, 2020-05-13)*	**provider response to user enquiries**	769 (4%)
8. Interaction *Example: "#RBLATL is the duel of last year's finalists! Who will prevail?* ***Leipzig 66,7 %*** ***Atletico 33,3 %*** ***9 votes – Final results**"* *(bwin Sportwetten, 2020-08-13)*	asking for feedback, **polls**, votes	230 (1%)

The analysis is based on 18,051 selected tweets during the observation period from 2019-03-27 to 2021-04-08. The number of content categories is higher than the number of tweets, as a tweet can be classified in several categories. The examples were translated by the authors

[a] Weedogonzales is the name of a user who had asked for help

News

News was the most prominent category containing 33% of the overall content (Table 3.4). The *news*-category appears to be informative rather than promotional. Typically, the providers address sector-specific issues, e.g., information on sports teams and line-ups. Most Twitter messages from *Aktion Mensch e.V.* and the three sports betting providers *Unibet Sportwetten*, *bet-at-home* and *mybet*, contained *news* (81% and 66%, 65%, 59%, respectively), but only few from the state lotteries *Lotto BW* (5%) and *LOTTO Bayern* (3%) and none from the lottery broker *Lottoland.com* (Table 3.5).

Product Advertising

Product advertising accounts for 21% of the overall content. This category includes advertising for specific gambling products, e.g., a URL that directly leads to a certain betting offer. 46% of *bwin Sportwetten*'s and 39% of *ADMIRALBET*'s content fall under this category. In contrast, *Aktion Mensch e.V.*, *Lottoland.com*, *Spielbanken Bayern* and *mybet* did not use this category at all. Although *mybet as well as bwin Sportwetten and ADMIRALBET* offer the same range of products, they used *product advertising* to varying degrees.

Additional information

Next in frequency was the category *additional information* (18%). This category includes supplementary information on gambling offers (e.g., odds or maximum winnings). Although some providers made use of this category (*LOTTO Bayern,* 36%, and *bwin Sportwetten,* 30%), it did not play any role for others (*Aktion Mensch e.V.*, *Lottoland.com* and *bet-at-home*). Again, no discernible trend evolved between providers of the same category.

Marketing

The percentage of overall content classified as *marketing* amounts to 11%. *Marketing* implies that providers promote their brand or advertise an engagement (e.g., team sponsoring); also, celebrity endorsement, raffles or company information belong to this category. Whereas the casino *Spielbanken Bayern* (55%) mostly relied on this category in its tweets, it played a minor role for some sports betting providers (e.g., *Unibet Sportwetten,* 2%), the lottery broker *LOTTO24.de* (5%) and the state lottery LOTTO Bayern (1%). Nonetheless, a clear trend between providers of the same sector could not be found.

Results

We classify 8% of the overall content as *results*. With the exception of *Lottoland.com* (58%), providers used *results*, such as winning totals or winning numbers, only rarely (which half of the sports betting providers did) or not at all (sports betting providers, social lotteries).

Responsible Gambling

Only 5% of the overall content classifies as *Responsible Gambling*. This category comprises harm-reduction and youth protection measures, for example, age limits. None of the tweets contained exclusively *Responsible Gambling* content and typically, the *Responsible Gambling* content was limited to an emoticon-sized symbol indicating the age limit.

Responsible Gambling content comprises 25% of *Lotto BW*'s and 23% of *LOTTO24*'s content, not in a very prominent form, as all tweets or images were merely supplemented by a subline referring to the age limit and potentially addictive character of the product. *Lotto*

BW also adds the free hotline of the Federal Centre for Health Education to its tweets. Nevertheless, these providers did make use of this category, whereas five[18] providers did not publish any harm-reductive content at all (*ADMIRALBET, Aktion Mensch e.V., bwin Sportwetten, LOTTO Bayern, Lottoland.com*), irrespective of the potential hazard of their products.

Other

The classification *other* accounts for 4% of the overall content. This category includes content that cannot be assigned to any other category, for example, responses to user enquiries. This category was rarely used except for *bet-at-home* and *Tipico*: 13% and 12%, of their tweets fell within this category, respectively.

Interaction

The classification *interaction* accounts for 1% of the content. This category refers to content that encourages users to interact either with the provider or the tweet, for example, requests for feedback, polls and votes. Only three providers worked with *interaction* in their tweets[19], and only one of them did so more intensely (*Lottoland.com*, 14%).

[18] Although Table 3.5 shows that both providers *bet-at-home* and *Spielbanken Bayern* also do not use *Responsible Gambling* content, this is due to a technical limitation in the data collection. Consequently, the two providers are not mentioned here.

[19] Due to a technical limitation in the data collection, the category *interaction* could not be considered for the provider *bwin Sportwetten*.

Table 3.5 Content categories by provider

Gambling provider	Number of tweets	Number of content categories	News (%)	Product advertising (%)	Additional information (%)	Marketing (%)	Results (%)	Responsible Gambling (%)	Other (%)	Interaction (%)	Coherence
State lotteries											
Lotto BW	2368	3150	5	18	27	11	8	25	5	-	0.44
LOTTO Bayern	1451	1801	3	34	36	1	22	-	4	-	0.48
Social lotteries											
Aktion Mensch e.V.	3191	3244	81	-	-	15	-	-	5	-	0.45
Sportlotterie	66	76	51	14	3	32	-	-[a]	-	-	0.56
Lottery brokers											
Lottoland.com	800	899	-	-	-	26	58	-	2	14	0.35
LOTTO24.de	468	851	4	20	27	5	12	23	9	-	0.57
Casino											
Spielbanken Bayern	285	420	10	-	12	55	14	9	-	-	0.49
Sports betting											
ADMIRALBET	2173	2717	29	39	21	11	-	-	-	-	0.45
bet-at-home	1186	1608	65	11	-	11	-	-[a]	13	-	0.61
bwin Sportwetten	3197	3579	17	46	30	7	-	-	-	-[a]	0.53
mybet	433	616	59	-	8	16	12	5	-	-	0.60
Tipico	597	608	15	15	14	20	13	11	12	-	0.50
Unibet Sportwetten	1836	2071	66	6	11	2	7	2	-	5	0.38

The analysis is based on 18,051 tweets during the observation period from 2019-03-27 to 2021-04-08. The number of content categories is higher than the number of tweets, as a tweet can be classified in several categories

[a] This content is used by the providers, but cannot be captured by topic modelling. Even if there is no capture of the data, the categories are considered to be present in the evaluation

In all, the exploratory mixed-methods approach adopted was demonstrated to be appropriate for using the results of the qualitative content analysis to guide the quantitative semi-supervised Anchored CorEx model. For the 650 randomly selected tweets, the results of the summative content analysis and the CorEx model showed high coherence in 75% of all cases (Table 3.3). The coherence ranged from 0.45 to 0.63 (Table 7.7). Finally, the analysis of the complete dataset of 18,051 tweets shows high correspondence with the random sample, especially in the categories *news*, *additional information*, *results*, *Responsible Gaming*, *other* and *interaction* (Table 3.6).

Table 3.6 Relative number of content categories

Category	Random sample of tweets (n^a = 650)		Complete dataset (n^b = 18,051)
	Qualitative analysis (%)	CorEx (%)	CorEx (%)
1. News	31	16	33
2. Product advertising	15	21	21
3. Additional information	12	20	18
4. Marketing	17	19	11
5. Results	8	11	8
6. Responsible Gambling	9	7	5
7. Other	4	5	4
8. Interaction	1	2	1

[a,b] *n* means the number of analysed tweets of the observation period from 2019-03-27 to 2021-04-08

3.4 Discussion

In Germany, Twitter does not seem to be as important for providers of gambling products regarding scope, frequency of tweets and interaction as, for example, in the UK. In the present study, only one account has as many as 78,105 followers, whereas all others attract low four-figure numbers of followers or even less. In contrast, British sports betting providers may easily attract more than 100,000 followers (Bradley & James, 2019; Houghton et al., 2019; Killick & Griffiths, 2020). Possibly other social media are more important for providers operating in Germany. *Unibet Sportwetten*, for example, has only 4,500 Twitter followers, compared to 15,000 Instagram subscribers and 930,000 Facebook

followers. Similar figures apply for the sports betting provider *bwin Sportwetten* and the state lotteries *Lotto BW and LOTTO Bayern*.

Similarly, all Twitter activities are rather low-level in our study. The providers send between 0.09 and 4.30 tweets per day, whereas Bradley and James (2019) report 89 tweets per day for the least active provider in the UK, Houghton et al. (2019) 25 and Killick and Griffiths (2020) report 33 tweets per day. Likewise, the most active provider in our study received 1.66 retweets and 4.66 likes per tweet, compared to 18.2 retweets and 72.8 likes by the sports betting provider *Paddy Power* in the UK (Bradley & James, 2019). However, the exact number of tweets that followers receive as push messages or that are displayed on their start screen also depends on the mechanics of Twitter's timeline algorithm.

The potential of Twitter as an advertising, marketing and interaction channel has not yet been fully exploited by gambling providers in Germany, suggesting that there is a need for implementing the corresponding regulatory measures before advertising proliferates. Higher advertising volumes are to be expected with the admission of new forms of gambling into the German market by the new State Treaty of Gambling. Since exposure to gambling advertising might be positively associated with problem gambling (Syvertsen et al., 2022), an increase in the latter might be expected. This will fuel the demand for the regulation of gambling advertising that, thus far, has not been considered by regulators.

As both, the qualitative and quantitative analysis show, most of the content can be classified as *news*. The neutral presentation gives the tweets a professional and matter-of-fact touch, adding credibility to the provider. Despite minor differences between the categories *product advertising*, *additional information* and *results*, it is also evident that most tweets combine the *news* category with another, usually less neutral category. In our study, about one-fifth (21%) of the analysed content was direct advertising for gambling products, and a large share of the remaining tweets were directly linked to gambling products and gambling opportunities. Previous studies have shown that easy and fast accessibility, in combination with a permanent presence of gambling, contribute to the normalisation of gambling, i.e., it becomes part of everyday life (Binde, 2007; Gainsbury, Delfabbro et al., 2016; Gainsbury, King et al., 2016; McMullan & Miller, 2010; Sproston et al., 2015). The mere perception of gambling advertising can act as a trigger to participate in gambling, in particular, for disordered gamblers or persons who want to reduce or quit gambling (Binde, 2009;

Hing, Cherney et al., 2014; Hing et al., 2013). If information on and reminders about gambling become a daily companion for Twitter users, this is likely to contribute to more harm and vulnerability (Binde, 2007). Young people are at special risk, since children and youth have an increased risk for developing gambling problems (Derevensky & Gilbeau, 2015; Guillou-Landreat et al., 2021; Hanss et al., 2015; Li et al., 2018). This age group forms a large part of Twitter users. Moreover, our study has confirmed results from previous research that harm reductive or responsible gambling content rarely occurs (Bradley & James, 2019; Gainsbury, King et al., 2016; Houghton et al., 2019; Killick & Griffiths, 2020; Sproston et al., 2015; Thomas et al., 2015; Torrance et al., 2021) and, even if it is present, it does not stand out.

With one exception, a clear pattern between the use of certain categories and belonging to a certain sector did not evolve in our study. The category *news* was preferentially used by sports betting providers as well as social lotteries and to a far lesser degree by the state lotteries, the lottery brokers and the casino. Krawczyk and Własiuk (2021) report more aggressive advertising slogans from providers of potentially less harmful products, such as lotteries, like *Aktion Mensch e.V.* and *Sportlotterie* in our case.[20] So possibly, this category is used by providers of potentially more harmful products, like sports betting, to increase credibility and encourage the so-called "gamblification" of sports (Lopez-Gonzalez & Griffiths, 2018). However, it is equally conceivable that *news* relating to sports events are more attractive to a larger audience than *news* about lottery drawings. The use of all other categories was distributed unequally. The providers in our study may pursue different aims irrespective of the sector they belong to.

3.5 Limitations and Future Directions

Although the observation period in our study covered more than two years, the results are not necessarily representative for longer and especially future periods. Providers might change their marketing strategies at short notice and/or flexibly adapt their appearance in social media. Most particularly, in the wake of the COVID-19 pandemic, the gambling

[20] This could be due to the fact that potentially less harmful forms of gambling might have less strict advertising guidelines. The study by Krawczyk and Własiuk (2021) considers slogans from a wide variety of countries without investigating the differences between various countries and regulation systems, leaving this question unanswered.

market was subject to severe restrictions, especially in 2020. During the lockdown, land-based gambling services had to close and sporting events were temporarily banned (Auer et al., 2023; Håkansson et al., 2021; Nosal & Lopez-Gonzalez, 2021). It seems likely that the providers adapted their marketing strategies to the prevailing conditions.

Another limitation is of a technical nature. The Twitter API can only collect 3200 tweets per account. Some providers, whose accounts comprised more than 3200 tweets, had slightly lower numbers. The most likely explanation was that some tweets had been deleted by the providers themselves before the time of the investigation.

For topic modelling, the images used in the tweets are to some extent problematic. These are often accompanied by text, which is often only reproduced fragmentarily or incorrectly and thus cannot be used for the analysis. For this reason, the *Responsible Gambling* category was not taken into account for the providers *Sportlotterie* and *bet-at-home*. For example, in the second case, this was limited to an emoticon-sized symbol indicating the age limit.

A similar problem occurred with the provider *bwin Sportwetten*. This provider used polls to interact with its users. However, this Twitter feature could not be read out by the API, which is why the *interaction* category for this provider is not taken into account in the analysis.

Another challenging aspect of a semi-supervised approach can be the semantic spectrum of the related categories. It may prove difficult to describe these to the full extent and to attach specific anchor words to them. For example, the providers of sports betting report on different sports, different competitions and athletes in the tweets classified as *news*. They do not restrict their coverage to one country, i.e. one tweet is about football in Germany, the next about tennis in France. In any case, comprehensive preparatory work is required to determine the categories precisely in order to guide the algorithm to an accurate classification and to classify the remaining content into an open category *other*.

In general, we do not know how many users actually read a tweet and even if they do, if they are influenced by the tweets and to what degree. The sheer volume of the providers' activities only permits limited conclusions on the effects on (potential) users. This could

only be investigated in studies with users. Neither do we know who the users are—recreational or disordered gamblers, adults or minors. In general, social media appeal to young people. According to Twitter's terms and conditions, an account can be created from the age of 13, but this might not prevent younger users from doing so. Participation in gambling however requires a minimum age of 18 in Germany. Therefore, future studies should assess the effects of tweets on the gambling attitudes, gambling intentions and gambling behaviour of different user groups.

3.6 Conclusion

Our paper is dedicated to filling a literature gap on the categorisation of Twitter messages of the major German gambling providers using a novel approach, which combines qualitative and quantitative analysis. We used qualitative analysis performed by experts in the gambling research field in order to derive a categorisation of topics and the related keywords. Afterwards we used these qualitative results as seeds, or namely guides, for the semi-supervised topic modelling using the CorEx model. The given mixed-methods approach revealed eight distinct topics, ranked according to their share in the complete corpus of Tweets: *news*, *product advertising*, *additional information*, *marketing*, *results*, *Responsible Gambling*, *other* and *interaction*. Our findings suggest that the agreement between the qualitative and the quantitative analysis with respect to these categories was relatively high.

The top category *news* can be considered as an indirect promotion of gambling services since information about sport events is communicated together with logos and colour schemes of the providers, inviting the customers to engage in gambling. The category *product advertising* relates to direct promotion and was on the second place for the complete corpus. Thus our findings indicate that indirect and direct promotion dominate in the corpus of the German gambling provider Tweet messages. The category *Responsible Gambling* has a share of only 5% for the corpus of Tweets with *interaction* having the lowest share. Therefore, we would like to highlight the importance of regulation of advertisements on social networks and media, since providers actively use platforms like Twitter for direct and indirect advertising. The fact that many persons from vulnerable target groups and in

particular minors are actively using these social media platforms amplifies the policy implications of our findings.

The social media activities of gambling providers in Germany need to be understood in the context of the new State Treaty on Gambling in Germany. It is to be expected that the legalisation of various forms of online gambling will lead to an increase in the social media activities of the relevant providers. Moreover, the State Treaty provides for liberal advertisement practices due to its generally worded regulations. Accordingly, the State Treaty (Glücksspielstaatsvertrag 2021 - GlüStV 2021, 2020) stipulates that advertising may not be *excessive*. Furthermore, minors and comparably vulnerable target groups may not be addressed explicitly, whereas minors are to be excluded as recipients of *advertising if possible*. Which advertising measures are considered *excessive*, and *whether it is possible* to exclude minors from advertising, not only involves numerous complex technical and legal aspects but is certainly viewed differently by stakeholders (gamblers, providers, addiction experts, regulators, policy makers). Most probably, these issues will become a matter for the German courts in the event of dispute. In this case, a considerable amount of time will pass before potential judicial clarification.

Thus, if such liberal handling leads to the population being massively penetrated by gambling advertisement, restrictions (including advertising bans), as in other countries [e.g., Australia, Belgium or Italy (Newall et al., 2019), could be among potential consequences, for example in the form of binding advertising guidelines. Consequently, social media and Twitter in particular, which are not explicitly referred to in the German State Treaty on Gambling, could become significantly more important as advertising channels.

4 Stigmatisation of Gambling Disorder in Social Media: A Tailored Deep Learning Approach for YouTube Comments

by Johannes Singer[21]

Abstract

Background The stigmatisation of gamblers, particularly those with a gambling disorder, and self-stigmatisation are considered substantial barriers to seeking help and treatment. To develop effective strategies to reduce the stigma associated with gambling disorder, it is essential to understand the prevailing stereotypes. This study examines the stigma surrounding gambling disorder in Germany, with a particular focus on user comments on the video platform YouTube.

Methods The study employed a deep learning approach, combining guided topic modelling and qualitative summative content analysis, to analyse comments on YouTube videos. Initially, 84,024 comments were collected from 34 videos. After review, two videos featuring a person who had overcome gambling addiction were selected. These videos received significant user engagement in the comment section. An extended stigma dictionary was created based on existing literature and embeddings from the collected data.

Results The results of the study indicate that there is substantial amount of stigmatisation of gambling disorder in the selected comments. Gamblers suffering from gambling disorder are blamed for their distress and accused of irresponsibility. Gambling disorder is seen as a consequence of moral failure. In addition to stigmatising statements, the comments suggest the interpretation that many users are unaware that addiction develops over a period of time and may require professional treatment. In particular, adolescents and young adults, a group with a high prevalence of gambling-related disorders and active engagement with social media, represent a key target for destigmatisation efforts.

[21] Support was provided by Lorenz Weißenberg, who assisted in coding the topics and ensured inter-rater reliability. The author would like to thank Andrea Wöhr, Dr. Vadim Kufenko and Dr. Steffen Otterbach for valuable comments and discussions. The idea for the project was presented at five events (International Gambling Research Colloquium – Meeting of early career researchers, September 29th, 2022; Brown Bag Seminar, University of Hohenheim, December 20th; Current Advances in Gambling Research (CAGR), King's College London, June 28th, 2023; Deutscher Suchtkongress 2023, September 20th, 2023; Hybrid Seminar, Bristol Hub for Gambling Harms Research, August 21st, 2024).

Conclusions It is essential to address the stigmatisation of gambling disorder, particularly among younger populations, in order to develop effective strategies to support treatment and help-seeking. The use of social media offers a comprehensive platform for the dissemination of information and the reduction of the stigmatisation of gambling disorder, for example by strengthening certain models of addiction.

Keywords Stigma · Self-stigma · Gambling · Gambling disorder · Personal responsibility · Social media · YouTube · Guided topic modelling

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4.1 Background

A new State Treaty on Gambling entered into force in Germany in 2021. This first uniform federal regulation led to the liberalisation of the German gambling market by legalising previously illegal forms of gambling such as online sports betting and virtual slot machines (Glücksspielstaatsvertrag 2021 - GlüStV 2021, 2020). The role of the state in protecting the population from harm caused by gambling is emphasised. The objective is to further reduce the prevalence of gambling disorders[22] and ensure effective player protection, especially for children and young people. Recent surveys indicate that 2.4% of the German population suffers from a gambling-related disorder (Buth et al., 2024). Negative consequences include financial problems, psychological distress, criminal activity (Browne et al., 2016) and even suicide (Wardle et al., 2024). The personal environment of affected persons, such as their partners and families, often suffers from the situation as well, as personal relationships are disrupted and the risk of domestic violence increases (Wardle et al., 2024). Gambling disorder is considered a behavioural addiction and is on a par with smoking, problematic drinking and recreational drug use (Browne et al., 2020). Of particular concern is the fact that adolescents and young adults represent the group with the highest incidence of gambling disorder in Germany (Buth et al., 2024). Among 18–25 year-olds, the prevalence reaches 4.9%, while among 26–35 year-olds, it stands at 3.7%. Therefore, protecting vulnerable groups from developing a gambling disorder is paramount and underlines the necessity of the German State Treaty's objective to create conditions for effectively combating gambling addiction, for example through prevention strategies and therapy offers. Although gambling in Germany is only permitted from the age of 18, 0.4% of 16-to 17-year-olds suffer from a gambling disorder (Buth et al., 2024). In order to mitigate the early onset of gambling-related harm among minors, it is essential to implement robust age verification processes and strictly enforce age restrictions, in addition to providing treatment and therapy.

The effects and consequences of gambling on individuals and society are a global phenomenon, with implications that extend across national boundaries. This conclusion was presented by the Lancet Public Health Commission on Gambling in a recent

[22] The existing literature uses the term *problem gambling*. Recent reports (such as Livingstone and Rintoul (2021) and GambleAware (2023)) recommend the use of other terms that do not themselves have a stigmatising effect. For this reason, this study uses the term *gambling disorder* rather than *problem gambling*, as in the (DSM-5 Substance Abuse and Mental Health Services Administration (US) (2016)).

report.(Wardle et al., 2024), that clarified that gambling represents a global public health problem. Estimates suggest that in 2023, 46.2% of the adult population and 17.9% of adolescents worldwide were involved in gambling activities. The figures for possible gambling-related disorders varied between 0.4% and 1.7% for women and 1.8% and 4.1% for men, depending on the region (Wardle et al., 2024).

In general, addictive disorders present significant challenges to public health, given that they are among the most stigmatised health conditions (Room et al., 2001; Schomerus et al., 2011). The stigmatisation of addictive disorders can be categorised into two distinct forms: public stigma, which encompasses the negative attitudes and beliefs held by the general public towards a particular population group (Corrigan et al., 2009), and individual stigma, which reflects the perception of stigmatisation by the public on the part of the individual affected (Smith et al., 2016). Both forms of stigma are problematic as they have been shown to be significant barriers to seeking treatment for people with addictive disorders (Da Silveira et al., 2018; Fareed, 2020; Greiner & Dixon, 2021; Gutierrez et al., 2020; Luoma, 2011; Tuliao & Holyoak, 2020; Volkow, 2020). In this regard, public perception of addictive disorders is of importance, as it influences the extent to which addictive disorders are associated with public stigma (Rundle et al., 2025; Rundle et al., 2024). Different models of addiction (MOAs) provide explanations for the development and maintenance of addictive disorders (Rundle et al., 2025). For instance, Rundle et al. (2025) demonstrate, that the moral model results in increased stigmatisation of addictive disorders, as addiction is perceived as a moral transgression on the part of the individual affected. Conversely, the psychological MOA, which categorises addiction as psychological issue (Wiens & Walker, 2015), can assist in reducing public stigma (Rundle et al., 2025). Thus, certain MOAs can contribute to the reduction of the stigma associated with addictive disorders.

Gambling disorder is often associated with stigma (Carroll et al., 2013; Hing, Holdsworth et al., 2014; Hing, Russell et al., 2015; Horch & Hodgins, 2008). While existing studies clearly demonstrate the negative consequences of gambling disorder, research on stigmatisation is limited (Hing, Holdsworth et al., 2014; Wöhr & Wuketich, 2021). In addition to the adverse effects on the individual's personal well-being, people who suffer from a gambling disorder are also affected by social distancing (Dhillon et al., 2011; Hing, Russell, & Gainsbury, 2016; Hing, Russell et al., 2015; Palmer et al., 2018; Peter et al.,

2019). Moreover, the stigmatisation of gambling disorder is reflected in the fact that people affected by it are labelled with negative attributes. These stereotypes portray them as compulsive, impulsive, desperate, irresponsible, prone to risk-taking, depressed, greedy, irrational, anti-social, and aggressive (Horch & Hodgins, 2013). In line with previous research indicating that addictive disorders are frequently perceived as moral failure (Berridge, 2017; Frank & Nagel, 2017; Rise & Halkjelsvik, 2019), affected persons are blamed for their own situation. As noted by Miller and Thomas (2017), the condemnation and stigmatisation of individuals with gambling disorder are based on the ascription of exclusive personal responsibility. Addictive behaviour is depicted as personal misconduct, attributed to inherent weakness, character flaws, and a lack of self-control (Carroll et al., 2013; Horch & Hodgins, 2008).

While most studies focus on the stigma associated with gambling disorder (Miller & Thomas, 2017), Horch and Hodgins (2015) showed that, in general, most forms of gambling are stigmatised to a certain extent, regardless of whether those affected are afflicted with a gambling disorder. In addition to its negative impact on personal life, public stigma can lead to self-stigmatisation (Carroll et al., 2013, 2013, 2013; Corrigan, 2004; Hing, Nuske, Gainsbury, & Russell, 2016; Hing & Russell, 2017a). It is irrelevant whether those affected perceive public stigma, or whether they are directly or personally affected. In the process of self-stigmatisation, the affected person internalises prevailing negative attributions and prejudices (Carroll et al., 2013; Corrigan & Watson, 2002; Corrigan et al., 2006; Hing, Nuske, Gainsbury, & Russell, 2016; Hing & Russell, 2017a), referred to as individual stigma (Rundle et al., 2024) or internalised stigma (Smith et al., 2016). This results in the person adopting stereotypes, which causes additional psychological distress and can lead to lowered self-esteem. As a result, those affected blame themselves for their personal problems and tend to withdraw from their social environment. Those affected frequently encounter difficulties acknowledging their gambling disorder because of concerns about potential self-image deterioration (Hing, Holdsworth et al., 2014). This makes it challenging to seek available help and hinders the development of self-confidence in those affected, impending their ability to seek treatment (Carroll et al., 2013). Consequently, the stigmatisation of gambling disorder is considered a major barrier to treatment (Hing, Holdsworth et al., 2014; Hing, Nuske, Gainsbury, & Russell, 2016; Hing, Nuske, Gainsbury, Russell, & Breen, 2016; Hing & Russell, 2017a; Hing,

Russell et al., 2015; Miller & Thomas, 2017), and also a cause of treatment discontinuation (Sirey et al., 2001), as attending therapy can carry stigma itself (Corrigan, 2004).

To comply with the stipulations of the German State Treaty on Gambling (Glücksspielstaatsvertrag 2021 - GlüStV 2021, 2020), a fundamental objective of public health is to safeguard vulnerable populations from gambling disorder and diminish the prevalence of gambling-related disorder. Reducing stigma is a strategy to encourage more individuals to seek treatment (Hing, Nuske, Gainsbury, & Russell, 2016; Hing, Nuske, Gainsbury, Russell, & Breen, 2016; Hing & Russell, 2017a, 2017b). Increased awareness and a different perception of the MOA associated with gambling disorder among those affected by a gambling-related disorder, as well as the general public, can help reduce stigma (Brown & Russell, 2020; Hing, Nuske, Gainsbury, & Russell, 2016; Miller & Thomas, 2017). Social media represents a promising channel for outreach. In Germany, where 60% of the population use social media at least once a week (Müller, 2024), this channel holds substantial potential. It is notable that among children, adolescents, and young adults aged 14 to 29 years, 92% engage with social networks on a weekly basis, with 62% accessing these networks on a daily basis (Müller, 2024). However, these groups of young people are not only the most active users of social media (Müller, 2024), but also coincide with the groups with the highest prevalence of gambling disorder. The most affected age groups are those aged 18–25 and 26–35 (Buth et al., 2024).

A wide range of social networks, including Facebook, Instagram, TikTok, Twitter, and YouTube, have become an integral part of our daily lives. These platforms operate through user-generated content that may take the form of uploading pictures, sending tweets, or engaging in video commentary. The popularity of video platforms, particularly YouTube, has grown significantly in recent years. Currently, YouTube is the second largest social network in the world with over 2.5 billion monthly users (We Are Social et al., 2025b). In Germany, 81% of children and young people use this social network at least once a week (Kupferschmitt, 2024). It is important to note that social media has evolved beyond its role as a pure entertainment platform, becoming a dynamic space for information and interaction. Users actively seek to connect, exchange ideas and perspectives, and share their emotions.

Content from social media offers researchers nearly unlimited user-generated data that can be used in scientific research. Textual data can be extracted from social networks by leveraging appropriate Application Programming Interfaces (APIs). Due to the large amount of data, Natural Language Processing (NLP) has emerged as a useful tool for identifying the specific content of interest in text data. In addition to established topic modelling techniques, such as Latent Dirichlet Allocation (LDA), contemporary research is increasingly employing deep learning models. One such example is the Bidirectional Encoder Representations from Transformers, commonly referred to as BERT (Devlin et al., 2019). BERT is considered to be one of the most powerful NLP tools, because of its pre-trained word embedding model, which allows it to map more precise representations of words to sentences than comparable machine learning methods (Devlin et al., 2019; Kaliyar et al., 2021). For instance, BERT has been employed to analyse a range of content, including fake news (Kaliyar et al., 2021; Singhal et al., 2019; Tacchini et al., 2017), offensive language (Aggarwal et al., 2019; Liu et al., 2019; Pitsilis et al., 2018; Zampieri et al., 2019), online hate (Salminen et al., 2020), sentiment (Wang et al., 2020; Yulita et al., 2023), racism, stigmatisation (Pei & Mehta, 2022) and drug event detection (Fan et al., 2020) on social networks.

Previous studies have provided clear evidence of the nature and (negative) consequences of stigma associated with gambling disorder (Dhillon et al., 2011; Hing, Russell, & Gainsbury, 2016; Hing, Russell et al., 2015; Palmer et al., 2018; Peter et al., 2019). Most studies are based on interviews or surveys to identify prevailing stereotypes (Carroll et al., 2013; Hing, Nuske, Gainsbury, & Russell, 2016; Hing, Russell, Gainsbury, & Nuske, 2016; Horch & Hodgins, 2008, 2013; Miller & Thomas, 2017). To our knowledge, however, there are no studies for Germany and no approaches that take social media into account. This study represents the first attempt to investigate stigmatisation associated with gambling disorder in social media by employing a deep learning approach. (i) After employing the deep learning approach, (ii) the results were validated using a qualitative summative content analysis and (iii) compared with the results from guided topic modelling. Finally, (iv) the categories of stigma associated with gambling disorder and supporting statements are discussed.

4.2 Method

4.2.1 Identification of YouTube videos

The first step is to select suitable videos whose content stimulates the exchange of users in the comments section and directs the conversation on the issue of gambling disorder. Therefore, videos are sought to (1) explicitly address gambling disorder and (2) feature a person who suffers from or has overcome a gambling disorder. For this purpose, five keywords, which were self-defined as in other research approaches (Obadimu et al., 2021; Sánchez et al., 2022), were determined. The following keywords were identified as relevant to this study: *Gambling, sports betting, casino streams, gambling influencers, gambling addiction*. In addition, the following selection criteria were established: (3) the videos and comments must be in German, and (4) a video must have at least 1000 comments.

To avoid the YouTube algorithm from skewing the results based on the history of past searches it is necessary to conduct the search in a private browser window and perform the search without logging in to a YouTube account. The search was then performed separately for each keyword, and a list of the top 10 most viewed videos with at least 1000 comments was created. These lists were matched and duplicates were removed. This process yielded 34 distinct videos with 84,024 comments (see Appendix: Figure 7.2). A subsequent review of the videos was conducted to ensure that a person who suffers from or has overcome a gambling disorder was the focus of the content. Two videos from the channel 'Leroy wants to know!'[23] were identified as being of particular interest. These videos are characterised by a high degree of seriousness, given that the channel is part of the content network of German public television called funk, represented by the first public channel (ARD[24]) and the second public channel (ZDF[25]). Both videos were comparatively up-to-date, with 11,813 comments in total. Although the videos are also available on the official website of ZDF[26] and funk[27], only YouTube provides the functionality for users to post comments. In the first video, a person who has overcome a gambling

[23] The German name for the channel is ‚Leroy will's wissen!'
[24] Working Group of the Public Broadcasting Authorities of the Federal Republic of Germany.
[25] Second German Television.
[26] Sample link to the second video in the ZDF media library: https://www. zdf.de/funk/leeroy-wills-wissen-12187/funk-update-spielsuechtiger-trifft- casinobesitzer---das-treffen-102.html
[27] Sample link to the second video in the funk media library: https://play. funk.net/channel/leeroy-wills-wissen-12187/spielsuechtiger-trifft-casin obesitzer-das-treffen-1796297

disorder recounts his experiences of living with a gambling addiction. In the second video, a person who has overcome a gambling disorder engages in a discussion with a former casino owner about the moral implications and responsibilities associated with gambling. In both videos, the person who has overcome a gambling disorder is featured throughout the entire video.

4.2.2 Data collection and processing

The YouTube Search Data APIv3 was leveraged to extract the title, URL, upload date, number of views, and comments of the selected videos, as well as the upload channel. This requires a Google account and a personalised access key to the YouTube API. Table 4.1 provides an overview of the data collected: 11,813 comments from two videos were collected on November 23, 2022.

The deep learning approach, including pre-processing and guided topic modelling, was conducted using Python[28] programming language and a range of packages.[29] As part of the pre-processing, the text was converted to lower case, and German diacritics were converted to their non-diacritical combinations. URLs, punctuation, single letters, spaces, numbers and German stop words were excluded. Additionally, short words with fewer than three letters were removed to reduce noise in the data. A special tagger for the German language (Wartena, 2019) was employed to lemmatise each word. Although the lemmatiser yields superior results to conventional stemmers, some words require manual correction. To minimise noise in the data, short sentences with fewer than ten words and rare words with fewer than 20 occurrences were also removed from the corpus after tokenisation. The final corpus for both videos consisted of 9451 tokens.

[28] The following version of Python was used during the work on this paper: 3.9.16.
[29] Additional functions were used from the Gensim Rehurek and Sojka (2011), NLTK Bird et al. (2009), NumPy Harris et al. (2020) and Pandas McKinney (2010) packages.

Table 4.1 Information about the selected videos

Video title	Channel name[a]	URL	Upload date	Views (n)	Comments (n)	Gambling content[b]	Person with a gambling disorder[b]
GAMBLING ADDICT meets CASINO OWNER | The meeting	Leeroy will's wissen!	vYGEkC_0LX0	2022-04-07	3,454,674	6864	Yes (100%)	Yes (100%)
What is it like TO BE ADDICTED TO GAMBLING?	Leeroy will's wissen!	PK_FTp4iHaQ	2020-08-31	1,470,656	4949	Yes (100%)	Yes (100%)

The data was collected at 23.11.2022. The video title was translated by the author. The videos are arranged in a chronological descending order based on their views

[a] Channel names have not been translated as they are proper names

[b] Indicate the percentage of the total duration of the video which is dedicated to gambling content, or alternatively, the length of time that the person is visible within the video

4.2.3 Creation of an extended stigma dictionary

As a preliminary step in the process of guided topic modelling, a stigma dictionary was created. In the context of NLP, so-called dictionaries are indispensable components. They serve as the basis for the recognition of linguistic phenomena in textual data, including stigmas (Gottipati et al., 2021; Oscar et al., 2017; Pokharel & Bhatta, 2021). For this reason, a stigma dictionary is created in three steps that contains terms associated with the stigmatisation of gambling disorder. The initial step was to select words from the existing research. One limitation of previous studies is that they were based exclusively on interviews and surveys. It can be assumed that people express prevailing stereotypes differently in an anonymous setting, such as the comments section of YouTube, than in a research setting. A review of the data revealed that only three of the 19[30] negative

[30] The full list of negative attributions is as follows: *aggressive, anti-social, compulsive, depressed, desperate, stupid, greedy, impulsive, irrational, irresponsible, lazy, naïve, risk-taking, selfish, foolish, uncontrolled, unproductive, untrustworthy, weak-willed.*

attributions identified in previous studies (Hing, Nuske, Gainsbury, & Russell, 2016; Horch & Hodgins, 2013; Miller & Thomas, 2017), were present in the data set under study: *foolish*, *naive*, and *stupid* (Table 4.2).

Table 4.2 Stigmatising terms from the literature found in the dataset

Terms	**n**
Foolish	40
Naïve	39
Stupid	225

For the purposes of the stigma dictionary, the terms were translated into German as follows: *blöd*, *naiv*, *dumm*

In the second step, four additional terms were added to the dictionary: *addiction*, *addict*, *gambling addicted* and *gambling addict*. As our approach is data-driven, we increased the basis on which embeddings can be used to search for terms that can be associated with the stigmatisation of gambling disorder. This is the third step. The use of embeddings is well established in NLP methods, such as the detection of hate speech on social media (Djuric et al., 2015; Nobata et al., 2016; Salminen et al., 2018). As elucidated by Young et al. (2018), the supposition underlying the use of embeddings is that words with analogous meanings are situated in similar contexts. The utilisation of embeddings does not constrain the creation of a stigma dictionary to terms from the extant research literature; rather, it permits the identification of terms that may be associated with the stigmatisation of gambling disorder in the aggregated data. Table 4.3 illustrates the ten most frequent embeddings[31] for the three existing negative attributions in our dataset and the four additional terms that have been added. Among these terms, those that exhibit similarities to the stereotypes identified in the literature are included in the stigma dictionary. For instance, the word *guilty* was selected because it can stigmatise gamblers with a gambling-related disorder by ascribing guilt to them. Other terms that cannot be associated with stigmatisation gambling disorder are disregarded. All terms in bold in Table 4.3 are included in the stigma dictionary.

[31] The FastText Bojanowski et al. (2016) package was used to find embeddings.

Table 4.3 Embeddings of the stigmatising terms from the literature found in the dataset and the additional terms

Terms	Embeddings
Foolish	intelligence, over, total, run, position, nothing, rich, broke, opinion, insight
Naïve	nowadays, **guilty**, **weakness**, bad, **stupid**, just, **weak**, exist, rip off, possibly
Stupid	smart, **guilt**, statement, complete, people, itch, person, no matter, such, **stupidity**
Addiction	**gambling addicted**, bad, issue, year, environment, **gambling addicts**, video, drug addiction, **gambling addict**, problem
Addicted	**guilt**, understand, casino, no matter, **responsibility**, casino owner, **responsible**, normal, people, owner
Gambling addicted	**Gambling addicts**, operator, **addiction**, casino, gambling hall, gamble away, casino owner, lose, **criminal**, **gambling addict**
Gambling addict	***Honest***, franklin, ***respect***, ***wish***, ***sympathetic***, speak, ***honesty***, interview, understand, ***strong***

The embeddings and terms were translated by the author
All terms in bold are included in the Stigma Dictionary

The stigma dictionary comprises three categories of terms: (1) terms that have been identified in existing research, (2) additional terms that explicitly refer to (gambling) addiction, and (3) terms from embeddings that can be associated with stigmatisation of gambling disorder. The aim was to supplement known stereotypes with negative attributions derived from the aggregated data. In this way, the utterances of users can be considered unfiltered, and it becomes clear how the stigmatisation of gamblers with a gambling-related disorder is produced in the everyday language of users. By extending the stigma dictionary, a total of 16 negative attributions were identified (Table 4.4). This extended stigma dictionary serves as a guideline for the guided topic modelling procedure carried out in the next step.

Table 4.4 Extended stigma dictionary

Terms from the literature (n=3)	Additional terms (n=4)	Embeddings (n=9)
Foolish, naïve, stupid	Addiction, addicted, gambling addicted, gambling addict	Guilty, guilt, stupidity, responsible, responsibility, weak, weakness, criminal, gambling addicts

The embeddings of the term *gambling addict* indicates that not only are negative attributions expressed towards gambling disorder, but also supportive statements. The semantic field of the term contains positive attributes such as *honest*, *respect*, *wish*, *sympathetic*, *honesty* and *strong* (Table 4.3). This finding suggests that users want to support gamblers with a gambling-related disorder. A second dictionary was created to test this hypothesis (Table 4.5). The support dictionary comprising six terms, serves as an additional starting point for guided topic modelling.

Table 4.5 Support dictionary

Embeddings (n=6)
Honest, respectful, desirable, sympathetic, honesty, strong

4.2.4 Guided Topic Modelling with BERT

The application of machine learning techniques to the analysis of social media data is a valuable tool. NLP techniques, such as topic modelling approaches, facilitate the identification of topics within large amounts of text data. By incorporating additional information, in this case the extended stigma dictionary, the topic model is guided to search for specific content, that is all comments associated with the stigma of gambling disorder, and to place them in the same category. Currently, BERT[32] represents one of the most powerful tools and demonstrates state-of-the-art performance in NLP tasks (Devlin et al., 2019). In contrast to other well-known methods, such as LDA (as in (Blei et al., 2001)), BERT is a deep neural network involving bi-directional transformers that implement attention mechanisms. This specific architecture enables accelerated training and concentration on the essence of texts. BERT pre-trains deep bi-directional representations of unlabelled text, thereby enabling more accurate words-to-sentences representations than comparable machine learning methods (Devlin et al., 2019; Kaliyar et al., 2021). BERT is a relatively new model, and to our knowledge, this is the first time that it has been applied to German text data from YouTube.

The initial stage of the proposed deep learning approach to analysing the stigmatisation of gambling disorder in YouTube comments involves guided topic modelling using BERT. By assigning negative (stigma) and positive (support) attributes to different seed

[32] The following version of BERT was used during the work on this paper: 0.13.0.

topics, the model can assign specific keywords to different content categories (Grootendorst, 2022). BERT serves as a filter for the aggregated dataset by filtering all tokens that can be associated with the stigma of gambling disorder into a topic based on the extended stigma dictionary. A similar process was employed for the positive attributions and the support dictionary. In the second step, a qualitative summative content analysis was conducted to assess the plausibility of the assignment of each token to the stigma and support content categories.

Analysing social media data using machine learning methods is challenging. For NLP methods to function effectively, the data must undergo pre-processing. This is particularly evident in the sometimes slang-like German YouTube comments. Social media users do not adhere to standard language conventions, and language correction and lemmatisation are less effective in German than in English. Although short sentences of less than 10 words were removed during pre-processing, the remaining data were often still short sentences. As these have limited semantic content, BERT is not able to assign these tokens to a topic in a meaningful manner and marks them as outliers that cannot be assigned to any of the topics. For optimisation purposes, during the exploratory stages of our work, the following parameters yielded the best performance in reducing the number of outliers and avoiding the generation of identical topics (Table 4.6): *min_topic_size* was set to 30 to adjust the minimum size of a topic. This was done with the intention of minimising the number of outliers and including as many comments as possible in the model. A greater number of topics results in the creation of identical categories. Conversely, a smaller number of topics would preclude the possibility of defining categories defined by a limited number of tokens, potentially leading to their integration into other topics. Furthermore, the number of generated topics was constrained to 10 (*nr_topics* = 10) to divide the tokens into as few different categories as possible, while also preventing the generation of identical categories. Finally, the algorithm is permitted to form bigrams from individual tokens (*n_gram_range* = (1, 2)). This enables the examination of words used in combination, such as “gambling addiction”, rather than individual words alone. For example, bigrams enable our model to differentiate between gambling disorder in Topic 0 (“gambling addict”) and other addictions in Topic 4 (“addicted”; “alcohol”; “cigarette”) (Table 4.7).

Table 4.6 Optimal parameters for BERT

Parameter	min_topic_size	Nr_topics	n_gram_range
Value	30	10	1,2

4.2.5 Qualitative summative content analysis

Due to known difficulties of machine learning methods in analysing data from social media, a qualitative summative content analysis (Hsieh & Shannon, 2005) was performed to validate the findings of the guided topic modelling. For this purpose, all comments associated with the stigmatisation of gambling disorder (Topic 0) and the support for the person affected (Topic 6) were subjected to manual review. The qualitative analysis was carried out independently by two researchers, to ensure inter-rater reliability, and was based on the methodological guidelines of Hsieh and Shannon (Hsieh & Shannon, 2005) for qualitative summative content analysis. The process is both inductive and deductive, as keywords can be defined before and during analysis. In this case, terms that have been previously identified as relevant to the stigmatisation of gambling disorder are taken up from the existing literature (stigma dictionary) and supplemented by corresponding embeddings from the aggregated dataset (extended stigma dictionary). All comments to be analysed were saved in an Excel spreadsheet for manual coding. Cohen's κ (1960) was calculated to measure the inter-rater reliability between the two researchers.

4.3 Results

4.3.1 Results of the deep learning approach

The results of the deep learning approach are listed in Table 4.7. For each of the ten topics generated, ten essential keywords can be seen. As specified in the hyperparameters (*nr_topics*), BERT filters the tokens of the aggregated dataset into ten topics. A look at the keywords suggests that Topic 0 can be associated with stigmatising gambling disorder, and Topic 6 with supporting gamblers with a gambling-related disorder (Table 4.7). The keywords in the topics matched the terms in the dictionaries created. Six of the ten terms in Topic 0 matched the stigma dictionary. Topic 6 contained four terms, whereas the support dictionary contained six terms. If we include the term *gambling addict*, there are even eight matches. In contrast, the other topics had comparatively fewer matches with the dictionaries (Table 4.7).

Table 4.7 Top terms per topic and match with the dictionaries

Topic	Keywords	Matching keywords with stigma dictionary (n=16)	Matching keywords with support dictionary (n=6)
0	**Guilt**, **guilty**, **responsibility**, **responsible**, human, money, **stupid**, **gambling addict**, people, moral	**6**	0
1	Euro, year, money, feel, addicted, win, gaming hall, cheesburger, life	1	0
2	Video, video video, interesting, super, format, interesting video, super video, gambling addict, channel, respect	1	1
3	Money, lose, human, invest, earn, addicted, gaming hall, gambler, win, gamble away	1	0
4	Alcohol, alcoholic, addicted, drink, guilt, human, casino, sell, responsible, cigarette	3	0
5	Youtubestreamer[a], youtubeinfluencer[b], youtube, youtubestreamer, youtuebstreamer, video, youtubeinfluencer youtubestreamer, youtubeinfluencer youtubeinfluencer, youtubereporter[c], format, video youtubestreamer	0	0
6	Gambling addict, **sympathetic**, **hope**, gambling addict gambling addict, **wish**, **strong**, gambling addict sympathetic, gambling, make, sympathetic gambling addict	1	**4**
7	Channel, activate, bell, subscribe, channel activate, bell subscribe, activate bell, subscribe channel, topic, gladly channel	0	0
8	Algae[d], algae algae, addiction, addicted, first, out, please, gamble away, hello, gaming hall	2	0
9	Format, interesting, super, cool format, cool[e] format, cool[e], cool, super format, format format, format interesting	0	0

The terms were translated by the author. Bigrams permit the naming of terms twice and the use of different combinations of words

[a-c] The terms reprsent pre-processed categories of proper names of corresponding streamers, influencers and reporters on YouTube

[d] The term is used to describe a symbol that is displayed on a slot machine game

[e] In German, the term '*geil'* is used. Its literal translation is '*horny'*, but in everyday language, it is used more like *'cool'* or '*nice'*

Following the completion of the Guided Topic Modelling process, BERT classified 5245 comments as outliers, indicating that they could not be assigned to a topic. The remaining 4206 tokens were filtered into the 10 created topics. As shown in Table 4.8, 850 comments can be assigned to the stigmatisation of gambling disorder. The number of tokens that can be attributed to the support of gamblers with a gambling-related disorder was 335. After excluding outliers, BERT sorts 28% of the comments in our aggregated dataset into two topics that we are seeking. Of these, BERT classified 20% of the comments as stigmatising and 8% as supportive.

Table 4.8 Stigmatisation and support for gambling disorder in the dataset

Topic	**n**	**Proportion of classified comments (4206)**
Stigmatisation	850	20 %
Support	335	8 %

4.3.2 Results of the qualitative summative content analysis

A qualitative summative content analysis (Hsieh & Shannon, 2005) was conducted to assess the viability of the guided topic modelling approach. A total of 1185 tokens from Topic 0 and Topic 6 were coded manually. This qualitative classification is based on knowledge about the stigma associated with addictive disorders, particularly gambling disorder. The results are of interest because they enable an analysis of the way in which users create such stereotypes in their everyday language use. However, they are primarily intended to serve the purpose of testing the categorisation of the guided topic modelling approach. To ensure inter-rater reliability, the comments were coded by a second researcher. Cohen's κ was calculated to measure the inter-rater reliability (Cohen, 1960). Table 4.9 demonstrates a consistently high level of inter-rater reliability between the two researchers, with Cohen's κ values of 0.92 and 0.98.

Table 4.9 Topics of the 1,185 classified comments

	BERTopic		Qualitative Analysis			Agreement between BERTopic and the qualitative analysis
	n	%	n	%	Cohen's κ[a]	%
Stigma-tisation	850	20	666	16	0.92	78
Support	335	8	168	4	0.98	50

[a] The value for Cohen's κ refer to the agreement of the two researchers regarding the qualitative coding of the 1,185 comments identified by BERT as topics for stigmatisation and support

4.3.3 Comparison of the guided topic modelling and the qualitative analysis

The results of the qualitative analysis indicated inaccuracies in the guided topic modelling process (Table 4.8). BERT filters 1185 tokens from the aggregated dataset into Topic 0 and Topic 6. The qualitative analysis revealed that only 666 tokens could be attributed to stigmatising gambling disorder, and only 168 tokens indicate support for gamblers with a gambling-related disorder. In comparison to the deep learning approach, the proportion of stigmatising comments in the total data set was thus 16% instead of 20%, while the proportion of supportive comments was 4% instead of 8%.

4.3.4 Categories of stigma associated with gambling disorder and supporting statements

The results of the deep learning approach in combination with a qualitative summative content analysis offer valuable insights into the practices of users expressing themselves in the comment sections of the selected YouTube videos. The aggregated dataset reveals the presence of tokens that can be associated with both stigmatisation of gambling disorder and supportive expressions towards gamblers with a gambling-related disorder. For instance, users describe the person who has overcome a gambling disorder in the videos as sympathetic or strong. Furthermore, they also try to give him a sense of self-belief and hope that he will remain healthy.

Table 4.10 presents a series of illustrative examples of stigmatisation as identified by the BERT classification and qualitative summative content analysis. These examples demonstrate that stigma associated with gambling disorder manifests in various forms. On the one hand, there are personal insults, which label the person with gambling-related disorder as stupid, weak (Table 4.10, comment number 132), or not intelligent, and pejorative terms, such as loser or junkie. Other terms suggest that the person with gambling-related disorder lacks personal responsibility (Table 4.10, comment number 166). Some statements also point to the stereotype that individuals with gambling-related disorders attempt to shift blame to others for their situation instead of taking personal responsibility for their own lives (Table 4.10, comment number 1). Regarding personal responsibility, it is argued that it is not feasible to protect all individuals from potential harm to their health. Otherwise, the autonomy of other members of society would have to be constrained to an extensive degree (Table 4.10, comment number 684). Comparisons were made with other addictions such as alcohol, tobacco or shopping addiction. By making this comparison, some users marginalise the problem of gambling disorder and use this relativisation to place responsibility for developing a gambling disorder solely on the individual (Table 4.10, comment number 628). Some users even doubt that addiction exists (Table 4.10, comment number 294) and argue that the concept of addiction either serves as an excuse for those affected or deprives them of the opportunity to take responsibility for their own situation (Table 4.10, comment number 53). It is also important to note that a small proportion of users reported that they themselves suffer or have suffered from a gambling-related disorder. This reinforces the stereotypes described as a form of self-stigmatisation. Not only have the individuals internalised the prevailing stereotypes, but they also confront others with them (Table 10, comment number 568).

Table 4.10 Examples of different categories of stigma associated with gambling disorder in the aggregated dataset

Comment number[a]	Content of the comment	Type of stigmatisation
132	*'stupid and weak meets strong and smart, is not hate but that's just how I see it'*	Personal insult.
166	*'Mario[b] takes no responsibility for himself and his actions it seems'*	Not taking responsibility.
1	*'The gambler blames others instead of himself'*	Blaming others.
53	*'Those who play and become addicted have only themselves to blame'*	Own fault.
294	*'@Dr. D The fact that addiction is always and repeatedly seen as a disease is an absolute problem. With this argumentation, all responsibility is swept away. Addiction is a choice. You can't do anything for a disease. That is an immense difference. That's where I criticise all psychologists and doctors. It's terrible.'*	Gambling addiction is not an addictive disease.
684	*'Good that you say that. The thought came to me immediately. In the "self-determined" system that we want (with all its freedoms and duties), we have to reckon with outliers. Otherwise we would have to regulate everyone and that would take away our freedom.'*	Restriction of personal freedom.
628	*'I can understand both sides, but I would never blame an arcade owner, because at the end of the day there are so many addictions. Take shopping addiction, for example. Do you want to blame clothes manufacturers and ask them, "Why do you make clothes?'*	Relativising gambling addiction.
568	*'@Gloria Viktoria I was an addict myself and that's why I have this opinion. it's always your own decision if and how you do something. if you look for excuses afterwards and don't think that it was/is your fault, I think it just shows how weak the person is. and I don't even mean that in a bad way ^^ a simple example would be do you cheat on your partner because you feel the need to or don't do it because it's against your morals? a simple decision for everyone and yet some people do it. do you want to tell me that the person is not responsible for that?'*	Self-stigmatisation.

The examples were corrected and translated by the author

[a] Comment number indicates the position of the comment in the whole dataset

[b] *Mario* is the name of the person in the two videos who suffered from a gambling disorder

4.4 Discussion

This study contributes to existing research on stigmatisation of gambling disorder. User data provided by social media were used for the analysis of linguistic phenomena. By employing a deep learning approach, it is possible to identify statements that can be associated with the stigmatisation of gambling disorder in the aggregated data set derived from the comment section of two selected videos on the video platform YouTube. An extended stigma dictionary was created for analysis. In addition to terms from the existing literature, terms and their embeddings from the aggregated data set were used as the basis for identifying stigma associated with gambling disorder. Despite the differences between the guided topic model and qualitative summative content analysis, statements can be made about how stigmatising statements about gambling disorder are produced in the language used by users. For example, people are labelled with negative attributes, a lack of personal responsibility is attributed to them, or they are blamed for their situation (Table 4.10). In addition, some statements show a tendency towards self-stigmatisation. These findings are consistent with previous studies (Carroll et al., 2013; Hing, Russell et al., 2015; Horch & Hodgins, 2013; Miller & Thomas, 2017) and show that the prevailing stereotypes are associated with moral judgements about the behaviour of gamblers with a gambling-related disorder.

The findings are cause for concern, as stigmatisation and self-stigmatisation are considered major barriers to the treatment of gambling-related disorder (Brown & Russell, 2020; Hing, Holdsworth et al., 2014; Hing, Nuske, Gainsbury, & Russell, 2016; Hing, Nuske, Gainsbury, Russell, & Breen, 2016; Hing & Russell, 2017a; Horch & Hodgins, 2015; Miller & Thomas, 2017). In Germany, the number of people with a gambling-related disorder is highest among adolescents and young adults (Buth et al., 2024). The objective of public health care is to safeguard the population, particularly vulnerable groups, from the adverse effects of gambling. Social media represents a potential starting point in this regard, as children and young people in particular are the most active user group of social networks (Koch, 2023). Social media has considerable potential as a tool for engaging with vulnerable groups. It offers a platform for raising awareness of the issue of stigma and gambling disorder, and thus contributes to the destigmatisation of gambling-related disorders.

Existing research has shown that perceptions of addictive disorders are linked to public perceptions of their development and maintenance (Rundle et al., 2025). Different MOAs can lead to varying levels of public stigma (Rundle et al., 2021; Rundle et al., 2025; Rundle et al., 2024). For example, the moral MOA leads to higher levels of stigma towards some addictive disorders, including gambling disorder (Rundle et al., 2025). Here, the cause of the disorder is attributed to voluntary choice and moral failing (Fareed, 2020; Rundle et al., 2021; Volkow et al., 2021; Volkow & Koob, 2015), which is partly reflected in the comments from the aggregated data set that may be associated with the stigmatisation of gambling disorder (Table 4.10). However, there are also positive statements that do not accuse the person affected of moral failure and are meant to be supportive. As McGinty and Barry (2020) showed, language can make an important contribution to reducing stigma, depending on how it is used to communicate with, define and educate others. Strengthening certain MOAs, such as the psychological MOA, can not only help reduce the public stigma of addictive disorders, including gambling disorder (Rundle et al., 2025), but also prevent those affected from reinforcing existing stereotypes and experiencing self-stigmatisation (Cunningham, 2005; Delfabbro, 2012; Hing et al., 2012; Hing, Nuske, Gainsbury, & Russell, 2016). The destigmatisation and prevention of self-stigmatisation are important public health strategies to protect people, especially vulnerable groups, from public stigma and its negative consequences.

4.5 Limitations and future directions

A limitation of the present study is the exclusive focus on a single social network, YouTube. The requirements of the video platform allow users to appear anonymously without their real-world names. Therefore, we cannot say who has watched the selected videos or who the authors of the individual comments are, as we do not have further information such as age or gender. This aspect may influence what users say, for example if they make a stigmatising comment or insult under the protection of anonymity. Future research should try to collect additional user data, such as demographic data, and consider other social networks to analyse the stigma associated with gambling disorder. In this way, more precise statements can be made and differences between genders and age groups can be identified. The same applies to language choice. While only German

videos and comments were considered in this study, other languages can be included in the analysis of other studies.

Furthermore, the selection of videos was limited to one channel on YouTube, which is subsidised by the public broadcaster in Germany. Although we were not able to collect user data, it can be assumed that the audiences for different videos on different channels may differ, possibly also by language. It is also conceivable that attitudes may differ, for example in the perception of gambling addiction. Future approaches should take this into account.

The selection of YouTube videos was based on the consideration that individuals who have (overcome) a gambling disorder are featured for the entire duration. The videos were selected because their content stimulates user dialogue in the comments section and directs conversation towards the topic of gambling disorder. This results in a data frame with a sufficient number of 11,813 comments, which is reduced to 9451 tokens after preprocessing. Therefore, the two selected videos are not representative of other videos in which gamblers, for example, only appear as peripheral figures or other social networks. For future research, it would be beneficial to aggregate larger amounts of data in order to be able to make more representative statements about prevailing stereotypes associated with gambling disorder.

Overall, when analysing the stigmatisation of gambling disorder, it seems useful to consider different social networks, languages and larger amount of data. In particular, for the development of specific prevention strategies, it seems useful to examine different social networks to consider the specificities of the respective platforms. The different functions of social networks pose different challenges for the development of stigma reduction interventions, but at the same time offer different opportunities, such as raising awareness through different forms of communication including notifications, comments, pictures, or videos.

The language and some expressions used on social media present a challenge for the application of NLP techniques. This is because of the way users express themselves on social media, which often involves short sentences, sometimes single words or meaningless statements. By contrast, BERT is trained on long coherent sequences (Devlin et al., 2019). Speech recognition or lemmatisation packages often deliver comparatively

poorer results in German than in English. Consequently, a significant proportion of terms and words had to be manually corrected during the pre-processing stage. Approximately half of the tokens could not be assigned to a specific topic and were classified as outliers; therefore, they were excluded from further analysis. This resulted in a reduction of the data set from 9451 comments after pre-processing to 4206 comments at the end. Further research could concentrate on the refinement of the pre-processing and optimisation of the model parameters, enhancing the informative value of the model and therefore reducing the number of outliers to a minimum extent. It would also be beneficial to analyse data from social media using so-called Large Language Models (LLMs), given that they deliver superior results when processing textual data in comparison to classic NLP models (Demszky et al., 2023). For example, these models are able to detect moral framings in textual data, as shown in a recent study by Sun and Fang (2024). If a more precise differentiation is possible, a distinction between different forms of stigma would be conceivable, for example between public stigma and self-stigmatising statements.

A qualitative summative content analysis was conducted to verify the plausibility of the results from the guided topic modelling process. This method is subject to a degree of subjectivity on the part of the researchers. To minimise this limitation, the coding of the data was carried out by two researchers and Cohen's κ (1960) was calculated, to measure inter-rater reliability. Although the comparison between the qualitative analysis and deep learning approach shows inaccuracies, with agreements of 78% for Topic 0 and 50% for Topic 6, the results are still interpretable. The primary aim of the study was not to quantify stigmatising statements, but rather to investigate how prejudices and stereotypes towards gambling disorder are created in the language used by users. However, only the comments were analysed using qualitative summative content analysis, which was classified in the first step using the deep learning model. In addition to improved NLP techniques, such as LLMs, to analyse larger amounts of text data, it would also be conceivable to use qualitative methods to obtain a detailed picture of stigmatisation on the one hand and supportive statements on the other. An in-depth understanding could be the basis for some destigmatisation approaches.

4.6 Conclusions

This study represents a first approach for Germany to analyse the stigmatisation of gambling disorder in social media using a deep learning approach. The results of the guided topic modelling and qualitative summative content analysis demonstrate that deep learning methods, in this case BERT, are capable of identifying linguistic phenomena in text data. The model revealed the presence of various statements that can be associated with the stigmatisation of gambling disorder on the video platform YouTube. As demonstrated in previous studies (Carroll et al., 2013; Hing, Holdsworth et al., 2014; Hing, Russell, Gainsbury, & Nuske, 2016; Hing, Russell et al., 2015; Horch & Hodgins, 2008; Miller & Thomas, 2017), gambling disorder is associated with negative attributions and moral judgements. Future approaches could attempt to further optimise the model parameters to analyse as much semantic information as possible, by reducing the number of outliers. The use of Large Language Models could also be considered, as they have been shown to deliver superior results when processing text data compared to classic NLP methods (Demszky et al., 2023).

Public understanding of how addictions develop and are maintained is crucial for the perception of addictive disorders (Rundle et al., 2025). Different MOAs may result in varying levels of stigmatisation (Rundle et al., 2021; Rundle et al., 2025; Rundle et al., 2024). The statements in the aggregated data set that can be associated with the stigma of gambling disorder exhibit similarities to the moral MOA, in that addiction is attributed to a moral failure on the part of the person affected (Rundle et al., 2021). Previous studies have demonstrated that the stigmatisation and self-stigmatisation associated with gambling disorder represents a significant barrier to treatment for those affected (Brown & Russell, 2020; Hing, Holdsworth et al., 2014; Hing, Nuske, Gainsbury, & Russell, 2016; Hing, Nuske, Gainsbury, Russell, & Breen, 2016; Hing & Russell, 2017a; Horch & Hodgins, 2015; Miller & Thomas, 2017). To address this issue, it is essential that public health plays a role in the implementation of effective prevention measures. Strengthening specific MOAs can lead to a change in the public perception of addictive disorders and, consequently, to a reduction in the stigma attached to gambling disorder. Reducing stigma also helps prevent self-stigmatisation of those affected by making it less likely that stereotypes will be internalised (Cunningham, 2005; Delfabbro, 2012; Hing et al., 2012; Hing, Nuske, Gainsbury, & Russell, 2016). As demonstrated by (Rundle et al., 2025), the psychological MOA can

help reduce the stigma associated with addictive disorders, including gambling disorder. This is because it leads to a more compassionate and empathetic understanding of individuals struggling with a gambling disorder (Rundle et al., 2024), as suggested by the supportive expressions in our aggregated data set. Furthermore, it is a public health responsibility to provide comprehensive treatment options and clearly communicate their availability and where to access them (Livingstone et al., 2019). The dissemination of information via social media represents an appropriate channel for reaching the general public, particularly vulnerable groups. This further underscores the potential of this platform in contributing to the destigmatisation of gambling-related disorders. Those with a gambling-related disorder must be made aware that treatment is available, that recovery is possible (Brown & Russell, 2020) and that seeking help is not a sign of weakness but, above all, a sign of strength (Brown & Russell, 2020; Carroll et al., 2013).

5 General Conclusions

Digitalisation has facilitated the global accessibility of social media and has significantly contributed to the expansion of the gambling industry worldwide. In response to these dynamic developments within the rapidly evolving media landscape, the State Treaty on Gambling legalised online gambling in Germany in 2021 (Glücksspielstaatsvertrag 2021 - GlüStV 2021, 2020). Consequently, providers are now authorised to employ advertising strategies to guide interested individuals in the legal gambling market. As the German gambling authority regulates the legal gambling market, providers are required to adhere to applicable regulations, with the primary objective of safeguarding the population, particularly vulnerable groups, from gambling-related harm. Nevertheless, the promotion of gambling poses potential risks, particularly for children and adolescents (McGrane et al., 2023). A notably high volume of gambling advertisements is prevalent on social media as these platforms have emerged as attractive platforms for advertising (Torrance et al., 2021). Given that children and adolescents are the most active social media users in Germany (Müller, 2024), they are likely to be exposed to substantial gambling advertising on these platforms. In this context, this dissertation undertakes the first analysis of gambling advertising on social media in Germany.

Chapter 2 provides a comprehensive review of the literature on the advertising strategies employed by gambling providers and their impact on social media. It is evident that social media plays a central role in these providers' advertising strategies. They demonstrate adaptability in order to align their strategies with prevailing conditions such as legal requirements or societal frameworks. This fact is concerning, given the increasing intensity and complexity of gambling advertising, which is leading to the lines between advertising and neutral content becoming blurred. Vulnerable groups, notably children and adolescents, are at heightened risk as contemporary advertising is demonstrably appealing to them. Furthermore, the rapid pace of developments poses challenges for regulatory authorities in keeping up.

In this context, Chapter 3 presents an initial analysis and comparison of the advertising strategies employed by German gambling providers across various sectors. The findings derived from a mixed-method approach, which integrates semi-supervised guided topic modelling with summative content analysis, indicate that social media platforms are not

extensively utilised for advertising purposes by gambling providers in Germany, in contrast to the practices observed in other countries. Notably, aside from the predominant use of the "News" category by sports betting providers, no clear patterns emerge in the advertising strategies of providers from different sectors. However, the "News" content category is frequently combined with less neutral content categories. Coupled with the scarcity of age or warning labels, this poses a concern because the distinction between neutral content and gambling advertising may become ambiguous in such tweets, particularly if they are not explicitly identified as advertising content. This situation presents a risk, especially for young individuals who are classified as particularly vulnerable under the State Treaty on Gambling.

Stigmatisation and self-stigmatisation constitute substantial barriers to help-seeking and therapy for gambling-related disorders (Brown & Russell, 2020; Hing, Holdsworth et al., 2014; Hing, Nuske, Gainsbury, & Russell, 2016; Hing, Nuske, Gainsbury, Russell, & Breen, 2016; Hing & Russell, 2017a; Miller & Thomas, 2017). Given that young individuals in Germany are predominantly affected by gambling-related harm (Buth et al., 2024), Chapter 4 investigates the prevalence and characteristics of stigmatisation of gambling addiction on the video platform YouTube. The analysis employed a deep learning approach that integrated guided topic modelling with summative content analysis. The model revealed the presence of various statements associated with the stigmatisation of gambling addiction, wherein this addiction is linked to negative attributes and moral judgments. As children and young people are the most active users of social media in Germany (Müller, 2024), there is a risk that they will encounter stigmatisation of gambling addiction. Conversely, social media serves as an effective platform for disseminating information and reaching the public, particularly vulnerable groups. This finding highlights the potential of social media in destigmatising gambling addiction. For instance, affected individuals, including young people, can be informed that treatment options are available, recovery is attainable, and seeking help is not indicative of weakness, but is rather a sign of strength.

In summary, the role of social media in the context of the State Treaty on Gambling is ambivalent. Social media serves as an appealing advertising platform for gambling providers (Torrance et al., 2021), allowing them to reach interested individuals and guide them to the state-regulated, legal gambling market. In this capacity, social media helps to

protect the public from gambling-related harm. Unlike illegal gambling offers, legal gambling providers are subject to the oversight of the state gambling supervisory authority and must adhere to player protection regulations, including advertising rules. Additionally, social media provides an opportunity to engage with younger population groups, informing them about prevention measures and available support services. By contrast, young people, who are the most active social media users in Germany (Müller, 2024), are highly exposed to gambling advertisements. Given that young people in Germany are most frequently affected by gambling-related disorders (Buth et al., 2024), this exposure is concerning. The high volume of gambling ads poses health risks (McGrane et al., 2023), particularly because such content often lacks age restrictions and responsible gambling messages, blurring the lines between harmless content and gambling advertising. Moreover, gambling providers can swiftly adjust their advertising strategies on social media to suit the changing circumstances. The rapid evolution of the media landscape and advertising practices of gambling providers ultimately challenge regulatory authorities to keep up with these dynamic developments.

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7 Appendix

Table 7.1 Frequency of tweets by provider

Gambling provider	Number of tweets	
	Total	Per day
State lotteries		
Lotto BW	2368	3.19
LOTTO Bayern	1451	1.95
Social lotteries		
Aktion Mensch e.V.	3191	4.29
Sportlotterie	66	0.09
Lottery brokers		
Lottoland.com	800	1.08
LOTTO24.de	468	0.63
Casino		
Spielbanken Bayern	285	0.38
Sports betting		
ADMIRALBET	2173	2.92
bet-at-home	1186	1.60
bwin Sportwetten	3197	4.30
mybet	433	0.58
Tipico	597	0.80
Unibet Sportwetten	1836	2.47

The analysis is based on 18,051 tweets during the observation period from 2019-03-27 to 2021-04-08

Table 7.2 Interaction with the tweets by provider

Gambling provider	Number of tweets			Retweets		Likes	
	Total	Per day	With own content	Total	Per tweet	Total	Per tweet
State lotteries							
Lotto BW	2368	3.19	2236	122	0.05	2272	1.02
LOTTO Bayern	1451	1.95	1429	514	0.36	2024	1.42
Social lotteries							
Aktion Mensch e.V.	3191	4.29	3166	5,271	1.66	14,738	4.66
Sportlotterie	66	0.09	66	20	0.3	53	0.8
Lottery brokers							
Lottoland.com	800	1.08	799	750	0.94	1592	2
LOTTO24.de	468	0.63	468	34	0.07	627	1.34
Casino							
Spielbanken Bayern	285	0.38	285	28	0.1	72	0.25
Sports betting							
ADMIRALBET	2173	2.92	2068	41	0.02	241	0.12
bet-at-home	1186	1.6	1182	74	0.06	900	0.76
bwin Sportwetten	3197	4.3	3175	240	0.09	1065	0.34
mybet	433	0.58	300	6	0.02	55	0.18
Tipico	597	0.8	423	67	0.16	1279	3.02
Unibet Sportwetten	1836	2.47	1760	594	0.33	5172	2.94

The analysis is based on 18,051 tweets during the observation period from 2019-03-27 to 2021-04-08

Table 7.3 Tweet content by provider

Gambling provider	Number of tweets					Replies	
	Total	Use images		Use URL			
		Total	(%)	Total	(%)	Total	(%)
State lotteries							
Lotto BW	2368	853	36.02	2457	82.84	178	7.52
LOTTO Bayern	1,451	372	25.64	1051	72.38	62	4.27
Social lotteries							
Aktion Mensch e.V.	3191	597	18.69	3,015	91.92	147	4.61
Sportlotterie	66	30	45.45	62	91.18	3	4.55
Lottery brokers							
Lottoland.com	800	211	26.38	531	66.38	120	15.00
LOTTO24.de	468	236	50.43	160	33.97	189	40.38
Casino							
Spielbanken Bayern	285	268	94.04	183	61.41	3	1.05
Sports betting							
ADMIRALBET	2173	87	4.00	2,538	92.53	12	0.55
bet-at-home	1186	550	46.37	493	41.39	168	14.17
bwin Sportwetten	3197	246	7.69	2207	68.97	172	5.38
mybet	433	253	58.43	181	41.51	15	3.46
Tipico	597	322	53.94	233	38.70	95	15.91
Unibet Sportwetten	1836	1718	93.57	815	43.96	29	1.60

The analysis is based on 18,051 tweets during the observation period from 2019-03-27 to 2021-04-08. When the number of URLs exceeds the number of tweets, several URLs were used in one tweet

Table 7.4 Top 10 hashtags of all providers

Hashtags	Number
lotto6aus49	1396
bundesliga	1250
jackpot	1227
unibet	1160
admiral	1104
eurojackpot	964
lottobw	764
inklusion	548
quotenboost	535
ucl	533

The analysis is based on 18,051 tweets during the observation period from 2019-03-27 to 2021-04-08

Table 7.5 Top 5 hashtags per provider

Gambling provider	Hashtag	Gambling provider	Hashtag
Lotto BW	lotto6aus49	LOTTO Bayern	jackpot
	lottobw		lotto6aus49
	jackpot		legalbeimoriginal
	eurojackpot		eurojackpot
	lottozahlen		6aus49
Aktion Mensch e.V.	inklusion	Sportlotterie	sportlotterie
	behinderung		
	barrierefreiheit		
	corona		
	teilhabe		
Lottoland.com	euromillions	LOTTO24.de	lotto24
	lottozahlen		glücklichmacher
	eurojackpot		eurojackpot
	powerball		lotto
	lotto		lotto6aus49
Spielbanken Bayern	spielbankenbayern	bet-at-home	Blog
	spielbank		bundesliga
	casino		premierleague
	spielbanken		Ucl
	bayern		fcbayern
ADMIRALBET	admiral	mybet	fussball
	quotenboost		sport
	topquoten		sportwetten
	bonus		mybetmeister
	bundesliga		bundesliga
bwin Sportwetten	bundesliga	Unibet Sportwetten	unibet
	ucl		bundesliga
	bvb		bvb
	fcbayern		fcb
	b04fcb		Borussia
Tipico	bundesliga		
	topfakt		
	scheinderwoche		
	tipicotopfakt		
	zahlendesspieltags		

The analysis is based on 18,051 tweets during the observation period from 2019-03-27 to 2021-04-08

Table 7.6 Inter-rater reliability between summative content analysis and semi-supervised topic modelling

Gambling provider	Category	Fleiss' κ	p-value
Lotto BW	K1	0.650	0.000
	K2	0.554	0.000
	K3	0.543	0.000
	K4	0.840	0.000
	K6	0.767	0.000
	K7	0.789	0.000
	K8	0.656	0.000
LOTTO Bayern	K1	0.917	0.000
	K2	0.876	0.000
	K3	0.781	0.000
	K4	0.789	0.000
	K7	1	0.000
	K8	0.656	0.000
Lottoland.com	K3	1.000	0.000
	K4	0.890	0.000
	K5	0.787	0.000
	K8	1.000	0.000
LOTTO24.de	K1	0.579	0.000
	K2	0.692	0.000
	K3	0.621	0.000
	K4	0.479	0.001
	K6	0.672	0.000
	K7	0.504	0.000
	K8	0.077	0.586
Aktion Mensch e.V.	K4	0.096	0.498
	K7	-0.042	0.768
	K8	0.645	0.000
Spielbanken Bayern	K2	1	0.000
	K3	0.458	0.001
	K4	-0.389	0.006
	K6	0.645	0.000
	K7	0.608	0.000
Sportlotterie	K1	0.840	0.000
	K2	0.728	0.000
	K4	0.201	0.155
	K7	0.080	0.573

ADMIRALBET	K1	0.673	0.000
	K2	0.563	0.000
	K4	0.452	0.001
	K7	-0.282	0.046
bet-at-home	K1	0.543	0.000
	K4	0.912	0.000
	K7	-0.250	0.077
	K8	0.240	0.149
bwin Sportwetten	K1	0.756	0.000
	K2	0.578	0.000
	K4	0.368	0.009
	K7	-0.639	0.000
mybet	K2	0.285	0.044
	K3	0.185	0.191
	K4	0.766	0.000
	K6	0.534	0.000
	K7	0.015	0.917
Tipico	K1	0.357	0.012
	K2	0.003	0.981
	K3	0.811	0.000
	K4	0.299	0.035
	K6	0.534	0.000
	K7	-0.515	0.000
	K8	-0.136	0.335
Unibet Sportwetten	K1	0.905	0.000
	K2	-0.033	0.813
	K3	1.000	0.000
	K4	0.539	0.000
	K5	0.558	0.000
	K6	0.368	0.009
	K7	-0.683	0.000

Table 7.7 Content categories by provider (CorEx analysis of 50 tweets per provider)

Gambling provider	Number of categories (%)	Product advertising (%)	Additional information (%)	Results (%)	Marketing (%)	Interaction (%)	Responsible Gambling (%)	News (%)	Other (%)	Coherence
State lotteries										
Lotto BW	59	17	27	15	19	-	15	5	2	0.49
LOTTO Bayern	62	31	45	16	5	-	-	2	1	0.63
Social lotteries										
Aktion Mensch e.V.	54	-	-	-	24	-	-	69	7	0.45
Sportlotterie	56	25	7	-	43	-	- [a]	25	0	0.51
Lottery brokers										
Lottoland.com	56	-	-	64	20	14	-	-	2	0.61
LOTTO24.de	75	19	23	9	34	-	24	7	15	0.48
Casino										
Spielbanken Bayern	76	-	14	20	50	-	45	11	-	0.47
Sports betting										
ADMIRALBET	82	38	41	-	9	-	-	12	-	0.52
Bet-at-home	51	35	-	-	2	0	0 [a]	31	20	0.50
bwin Sportwetten	56	48	27	-	5	- [a]	-	21	-	0.49
mybet	52	-	52	13	31	0	21	17	-	0.47
Tipico	61	31	15	8	13	0	16	5	11	0.46
Unibet Sportwetten	52	29	29	4	8	17	4	10	-	0.47

The analysis is based on 650 randomly selected tweets (50 tweets per provider) during the observation period from 2019-03-27 to 2021-04-08. The number of content categories is higher than the number of tweets, as a tweet can be classified in several categories

[a] This content is used by the providers, but cannot be captured by topic modelling. Even if there is no capture of the data, the categories are considered to be present in the evaluation

(Social media OR social media channel* OR social network* OR social network* channel* OR social platform* OR online platform* OR online environment* OR online sphere* OR facebook OR twitter OR instagram OR tiktok OR twitch OR youtube OR weibo OR wechat) AND (Gambling OR online gambling OR gambling operator* OR gambling provider* OR gambling marketing OR gambling advertisement OR gambling advertising OR gambling industry OR gambling industry marketing OR digital gambling marketing).

Figure 7.1 Search String

Figure 7.2 YouTube video information by keyword

Gambling							
Video title	**Channel name**[1]	**URL**	**Upload date**	**Views (n)**	**Comments (n)**	**Gambling content**	**Person with a gambling disorder**
Coin Master - Rip-off with FUN | NEO MAGAZIN ROYALE with Jan Böhmermann - ZDFneo	ZDF MAGAZIN ROYAL	hTeTjx4k9jQ	2019-10-10	3.469.481	4.923	Yes (100%)	No
KNOSSIS biggest BOOK OF DEAD WIN EVER! 😱💘	Knossi	7vb5WpYNbvA[b]	2019-07-30	3.255.124	1.861	Yes (100%)	No
How rich will I get from gambling? - Self-experiment in a gambling hall	tomatolix	zvGFT1g35gc	2017-09-16	2.931.371	4.044 / 4.037	Yes (100%)	Yes (23%)
Gambling addiction - The business of gambling halls	Y-Kollektiv	GegsXxdH2zI	2017-01-12	1.844.735	1.689	Yes (100%)	Yes (22%)
Online gambling in Schleswig-Holstein | ZDF Magazin Royale	ZDF MAGAZIN ROYAL	9RV6i_zjoFI	2020-11-20	1.301.332	3.025	Yes (100%)	No

Figure continued

Figure 7.2 continued

Gambling addiction: What makes gambling at the slot machine so dangerous? || PULS Reportage	PULS Reportage	KTTu1FZkIEs	2020-01-08	1.243.801	2.646	Yes (100%)	Yes (52%)
Elena LOSES at Gambling + Embarrassing Story | Talk with Elena	Cheasy	Rbuy_oX5-5g	2020-04-26	785.516	1.109	No	No
Online casino - How the gambling hype works on Twitch	Y-Kollektiv	3x8mIaaba0s	2019-12-05	616.705	2.152	Yes (100%)	Yes (10%)
1 week online casino - 500€ turned into --€ | self-experiment	Tomary	Tj6TbacnbkQ	2020-05-09	654.732	1.240	Yes (100%)	Yes (12,5%)
40 hours in the arcade: Do the staff intervene? | stern TV (2013)	stern TV	Cnok4vLIJJM	2022-08-23	509.553	1.091	Yes (100%)	No

Figure continued

Figure 7.2 continued

Sports betting							
Video title	**Channel name**[1]	**URL**	**Upload date**	**Views (n)**	**Comments (n)**	**Gambling content**	**Person with a gambling disorder**
Exclusive: Members of the betting mafia spill the beans | STRG_F	STRG_F	Y79yUhdGhrU	2018-11-26	1.957.584	2.757 / 2.754	Yes (12%)	No
Money laundering at Tipico shops & co | STRG_F	STRG_F	GKJ3_bf9m8U	2019-06-11	1.093.583	1.710	No	No
Are sports bets dangerous? Meini vs. gambling || PULS Reportage	PULS Reportage	TyPSB-5CPJo	2020-10-28	458.358	1.135	Yes (100%)	Yes (30%)
I bought manipulated sports betting results on the Darknet!	Torben Platzer	wNEuSJIQYko	2022-10-30	439.446	1.346 / 1.347	No	No

Figure continued

Figure 7.2 continued

Through SPORTS BET-TING to the ROLEX | Trade Up '05 | @Dave	DAVE	AfNlH_rA4EY	2021-01-12	425.689	1.769	Yes (100%)	No
Getting rich through sports betting? (Matched Bet-ting Experiment)	SELTIX	ZuKEcnN6_Eo	2021-02-27	417.000	1.575	Yes (100%)	No
Getting rich through betting experts? (experi-ment)	SELTIX	sD-Sl5BM9jg	2021-04-28	225.899	1.092	Yes (100%)	No
Casino Streams							
Video title	**Channel name**[1]	**URL**	**Upload date**	**Views (n)**	**Com-ments (n)**	**Gambling content**	**Person with a gambling dis-order**
ALGE ALGE! MEGA WINN! 😱 | RAZOR SHARK	Knossi	-NKbRwwWMIU[b]	2019-09-07	4.036.995	2.808	Yes (100%)	No

Figure continued

Figure 7.2 continued

KNOSSIS biggest BOOK OF DEAD WIN EVER! 😱 💵	Knossi	7vb5WpYNbvA[b]	2019-07-30	3.255.124	1.861	Yes (100%)	No
MONTE donates €1000 to KNOSSI LIVE in STREAM! 😱	Knossi	BUXW0bWxm_0[b]	2019-05-20	3.016.542	1.278	Yes (100%)	No
KNOSSI on a VISIT! 😂 Spider in the Gaming Room - Part 1 | MontanaBlack Stream Highlights	Die Crew	xRoQM60zXPE	2021-07-31	2.930.587	1.122	Yes (13%)	No
MONTANABLACK on times as a drug junkie, scandals, casino streams (Realtalk) & his drive (+Yapi).	Tim Gabel	STD9LvUqGMI	2020-03-15	2.635.055	4.558 / 4557	Yes (12,5%)	No
MOST Twitch Subscribers Worldwide Live Cracked feat. Knossi 😱 | MontanaBlack Stream Highlights	Die Crew	3yD3olxiwI8	2019-09-02	2.534.139	3.046	No	No

Figure continued

Figure 7.2 continued

Original XXL Rolex 😱 12,000€ won at the casino 🤑 MontanaBlack Stream Highlights	Die Crew	TtgBVvTZMhA	2019-06-19	1.188.397	1.965	Yes (37,5%)	No
RUNA RUNA! | Stream EXCALATES COMPLETELY 😱 | Book of the Dead	Knossi	1oFvhoIfji8[a]	2020-04-07	1.157.550	1.416	Yes (100%)	No
dangerous CASINO ADDICTION in GTA5 | Part 2 | SpontanaBlack	SpontanaBlack	_FfUg0UpZKA	2021-05-22	960.042	1.043	Yes (60%)	No
Casino streams regretted? 🤔 Criticism of the community + call to KNOSSI 😱 MontanaBlack Realtalk	Richtiger Kevin	nc2pSJ61MMQ	2020-01-31	877.312	1.336	Yes (70%)	No
Gambling Influencer							
Video title	**Channel name**[1]	**URL**	**Upload date**	**Views (n)**	**Comments (n)**	**Gambling content**	**Person with a gambling disorder**

Figure continued

Figure 7.2 continued

Online casino - How the gambling hype works on Twitch	Y-Kollektiv	3x8mIaaba0s	2019-12-05	616.705	2.152	Yes (100%)	Yes (10%)
Online casinos: How Influencers Earn from the Addiction of Others | frontal	ZDFheute Nachrichten	3RoueSVblTI	2020-10-29	239.485	2.056	Yes (100%)	Yes (20%)
Gambling addiction							
Video title	**Channel name**[1]	**URL**	**Upload date**	**Views (n)**	**Comments (n)**	**Gambling content**	**Person with a gambling disorder**
GAMBLING ADDICT meets CASINO OWNER | The meeting	Leeroy will's wissen!	vYGEkC_0LX0	2022-04-07	3.454.674	6.864	Yes (100%)	Yes (100%)
How rich will I get from gambling? - Self-experiment in a gambling hall	tomatolix	zvGFT1g35gc	2017-09-16	2.931.371	4.044	Yes (100%)	Yes (23%)

Figure continued

Figure 7.2 continued

Gaming addiction in Korea | Galileo | ProSieben	Galileo	_C9KLfqIQx0	2016-07-16	2.676.917	7.418	No	No
In the GAMBLING HELL - The addiction to gambling - A look behind the scenes of the industry | HD Doku	WELT Doku	mFJGBL4uQiQ	2019-10-08	1.906.796	2.109 / 2.107	Yes (100%)	Yes (4%)
Gambling addiction - The business of gambling halls	Y-Kollektiv	GegsXxdH2zI	2017-01-12	1.844.735	1.689	Yes (100%)	Yes (22%)
What is it like TO BE ADDICTED TO GAMBLING?	Leeroy will's wissen!	PK_FTp4iHaQ	2020-08-31	1.470.656	4.949	Yes (100%)	Yes (100%)
Gambling addiction: What makes gambling at the slot machine so dangerous? || PULS Reportage	PULS Reportage	KTTu1FZkIEs	2020-01-08	1.243.801	2.646	Yes (100%)	Yes (52%)

Figure continued

Figure 7.2 continued

Addicted to Gambling with Hartz IV | Poor Germany | RTLZWEI Dokus	RTLZWEI Dokus	usvUxAa0rB0	2020-06-28	1.241.186	1.952	Yes (33%)	No
Gambling addiction - A self-experiment	maiLab	zARjpQF2WCs	2019-07-26	689.064	3.721	Yes (100%)	No
How 7 vs Wild helped me with my gambling addiction | Conclusion	RELOADIAK	SSZG8UA3hTQ	20220-01-08	597.450	1.231	Yes (10%)	Yes (10%)

Note: The data was collected on 11/23/2022. The video title was translated by the author. The videos are arranged in a chronological descending order based on their number of views

[a]: The channel names have not been translated as they are proper names

[b]: The videos were no longer available at the time of last review on 07/23/2023