

Understanding the Emotions of Those With a Gambling Disorder: Insights From Automated Text Analysis

Terrence Brown,¹ Albert Caruana,² Michael Mulvey,³ & Leyland Pitt⁴

¹ Unit of Sustainability, Industrial Dynamic & Entrepreneurship, Royal Institute of Technology (KTH), Stockholm, Sweden

² Department of Corporate Communication, University of Malta, Msida, Malta

³ Telfer School of Management, University of Ottawa, Ottawa, Canada

⁴ Beedle School of Business, Simon Fraser University, Vancouver, Canada

Abstract

The diffusion and growth of the web and the social media applications that it has provided have seen people increasingly turn to social media to express their feelings, frustrations, and ambitions and to generally share life events. Like other internet users, those with a gambling disorder are also known to use specialized online forums to read the experiences articulated by others and to open up, share, and express themselves online. In this study, we examined how those with a gambling disorder talk about their emotions and express sentiment through their online comments. Sentiment Analysis in IBM Watson was used to capture expressed emotions (anger, disgust, fear, happiness, sadness, and surprise) and sentiments. These data were then used as input to a latent class cluster modelling procedure aimed at categorizing those with a gambling disorder into distinct groups. The findings show how qualitative online data can be transformed into quantitative insights in order to identify different categories of people with a gambling disorder. The technique offers a non-intrusive method of data collection that can provide useful insights into the emotions felt and expressed by those with a gambling disorder.

Keywords: emotions, gambling disorder, automated text analysis

Résumé

L'usage répandu d'applications Internet et de médias sociaux a conduit les gens à se tourner de plus en plus vers les réseaux sociaux pour communiquer leurs sentiments, leurs ambitions et ce qui se passe dans leur vie. À l'instar d'autres internautes, les personnes qui ont des problèmes de jeu fréquentent des forums spécialisés en ligne pour s'exprimer et savoir ce que vivent des gens ayant des problèmes semblables aux

leurs. Cette étude examine, à travers leurs commentaires en ligne, comment ces personnes aux prises avec une dépendance au jeu parlent de leurs émotions. Nous nous servons de la fonction d'analyse des sentiments d'IBM Watson pour capturer les émotions exprimées (colère, aversion, peur, joie, tristesse et étonnement) et autres sentiments. Ces données font ensuite l'objet d'une modélisation conjuguant l'analyse des classes latentes et l'analyse par grappe, et qui vise à constituer des sous-groupes de joueurs ayant un problème de dépendance. Les résultats font voir que les données qualitatives en ligne peuvent être transformées en données quantitatives qui permettent de distinguer des sous-groupes parmi les personnes aux prises avec une dépendance au jeu. Nous traitons dans cet article de la possibilité de traitements ciblés à l'intention de ces sous-groupes, ainsi que des limites de cette méthode.

Introduction

In the movie *Owning Mahowny*, featuring the story of Dan Mahowny, a Toronto banker, the lead character misappropriates more than \$10 million from the bank where he works to fund his gambling disorder. Mahowny (known as Brian Molony in real life) is portrayed as a highly intelligent individual who is unable to profit from or control his gambling (Ross, 2002). Mahowny epitomizes the compulsive gambler who is unable to overcome his gambling disorder despite the negative consequences of his actions. The actor Philip Seymour Hoffman played the real Brian Molony in the movie. In an interview with his publishers, Gary Ross (2011), the author of the book *Stung* on which the movie is based, is asked, “Is Philip Seymour Hoffman’s portrayal of Dan Mahowny anything like the real Brian Molony?” He responds: “Remarkably so. They have the same stocky build, bushy moustache, glasses, slightly unkempt look, and earnestness. And Philip somehow managed to assimilate the psychic essence of Molony – a yawning emptiness that nothing except gambling was able to fill (Penguin Random House, n.d., Author Q&A section).

Severe problem gambling, sometimes referred to as compulsive gambling by gamblers or as pathological gambling, is now considered a disorder (Petry et al., 2014). The American Psychiatric Association (APA) defines it as involving “repeated problematic gambling behaviour that causes significant problems or distress” (2018). The latest edition of the *Diagnostic and Statistical Manual of Mental Disorders* (APA, 2013) lists pathological gambling as a disorder under substance-related and addictive disorders, rather than impulse-control disorders. Despite recent calls for conditions such as digital addictions to be similarly recognized (Berthon et al., 2019), gambling disorder remains the only non-substance disorder to be so acknowledged. This classification results from the symptoms of the disorder resembling an addiction similar to that of substance abuse (Christensen et al., 2015). The distinguishing feature of individuals with a gambling disorder is “persistent and recurrent maladaptive gambling behavior that disrupts personal, family, and/or vocational

pursuits,” with one of its characteristics being “the frequent, and often long-term, pattern of ‘chasing’ one’s losses” (APA, 2013, p. 586). Gambling disorder is prevalent in many national populations, with estimates ranging from 1% to 3.5% among adults (Lorains et al., 2011; Williams et al., 2012) and even higher among young adults, at between 6% and 9% (Barnes et al., 2010). Those with a gambling disorder are unable to resist their impulses. Much like drug addicts and alcoholics, they usually relate the same story of being unable to stop, a deterioration or breakdown in family life and loss of contact with partners or children, accumulation of debts that they are unable to handle, and engagement in criminal activity. As in the case of Mahowny/Molony, criminal activity usually occurs as they seek to raise funds either to cover their losses or to be able to continue their habit. Despite these manifestations, in many societies, problem gambling remains a hidden disorder that carries considerable stigma. Most major religious faiths take a dim view, believing it to be wasteful and possibly sinful. Indeed, monotheistic religions tend to condemn gambling, whereas polytheistic or animistic religions tend to be more accepting (Binde, 2007). Of course, shifting attitudes towards religion and changing mindsets, particularly in Western society, have seen the widespread acceptance of gambling as entertainment. This transition has resulted from the socio-economic improvements in the post-World War II era and a shift in thinking that views citizens as consumers (Cosgrave & Klassen, 2001). As in the case of alcohol in which consumption in moderation is generally acceptable, occasional gambling for fun is also acceptable. However, compulsive consumption or engagement can have devastating consequences for individuals, those close to them, and society as a whole.

Studies in both the psychology and the gambling literature has frequently focused on people with a gambling disorder, its management, its regulation, and related issues concerning health and addiction (e.g., Auer & Griffiths, 2013; Buil et al., 2015; Gainsbury et al., 2014; Griffiths, 2013; McAllister, 2014; Philander & MacKay, 2014; Rousseau & Venter, 2002; Sutton & Griffiths, 2007; Wardle et al., 2011). Indeed, in the United Kingdom, the recognition of problem gambling as a psychological disorder has led to suggestions that it should have parity of esteem with other mental disorders such as alcohol, drug, and tobacco addiction. Therefore, its treatment “should be a core element of addictions treatment provision within the NHS” (Bowden-Jones et al., 2017, p. 4). However, as has recently been pointed out, there is much about the problem gambler that is not known (Harries et al., 2018).

The research reported in this paper concerns the emotions and sentiment expressed by those with a gambling disorder as they share their stories online. The objective of the research described was to identify homogenous subgroups among this population, so that more finely targeted approaches to their counselling can be provided. We begin with a brief review of the literature on emotions, sentiment, and the use of automated sentiment analysis (SA) and its relevance to gambling addiction. The SA tool uses artificial intelligence to score the emotions and sentiment of those with a gambling disorder in an online forum. The resultant scores are inputted into a latent class cluster modelling procedure that allows the categorization of people with a gambling disorder into distinct groups.

Emotions, Sentiment, and SA

Emotions are central to the phenomenology of addiction and are integral to both the feeling state and to attributional reasoning and sensemaking (Hirschman, 1992). Emotions represent complex psychological states that act as motivators and play an essential role in the life of humans. However, emotions are difficult to define, and the psychology literature provides a large number of definitions. Indeed, the difficulty is reflected in the attempt undertaken by Izard (2010) to better understand what they are. The author surveyed 34 emotion researchers and came up with 34 different definitions that proved challenging to synthesize.

In the 1960s, Paul Ekman proposed six basic emotions: happiness (or joy), fear, anger, disgust, sadness, and surprise. He subsequently investigated whether facial expressions of emotion were universal (Ekman & Friesen, 1971). It has been argued that, besides these six emotions, contempt should be included as a further basic emotion (Izard & Haynes, 1988; Matsumoto, 1992; Russell, 1991). However, the meta-analysis by Elfenbein and Ambady (2002) supports Ekman's six basic emotions as having universal application and suggests that although contempt showed significant cross-cultural accuracy, it had the lowest accuracy level of the individual emotions.

The six emotions identified by Ekman are among the most common to be highlighted:

- *Happiness (Joy)*: whereas happiness is an active or passive state of pleasure or pleasurable satisfaction, joy is the emotion evoked by well-being, success, or good fortune or by the prospect of possessing what one desires.
- *Fear*: a distressing emotion aroused by impending danger, evil, or pain.
- *Anger*: a strong feeling of displeasure and belligerence aroused by a wrong.
- *Disgust*: a strong feeling of dislike for something that has a very unpleasant appearance, taste, or smell.
- *Sadness*: showing, expressing, or feeling sorrow or unhappiness.

Discrete emotion theory holds that humans possess an innate set of basic emotions consisting of happiness (or joy), fear, anger, disgust, and sadness. They represent positive and negative affect and are distinguishable across cultures from facial expressions and biological processes. The consensual model of emotion (Watson et al., 1988) holds that positive and negative affect are two separate systems, with fear, anger, disgust, and sadness considered as negative emotions. Each emotion state is defined by its valence, reflecting the level of arousal.

The theoretical grounding adopted has influenced the measurement instrument used to capture emotions. Researchers seeking to measure subjectively experienced

emotions commonly rely on scales that assess broad dimensions of affect (positivity and negativity). In such cases, the Positive and Negative Affect Schedule has primarily been used (Watson et al., 1988). In an attempt to overcome the shortcomings of this and other measures and to capture situations of blended emotions, the Discrete Emotions Questionnaire was proposed as an alternative (Harmon-Jones et al., 2016). However, since individuals experience changes in emotions throughout their lives (Van Esch & Cui, in press), their written thoughts and feelings may be quite revealing, as demonstrated by Pennebaker (1997). In this study, we therefore sought to infer emotions directly from written text.

Stout (1899) was among the first to distinguish sentiment from emotion. He observed that sentiments are not actual feelings, but are dispositions, and that an essential feature of the structure of sentiments is their state of readiness for a response. McDougall (1908/2015) argued that “sentiment” should “denote all those acquired conjunctions of ideas with emotional-conative tendencies or dispositions” (p. ix). McDougall also made the critical observation that sentiments usually connect primary emotions with action. A sentiment is the combination of emotion and thought. It is the subjective experience of our emotions. An emotion becomes a sentiment to the extent that we become aware of it. That is to say, a sentiment involves both the physiological reaction and a cognitive, subjective component. Thus, a sentiment is when we put a name to an emotion and decide how we react to it. Sentiments are therefore organized dispositions that are influenced by emotions that allow individuals to respond.

The link of sentiments to behaviour has fostered interest in how it can be captured and has given rise to SA, or opinion mining, as it is alternatively known. SA of online text has developed as a tool to make quantitative sense of what is primarily qualitative data. It aims to determine the sentiment (as defined earlier) of the speaker or author of a piece of text and can be scored from negative to positive on whichever scale the particular SA software uses. This scaling is sometimes referred to as the “polarity” of the document (e.g., Turney, 2002).

Automatic text analysis has been used to trace emotional language in consumer discourse. (It has also been used in a gambling context to investigate media discourse and consumer response and how they address the idea of emotion polarization and track changes in language valence and emotion (anxiety, sadness, and anger) over time (Humphreys, 2010; Humphreys & Latour, 2013). SA is a relatively new text analysis tool, but it is increasingly being adopted in different contexts, including general applications on the microblogging platform Twitter (e.g., Pak & Paroubek, 2010) and in more specific applications, such as to understand patients’ reactions to knee replacement surgery (Pitt et al., 2019). It has in addition been used to determine the emotions expressed on artists’ websites (Pitt et al., 2018) and the sentiments expressed in overviews of wine tourism experiences (Treen et al., 2018). However, its use to investigate the emotions and sentiments expressed by individuals with a gambling disorder and, more important, the insights that this type of analysis can provide, does not appear to have received much attention. Its use in this context

offers considerable opportunity to understand those with a gambling disorder better and to be able to tailor programs and supporting activities aimed at helping them, as well as providing them with opportunities to rebuild their lives.

Method

Analysis

SA with the AlchemyLanguage tool on IBM's Watson Developer Cloud lends itself best to the circumstances of this research because the platform uses natural language processing and machine learning to reveal insights from large amounts of unstructured data. The IBM Watson AlchemyLanguage service is a collection of text analysis functions that derive semantic information from any document, including text, HTML code, or the URL of a website. It exploits sophisticated natural language processing techniques to obtain a high level of comprehension of the content rapidly. A central feature of the technique is its ability to understand the emotions expressed from the text language used. Moreover, it allows the researcher to gain an overall indication of the sentiment of the document (<http://www.ibm.com/watson/what-is-watson.html>).

Data Source

The source of the data described in this study was the website Psychforums.com, which provides a platform for individuals with a range of psychological problems to post their thoughts, feelings, and experiences and receive feedback from others. The website provides a forum specifically for people with a gambling disorder to share their stories and talk about how their addiction has affected them and how they feel about themselves and their lives (<https://www.psychforums.com/gambling-addiction/>). We chose all the reviews on the website at the time of data gathering. These were all individuals who believed that they were problem gamblers and had used the forum as a vehicle for sharing their stories and feelings, perhaps hoping for empathy from others or that they might feel better by writing things down. Indeed, Pennebaker (1997) argues that when people write something down, rather than just talking about it, they feel better. We gathered 199 personal reviews from the website that were each copied and pasted as text into the AlchemyLanguage tool. The sample size exceeded the minimum criteria for qualitative text-based research as reported by Van Esch and Van Esch (2013). The IBM Watson software detects the emotions expressed in the text and scores them on a scale between 0 (*no emotion expressed*) and 1 or a value close to 1 (*emotion very strongly expressed*). In addition, the overall sentiment of each contribution is calculated on a scale ranging from -1 (*negative sentiment*) to +1 (*positive sentiment*), with 0 as the neutral sentiment. These resultant respondent scores for emotions and sentiment were saved in a spreadsheet for further analysis.

Results

In terms of demographics of the sample, 15% disclosed their gender as female, 26% as male, and 59% did not reply. The range of those who disclosed their age extended

Table 1
Basics for IBM Watson Emotion Analysis

Descriptive Statistics	Word count	Sentiment ^a	Happiness/Joy ^b	Fear ^b	Anger ^b	Disgust ^b	Sadness ^b
Mean	377.39	-0.50	0.47	0.28	0.26	0.15	0.61
SD	227.53	0.31	0.19	0.20	0.20	0.16	0.08
Maximum	1,577	0.71	0.71	0.72	0.71	0.74	0.99
Minimum	135	-0.97	0.01	0.06	0.05	0.02	0.00

^aScored -1 to 1. ^bScored 0 to 1.

from a 21-year-old male to a 70-year-old male. Descriptive data from the analysis appear in Table 1. The average number of words in each piece of text collected from gambling addicts was 377 ($SD = 227$), the most extensive review analysed being 1,577 words and the shortest being 135 words. The descriptive statistics for the scores of the five emotions of joy, fear, anger, disgust, and sadness are shown in Table 1. Values for emotions range from 0 to 1 and sentiment from -1 to 1, indicating a negative and positive sentiment, respectively.

One of the key advantages of using the *AlchemyLanguage* tool in IBM Watson is the ability to identify respondents who exhibit the highest and lowest scores for sentiment and each of the five emotions. This option facilitates the inspection of contributions in order to understand the actual words used by participants to express their position. Some examples of the extreme scores and the words used appear in the following sections.

Highest Sentiment (0.71), Respondent 28, Gender Not Disclosed

Hi all, today is day 4 of my quit! I have done many day 4s, just simply not gambling, but this is the fourth day I am adding to my Recovery!

I decided to go to Gamblers Anonymous... It was wonderful. It was tough and sad and scary, but it was wonderful. I teared up listening to everyone. But they were all oh, so welcoming. Many chose to share their rock bottom stories because there was a Newbie there.

There was a lot of strength in that room. Many said that you need to work the steps in order to get everything you can from GA, so my task is to learn more about doing that...

I was so welcomed. So welcomed. I repeat this, because feeling so low, so broken, and finding the sympathy and understanding from the only people on this earth who understand how you hurt and how sorry you are, but what keeps leading you back... So welcomed.

I will be returning on Monday! This may not be everyone's cup of tea, but I think it will be helpful in my recovery!

Cheers!

Lowest Sentiment (-0.97), Respondent 20, Gender Not Disclosed

I've just lost over £65000 through sports betting in the recent built up, I have maybe around £10000 or little over, I recovered over £50000 last year and just this month I ended up losing back 50000 plus another 15000, I don't know how to deal with these losses, I want to get over it but it's almost impossible. my head is spinning out of control and I'm feeling sick every moment of my life now. I don't know if I can tell my parents I've lost this much money because it would be a burden to them! should I be telling my parents about my huge loss? I don't want to commit suicide either because it would burden them also, I need any advice which would help, I want to avoid gambling ever again because it's making me sick and been a waste of my life in the past year.

Highest Joy (0.71), Respondent 172, Male

"I had enough courage to tell my closest friends...." "I just want to get back to living a normal happy life."

Highest Fear (0.72), Respondent 145, Gender Not Disclosed

Knowing I let my family down, my soul hurts. My head hurts. It all hurts. I don't know where to go from here.

Highest Anger (0.71), Respondent 12, Gender Not Disclosed, and Respondent 115, Female***Respondent 12***

Huge loss, never lost this much except for a Vegas trip which I feel like ok to lose then, but not when I'm at home not on vacation. Horrible.

Respondent 115

"Change screen if husband stirs so he does not see. How sly." (gambling online on a tablet at home in bed at night while her husband sleeps next to her)

Highest Disgust (0.74), Respondent 109, Female

I know what to do, did it then ####\$ up I am afraid of myself my future. My husband does not deserve me or my grown children.... Know I will lose overall makes life torture. I am mentally ill....I loathe myself.

Highest Sadness (0.99), Respondent 58, Gender Not Disclosed

I've been here for a while, usually just get off and come back when I want to die basically..... I only work 35 hours a week, minimum wage job, too depressed for school, turned to gambling.... really want to just die right now, kind of tempted to take a bunch of pills, I've wasted 5 years of my life to this \$#%^, I can't be okay with making 400\$ a week, when I know I've lost over 50,000\$ already... .. I just can't believe, I lost everything again, I've wasted like 5 years of my life, and I HAVE LITERALLY NOTHING.

Latent Class Cluster Modelling

Latent class cluster modelling analysis was undertaken to further investigate the data summarized in Table 1 and to identify whether there are subgroups of individuals included in this study who have emotions and sentiment in common. The approach seeks to determine how individuals cluster together from the patterns of emotions conveyed in their reviews. Latent class cluster models are useful in capturing the heterogeneity in sets of indicator variables and in understanding holistic patterns that may exist across subgroups of individuals. Specifically, the aims of the current analyses were to (a) extract latent classes of reviews from five emotion indicators and (b) determine how those classes differ on demographic and perceptual correlates.

To determine the number of classes, we used LatentGOLD 5.1 (Vermunt & Magidson, 2015) to fit a series of latent class regression models, beginning with a parsimonious one-class model and sequentially increasing the number of latent classes while examining the fit statistics. Fit indices for one- through 12-class models are provided in Table 2. The Bayesian information criterion and consistent Akaike

Table 2
Comparison of Fit Indices for Model Selection

Model	LL	BIC (LL)	CAIC (LL)	Number of parameters	Classification error
1-Cluster	422.0	-791.0	-781.0	10	0.000
2-Cluster	799.6	-1488.1	-1467.1	21	0.005
3-Cluster	928.2	-1687.1	-1655.1	32	0.013
4-Cluster	1023.6	-1819.7	-1776.7	43	0.016
5-Cluster	1068.7	-1851.5	-1797.5	54	0.014
6-Cluster	1133.4	-1922.8	-1857.8	65	0.005
7-Cluster	1158.5	-1914.7	-1838.7	76	0.002
8-Cluster	1202.7	-1945.0 ^a	-1858.0 ^a	87	0.003
9-Cluster	1230.5	-1942.2	-1844.2	98	0.015
10-Cluster	1246.3	-1915.7	-1806.7	109	0.003
11-Cluster	1258.8	-1882.4	-1762.4	120	0.036
12-Cluster	1285.0	-1876.5	-1745.5	131	0.009

Note. LL = log likelihood; BIC = Bayesian information criterion; CAIC = consistent Akaike information criterion (CAIC).

^aMinimum values of BIC and CAIC, indicating the best-fitting latent class model.

information criterion supported an eight-class solution (Class 1: $N = 75$; Class 2: $N = 27$; Class 3: $N = 24$; Class 4: $N = 22$; Class 5: $N = 15$; Class 6: $N = 13$; Class 7: $N = 12$; Class 8: $N = 11$). The entropy value (0.993) indicated that the latent classes are highly discriminating. A test of parameter stability with a bootstrap resampling method (500 replications) showed that the eight-class model provided a significantly better fit ($p < .0001$) than the seven-class model did. From the statistical fit and interpretability of classes, we therefore selected the eight-class model as the final model.

Table 3 shows the parameter estimates for the eight-cluster model. Each of the five emotion indicators contributed significantly to the overall model (see intercepts and Wald values), with sadness (intercept = 0.61) exhibiting the highest level of intensity across clusters. Sadness was followed by Joy (0.42), Fear and Anger (0.34), and Disgust (0.20). As indicated by the parameter estimates, Wald (=) and R^2 values, cluster membership was largely explained by variance in the expression of Disgust ($R^2 = 0.889$) followed by Fear ($R^2 = 0.774$), Joy ($R^2 = 0.772$), Anger ($R^2 = 0.722$), and Sadness ($R^2 = 0.135$). As a whole, the reviews were tinted with sadness, yet each of the eight classes was marked by distinct levels of Joy, Anger, Disgust, Sadness, and Fear.

Table 4 presents the corresponding class plot of mean emotional intensities and sentiment by cluster. The relative intensities of the five emotion indicators across, within, and between the eight clusters, along with test results of significant differences, assisted with interpretation. Cluster 1 (which we termed “melancholy”) was characterized by a mix of joy and sadness. Cluster 2 (which we termed “surprise”) registered a mix of fear and joy. Cluster 3 (which we termed “despair”) posted reports marked mostly by sadness. Cluster 4 (which we termed “righteous”) blended joy and anger. Cluster 5 (which we termed “revulsion”) mixed disgust with fear and anger. Cluster 6 (which we termed “prejudice”) fused disgust, joy, and anger. Cluster 7 (which we termed “betrayal”) showed anger and sadness. Cluster 8 (which we termed “hatred”) wrought fear, joy, and anger.

Next, the Step3-Dependent submodule in LatentGold 5.1 (which corrects for classification error to prevent bias) was used to test the extent to which class membership predicted the distal outcome of overall sentiment (using the Watson score). The sentiment of those with a gambling disorder was significantly related to their emotion clusters (Wald = 667.6, $p < .001$), accounting for 10.6% of the variance. Sentiment was most positive among Cluster 1 (melancholy) (beta = 0.14) and Cluster 2 (surprise) members (beta = 0.08), in contrast to Cluster 5 (revulsion) (beta = -0.14) and Cluster 7 (betrayal) (beta = -0.16) members, whose sentiment was significantly more negative ($p < .01$). A Step3-Covariate test to explore differences in demographics (the gender information we did have) found no significant differences across classes.

To obtain a systemic view of the underlying emotional relations among the set of reviews, we used multidimensional scaling analysis. A *review* \times *emotion* matrix

Table 3
Parameter Estimates for the Eight-Cluster Model Solution

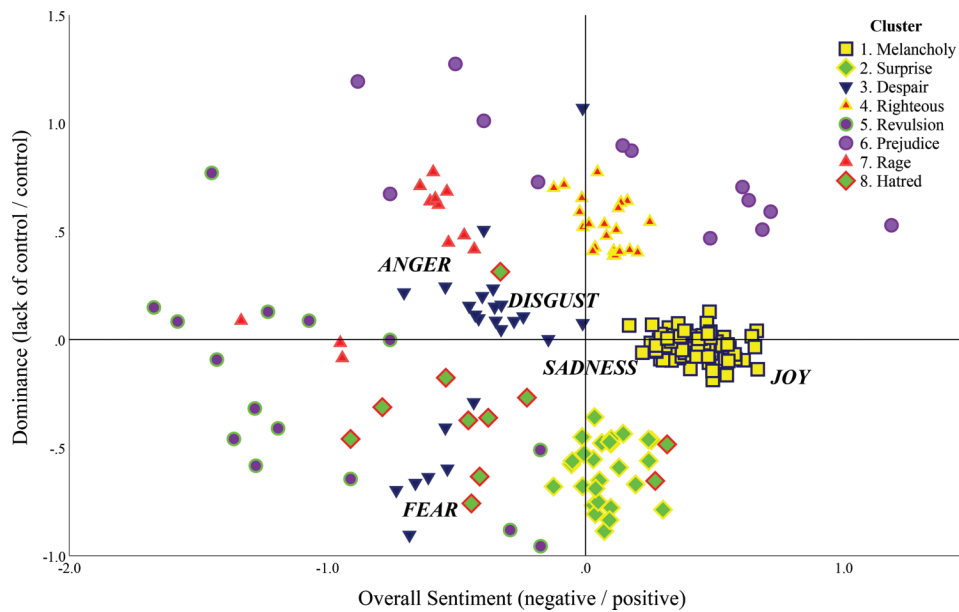
Model	Intercept		Cluster		1	2	3	4	5	6	7	8		
	Overall	Wald	p-Value	Wald (=)									p-Value	R ²
Intercept					101.3	<.001	1.30	0.28	0.16	0.08	-0.30	-0.42	-0.52	-0.59
Indicators														
Joy	0.42	1728.6	<.001	2170.9	2170.9	<.001	0.772	0.14	-0.29	0.13	-0.04	0.03	-0.28	0.15
Fear	0.34	1102.3	<.001	1168.0	1168.0	<.001	0.774	0.20	-0.05	-0.20	0.28	-0.20	-0.05	0.21
Anger	0.34	682.7	<.001	998.3	998.3	<.001	0.722	-0.21	-0.19	0.17	0.13	-0.01	0.22	0.10
Disgust	0.20	875.3	<.001	479.3	479.3	<.001	0.889	-0.12	-0.10	-0.10	0.36	0.27	-0.08	-0.10
Sadness	0.61	4804.7	<.001	21.8	21.8	0.003	0.135	0.02	0.04	0.00	0.02	-0.08	0.05	-0.06
Dependent														
Sentiment	-0.55	667.6	<.001	47.3	47.3	<.001	0.106	0.08	-0.06	0.04	-0.14	0.01	-0.16	0.09

Table 4
Emotion Intensities by Cluster

Cluster	Size	Emotion Intensities (means)					Sentiment	Key Emotions
		Joy	Fear	Anger	Disgust	Sadness		
1. Melancholy	37.5%	0.57 ^a	0.15 ^a	0.13 ^a	0.09 ^a	0.62 ^a	0.14 ^a	Joy + Sadness
2. Surprise	13.5%	0.56 ^{a,b}	0.54 ^b	0.13 ^a	0.08 ^{a,b}	0.63 ^{a,b}	0.08 ^{a,b}	Guilt (Joy + Fear)
3. Despair	12.0%	0.13 ^c	0.29 ^c	0.16	0.09 ^{a,b,c}	0.64 ^{a,b,c}	-0.06 ^{b,c}	Sadness
4. Righteous	11.1%	0.55 ^{b,d}	0.14 ^{a,d}	0.52 ^b	0.10 ^{b,c,d}	0.60 ^{a,c,d}	0.04 ^{a,b,c,d}	Pride (Joy + Anger)
5. Revulsion	7.6%	0.38 ^e	0.61 ^e	0.47 ^{b,c}	0.56 ^e	0.63 ^{a,b,c,d,e}	-0.14 ^{c,e}	Shame (Fear + Disgust)
6. Prejudice	6.7%	0.45 ^{d,e}	0.14 ^{a,d}	0.33 ^{c,d}	0.47 ^e	0.53 ^{a,b,c,d,e,f}	0.01 ^{a,b,c,d,e,f}	Disgust
7. Betrayal	6.1%	0.13 ^c	0.28 ^c	0.56 ^{b,c}	0.12 ^{c,d,f}	0.65 ^{b,c,e}	-0.16 ^{c,e,f}	Sadness + Anger
8. Hatred	5.6%	0.56 ^{a,b,d}	0.54 ^{b,e}	0.44 ^{b,c,d}	0.10 ^{a,c,d,f}	0.55 ^f	0.09 ^{a,b,c,d}	Fear + Anger

Note. Values sharing a subscript in a column are not significantly different from each other at $p < .05$.

Figure 1
Visualization of the Review Emotion Space by Cluster.



(199 reviews \times 5 emotion ratings) was transformed into a *review* \times *review* proximity matrix and then inputted into the IBM SPSS Statistics 25 - PROXSCAL algorithm to produce a two-dimensional spatial configuration. The map, shown in Figure 1 with each review and cluster membership, provides a high level of goodness of fit (dispersion accounted for = 95.9%) and is easy to read. The horizontal axis reflects the level of overall sentiment, moving from negative (anger) to positive (joy). The vertical axis reflects the level of dominance or the extent to which emotions are associated with the actions of oneself or others. The intense negative emotions associated with Cluster 5 (revulsion) and Cluster 7 (betrayal), located at the upper left of the map, stand in stark contrast to the more moderate emotional states associated with Cluster 1 (melancholy) and Cluster 2 (surprise), located at the lower right of the map.

Discussion

Managerial Implications

Analysing what is primarily qualitative data by using the AlchemyLanguage function in IBM Watson provides a methodology that can convert qualitative data in the form of online text into quantitative data that can be used for various statistical purposes. The technique offers a non-intrusive method of data collection that can provide useful insights into the emotions felt and expressed by those with a gambling disorder.

Robert L. Custer was a leading medical professional who was instrumental in the inclusion of pathological gambling in the third edition of the *Diagnostic and*

Statistical Manual of Mental Disorders (Rosenthal, 2020). He is also credited with identifying six types of gambling categories: professional, antisocial personality, casual social, serious social, relief and escape, and compulsive-pathological. Rosecrance (1985) notes that troubled gamblers progressively lose control over their behaviour and quotes Custer (1980) in support, who describes compulsive gambling as

a progressive behavior disorder in which an individual becomes dependent upon gambling to the exclusion of everything else in life. Eventually, the compulsive gambler loses all ability to control the gambling impulse and is literally unable to function without gambling. This definition does not include the social or professional gambler, or even a person who gambles heavily every day. Compulsive gamblers are a separate group whose betting behavior is obsessive and uncontrollable. (p. 75)

The first inpatient treatment hospital for gambling addiction overseen by Custer at Brecksville, Ohio, stressed counselling and group therapy, with regular contact with Gamblers Anonymous (Lesieur & Custer, 1984; Rosecrance, 1985). Evidence that gambling addiction may have neurochemical bases has witnessed the use of drugs that act on the neurotransmitters to treat gambling addicts. Just as individuals with substance abuse are usefully prescribed cognitive behavioural therapy, psychoeducational programs, and psychoanalytic treatment, these same treatments can also help gambling addicts overcome their addictions (Golebiowska & Golebiowska, 2018). In the context considered in this paper, the approach adopted can provide useful insights into support and care agencies. Our results show that the feelings expressed by those with gambling disorders are nearly as diverse as the variety of games they play. Compare the introspective despair and shame of a financially damaged gambler (Cluster 3) to another who angrily blames the casino for facilitating the situation (Cluster 7). Similarly, the melancholy tenor of a gambler in recovery (Cluster 1) may radiate joy and hope that is absent among those caught in a fearful cycle of self-loathing (Cluster 5). These results suggest that not all of those with a gambling disorder are the same and that the different clusters may require different combinations of available therapies. It may be that clusters that exhibit high fear, anger, and disgust emotions may benefit more from cognitive behavioural therapy than from other available therapies. However, any treatment considerations must necessarily require focused experimental research.

One possible variation of psychoanalytical treatment that goes beyond in-depth talking with those with a gambling disorder is to encourage problem gamblers to write down their thoughts and feelings. There is good evidence from linguistic psychology that when people who had experienced a period of upheaval in their lives were required to write down their feelings and life stories, they began to feel better (Pennebaker, 1997, 2011; Pennebaker & Francis, 1996; Pennebaker et al., 2003). Having clients write down their thoughts and feelings might not only help them feel better, but might also enable carers to use the resultant text as input to the *AlchemyLanguage* in IBM Watson to obtain scores of the emotions and sentiment of

participants. These scores can allow carers to classify participants according to one of the eight clusters identified in this research, thereby potentially facilitating a more finely tuned and nuanced way of addressing their problems. Encouraging those with a gambling disorder to record their thoughts and feelings in writing over time can not only benefit participants, but can also allow caregivers to track the progress (or lack thereof) of individuals and identify shifts in emotions and sentiment.

Online gambling has grown considerably in recent years, and firms in the sector are under increasing pressure from regulators to have in place systems that can flag problem gamblers. The data collection required for running the AlchemyLanguage in IBM Watson can be undertaken online with ease and in a non-intrusive manner. These characteristics suggest that online gambling firms may be able to use their customer data sources (email correspondence and call centre logs) to flag, at an early stage, customers prone to gambling addiction.

Limitations

The analytical process is not without its limitations, and generalizations of the clusters reported must be undertaken with caution. Not all those with a gambling disorder contribute to online forums, as some individuals are not aware of them, or know about them but prefer not to contribute. Moreover, those contributing to online forums may not possess gambling disorder to the same degree. Therefore, persons posting on forums such as the forum investigated here might come from two ends of a spectrum. On the one hand, there are those individuals who might feel that, at least temporarily, they are in control and want to share their positive emotions (joy). On the other hand, there are those individuals who are at a low point and need to share their frustration in the form of self-loathing (disgust), anger (at themselves and the system), fear (of what might happen), and sadness. In these circumstances, any drawing of broad conclusions about those with a gambling disorder needs to be undertaken with caution and subject to further research and conformation. A further concern is related to the use of the IBM Watson AlchemyLanguage. Other SA packages such as TextBlob, VADER, and Flair are available. The sentiment results obtained from these different packages will necessarily be influenced by the algorithm that each package uses. Different SA tools can, therefore, come up with different sentiment scores for the same piece of text.

Future Research

The study suggests several avenues for future research. First, it would be worthwhile to investigate the link between the emotions and sentiment expressed by individuals and their demographic characteristics, including gender, age, education level, and employment status. These links could indicate the extent to which different demographic categories express different emotions and sentiment. This type of investigation was not possible with the data collected in this study, as the demographic characteristics in the forum were incomplete. However, such an investigation could prove possible in situations in which problem gamblers seek face-to-face help

and can be persuaded to provide written expressions of their thoughts and feelings, as well as their demographic characteristics. Second, the IBM Watson suite used in this study could also be used in other forms of text analysis of the same corpus. For example, the IBM Watson suite also includes a Big Five personality (Goldberg, 1990) analysis platform that permits a researcher to gain insight into the Big Five personality traits of the authors of the texts analysed. In this way, not only can the personality traits of those with a gambling disorder be determined from the text analysis, but individuals could also be explored in terms of how they link to their expressed emotions and sentiment. Third, the same text could also be analysed by using a dictionary-based automated text analysis tool such as Linguistic Inquiry and Word Count (LIWC; Pennebaker et al., 2015). The consensual model of emotion (Watson et al., 1988) holds that positive and negative affect are two separate systems, with fear, anger, disgust, and sadness considered as negative emotions. It is therefore possible to use LIWC to generate the appropriate measures to create indices for positive emotion (based on 406 words) and negative emotion (based on 499 words), thereby grouping positive and negative emotions separately, and rerun the analysis to see whether meaningful clusters can be identified. The LIWC software also enables identification of other aspects of behaviour revealed in the text, including the extent to which the authors of the text are analytic in their expression, whether they speak with “clout” or authority, whether they are authentic (or honest), and what tone they use. The latter measure of tone could serve as an indication of the validity of the sentiment measure in IBM Watson because tone is measured on a scale that indicates the extent to which text is negative or positive. Validation of the IBM Watson Tone Analyser is discussed in “The Science Behind the Service” (IBM Watson, 2021). Moreover, SA results from IBM Watson can be compared to those obtained from other packages such as TextBlob, Vader, and Flair.

Aside from its human costs in terms of family, work, and personal life, gambling disorder has a massive financial impact. Fay (n.d.) on the debt help organization website Debt.org reports that around 23 million Americans go into debt because of gambling each year and that the average per capita loss of these individuals is around \$55,000. In many countries, the legal barriers to gambling are lower than they once were, and licensed casinos, state lotteries, and other opportunities to wager have proliferated in the physical environment. Moreover, the ability to gamble online has made it possible to place a bet via desktop and laptop computers at home and in the office, on tablet computers, and of course on the ubiquitous smartphone. For most people, these developments may not create problems. However, for those with a gambling disorder, the temptation to “try their luck” just one more time may prove overwhelming. It is hoped that a better understanding of the emotions and sentiment that these individuals experience and express will lead to better treatment for what is undoubtedly a major, yet mostly unrecognized, public health problem.

References

American Psychiatric Association. (2013). *Diagnostic and statistical manual of mental disorders* (5th ed.). <https://doi.org/10.1176/appi.books.9780890425596>

- American Psychiatric Association. (2018). *What is gambling disorder?* <https://www.psychiatry.org/patients-families/gambling-disorder/what-is-gambling-disorder>
- Auer, M., & Griffiths, M. (2013). Voluntary limit setting and player choice in most intense online gamblers: An empirical study of gambling behaviour. *Journal of Gambling Studies*, 29(4), 647–660. <https://doi.org/10.1007/s10899-012-9332-y>
- Barnes, G. M., Welte J. W., Hoffman, J. H., & Tidwell, M.-C. O. (2010). Comparisons of gambling and alcohol use among college students and noncollege young people in the United States. *Journal of American College Health*, 58(5), 443–452. <https://doi.org/10.1080/07448480903540499>
- Berthon P., Pitt L., & Campbell C. (2019). Addictive de-vices: A public policy analysis of sources and solutions to digital addiction. *Journal of Public Policy & Marketing*, 38(4), 451–468. <https://doi.org/10.1177/0743915619859852>
- Binde, P. (2007). Gambling and religion: Histories of concord and conflict. *Journal of Gambling Issues*, 20, 145–165. <http://dx.doi.org/10.4309/jgi.2007.20.4>
- Bowden-Jones, H., Thomas, S., & Drummond, C. (2017). *Rapid evidence review of evidence-based treatment for gambling disorder in Britain*. Royal College of Psychiatrists. https://www.rcpsych.ac.uk/pdf/RAPID_EVIDENCE_REVIEW_PG_RCPSYCH-DEC2016.pdf
- Buil, P., Moratilla, M. J. S., & Ruiz, P. G. (2015). Online gambling advertising regulations in Spain: A study on the protection of minors. *Adicciones*, 27(3), 198–204.
- Christensen D R., Jackson A C., Dowling N A., Volberg R A., & Thomas S. A. (2015). An examination of a proposed DSM-IV pathological gambling hierarchy in a treatment-seeking population: Similarities with substance dependence and evidence for three classification systems. *Journal of Gambling Studies*, 31(3), 787–806. <https://doi.org/10.1007/s10899-014-9449-2>
- Cosgrave J., & Klassen T. R. (2001). Gambling against the state: The state and the legitimation of gambling. *Current Sociology*, 49(5), 1–15. <https://doi.org/10.1177/0011392101495002>
- Custer, R. L. (1980, January 28). How problem gamblers can get help. *U.S. News and World Report*, 88, 75.
- Ekman P., & Friesen W.V. (1971). Constants across cultures in the face and emotions. *Journal of Personality and Social Psychology*, 17(2), 124–129. <https://doi.org/10.1037/h0030377>

Elfenbein H A., & Ambady N. (2002). On the universality and cultural specificity of emotion recognition: A meta-analysis. *Psychological Bulletin*, 128(2), 203–235. <https://doi.org/10.1037/0033-2909.128.2.203>

Fay, M. (n.d.). *Gambling and debt*. Debt.org. <https://www.debt.org/advice/gambling/>

Gainsbury S., Suhonen N., & Saastamoinen J. (2014). Chasing losses in online poker and casino games: Characteristics and game play of Internet gamblers at risk of disordered gambling. *Psychiatry Research*, 217(3), 220–225. <https://doi.org/10.1016/j.psychres.2014.03.033>

Goldberg, L. R. (1990). An alternative “description of personality”: The Big-Five factor structure. *Journal of Personality and Social Psychology*, 59(6), 1216–1229. <https://doi.org/10.1037//0022-3514.59.6.1216>

Golebiowska, M., & Golebiowska, B. (2018). Newest findings on gaming addiction treatment. *Journal of Education, Health and Sport*, 8(8)112–122. <https://doi.org/10.5281/zenodo.1298732>

Griffiths, M. D. (2013). Addiction on the Internet or addiction to the Internet? The case of online gambling addiction. *Journal of Behavioral Addictions*, 2(Suppl. 1), 16.

Harmon-Jones, C., Bastian, B., & Harmon-Jones, E. (2016). The Discrete Emotions Questionnaire: A new tool for measuring state self-reported emotions. *PLoS ONE*, 11(8), e0159915. <https://doi.org/10.1371/journal.pone.0159915>

Harries M. D., Redden S. A., & Grant J. E. (2018). An analysis of treatment-seeking behavior in individuals with gambling disorder. *Journal of Gambling Studies*, 34(3), 999–1012. <https://doi.org/10.1007/s10899-017-9730-2>

Hirschman, E. C. (1992). The consciousness of addiction: Toward a general theory of compulsive consumption. *Journal of Consumer Research*, 19(2), 155–179. <https://doi.org/10.1086/209294>

Humphreys, A. (2010). Megamarketing: The creation of markets as a social process. *Journal of Marketing*, 74(2), 1–19. <https://doi.org/10.1509/jm.74.2.1>

Humphreys, A., & Latour K. A. (2013). Framing the game: Assessing the impact of cultural representations on consumer perceptions of legitimacy. *Journal of Consumer Research*, 40(4), 773–795. <https://doi.org/10.1086/672358>

IBM Watson. (2021). *The science behind the service*. https://cloud.ibm.com/docs/services/tone-analyser?topic=tone-analyser-ssbts&mhsrsrc=ibmsearch_a&mhq=tone%20analyzer%20validation%20emotion

- Izard, C. E. (2010). The many meanings/aspects of emotion: Definitions, functions, activation and regulation. *Emotion Review*, 2(4), 363–370. <https://doi.org/10.1177/1754073910374661>
- Izard, C. E., & Haynes O. M. (1988). On the form and universality of the contempt expression: A challenge to Ekman and Friesen's claim of discovery. *Motivation and Emotion*, 12(1), 1–22. <https://doi.org/10.1007/BF00992469>
- Lesieur, H. R., & Custer R. L. (1984). Pathological gambling: Roots, phases, and treatment. *The Annals of the American Academy of Political and Social Science*, 474(1), 146–156. <https://doi.org/10.1177/0002716284474001013>
- Lorains, F. K., Cowlshaw, S., & Thomas, S. A. (2011). Prevalence of comorbid disorders in problem and pathological gambling: Systematic review and meta-analysis of population surveys. *Addiction*, 106(3), 490–498. [10.1111/j.1360-0443.2010.03300.x](https://doi.org/10.1111/j.1360-0443.2010.03300.x).
- Matsumoto, D. (1992). More evidence for the universality of a contempt expression. *Motivation and Emotion*, 16(4), 363–368. <https://doi.org/10.1007/BF00992972>
- McAllister, I. (2014). Public opinion towards gambling and gambling regulation in Australia. *International Gambling Studies*, 14(1), 146–160. <https://doi.org/10.1080/14459795.2013.861001>
- McDougall, W. (2015). *An introduction to social psychology* (14th ed.). Taylor & Francis. (Original work published 1908)
- Pak, A., & Paroubek, P. (2010). Twitter as a corpus for sentiment analysis and opinion mining. In *Proceedings of the International Conference on Language Resources and Evaluation (LREC'10)*(pp. 1320–1326). European Language Resources Association (ELRA). http://www.lrec-conf.org/proceedings/lrec2010/pdf/385_Paper.pdf
- Penguin Random House. (n.d.). *Stung: The incredible Obsession of Brian Molony by Gary Stephen Ross*. <https://www.penguinrandomhouse.com/books/157667/stung-by-gary-stephen-ross/>
- Pennebaker, J. W. (1997). Writing about emotional experiences as a therapeutic process. *Psychological Science*, 8(3), 162–166. <https://doi.org/10.1111/j.1467-9280.1997.tb00403.x>
- Pennebaker, J. W. (2011). *The secret life of pronouns*. Bloomsbury Press.
- Pennebaker, J. W., Boyd, R. L., Jordan, K., & Blackburn, K. (2015). *The development and psychometric properties of LIWC2015*. University of Texas at Austin.

- Pennebaker, J. W., & Francis, M. E. (1996). Cognitive, emotional, and language processes in disclosure. *Cognition & Emotion, 10*(6), 601–626. <https://doi.org/10.1080/026999396380079>
- Pennebaker, J. W., Mehl, M. R., & Niederhoffer K. G. (2003). Psychological aspects of natural language use: Our words, our selves. *Annual Review of Psychology, 54*(1), 547–577. <https://doi.org/10.1146/annurev.psych.54.101601.145041>
- Petry, N. M., Blanco, C., Auriacombe, M., Borges, G., Bucholz, K., Crowley, T. J., Grant, B. F., Hasin, D. S., & O'Brien, C. (2014). An overview of and rationale for changes proposed for pathological gambling in DSM-5. *Journal of Gambling Studies, 30*(2), 493–502. <https://doi.org/10.1007/s10899-013-9370-0>
- Philander, K. S., & MacKay, T. L. (2014). Online gambling participation and problem gambling severity: Is there a causal relationship? *International Gambling Studies, 14*(2), 214–227. <https://doi.org/10.1080/14459795.2014.893585>
- Pitt, C. S., Kietzmann, J., Wallstrom, A., & Botha, E. (2018). Emotions and sentiment: An exploration of artist websites. *Journal of Public Affairs, 18*(2), 1–4. <https://doi.org/10.1002/pa.1653>
- Pitt, C. S., Mulvey, M., & Kietzmann, J. (2019). Quantitative insights from qualitative data: An example from the healthcare sector. *Psychology & Marketing, 35*(12), 1010–1017. <https://doi.org/10.1002/mar.21152>
- Raz, G. (Host). (2012, December 2). ‘Bartholomew Biddle’: A writer’s 15-year adventure [Audio podcast episode]. In *Author interviews*. NPR. <https://www.npr.org/transcripts/166165421?storyId=166165421?storyId=166165421&t=1580022093139>
- Rosecrance, J. (1985). Compulsive gambling and the medicalization of deviance. *Social Problems, 32*(3), 275–284. <https://doi.org/10.2307/800687>
- Rosenthal, R. J. (2020). Inclusion of pathological gambling in DSM-III, its classification as a disorder of impulse control, and the role of Robert Custer. *International Gambling Studies, 20*(1), 151–170. <https://doi.org/10.1080/14459795.2019.1638432>
- Ross, G. S. (2002). *Stung: The incredible obsession of Brian Molony*. McClelland & Stewart.
- Rousseau, G. G., & Venter, D. J. L. (2002). Measuring consumer attitudes towards gambling. *SA Journal of Industrial Psychology, 28*(2), 87–92. <https://doi.org/10.4102/sajip.v28i2.50>
- Russell, J. A. (1991). Negative results on a reported facial expression of contempt. *Motivation and Emotion, 15*(4), 285–292. <https://doi.org/10.1007/BF00995646>

- Stout, G. F. (1899). *A manual of psychology*. University Correspondence College Press.
- Sutton, R., & Griffiths, M. D. (2007). The Casino Attitudes Scale: The development of a new brief psychometric instrument. *International Journal of Mental Health and Addiction*, 6(2), 244–248. <https://doi.org/10.1007/s11469-007-9127-z>
- Treen, E. R., Ferguson, S. T. L., Pitt, C. S., & Vella J. (2018). Exploring emotions on wine websites: Finding joy. *Journal of Wine Research*, 29(1), 64–70. <https://doi.org/10.1080/09571264.2018.1433139>
- Turney, P. D. (2002). Thumbs up or thumbs down? Semantic orientation applied to unsupervised classification of reviews. In *Proceedings of the 40th Annual Meeting of the Association for Computational Linguistics (ACL '02)* (pp. 417–424). <https://www.aclweb.org/anthology/P02-1053.pdf>
- Van Esch, P., & Cui, Y. (in press). Does consumer promiscuity influence purchase intent? The role of AI, change seeking, and pride. *Journal of the Association for Consumer Research*.
- Van Esch, P., & Van Esch, L. (2013). Justification of a qualitative methodology to investigate the emerging concept: The dimensions of religion as underpinning constructs for mass media social marketing campaigns. *Journal of Business Theory and Practice*, 1(2), 214–243. <https://doi.org/10.22158/jbtp.v1n2p214>
- Vermunt, J. K., & Magidson J. (2015). *Upgrade manual for Latent GOLD 5.1*. Statistical Innovations.
- Wardle, H., Moody, A., Griffiths, M., Orford, J., & Volberg, R. (2011). Defining the online gambler and patterns of behaviour integration: Evidence from the British Gambling Prevalence Survey 2010. *International Gambling Studies*, 11(3), 339–356. <https://doi.org/10.1080/14459795.2011.628684>
- Watson, D., Clark, L. A., & Tellegen, A. (1988). Development and validation of brief measures of positive and negative affect: The PANAS scales. *Journal of Personality Social Psychology*, 54(6), 1063–1070. <https://doi.org/10.1037/0022-3514.54.6.1063>
- Williams, R., Volberg, R., & Stevens, R. M. G. (2012). *The population prevalence of problem gambling: Methodological influences, standardised rates, jurisdictional differences and worldwide trends*. Report prepared for the Ontario Problem Gambling Research Center and the Ontario Ministry of Health and Long-Term Care. <https://hdl.handle.net/10133/3068>

Submitted November 15, 2020; accepted January 5, 2021. This article was peer reviewed. All URLs were available at the time of submission.

For correspondence: Terrance Brown PhD., Associate Professor, Unit of Sustainability, Industrial Dynamic & Entrepreneurship, Royal Institute of Technology (KTH), Stockholm, Sweden.

E-mail: terrence@kth.se

Competing interests: None reported (all authors).

Ethics approval: This study used secondary de-identified data.

Acknowledgements and/or Funding: None reported (all authors).