Risk Manag
https://doi.org/10.1057/s41283-018-0037-0

ORIGINAL ARTICLE

Managerial hubris detection: the case of Enron

Eyal Eckhaus[1] · **Zachary Sheaffer**[1]

Abstract Hubris is a known risk for leadership failure. We show that hubristic tendencies can be detected semantically ex-ante in textual reports, and offer a novel methodology aimed at detecting real-time hubristic propensities. The methodology employs text mining based on natural language processing (NLP) on Enron email corpus. NLP can capture information about employees and predict change patterns. Employing NLP real-time mechanism, Enron executives' hubristic tendencies were detected. Findings indicate that hubristic expressions amongst senior executives are significantly more frequent than amongst their non-senior counterparts, and that the frequency of hubristic expressions increases the closer one gets to Enron's collapse. Whilst both Enron's CEO's were hubristic, we found Skilling to be typified with severer hubris. Our study is the first to employ NLP real-time analytical process to detect the hubris disposition. Predicated on Enron's case study, we demonstrate the methodology's strengths, notably immediate recognition of accumulated symptoms and prevalence.

Keywords Hubris · Leadership · Enron · Natural language processing · Risk

Introduction

Hubris is an exaggerated pride or self-confidence, often resulting in retribution (Lewis 2006), and unbridled leadership, and hence, it constitutes a tangible

✉ Eyal Eckhaus
eyale@ariel.ac.il

Zachary Sheaffer
zacharys@ariel.ac.il

[1] Department of Economics and Business Administration, Ariel University, Ariel, Israel

Published online: 10 April 2018

corporate risk factor (Brennan and Conroy 2013). Hubristic CEOs engage in excessive risk-taking (Hollow 2014), biased reporting (Zeidan and Müllner 2015), and overestimate their ability to succeed (Hayward and Hambrick 1997). Throughout history hubris has been regarded a common reason for leadership Failure (Kroll et al. 2000), and the cause of colossal business failures including the Farrow Bank 1920 collapse, the Bricklin Project, an archetypal case of entrepreneurial hubris, and the Enron downfall, attributed to hubris-related fraud (Palus et al. 2011). History repeats itself despite the cataclysmic effects of managerial hubris associated with the 2008 global financial crisis. Studies on hubris offer guidelines aimed at detecting and preventing this syndrome (Kerfoot 2010) though organisations rarely address its causes. Our methodology detects real-time hubristic tendencies. Specifically, we argue that hubristic tendencies can be detected semantically ex-ante in textual reports. Detection may be undertaken in real-time based on emails. We make several contributions. First, we extend the semantic detection of Top Management Team's (TMT)'s hubris in textual context. Prior research on hubris examined transcribed samples produced by specific leaders, alleged as meeting hubris criteria (*cf.* Garrard et al. 2014). However, these studies fall short of validating findings by examining if the same hubris cues are used to identify it in different contents, or how hubris cues may be employed in other contents to generalise study findings. We present a case study based on this methodology, and we employ it to recognise and accumulate hubris cues. Second, we show that TMT's hubris can be detected in real-time before leaders engage in hubris-related inappropriate actions (Hollow 2014), with high impact on the risk management practice (Zhang et al. 2016). We employ NLP real-time procedure to expose and characterise top executives' hubristic predispositions. Predicated on the Enron email corpus, we evaluate whether hubristic dispositional symptoms typify seniors and non-senior managers. We also endeavour to detect hubristic tendencies longitudinally in order to explore whether they evolve and worsen overtime, commensurate with firms' gradual demise.

Theory

Hubris

The concept of hubris emanates from Greek mythology to illustrate "hamartia", or imperfections typifying sovereigns or conquerors in Greek tragedies (Antonacopoulou and Sheaffer 2014). Essentially, hubris is a cognitive bias that often affects managerial choices (Li and Tang 2010), and hence, it epitomises overconfidence and haughtiness that thwart comprehension or acceptance of human bounds (Petit and Bollaert 2012), specifically overestimation of leaders' endowments and capabilities (Hayward 2007). Bias breeds a delusion of control, fanciful anticipations and unfounded optimism (Fabre and François-Heude 2009). Hiller and Hambrick (2005) contend that hubris lies at the intersection of social comparison and self-serving bias, and that conceptually it overlaps with such social constructs as hyper-core self-evaluation (Cheung et al. 2016), brazenness (Hayward et al. 2004), and other counterproductive behavioural digressions. In Greek mythology, hubris is punished

by Nemesis (the spirit of divine vengeance) (Onayemi 2008). Similarly, business performance typically penalises managerial overconfidence (Anderson et al. 2008), because it instigates predisposition to endeavour risky strategies that typically precede cataclysmic consequences. Hubris is considered a vocational hazard for leaders in every domain. Hubris Syndrome–conceivably an acquired personality disorder (Owen and Davidson 2009), evolves when individuals assume positions of considerable power. Hubris has been typified as exaggerated self-belief (Brennan and Conroy 2013), disdain of peers' advice and critique, and disproportionate self-confidence. Hubris is related to a lack of humility (Chang and Diddams 2009) and engenders a sense of being 'intoxicated by power' (Owen 2006). The consequences of Hubris for military leaders including Napoleon, Saddam or Milosevic (Kroll et al. 2000), were profound and eventually self and nationally destructive. Likewise, business leaders' hubris results in such adverse corporate repercussions as loss of market share, diminishing strategic positioning and falling revenues (Haynes et al. 2015).

Scholarly discourse and media reports associate Enron's TMT with severe hubristic behaviour. Boje et al. (2003) referred to Enron's hubris-imbued corporate culture, where blatant evidences of TMT hubris were intertwined with the firm's ultimate collapse. The '*brutal competition*' between two top executives' hubris ultimately wrecked Enron (Peraino et al. 2002). Rapoport (2003) attributes Enron's collapse to '*humans and their hubris'*, whilst Chatterjee (2003, p. 145) suggests that Enron was a vivid instance of '*uncritical acceptance of accolade and narcissism*'. Hubris, then, is studied as self-deception or egocentric prejudice resulting in sub-conscious cognitive bias in corporate narratives (Merkl-Davies et al. 2011). This aspect has heretofore attracted scant scholarly interest in the disclosure literature (Brennan and Merkl-Davies 2013). This approach draws on impression management that postulates managers' opportunistic exploitation of information asymmetries between them and organisational audiences, by means of biased reporting (Merkl-Davies and Brennan 2007), associated with managerial hubris. Whereas impression management constitutes opportunistic managerial behaviour aimed at manipulating organisational audiences (Bozzolan et al. 2015), in terms of firms' perceptions of performance, hubris signifies self-deception or egocentric bias (Vance and Stuart 2015) that results in managers' prejudice regarding their own performance. Goldman (2006) advocates 'toxin detectors' to expose highly 'toxic leaders' including leaders' narratives (Pelletier 2010), in corporate reports that surface in e-mail messages (Kozinets et al. 2010). Amernic and Craig (2006) advocate a thorough analysis of words used by CEOs, as they possess unsettling clues concerning CEOs' thinking and behaviour, often indicative of leadership dysfunction.

The case study: Enron

Enron Corporation was an American energy, commodities, and services company, based in Houston. Prior to its bankruptcy on 2 Dec. 2001, Enron workforce amounted to approximately 20,000 staff and had a globally diverse business industries, with quoted revenues of nearly $111 billion during 2000 (Mergent Online), almost wholly predicated on its alleged trading revenues. Fortune named Enron

'*America's most innovative company*' for six consecutive years (BBC 2006b), seventh largest in Fortune 500, valued at US$70 Billion. Wide ranging external constituents hailed Enron as one of the most promising US companies (Gordon 2002), specifically as a company endowed by an archetypal "innovativeness" (Bicksler 2003). This "innovative" tag camouflaged disorganised, chaotic and excessively competitive intra-organisational corporate culture. Oddly, this exaltation persisted almost until Enron's bankruptcy. At the end of 2001, Enron's reported financial portfolio was sustained markedly by an institutionalised, systematic, and imaginatively schemed accounting fraud (Li 2010), known since as the Enron scandal. Enron has since become a renowned instance of intentional corporate fraud and corruption. This also raised questions concerning accounting practices, followed by the Sarbanes–Oxley Act. This scandal affected global business by triggering the dissolution of the Arthur Andersen. Scholarly discourse (*cf*. Rapoport 2003) and media coverage address every facet of this catastrophic business collapse. A variety of antecedents, mechanisms and aftermaths at diverse levels of analysis attempt to comprehend what happened at Enron, why and what are the fundamental business ethics and corporate governance consequences (Heath and Norman 2004). Whilst individual-level antecedents include such factors as greed (Dugan 2002), and trust (Hake 2005), we specifically focus on hubristic leadership amongst Enron's top-level executives.

Skilling

Jeffery Skilling was nominated President and Chief Operating Officer in 1996, and CEO in February 2001. An example of Skilling's fraud intentions embedded in his 'creative accounting' was his letters to shareholders in which he stated Enron's record of $1.3 billion in net income, whereas net income in audited reports was $978 million (Brewer 2007). With Enron's fall, Skilling did not abandon his trademark arrogance, and instead of declining to exercise the Fifth Amendment by remaining silent, he kept on lecturing, thus enraging legislators concerning the intricacies of accounting rules (Chaffin 2004).

Lay

Kenneth Lay was Enron's CEO and founder. Following Skilling resignation, Lay returned as CEO, promising that there were no "*accounting issues, trading issues, or reserve issues*" at Enron (Sims and Brinkmann 2003). On Sept. 26, 2001, Lay was still confident about Enron's financial robustness, stating: ''*the balance sheet is strong*'', ''*third quarter is looking great*,'' and ''*Enron stock is an incredible bargain at current prices*'' (Parloff 2006). Lay was vilified by federal prosecutors and the media as being the key executive in a massive fraud that destroyed jobs, savings, and shareholder wealth (Ferrell and Ferrell 2011). Hubristic executives tend to fall into the trap of listening only to people whose opinions are compatible with their own, whilst discouraging open discourse (Kroll et al. 2000). Watkins, former corporate development VP for stated in an interview: "*In the end, Enron is a story of failed leadership and even though Ken Lay likes to say that he was duped, he is the one who did not want to hear bad news, and in many ways, he enabled and*

nurtured the "*dupers*" (Nance and Koerwer 2004). A culture of arrogance and greed was evident at Enron's TMT (Rezaee 2002). He used the company jet to ferry his daughter home from school in Europe Skilling was arrogant and publicly dismissive of critique. However, Lay is the one who built the company and thus was instrumental in inculcating and steering its poor ethical record and, essentially hubristic propensities.

Thematic comparison of the current study with Brennan and Conroy's (2013)

Brennan and Conroy (2013) investigate letters to shareholders in annual reports by manually examining letters exchanged amongst shareholders over a decade. This procedure identifies phrases indicative of hubris. In what follows we compare between our study involving hubris detection's automated mechanisms and Brennan and Conroy's methodology. The comparison highlights advantages of real-time automated technique as opposed to manual procedures.

General

The automated redesign process is a useful alternative compared to the manual time-consuming task (Krause et al. 2013), essentially in terms of volume and time. Automation enables real-time responses to dynamic changes in such domains as trading (Davis et al. 2013), crisis management (Nathan and Kovoor-Misra 2002), and service organisations (Madu 1996). We argue that real-time and ex-ante hubris detection are important for early exposure of the syndrome, prior to potential future damages. Additionally, NLP prevents investigators' bias, likely to transpire in qualitative research (Soltani et al. 2014). Finally, we show NLP usefulness in analysing e-mails in organisational settings.

Automation

Automatic identification and extraction of text-based opinions, emotions, and sentiments is an important technique for information analysts in governmental, commercial and political loci (Wiebe et al. 2005). Likewise, sentiment analysis and opinion mining have been increasingly useful in interpreting metaphors, narratives and viewpoints (Pang and Lee 2008). Typically, automated content analysis explores texts tone by counting relative frequency of pre-specified key single words (Apel and Grimaldi 2014), and is less prone to subjective judgment (Yu 2015), less labour intensive (Lazar et al. 2010), and is easier to replicate (Arroniz 2007). Automated content analysis facilitates the detection of patterns that could otherwise be likely missed (Apel and Grimaldi 2014). Thus, information and cognitive science' computerised approaches are valid methods for simplifying text analyses (Indulska et al. 2012).

On the other hand, these methods enable the detection of subtle regularities in judgments that human analysts are unable to notice (Rosé et al. 2008). Furthermore, automated processing is preferred and is a necessity when addressing

voluminous texts (Gonález-Bailón and Petchler 2015). Owing to the phenomenal upsurge of electronic information (Tibi et al. 2017), automation appears crucial. The proposed methodology is meant to fit requirements of post-modern real-world scenarios in digital environments. The research mimics settings of such real-world environments by exploring an avowedly large sample of email messages. The sheer volume of texts can hardly be processed and examined manually in terms of time and other resources.

Our technique may be implemented in organisations with the view of allowing control over often innate risks exemplified by leadership personalities susceptible to such syndromes as hubris or extravagant narcissism. This technique enables real-time risk mitigation actions, hence may be applied preemptively. Similar practice is employed by the NSA to trigger alert messages (Savage 2013). For example, the following are excerpts of texts from the Enron email corpus typified by higher frequency of hubris keywords count:

"I am too busy and important to go on such short notice"

"It was only an $87 million mistake. I don't know what the big deal was"

"I prefer to do it myself, I like the way it looks when I do it"

It is important to note that there might be some drawbacks of the automated approach. Language complexity implies that automated content analysis cannot replace thorough text reading (Grimmer and Stewart 2013). Validation is essential since this method's efficiency on new dataset cannot be guaranteed (ibid). Automated content analysis may occasionally be prone to errors. This happens in case of double meanings including nicknames that carry specific meanings (Vergeer and Hermans 2008). Pertinently, unlike humans, computers are devoid of commonsense. There exists no best automated method. Some function better than others in specific contexts (Calle-Alonso et al. 2013). Consequently, labour intensive manual content analysis is often required, notably in cases of unstructured vague or undistinguishable texts (Heidari and Felden 2015). Manual content analysis enables human coders to detect nuances embedded in texts (e.g. sarcasm), undetectable by computers (Guo et al. 2016). Another challenge regards stemming, the process of converting variations of a word into a concise and accurate representation (Alvares et al. 2005). Stemming is liable to result in ambiguity (Arendt and Karadas 2017). For example, when such keywords as "state" are employed (in speech contexts), stemming will necessarily add the word "states" implying a nation or territory, which are contextually irrelevant.

Volume and time

Studying, understanding and utilising documents' content require automated techniques designed to effectively extracting useful information (Rotella et al. 2015). Computational approaches' advantages refer to scalability, repeatability and consistency, which facilitate markedly the analysis of voluminous data that pose substantial difficulties if analysed manually (Indulska et al. 2012), that is time-consuming and more expensive (Li and Liu 2014).

Real-time detection

For competitiveness companies must bridge across time and space concurrently in order to facilitate decision-making (Coleman and Ward 1999). In post-modern information society, technology allows real-time monitoring of users' context (Baladrón et al. 2012). Increasingly, real-time technology is becoming important owing to growing dependence on instantaneous solutions (Malhotra 2005). We offer a real-time detection mechanism for the hubris syndrome, thus facilitate immediate board action in following detection of hubristic tendencies. In contrast, Brennan and Conroy (2013)'s methodology is manual and involves post-ante content scanning as opposed to real-time analysis, long after hubris has taken root, thus exacerbating potential corporate damage. Our methodology may be applied by organisations to detect hubristic tendencies automatically by observing changes or pronounced hubristic manifestations.

Ex-ante and post-ante detection

Preventing or reducing CEO's hubris constitutes a major organisational challenge (Petit and Bollaert 2012). Hubris is difficult to diagnose, either in leaders or in ourselves (Lines 1999). Moreover, as evidenced in the 2008 global financial crisis, consequences of leadership hubris are liable to spill over, thus entangle firms, industries and entire economies. Indeed, leaders' hubristic behaviour incurs grave repercussions globally (Lawrence et al. 2011). To prevent or tackle risky hubristic tendencies, it must first be detected. Indeed, critical to effective crisis management is detection of early warning signals (Sheaffer et al. 1998). Extant crisis literature shows that organisational early crisis detection strategies significantly improve crisis preparedness (Appelbaum et al. 2012; Sheaffer and Brender-Ilan 2014). Pertinently, early detection of fraud has been shown to be critical in federal agencies (Khanin and Mahto 2012). We argue that hubristic tendencies may be detected semantically ex-ante in textual reports by way of exposing real-time formation of hubristic predispositions. This facilitates appropriate solutions to hubris before it turns organisationally destructive.

Bias analysis

Bias often typifies hypotheses or theory (Goode and Evans 2007). It may be that findings are pointed to due to investigators' biases or observational habits (Cope 2014). Else, investigators make systematic errors in data analysis which often yields significant findings only for them (Sawin 2005). Aptly, Brennan and Conroy (2013) note that their study of CEO discourse is highly subjective and a second coder may arrive at different results. Hubris manual identification based on content analysis is liable to be innately subjective or biased since scientific objectivity cannot be applied to meaning-oriented content analysis in unmodified form (Merkl-Davies et al. 2014). Automated content analysis helps to mitigate human biases (Nunez-Mir et al. 2016). Thus, the need for reliable and scalable solutions in analysing messages calls for an automated-objective content analytical techniques (Scharkow 2013).

Noteworthy is that in some situations, automated approaches are liable to be prone to bias. In automated analyses, the frequency of keywords in the text is employed as a measure of the extent to which the text belongs to a predefined category (van der Meer 2016). These keywords need to be carefully constructed in order to avoid investigators' bias (Fteimi and Basten 2015).

Automated methods are also liable to language bias when validated predominantly with textual data in English whenever the analysed content is undertaken by non-English speakers (Haselmayer and Jenny 2017).

Applicability

We employ an analytical technique based on keywords mined from an organisational email corpus. Keywords are based on Garrard et al. (2014). The Enron email corpus is regarded a valuable research database (Crabb 2014). Prevalence of email enables the implementation of the proposed methodology aimed at detecting leaders' hubristic propensities. Brennan and Conroy (2013) investigate annual reports and letters to shareholders which are largely subjective and constitute a promotional text (Hyland 1998). Thus, as opposed to objective content analysis involving routine word counting (Smith and Taffler 2000), a subjective content analysis is liable to result in false conclusions. In their analysis of CEO's letters to petroleum industry shareholders, Prasad and Raza (2002) found that these letters were aimed at generating a certain attitude towards OPEC amongst recipients, that deflected attention from the crisis of legitimacy faced by oil companies domestically (Prasad and Raza 2002). Patelli and Pedrini (2015) analysed annual letters to shareholders and found specific language tones involving aggressive financial reporting to be positively associated with resolute, complex, and not engaging language. This suggests that annual reports may be written with similar style and thus identification of traits may occasionally be false.

Methodology

We employ text analysis procedures that include text mining, a variation of data mining (Raval et al. 2011), applicable for organisational research (Alvesson and Karreman 2000). Increasingly, large amounts unstructured textual data defy simple attempts to make sense of it (Lee et al. 2010). Owing to increased number of such readily available electronic information as digital libraries, emails and blogs, text mining popularity grows (Irfan et al. 2015). Unlike data mining, text mining is predicated on such unstructured or semistructured text documents as web pages, newsgroup postings or corporate documents (Kin-Nam et al. 2005). It involves computation of extracted meaningful information (Harpaz et al. 2014), aimed at gaining knowledge not explicitly stated in texts (Zweigenbaum et al. 2007),and it enables a solution for specific information needs (Cohen and Hunter 2013). The formation of new facts or hypotheses from extracted information may be further explored with other conventional means of experimentation (Dai et al. 2010). This contrasts traditional information retrieval in which no genuinely new information is found and the information simply coexists with other valid pieces of information

(Ojo and Adeyemo 2013). Moreover, manual curation is time-consuming, and does not scale with the growth of available literature (Winnenburg et al. 2008). Additionally, human text annotation is difficult for experts to agree on (Halevy et al. 2009). Text mining is suitable for qualitative research since content with similar topics may have different wording (Scherf et al. 2005), and although it involves word counting and seemingly a quantitative method, its data are still qualitative (Yu et al. 2011). This technique enables a high degree of consistency, most suitable for qualitative research, and has been frequently used in social media (Saif et al. 2016). To meet challenges of unstructured text, text mining employs wide ranging techniques associated with natural language processing (NLP). NLP is a computational analysis approach involving human language text classification (Al-Alwani 2015). In NLP, the most common text representation is '*Bag-of-Words'* (BOW) (Razavi et al. 2014), an illustrious knowledge structure-based approach (Thorleuchter and Poel 2016), in which documents are represented as a collection of words, regardless of grammar and word order (Cheng et al. 2010), and classification is based on the presence or absence of the predefined set of words (or terms) (Altinçay and Erenel 2014). This simple representation has proved successful in text classification tasks (Wallace 2015), and is recently dominating NLP research. The most basic, binary feature of this method specifies if a word appears within a specific content (bag) (Wu et al. 2014). We employ this technique on email corpus with arbitrary messages that require text mining (van der Aalst and Nikolov 2008), with the benefit of analysing email communications designed to capturing information about employees and prediction of change patterns (Grobelnik et al. 2009).

In May 2002, the Federal Energy Regulatory Commission (FERC) publicly released Enron's corpus of emails. FERC employs this procedure in order to improve public understanding of reasons underlying the investigation of Enron. We employ Enron corpus, known as a reliable source of data for research as it contains relatively recent conversational language (Lindsey et al. 2007). This dataset has been used extensively for research including data mining, text analysis, and NLP (Wilson and Banzhaf 2009). The sheer volume of email traffic makes email communication a suitable archive of organisational knowledge evolution (Storga et al. 2013). Such large corpora yield good results in text mining (Cohen et al. 2013). Akin with studies that used Enron corpus (*cf*. Eckhaus 2016), we employ a Structured Query Language (SQL)-based processed database of Enron corpus (Shetty and Adibi 2004). This procedure removed duplicate emails, computer generated folders, junk data, invalid email addresses and blank messages, and imports all email messages into a relational database. It enables query analysis using SQL, a relational database language that takes advantage of data's regular structure stored in tables (Özcan et al. 2006). In SQL, the result of the queries is data extracted which are then analysed statistically.

The personnel occupational status of a subset of Enron employees first utilised by Shetty and Adibi (2004), and later complemented by Carmeli and Sheaffer (2009), who classified employees into four occupational categories: senior managers, mid-level managers, traders and employees. These investigators automatically extracted social hierarchies from electronic communication data. Carmeli and Sheaffer (2009, p. 42) argue that their dataset follows "*research groups around the country who*

obtained and manipulated the dataset in a variety of ways in attempts to correct inconsistencies and integrity issues within the dataset". This study presents the complete list of the 149 employees with their job status. The four groups in our study have been employed in previous research, and hence, this is less prone to bias, which may have been the case had manual classification been conducted.

Since senior managers are more hubris prone (Lawrence et al. 2011), we generated two distinctive subsets; senior executives and all the rest. Next, we counted the number of hubris distinct expressions for each email sent. For hubris expressions, we followed Garrard et al. (2014) study who examined transcribed spoken discourse samples of two British Prime Ministers (Thatcher and Blair), who met hubris criteria, with detailed hubris tendencies during incumbency. Garrard et al. extracted keyword list using computerised means. An important leadership attribute applies to speaking and writing qualities. Business leaders, juggle diverse stakeholder groups, each with its preferred language and interests (Greatbatch and Clark 2005; Simons 2002). Since both politicians and business leaders are prone to hubris (Owen 2007), hubris keywords typifying politicians, also mirror their business leaders counterparts' speech and writing style. For instance, "*Soon after winning a second term as Prime Minister in 2001, Blair continued to display signs of HS when he introduced into his Downing Street office a new administrative structure under which decision-making on foreign affairs and defence strategy were effectively transferred from their respective Government departments*". Garrard et al. found that while both Thatcher and Blair's behaviour implied hubris, Blair's indications of hubris were more accentuated. For instance:

'…the use of the first person singular forms 'I' and 'me' have positive correlates, pointing to a growing sense in the speaker's estimation of his perceived personal importance), and

"*Blair's use of first person plural pronouns in comparison to their singular equivalents is higher, throughout his term of office*" (p. 12). Though Bair's and Teacher's word list is mostly different, some words are similar. Both have the unigram "Shall", and the bigram "I Shall". Since Blair's spoken discourse show higher markers of hubris, it is obvious that the word lists differ between two leaders typified by different levels of hubris. The word list is therefore symptom specific (hubris), and not person specific. We therefore followed Garrard et al.'s list of words used by Blair as a measure for hubris (Appendix). We use the entire set of 30 words presented by Garrard et al. top 10 positive unigram (single word), top 10 bigram (two occurring words), and top 10 trigram (three occurring words), which were consistently frequent during Blaire's incumbency. The word list is typically constructed from the most frequent occurrences of keywords, since no meaning can be inferred from low frequency words. In another example, Salter et al. (2013) constructed a keyword list used with the highest frequency by transformational leaders.

Findings

Senior management set includes 39 of 149 employees for whom job status was defined. The set includes 25,292 emails sent by these seniors, and 61,351 emails

Table 1 Comparing hubristic keywords: seniors versus non-seniors

Groups	*N*	Mean	SD	*t*
Non-seniors	61,351	1.43	1.27	− 12.4***
Seniors	25,292	1.55	1.29	

*** $p < .001$. *N* number of emails sent

Table 2 The difference between seniors and non-seniors in the use of plural expressions

Groups	*N*	Mean	SD	*t*
Non-seniors	61,351	0.72	0.9	− 26.28***
Seniors	25,292	0.91	0.96	

*** $p < .001$. *N* number of emails sent

sent by non-seniors, from a total of 252,693 emails left following 'cleansing' the entire Enron set. In order to ascertain that hubris is more prevalent amongst TMT members, we ran *t* tests to compare the number of hubristic expressions between the two subsets of employees (Table 1). Results indicate a statistically significant difference between seniors and non-seniors ($t = -12.4$; $df = 46{,}179$; $p < 0.001$), indicating that hubristic expressions amongst senior executives are significantly more frequent.

The tendency to speak in third person or use the Royal 'we', would predict that the frequency of the first person plural pronouns ('we', 'us' and 'our') will be high, in hubristic subjects' (Owen and Davidson 2009). We applied this technique and counted the number of appearances of plural occurrences ('we', 'us' and 'our'). Then, *t* test was used to compare seniors versus non-seniors in the use of plural. Results indicate (Table 2) a statistically significant difference between the subsets in the use of plural expressions ($t = -26.28$; $df = 44{,}207$; $p < 0.001$). Seniors' plural expressions are significantly higher.

Chatterjee and Hambrick (2007) note that the CEO's use first-person singular pronouns ('I', 'me' and 'my') is also indicative of narcissistic tendencies, and thus may lead to hubris. Consequently, we ran a *t* test that shows a significant difference between seniors and non-seniors in the use of singular expressions ($t = -13.86$; $df = 47{,}788$; $p < .001$), demonstrating that seniors' singular expressions are significantly more frequent than non-seniors'. This finding was expected since the words 'I' and 'Me' appear in the list of hubristic words used earlier, and it corroborates our findings. Meaning, in both cases, singular and plural expressions are used more often by seniors. In order to substantiate that the difference between seniors and non-seniors in the use of both plural and singular forms exist without mutual influence, we performed a univariate analysis where singular expressions are used as co-variant, when examining plural expressions (seniors vs. non-seniors). The univariate analysis (Table 3) shows the use of plural expressions to differ significantly between the subsets. Meaning, even when singular expressions are used as co-variant, we still identify statistical significance in the use of plural expressions. Specifically, seniors use plural expressions more frequently than non-seniors.

Table 3 Univariate analysis in which singular expressions ('I', 'me' and 'my') are co-variants

Groups	*N*	Mean	SE
Non-seniors	61,351	0.731	0.003***
Seniors	25,292	0.886	0.005

*** $p < .001$'. *N* number of emails sent

Finally, the manifestation of hubristic tendencies overtime is displayed. Senior executives' hubristic expressions for each day in the database (4 May 1999 to 25 March 2002).

Figure 1 shows that the frequency of hubristic expressions increases the closer one gets to Enron's collapse. On 22 October 2001, the shares of Enron plunged after SEC announced it was investigating suspicious deals, characterising them as "*some of the most opaque transactions with insiders ever seen*" (Norris 2001). Following the SEC announcement, an immediate decrease was recorded in Enron share price. On that specific day hubris expressions rose to the highest peak of 387.

Application of the methodology: a case study

Next, we describe our methodology's usefulness. We suggest that it cannot only recognise and accumulate hubris cues, but it also measures the extent of its prevalence. For this purpose, we compare hubristic tendencies between the two Enron CEOs, (Lay and Skilling), and show who was more hubristic.

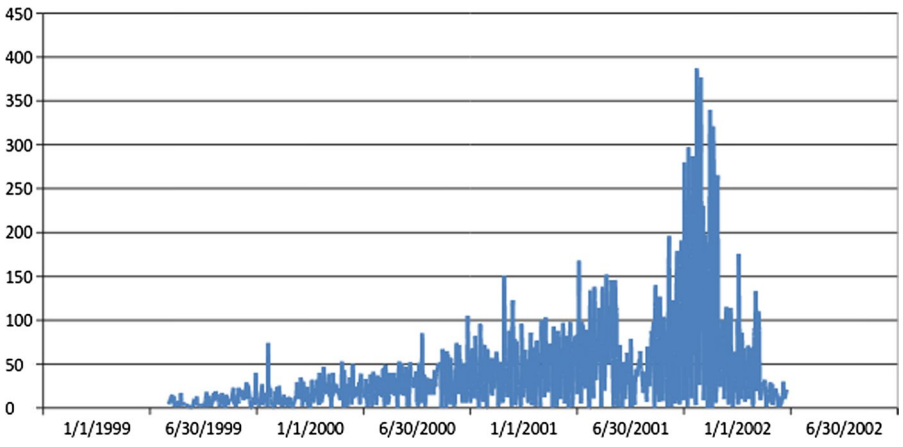

Fig. 1 Senior management's hubris expressions overtime

Case study analysis

We collected all emails in the database sent from Skilling ($n=72$) and Lay ($n=35$). Since the number of emails does not suffice to examine all hubristic expressions, we employ Owen's (2011) supposition that an effect of the hubris syndrome is the tendency to speak in the third person or use the royal 'we'. Hence, we counted plural occurrences ('we', 'us' and 'our') in both CEOs' emails.

Data were analysed using independent samples *t* test to examine who's hubristic behaviour was more prevalent (Table 4).

Case study results

In order to ascertain that hubris cues are more prevalent in Lay's e-mails, we compared the two CEO's using *t* test (Table 4). Results indicate a statistically significant difference between Skilling and Lay ($t=-3.15$; $df=105$; $p<0.01$).

Lay claimed he knew nothing about fraudulent actions, as Enron juror Baggett asked, ''*For a man that knew every aspect of that business and seemed to know every deal, why didn't he know what was going on*?" (Ferrell and Ferrell 2011). Oftentimes hubris arises from success. Powerful people become self-absorbed and being overconfident they downplay other viewpoints because they endorse information filtering, commensurate with their success (Kerfoot 2010). However, whilst both Lay and Skilling were hubristic, Skilling externalised it more than Lay (BBC 2006a, 23 October 20, p. 42). Thus, an external observer would deduce that Skilling was more hubristic than Lay, who allegedly concealed its indications. The case study analysis accentuates our methodology's usefulness as it provides empirical evidence than merely recognising and accumulating hubristic cues. Our methodology also enables the measurement of the extent of this phenomenon's prevalence.

Discussion

Such cognitive biases as hubris (Li and Tang 2010) incur potentially harmful consequences on corporate survival if afflicted leaders' behaviour is not being monitored, reported and addressed timely. Our study sheds light on the way such discourses as e-mail messages disclose purportedly detrimental hubristic symptoms. Following successful use in such domains as accounting, auditing and finance (Fisher et al. 2016), we use it for hubris detection. No other published study has thus far employed NLP analytical process to detect hubris. Predicated on an archetypal case

Table 4 Plural expression comparison ('we', 'us' and 'our') between lay and skilling

	N	Mean	SD	*t*
Lay	35	1.54	0.741	− 3.15**
Skilling	72	0.93	1.03	

** $p<.01$. *N* number of emails sent

study we demonstrated the methodology's strengths, notably immediate recognition of accumulated symptoms and their prevalence. The study of hubristic leaders has recently gained substantial momentum, notably following the 2008 global financial crisis that exposed embedded corporate weaknesses, including narcissism and hubris (Patel and Cooper 2014). Pertinently, these vulnerabilities often emanate from corporate leaders' hubristic propensities that engender biased, hence improbable perceptions that often delude them into underestimating risks whilst concurrently overrating their competences. Our ability to identify hubristic symptoms has improved dramatically, although documentation of hubris cues has been done invariably post-ante. A methodology is exemplified that enables ex-ante detection of hubris symptoms. Our contribution may be described along several parameters. First, automated or NLP procedure with which to detect hubris in voluminous email messaging. Second, our mechanism enables a real-time detection of hubris, which in-turn enables boards to effectuate their 'guarding dog' governance chore. Whilst evidently a delicate task, still tracking and identifying worrisome behavioural expressions may accurately, objectively and timely deter and attenuate leadership hubris. The mechanism we test enables real-time accumulative detection of hubris symptoms and compared to previous analyses is noticeably less time-consuming and may handle virtually limitless materials. Third, real-time detection process allows hubristic tendencies to be noticed semantically ex-ante in textual messages. This is done by way of identifying real-time formation of a newly evolving hubristic predispositions as opposed to manual content analysis that pertains post-ante content scanning after hubris has taken root. Fourth, in lieu of undertaking manual and arduous content analysis we demonstrate an automated, reliable and scalable solution. This neutralises or precludes investigators' subjective interference. Fifth, we employed NLP on an organisational email corpus showing that it may be effectively implemented to detect personal syndromes.

Detecting early warning signals is of paramount importance irrespective of whether these indications pertain to organisation-wide weakness symptoms else worrisome indications of leadership behaviour. Some significant progress has been made in accentuating the pivotal role of early warning signals in the extant organisational crisis, finance and risk management literatures. This applies to the finance domain (*cf.* Bussiere and Fratzscher 2006), notably the domain of (business) failure prevention (Li et al. 2012); risk management (Yang et al. 2001) and crisis management at large. That said, few have thus far investigated how top leaders' psychological state expressed by hubristic symptoms, enable perspicacious boards to identify looming problems. This task is necessarily ticklish since boards' overarching responsibilities do not involve in-depth analysis or evaluation of CEOs' mental or psychological disposition (Leary et al. 2013). This, despite the fact that in the end what drives leaders' behaviour at large and decision-making in particular is their personalities (Hannah et al. 2013). Pertinently, we showed how hubristic tendencies can be detected effectively in real time, and thus enable boards to identify evolving leadership dysfunctionalities liable to result in cataclysmic financial repercussions. The 'what if' question appears conspicuously relevant when asking what could be saved financially and otherwise if corporate boards were aware of the ability to identify executives' flagrant hubristic propensities prior to related corporate failure.

Limitations and future studies

Access the firms' intranet is a noticeable obstacle, particularly for scholarly research, and therefore, the likelihood of access to 'live' executives' electronic correspondence is avowedly limited. Hence, it seems highly implausible that firms would voluntarily enable investigators to access this means of correspondence. This, necessarily precludes NLP real-time analysis. This procedure, therefore, is inevitably constrained to internal auditing and as such it constitutes a powerful governance apparatus with which to closely track top executives' personalities as reflected by their messages wording and content. A conspicuous limitation in this study is that it draws on a single corporation's e-mail corpus, and thus precludes potentially useful comparisons. Moreover, NLP may be useful in identifying and interpreting additional psychological syndromes as well as overall leadership style. The study employs the Bag-of-Words Approach, which is a popular way of document representation. Future studies may extend this framework by employing other NLP techniques. Future investigators may extend the scope to a larger set of words. Our statistical analyses were evidently rudimentary, mirroring data constraints. Such additional analyses as Mancova may be employed in future studies contingent on the relative richness of the extracted data. Data on leadership style obtained through different wording identification (Salter et al. 2013), for instance may be conjoined with data from the same research population. This would enable a richer and more complex research model where leadership styles could be adjoined with leadership psychological dispositions.

Theoretical and practical implications

Leadership hubris has attracted scholarly interest for some 70 years, and the hubris phenomenon has been addressed extensively. Hubris has recently been addressed chiefly by students of ethics (McManus 2016), economics and decision-making (Boumans 2015), commensurate with such major occurrences in which leadership hubris surfaces, as global financial crises or wars. Recent theoretical implications span a variety of disciplines including psychiatry (paranoia), psychology (self-interest, self-assessment, self-aggrandisement, overconfidence and narcissism), business ethics, risk research, sociology (support of military options) and governance (social responsibility).

Our study points to several hands-on implications, not least of which is the detection of hubristic tendencies predicated on leaders' speech, writing and behavioural cues. Detection of hubristic predispositions may be applied by HRM tests involving selection and assessment of prospective managers. This enables a priori classification of embedded hubristic propensities. The detection of hubristic dispositions may also be applied by board of directors one of whose tasks is to oversee top executives' conduct. Early detection of hubristic tendencies may constitute a useful governance mechanisms designed to focus on excessive leadership self-centeredness (Carmeli and Sheaffer 2009) that often demarcate early warning signals.

Appendix: Garrard et al. (2014)'s Tony Blair words

1-grams[a]	2-grams[a]	3-grams[a]
Engagements	Position exactly	Will have further
Learned	Things about	I will have
Condolences	Our human	House my hon
ME	For allocation	And learned gentleman
Killed	I will	My engagements I
SURE	Get under	Hon and learned
I	Can working	Right that is
Listing	Rejoin the	Have further such
Important	Let me	Condolences to the
Antisocial	Of enforcing	Me in wishing

[a]N-gram is the sequence of n items

References

Al-Alwani, A. 2015. Improving email response in an email management system using natural language processing based probabilistic methods. *Journal of Computer Science* 11 (1): 109–119.

Altinçay, H., and Z. Erenel. 2014. Ternary encoding based feature extraction for binary text classification. *Applied Intelligence* 41 (1): 310–326.

Alvares, R.V., A.C.B. Garcia, and I. Ferraz. 2005. *STEMBR: A stemming algorithm for the Brazilian Portuguese language*. Paper presented at the 12th Portuguese Conference on Artificial Intelligence, EPIA, Covilhã, Portugal, December 5–8.

Alvesson, M., and D. Karreman. 2000. Taking the linguistic turn in organizational research: Challenges, responses, consequences. *The Journal of Applied Behavioral Science* 36 (2): 136–158.

Amernic, J., and R. Craig. 2006. *CEO-speak: The language of corporate leadership*. McGill-Queen's Press-MQUP.

Anderson, C., D.R. Ames, and S.D. Gosling. 2008. Punishing hubris: The perils of overestimating one's status in a group. *Personality and Social Psychology Bulletin* 34 (1): 90–101.

Antonacopoulou, E.P., and Z. Sheaffer. 2014. Learning in crisis: Rethinking the relationship between organizational learning and crisis management. *Journal of Management Inquiry* 23 (1): 5.

Apel, M., and M.B. Grimaldi. 2014. How informative are central bank minutes? *Jahrbuch für Wirtschaftswissenschaften* 65 (1): 53–75.

Appelbaum, S.H., S. Keller, H. Alvarez, and C. Bédard. 2012. Organizational crisis: Lessons from Lehman Brothers and Paulson & Company. *International Journal of Commerce & Management* 22 (4): 286–305.

Arendt, F., and N. Karadas. 2017. Content analysis of mediated associations: An automated text-analytic approach. *Communication Methods and Measures* 11 (2): 105–120.

Arroniz, I. 2007. *Extracting quantitative information from nonnumeric marketing data: An augmented latent semantic analysis approach*. Ann Arbor: University of Central Florida.

Baladrón, C., J.M. Aguiar, L. Calavia, B. Carro, A. Sánchez, and A. Cadenas. 2012. User-oriented environment for management of convergent services. *IEEE Communications Magazine* 50 (11): 142–149.

BBC. 2006a. Profile: Jeffrey Skilling. 23 Oct.

BBC. 2006b. Q&A: The Enron case.

Bicksler, J.L. 2003. What we know and what we don't know about corporate governance. *Business Economics* 38 (2): 69–73.

Boje, D.M., G.A. Rosile, R.A. Durant, and J.T. Luhman. 2003. Enron spectacles: A critical dramaturgical analysis. *Organization Studies* 25 (5): 751–774.

Boumans, M. 2015. *Hubris: Why economists failed to predict the crisis and how to avoid the next one*. London: Yale University Press.

Bozzolan, S., C.H. Cho, and G. Michelon. 2015. Impression management and organizational audiences: The Fiat group case. *Journal of Business Ethics* 126 (1): 143–165.

Brennan, N.M., and J.P. Conroy. 2013. Executive hubris: The case of a bank CEO. *Accounting, Auditing & Accountability Journal* 26 (2): 172–195.

Brennan, N.M., and D.M. Merkl-Davies. 2013. Accounting narratives and impression management. In *The Routledge companion to accounting communication*, ed. L. Jack, J. Davison, R.Craig. London: Routledge.

Brewer, L. 2007. A causal model of organizational performance and change. *The Journal for Quality and Participation* 30(1): 26-28, 48.

Bussiere, M., and M. Fratzscher. 2006. Towards a new early warning system of financial crises. *Journal of International Money and Finance* 25 (6): 953.

Calle-Alonso, F., C.J. Pérez, J.P. Arias-Nicolás, and J. Martín. 2013. Computer-aided diagnosis system: A Bayesian hybrid classification method. *Computer Methods and Programs in Biomedicine* 112 (1): 104–113.

Carmeli, A., and Z. Sheaffer. 2009. How leadership characteristics affect organizational decline and downsizing. *Journal of Business Ethics* 86 (3): 363–378.

Chaffin, J. 2004. Enron: The countdown to court leader of boys' club culture the chief executive. *Financial Times*, 2004 Feb 20, p. 25

Chang, G., and M. Diddams. 2009. Hubris or humility: Cautions surrounding the construct and self-definition of authentic leadership. *Academy of Management Proceedings*, 1–6.

Chatterjee, A., and D.C. Hambrick. 2007. It's all about me: Narcissistic chief executive officers and their effects on company strategy and performance. *Administrative Science Quarterly* 52 (3): 351–386.

Chatterjee, S. 2003. Enron's incremental descent into bankruptcy: A strategic and organisational analysis. *Long Range Planning* 36: 133–149.

Cheng, L.T.E., J. Zheng, G.K. Savova, and B.J. Erickson. 2010. Discerning tumor status from unstructured MRI reports—completeness of information in existing reports and utility of automated natural language processing. *Journal of Digital Imaging* 23 (2): 119–132.

Cheung, H.Y., J. Wu, and J. Tao. 2016. Predicting domain-specific risk-taking attitudes of mainland China university students: A hyper core self-evaluation approach. *Journal of Risk Research* 19: 79–100.

Cohen, K.B., and L.E. Hunter. 2013. Chapter 16: Text mining for translational bioinformatics. *PLoS Computational Biology* 9(4): e1003044.

Cohen, R., M. Elhadad, and N. Elhadad. 2013. Redundancy in electronic health record corpora: Analysis, impact on text mining performance and mitigation strategies. *BMC Bioinformatics* 14: 10.

Coleman, D., and L. Ward. 1999. Taking advantage of real-time collaboration tools. *IT Professional Magazine* 1 (4): 25–30.

Cope, D.G.P.A.B.C.A. 2014. Methods and meanings: Credibility and trustworthiness of qualitative research. *Oncology Nursing Forum* 41 (1): 89–91.

Crabb, E.S. 2014. Time for some traffic problems: Enhancing e-discovery and big data processing tools with linguistic methods for deception detection. *Journal of Digital Forensics, Security and Law* 9 (2): 167–179.

Creamer, G., R. Ryan, H. Shlomo, and J.S. Salvatore. 2009. Segmentation and automated social hierarchy detection through email network analysis. In *Advances in web mining and web usage analysis*, eds. Z. Haizheng, S. Myra, M. Bamshad, C.L. Giles, M. Andrew, N. Olfa, S. Jaideep, and Y. John, 40–58. Springer.

Dai, H.-J., Y.-C. Chang, R. Tzong-han Tsai, and W.-L. Hsu. 2010. New challenges for biological text-mining in the next decade. *Journal of Computer Science and Technology* 25 (1): 169–179.

Davis, M., A. Kumiega, and B. Van Vliet. 2013. Ethics, finance, and automation: A preliminary survey of problems in high frequency trading. *Science and Engineering Ethics* 19 (3): 851–874.

Dugan, I.J. 2002. Before Enron, greed helped sink the respectability of accounting. *The Wall Street Journal*, March, 14.

Eckhaus, E. 2016. Corporate transformational leadership's effect on financial performance. *Journal of Leadership, Accountability and Ethics* 13(1).

Fabre, B., and A. François-Heude. 2009. Optimism and overconfidence investors' biases: A methodological note. *Finance* 30 (1): 79–119.

Ferrell, O.C., and L. Ferrell. 2011. The responsibility and accountability of CEOs: The last interview with Ken Lay. *Journal of Business Ethics* 100 (2): 209–219.

Fisher, I.E., M.R. Garnsey, and M.E. Hughes. 2016. Natural language processing in accounting, auditing and finance: A synthesis of the literature with a roadmap for future research. *Intelligent Systems in Accounting, Finance and Management* 23 (3): 157–214.

Fteimi, N., and D. Basten. 2015. *Impact of dictionaries on automated content analysis-the use of compound concepts in analysing knowledge management research*. Paper presented at the ECIS.

Garrard, P., V. Rentoumi, C. Lambert, and D. Owen. 2014. Linguistic biomarkers of Hubris syndrome. *Cortex* 55: 167–181.

Goldman, A. 2006. High toxicity leadership: Borderline personality disorder and the dysfunctional organization. *Journal of Managerial Psychology* 21 (8): 733–746.

Gonález-Bailón, S., and R. Petchler. 2015. Automated content analysis of online political communication. In *Handbook of Digital Politics*, ed. S. Coleman, and D. Freelon, 433–450. London: Edward Elgar.

Goode, R., and K.D. Evans. 2007. The scientific method: Application to FDA-regulated industry. *Journal of Validation Technology* 13 (4): 329–335.

Gordon, J. 2002. When Enron means for the management and control of the modern business corporation: Some initial reflections. *The University of Chicago Law Review* 69: 1233–1250.

Greatbatch, D., and T. Clark. 2005. *Management speak: Why we listen to what management gurus tell us*. London: Routledge.

Grimmer, J., and B.M. Stewart. 2013. Text as data: The promise and pitfalls of automatic content analysis methods for political texts. *Political Analysis* 21 (3): 267–297.

Grobelnik, M., D. Mladenic, and B. Fortuna. 2009. Semantic technology for capturing communication inside an organization. *IEEE Internet Computing* 13 (4): 59–67.

Guo, L., C.J. Vargo, Z. Pan, W. Ding, and P. Ishwar. 2016. Big social data analytics in journalism and mass communication: Comparing dictionary-based text analysis and unsupervised topic modeling. *Journalism & Mass Communication Quarterly* 93 (2): 332–359.

Hake, E.R. 2005. Financial illusion: Accounting for profits in an Enron world. *Journal of Economic Issues* 595–611.

Halevy, A., P. Norvig, and F. Pereira. 2009. The unreasonable effectiveness of data. *IEEE Intelligent Systems* 24 (2): 8–12.

Hannah, S.T., P.A. Balthazard, D.A. Waldman, P.L. Jennings, and R.W. Thatcher. 2013. The psychological and neurological bases of leader self-complexity and effects on adaptive decision-making. *The Journal of Applied Psychology* 98 (3): 393–411.

Harpaz, R., A. Callahan, S. Tamang, Y. Low, D. Odgers, S. Finlayson, K. Jung, P. LePendu, and N.H. Shah. 2014. Text mining for adverse drug events: The promise, challenges, and state of the art. *Drug Safety* 37 (10): 777–790.

Haselmayer, M., and M. Jenny. 2017. Sentiment analysis of political communication: Combining a dictionary approach with crowdcoding. *Quality & Quantity* 51 (6): 2623–2646.

Haynes, K.T., M.A. Hitt, and J.T. Campbell. 2015. The dark side of leadership: Toward a mid-range theory of hubris and greed in entrepreneurial contexts. *Journal of Management Studies*.

Hayward, M. 2007. *Ego check: Why executive hubris is wrecking companies and careers and how to avoid the trap*. Chicago: Kaplan.

Hayward, M., V.P. Rindova, and T.G. Pollock. 2004. Believing one's own press: The antecedents and consequences of chief executive officer celebrity. *Strategic Management Journal* 25: 637–653.

Hayward, M.L.A., and D.C. Hambrick. 1997. Explaining the premium paid for large acquisitions: Evidence of CEO hubris. *Administrative Science Quarterly* 42 (1): 103–127.

Heath, J., and W. Norman. 2004. Stakeholder theory, corporate governance and public management: What can the history of state-run enterprises teach us in the post-Enron era? *Journal of Business Ethics* 53 (3): 247–265.

Heidari, M., and C. Felden. 2015. Impact of text mining application on financial footnotes analysis. In *New Horizons in Design Science: Broadening the Research Agenda: 10th International Conference, DESRIST 2015, Dublin, Ireland, May 20-22, 2015, Proceedings*, ed. B. Donnellan, M.

Helfert, J. Kenneally, D. VanderMeer, M. Rothenberger, and R. Winter, 463–470. Cham: Springer International Publishing.

Hiller, N.J., and D.C. Hambrick. 2005. Conceptualizing executive hubris: The role of (hyper-)core self-evaluations in strategic decision-making. *Strategic Management Journal* 26 (4): 297.

Hollow, M. 2014. The 1920 Farrow's bank failure: A case of managerial hubris? *Journal of Management History* 20 (2): 164–178.

Hyland, K. 1998. Exploring corporate rhetoric: Metadiscourse in the CEO's letter. *The Journal of Business Communication* 35 (2): 224–245.

Indulska, M., D.S. Hovorka, and J. Recker. 2012. Quantitative approaches to content analysis: Identifying conceptual drift across publication outlets. *European Journal of Information Systems* 21 (1): 49–69.

Irfan, R., C.K. King, D. Grages, S. Ewen, S.U. Khan, S.A. Madani, J. Kolodziej, L. Wang, D. Chen, A. Rayes, N. Tziritas, C.-Z. Xu, A.Y. Zomaya, and H. Li. 2015. A survey on text mining in social networks. *The Knowledge Engineering Review* 30 (2): 157–170.

Kerfoot, K.M. 2010. Leaders, self-confidence, and hubris: What's the difference? *Nursing Economics* 28 (5): 349–351.

Khanin, D., and R.V. Mahto. 2012. Regulatory risk, borderline legality, fraud and financial restatement. *International Journal of Accounting and Information Management* 20 (4): 377–394.

Kin-Nam, L., L. Kam-Hon, and Y. Ho. 2005. Text mining for the hotel industry. *Cornell Hotel and Restaurant Administration Quarterly* 46 (3): 344–362.

Kozinets, R., A.C. Wojnicki, S.J. Wilner, and K. De Valck. 2010. Networked narratives: Understanding word-of-mouth marketing in online communities. *Journal of Marketing* 74 (2): 71–89.

Krause, F., B. Marc-Andre, and G. Fridgen. 2013. Valuation of manual and automated process redesign from a business perspective. *Business Process Management Journal* 19 (1): 95–110.

Kroll, M.J., L.A. Toombs, and P. Wright. 2000. Napoleon's tragic March home from Moscow: Lessons in hubris. *The Academy of Management Executive* 14 (1): 117–128.

Lawrence, D.Y., F. Pazzaglia, and K. Sonpar. 2011. The Introduction of a non-traditional and aggressive approach to banking: The risks of hubris. *Journal of Business Ethics* 102 (3): 401–420.

Lazar, J., J.H. Feng, and H. Hochheiser. 2010. *Research methods in human-computer interaction*. NY: Wiley.

Leary, T.G., R. Green, K. Denson, G. Schoenfeld, T. Henley, and H. Langford. 2013. The relationship among dysfunctional leadership dispositions, employee engagement, job satisfaction, and burnout. *The Psychologist Manager Journal* 16 (2): 112.

Lee, S., J. Song, and Y. Kim. 2010. An empirical comparison of four text mining methods*. *The Journal of Computer Information Systems* 51 (1): 1–10.

Lewis, M. 2006. The self in self-conscious emotions. *Annals of the New York Academy of Sciences* 818: 119–142.

Li, G., and F. Liu. 2014. Sentiment analysis based on clustering: A framework in improving accuracy and recognizing neutral opinions. *Applied Intelligence* 40 (3): 441–452.

Li, J., and Y.I. Tang. 2010. CEO hubris and firm risk taking in China: The moderating role of managerial discretion. *Academy of Management Journal* 53 (1): 45–68.

Li, X., C.L. Escalante, J.E. Epperson, and L.F. Gunter. 2012. *Early warning models for bank failures: Lessons from the late 2000s great recession*. Paper presented at the Proceedings. Global Science and Technology Forum, Singapore.

Li, Y. 2010. The case analysis of the scandal of Enron. *Int'l Journal of Business and Management* 5 (10): 37–41.

Lindsey, R., V.D. Veksler, A. Grintsvayg, and W.D. Gray. 2007. *Be wary of what your computer reads: The effects of corpus selection on measuring semantic relatedness*. Paper presented at the 8th International Conference of Cognitive Modeling, ICCM 2007, Ann Arobor, MI.

Lines, P.M. 1999. Antigone's flaw. *Humanitas* 12 (1): 4.

Madu, C.N. 1996. Designing system availability into the service quality of automated facilities. *The International Journal of Quality & Reliability Management* 13 (6): 77–87.

Malhotra, Y. 2005. Integrating knowledge management technologies in organizational business processes: Getting real time enterprises to deliver real business performance. *Journal of Knowledge Management* 9 (1): 7–28.

McManus, J. 2016. Hubris and unethical decision making: The tragedy of the uncommon. *Journal of Business Ethics* 1–17 (Online).

Mergent Online. Enron Company Financials: Annual Income Statement.

Merkl-Davies, D.M., and N.M. Brennan. 2007. Discretionary disclosure strategies in corporate narratives: Incremental information or impression management? *Journal of Accounting Literature* 26: 116–194.

Merkl-Davies, D.M., N.M. Brennan, and S.J. McLeay. 2011. Impression management and retrospective sense-making in corporate narratives: A social psychology perspective. *Accounting, Auditing & Accountability Journal* 24 (3): 315–344.

Merkl-Davies, D.M., N.M. Brennan, and P. Vourvachis. 2014. *Content analysis and discourse analysis in corporate narrative reporting research: A methodological guide*. Paper presented at the Centre for Impression management in Accounting Communication (CIMAC) Conference, 6th June 2014, Bangor Business School London Centre.

Nance, L., and V.S. Koerwer. 2004. Featured interview Sherron Watkins, former VP for corporate development of Enron. *Journal of Leadership & Organizational Studies* 11 (1): 38–47.

Nathan, M.L., and S. Kovoor-Misra. 2002. No pain, yet gain: Vicarious organizational learning from crises in an inter-organizational field. *The Journal of Applied Behavioral Science* 38 (2): 245.

Norris, F. 2001. Where did the value go at Enron? *New York Times*, 23 Oct 2001.

Nunez-Mir, G.C., B.V. Iannone, B.C. Pijanowski, N. Kong, and S. Fei. 2016. Automated content analysis: Addressing the big literature challenge in ecology and evolution. *Methods in Ecology and Evolution* 7 (11): 1262–1272.

Ojo, A.K., and A.B. Adeyemo. 2013. Knowledge discovery in academic electronic resources using text mining. *International Journal of Computer Science and Information Security* 11 (2): 10–19.

Onayemi, F. 2008. Sin, punishment and forgiveness in ancient Greek religion: A Yoruba assessment. *Journal of Philosophy and Culture* 3 (1): 72–100.

Owen, D. 2007. *The hubris syndrome: Bush, Blair and the intoxication of power*. Politico's Publishing

Owen, D. 2011. Psychiatry and politicians-afterword commentary on… psychiatry and politicians. *The Psychiatrist* 35 (4): 145–148.

Owen, D., and J. Davidson. 2009. Hubris syndrome: An acquired personality disorder? A study of US Presidents and UK Prime Ministers over the last 100 years. *Brain* 132 (5): 1396–1406.

Owen, L.D. 2006. Hubris and nemesis in heads of government. *Journal of the Royal Society of Medicine* 99 (11): 548–551.

Özcan, F., D. Chamberlin, K. Kulkarni, and J.E. Michels. 2006. Integration of SQL and XQuery in IBM DB2. *IBM Systems Journal* 45 (2): 245–270.

Palus, S., P. Bródka, and P. Kazienko. 2011. Evaluation of organization structure based on email interactions. *International Journal of Knowledge Society Research* 2 (1): 1–13.

Pang, B., and L. Lee. 2008. Opinion mining and sentiment analysis. *Foundations and Trends in Information Retrieval* 2 (1–2): 1–135.

Parloff, R. 2006. The trial. *Fortune* 153 (1): 67–68.

Patel, P.C., and D. Cooper. 2014. The harder they fall, the faster they rise: Approach and avoidance focus in narcissistic CEOs. *Strategic Management Journal* 35 (10): 1528.

Patelli, L., and M. Pedrini. 2015. Is tone at the top associated with financial reporting aggressiveness? *Journal of Business Ethics* 126 (1): 3–19.

Pelletier, K. 2010. Leader toxicity: An empirical investigation of toxic behaviour and rhetoric. *Leadership* 6 (4): 373–389.

Peraino, K., A. Murr, and A.B. Gesalman. 2002. Enron's dirty laundry. *Newsweek* 11 March, 22–30.

Petit, V., and H. Bollaert. 2012. Flying too close to the sun? Hubris among CEOs and how to prevent it. *Journal of Business Ethics* 108 (3): 265–283.

Prasad, A., and M. Raza. 2002. Digging deep for meaning: A critical hermeneutic analysis of CEO letters to shareholders in the oil industry. *The Journal of Business Communication* 39 (1): 92–116.

Rapoport, N.B. 2003. Enron, Titanic, and the perfect storm. *Fordham Law Review* 71: 927–949.

Raval, K.S., R.S. Suryawanshi, and D.M. Thakore. 2011. An intelligent agent based text-mining system: Presenting concept through design approach. *International Journal of Computer Science and Information Security* 9 (4): 112–117.

Razavi, A.H., S. Matwin, J. De Koninck, and R.R. Amini. 2014. Dream sentiment analysis using second order soft co-occurrences (SOSCO) and time course representations. *Journal of Intelligent Information Systems* 42 (3): 393–413.

Rezaee, Z. 2002. The three Cs of fraudulent financial reporting. *The Internal Auditor* 59 (5): 56–61.

Rosé, C., Y.-C. Wang, Y. Cui, J. Arguello, K. Stegmann, A. Weinberger, and F. Fischer. 2008. Analyzing collaborative learning processes automatically: Exploiting the advances of computational

linguistics in computer-supported collaborative learning. *International Journal of Computer-Supported Collaborative Learning* 3 (3): 237–271.
Rotella, F., F. Leuzzi, and S. Ferilli. 2015. Learning and exploiting concept networks with ConNeKTion. *Applied Intelligence* 42 (1): 87–111.
Saif, H., Y. He, M. Fernandez, and H. Alani. 2016. Contextual semantics for sentiment analysis of Twitter. *Information Processing and Management* 52 (1): 5–19.
Salter, C., M.T. Green, M.N. Hodgson, and N. Joyner. 2013. The language of transformational leaders: Addressing the needs of followers. *The Journal of American Academy of Business* 19 (1): 60–68.
Savage, C. 2013. N.S.A. Said to Search Content of Messages to and From U.S. New York Times. (8 August 2013). Retrieved from http://www.nytimes.com/2013/08/08/us/broader-sifting-of-data-abroad-is-seen-by-nsa.html?pagewanted=all&_r=0.
Sawin, E.I. 2005. The scientific method and other bases for evaluation procedures. *et Cetera* 62(4): 386–404.
Scharkow, M. 2013. Thematic content analysis using supervised machine learning: An empirical evaluation using German online news. *Quality & Quantity* 47 (2): 761–773.
Scherf, M., A. Epple, and T. Werner. 2005. The next generation of literature analysis: Integration of genomic analysis into text mining. *Briefings in Bioinformatics* 6 (3): 287–297.
Sheaffer, Z., and Y. Brender-Ilan. 2014. Are sensation seekers in control? A study in crisis preparedness. *Risk Management* 16: 1–24.
Sheaffer, Z., B. Richardson, and Z. Rosenblatt. 1998. Early warning signals management: A lesson from the Barings crisis. *Journal of Contingencies and Crisis Management* 6 (1): 1–22.
Shetty, J., and J. Adibi. 2004. The Enron email dataset database schema and brief statistical report. Information Sciences Institute Technical Report, University of Southern California.
Simons, T. 2002. The high cost of lost trust. *Harvard Business Review* 80 (9): 18–19.
Sims, R.R., and J. Brinkmann. 2003. Enron ethics (or: Culture matters more than codes). *Journal of Business Ethics* 45 (3): 243–256.
Smith, M., and R.J. Taffler. 2000. The chairman's statement—A content analysis of discretionary narrative disclosures. *Accounting, Auditing & Accountability Journal* 13 (5): 624–646.
Soltani, E., K.P. Ahmed, Y. Ying Liao, and P. Anosike. 2014. Qualitative middle-range research in operations management. *International Journal of Operations & Production Management* 34 (8): 1003–1027.
Storga, M., A. Mostashari, and T. Stankovic. 2013. Visualisation of the organisation knowledge structure evolution. *Journal of Knowledge Management* 17 (5): 724–740.
Thorleuchter, D., and D. V. d. Poel. 2016. Identification of interdisciplinary ideas. *Information Processing & Management, In Press, Corrected Proof*, Available online 9 May 2016.
Tibi, O., E. Thuma, and G. Mosweunyane. 2017. *Selective collection enrichment in user-centred health information retrieval*. Paper presented at the Next Generation Computing Applications (NextComp), 2017 1st International Conference on.
van der Aalst, W.M.P., and A. Nikolov. 2008. Mining e-mail messages: Uncovering interaction patterns and processes using e-mail logs. *International Journal of Intelligent Information Technologies* 4 (3): 27–45.
van der Meer, T.G.L.A. 2016. Automated content analysis and crisis communication research. *Public Relations Review* 42 (5): 952–961.
Vance, R., and S. Stuart. 2015. Of Moby Dick and tartar sauce: The academically underprepared law student and the curse of overconfidence. *Duquesne Law Review* 53: 133–279.
Vergeer, M., and L. Hermans. 2008. Analysing online political discussions. *Javnost—The Public* 15 (2): 37–55.
Wallace, B.C. 2015. Computational irony: A survey and new perspectives. *The Artificial Intelligence Review* 43 (4): 467–483.
Wiebe, J., T. Wilson, and C. Cardie. 2005. Annotating expressions of opinions and emotions in language. *Language Resources and Evaluation* 39 (2–3): 165–210.
Wilson, G., and W. Banzhaf. 2009. *Discovery of email communication networks from the Enron corpus with a genetic algorithm using social network analysis*. Paper presented at the Evolutionary Computation, 2009. CEC '09. IEEE Congress.
Winnenburg, R., T. Wächter, C. Plake, A. Doms, and M. Schroeder. 2008. Facts from text: can text mining help to scale-up high-quality manual curation of gene products with ontologies? *Briefings in Bioinformatics* 9 (6): 466–478.

Wu, S., T. Miller, J. Masanz, M. Coarr, S. Halgrim, D. Carrell, and C. Clark. 2014. Negation's not solved: generalizability versus optimizability in clinical natural language processing. *PLoS ONE* 9 (11): e112774.

Yang, B., L.X. Li, H. Ji, and J. Xu. 2001. An early warning system for loan risk assessment using artificial neural networks. *Knowledge-Based Systems* 14 (5–6): 303–306.

Yu, C.H. 2015. Are positive trait attributions for the deceased caused by fear of supernatural punishments? A triangulated study by content analysis and text mining. *Journal of Psychology and Christianity* 34 (1): 3–18.

Yu, C.H., A. Jannasch-Pennell, and S. DiGangi. 2011. Compatibility between text mining and qualitative research in the perspectives of grounded theory, content analysis, and reliability. *The Qualitative Report* 16 (3): 730–744.

Zeidan, R., and J. Müllner. 2015. Firm, market and top management antecedents of speculation: Lessons for corporate governance. *Journal of Multinational Financial Management* 32–33: 42–58.

Zhang, Y., H. Luan, W. Shao, and Y. Xu. 2016. Managerial risk preference and its influencing factors: Analysis of large state-owned enterprises management personnel in China. *Risk Management* 18 (2): 135–158.

Zweigenbaum, P., D. Demner-Fushman, H. Yu, and K.B. Cohen. 2007. Frontiers of biomedical text mining: Current progress. *Briefings in Bioinformatics* 8 (5): 358–375.