Identifying linguistic markers of CEO hubris: a machine learning approach

Abstract

This paper explores the potential of machine learning for recognising and analysing linguistic markers of hubris in CEO speech. This research is based on three assumptions: hubris is associated with potentially destructive leader behaviours; linguistic utterances are a way of distinguishing between leaders who are likely to exhibit such behaviours; identifying hubris at-a-distance using machine learning techniques provides a reliable, automated and scalable method for the identification and prevention of destructive outcomes emanating from CEO hubris. Using machine learning techniques, we analysed spoken utterances from a sample of hubristic CEOs and compared them with non-hubristic CEOs. We found that machine learning algorithms have the ability to identify automatically hubristic versus non-hubristic speech patterns. One of the main implications of this study is building a foundation for future studies that are interested in the application of machine learning in the fields of hubristic and other forms of destructive leadership and in the study of the role that language plays in management and organisations more generally. We discuss the implications of automated data extraction and analysis for the prediction of CEOs', and other employees', category membership, intentions and behaviours. We offer recommendations for how hubristic and destructive leadership in organisations can be managed and curtailed more effectively, thereby obviating their negative consequences.

Keywords: CEOs; hubris; leadership; linguistic markers; machine learning

Linguistic markers of CEO hubris: a machine learning approach

Introduction

This article reports the development of a machine learning (ML) technique for the early, unobtrusive identification of linguistic markers of hubristic leadership amongst CEOs. The research is of theoretical and practical significance because hubristic leadership is a form of destructive leadership occupying 'darker', less well-explored sides of management and has significant detrimental consequences for individuals, organisations and industries. Its early identification could be of benefit to stakeholders in organisations (Aasland et al., 2010; Einarsen et al., 2016; Tourish, 2013). The article's contribution is both theoretical and methodological. We respond to a previous call by destructive leadership researchers (e.g., Schyns and Schilling, 2013, p.150) for the alternative forms of 'objective data' collection over and above the cross-sectional survey designs that tend to be the norm in this area. Our research also resonates with calls for the use of advanced computational techniques, such as machine learning, in order that areas of research which draw on psychology, such as business management, can become 'a more predictive [rather than exclusively explanatory] science' (Yarkoni and Westfall, 2017, p.1100). In so doing we are offer a theoretical contribution to the study of top managers which both explains and predicts their behaviours on the basis of the 'honest signals' (Pentland, 2010) afforded to observers by their natural language use (Pennebaker et al., 2003).

Background

Destructive leadership is defined as systematic, repeated volitional behaviours by a leader that can harm the organisation (Krasikova et al., 2013; Padilla et al., 2007). Destructive leadership exists in 'many shapes and forms' in 'active and passive variants' (Einarsen et al., 2016, p.324). Empirical research on destructive leadership is 'still rare' (Einarsen et al., 2016, p.325) even though examples of destructive leaders who have affected organisations negatively are well-known in the management and wider literature (Collins, 2009; Sadler-Smith et al., 2016).

An important, recently-emerged but under-researched category of destructive leadership is 'hubristic leadership' (Sadler-Smith, 2019; Sundermeier et al., 2020; Van der Kam et al., 2015). Hubris has its roots in the ancient Greek concept of *hybris*; its attributes are over-confidence, arrogance, pride, and contempt for the advice and criticism from others (Owen and Davidson, 2009). In the business leadership context, CEOs' hubris is fuelled by praise and prior success and is enabled by complicit followership. It manifests as over-ambition and recklessness in strategic choices which, in turn, lead to ill-informed and poorly-executed decisions resulting in unintended negative consequences for leaders, organizations, and even entire industries, as in the 2008 financial crisis (Hayward and Hambrick, 1997; Li and Tang, 2010; Picone et al., 2014). Given the potentially destructive outcomes of CEO hubris, its early identification and prevention could be an important for managing the risks associated with the 'occupational hazard' (Claxton et al., 2015, p.57) of CEO hubris.

However, researching CEO hubris, in common with researching top management teams (TMT) in general and negatively-connoted top manager characteristics in particular, is problematic because executives are a difficult-to-reach population and unlikely to agree to participate in studies of phenomena, such as hubris, perceived as being undesirable and reputationally detrimental. Management research needs to develop efficient and effective objective methods (Schyns and Schilling, 2013) for identifying and analysing CEO hubris. One such method is analysing CEOs' linguistic utterances. Previous research has used descriptive approaches to identify the features that would be expected, *a priori*, to characterise the speech and/or language associated with membership of a particular class, such as political hubris (Garrard et al., 2014a) and institutional success (Thorpe et al., 2016). More powerful, however, would be a predictive analytic approach (Yarkoni and Westfall, 2017) using objective data

(Schyns and Schilling, 2013), which would not be restricted by theoretical assumptions and would have the potential to reveal novel markers of class membership (such as 'hubristic leader'). Such predictive analytics are conducted routinely on large datasets using ML but have yet to make significant in-roads into business management research.

This article presents the results of a study of the application of ML for the objective and unobtrusive identification and prediction of CEO hubris in language samples. Einarsen and colleagues (2007) stated that 'understanding and preventing destructive leadership may be as important, or even more important, than understanding and enhancing positive aspects of leadership' (p.208). Kaiser and Craig (2014) argued it is important to reduce the likelihood of destructive leadership occurring in the first place or minimising the time that elapses before destructive behaviours are detected and corrected; they also lament that 'specific strategies [for doing so] are virtually non-existent' (p.277) calling for techniques for 'dark side assessments' (p.277). Following this, and on the basis that 'prevention is better than cure', our research addresses a gap for assessing, understanding and intervening in destructive leadership processes in organisations. It contributes theoretically (in the area of destructive leadership) and methodologically (to the application of computational linguistics in business management research) and offers a practical predictive risk management tool for early identification of hubristic leadership as a means of obviating its potentially destructive consequences.

Literature Review

The conceptual framework of our research is represented diagrammatically in Figure 1: contextual factors, antecedents (self-concept), attributes of hubristic leadership (i.e., over-estimation of abilities), and outcomes (i.e., risky strategic decision choices) and effects (i.e., loss of value in Mergers and Acquisitions, M&A). Solid lines indicate causal paths; dashed lines indicated diagnostic and interventional paths. The literature review discuss each of the elements of the conceptual framework as represented in Figure 1.

[INSERT FIGURE 1 HERE]

CEO hubristic leadership

Hubristic CEOs over-estimate their abilities and struggle with learning from failures (Aguzzoli et al., 2020). CEO hubris is characterised by preoccupations with prior successes, feelings of excessive self-efficacy, self-esteem, inauthentic pride, and self-importance (linked to leaders' self-concept) (Picone et al., 2014). It is allied to arrogance, contempt for advice and criticism from others, and imperviousness to learning; it manifests at firm-level in over-ambitious/reckless decision-making (thus linked to behavioural strategy) (Hayward and Hambrick, 1997; Hiller and Hambrick, 2005; Picone et al., 2014).

Hubris belongs to the same nomological net as over-confidence and hyper core self-evaluation (hCSE) (Haynes et al., 2015; Hiller and Hambrick, 2005) but is distinct from narcissism (Asad and Sadler-Smith, 2020; Bouras, 2018). The origins of hubris research in business are traced to behavioural finance research, specifically Roll's (1986) 'hubris hypothesis' of CEO over-confidence in M&A decisions. Hubris research has branched-out into strategic management (e.g., Hiller and Hambrick, 2005), leadership (Sadler-Smith et al., 2016) and entrepreneurship (e.g., Haynes et al., 2015; Hayward et al., 2010). In practical terms, the damaging effects of CEO hubris are manifest in the failures of Richard Fuld at Lehman Brothers (Stein, 2013), Fred Goodwin at Royal Bank of Scotland Group (Craig and Amernic, 2018), Kenneth Skilling and Jeffrey Lay at ENRON (Eckhaus and Sheaffer, 2018), John Meriwether at Long Term Capital Management (Lowenstein, 2000) and Lord John Browne at British Petroleum (BP) (Ladd, 2012). The financial costs of hubristic leadership to businesses, the taxpayer, and national economies have been significant; the UK taxpayers' bill for the

Government bailout of the Royal Bank of Scotland (RBS) group was a record £46bn (Mor, 2018).

Scholars position hubristic leadership as a form of destructive leadership (Sadler-Smith, 2019). Destructive leadership ranges from workplace bullying to tyranny and has detrimental effects on productivity, financial performance, employees' psychological well-being, and morale (Kaiser and Craig, 2014; Krasikova et al., 2013). Destructive leadership entails: (1) dominating, coercing and manipulating followers and situations rather than influencing, persuading and gaining commitment; (2) selfish orientation which focuses more on the leader's needs than those of the wider social group; (3) producing outcomes that compromise the quality of life for constituents (Einarsen et al., 2016; Kaiser and Craig, 2014; Schyns and Schilling, 2013).

Hubristic leadership is destructive because it: (1) involves dominance and coercion of followers and manipulation of circumstances to attain leader's goals and ambitions instead of using influence and persuasion to secure commitment; (2) focuses on leaders' needs, wants and ambitions through the use of power for self-serving decisions rather than a selfless orientation towards the needs of the wider social group, for which reason it has been referred to as an 'intoxication with power' (Garrard and Robinson, 2016); (3) creates the conditions for outcomes to arise, albeit unintentionally, that are detrimental to the individual and the wider context of which s/he is part (Sadler-Smith, 2019). The issue of intentionality is important: hubristic leaders do not set-out to bring about destructive outcomes. They behave *ex ante* in ways not intended to cause harm, but their actions nonetheless prepared the way for, and resulted in, detrimental outcomes *ex post* (Einarsen et al., 2007, p.209). As a further example, MacKay and Chia's (2013) study of the rise/fall of an automotive business found that volitional actions interacting with environmental circumstances can produce unintended consequences that can be decisive in bringing about negative outcomes.

Hubristic leadership entails ‘destructive decision-making’ (Kaiser and Craig, 2014) in which ill-advised choices are overtaken by processes that result in negative unintended consequences. This is consistent with theory and findings from behavioural finance (Roll, 1986) whereby executive hubris resulted in loss of value for acquiring firms in M&As. The fact that hubristic leaders systematically and repeatedly engage in such behaviours, often against contrary advice, leads us to expect unintended negative consequences to accrue in a hubristic leadership process. We need an ‘early warning system’ to manage associated risks and protect shareholder value and interests.

CEO Self-concept

Prior research shows that psychological antecedents of hubristic leadership is linked to leader’s self-concept (Hiller and Hambrick, 2005). Cognitive manifestations of leaders’ self-concept have important consequences for strategic decision choices and behavioural strategy more generally (Hayward and Hambrick, 1997; Li and Tang, 2010). How individuals evaluate themselves and their relationships with their environment are reflected in their self-concept, but self-concept is not unequivocally positive—it can have positive/negative effects. CEOs with highly positive self-concept (core self-evaluations, CSE) create and seize opportunities and motivate their organisations in ways that less confident executives cannot. On the other hand, highly-, or overly-, confident CEOs may be more likely to engage in uninformed, unnecessary and excessive risk-taking due to over-estimations of personal abilities (Hiller and Hambrick, 2005; Picone et al., 2014). Likewise, healthy amounts of self-efficacy, self-esteem and locus of control combined with low levels of anxiety, based on secure self-concept, allows CEOs to function successfully, whilst surplus can lead to dangerous excesses in attempts to compensate for an insecure self-concept. Hiller and Hambrick (2005) refer to this as hyper core self-evaluation (hCSE).

Hubris has also been linked to narcissism. Hubris and narcissism can coexist, they overlap in certain respects, and narcissism may be a disposition in the development of hubris (Picone et al., 2014). Despite parallels between hubristic and narcissistic leadership, considering them indistinguishable is incorrect (Bouras, 2018). Narcissism is a personality trait characterised by inflated self-view, grandiosity, self-absorption, vanity, low empathy, and incessant need for adulation and power (Campbell et al., 2011; Rosenthal and Pittinksy, 2006). Positions of power contribute to elevated self-confidence, create opportunities of self-enhancement, satisfy needs to dominate decision-making, instilling a sense of superiority (Brunell et al., 2008; Chatterjee and Pollock, 2017). Narcissists use power and positions of authority to sustain and enhance a grandiose self-image, but commonly fail to deliver consistently longer-term (Asad and Sadler-Smith, 2020; Nevicka, Baas and Ten Velden, 2016).

Unlike narcissism (stable trait-like phenomenon with pathological dimensions), hubris is an acquired personality change (Owen, 2012) triggered by accession to a position of significant power, amplified by overestimations of one's abilities based on a track record of prior success and facilitated by complicit followership and lack of constraints (Asad and Sadler-Smith, 2020). Hubris, as an 'intoxication with power' (Garrard and Robinson, 2016), is an acquired condition with a 'rate of ascent and descent' often remitting once power is lost (Lovelace et al., 2018; Owen and Davidson, 2009; Picone et al., 2014). Unlike narcissism ('intoxication with self'), hubris ('intoxication with power') is a reactive disorder. Nonetheless, it influences CEO behaviours in maladaptive and unproductive ways and creates conditions for negative, unintended consequences to arise if CEOs over-estimate what can go right and under-estimate what can go wrong (Taleb et al., 2009).

CEO's Lexical Choices

Leaders' lexical choices are an outward manifestation of hubris (Garrard et al., 2014). According to Pennebaker's theory of 'natural language use', psychological changes (such as the reactive onset of a hubristic state) are associated with distinctive patterns of spoken/written discourse (Pennebaker et al., 2003) thus providing windows into leader's personality and self-concept and offering a diagnostic for destructive leader behaviours (Craig and Amernic, 2018). Linguistic markers afford 'honest signals' (Pentland, 2010) to observers because speakers are often unaware of subtle patterns in lexical choices and largely unable to conceal them, or not without considerable cognitive effort. It follows that CEOs will express hubris through language (Craig and Amernic, 2018). These relationships are discussed in more depth in the subsequent section.

Outward manifestations of hubristic leadership have important consequences for behavioural strategy, hence are relevant to strategic decision-making and behavioural strategy research and practice (Hayward and Hambrick, 1997; Hiller and Hambrick, 2005; Li and Tang, 2010). Behavioural strategy is a new sub-field of strategic management research (Hambrick and Crossland, 2018) that seeks to merge cognitive/social psychology with strategic management. Hubristic leadership and behavioural strategy research are mutually enhancing because of a number of core processes of common interest, including individual decision-making by top executives, the dysfunctional and darker-sides of senior leaders' behaviours, and TMT decision-making. Behavioural strategy researchers argue that executive hubris, related to delusional optimism and groupthink, can be a 'fertile breeding ground' for biased decision-making (Powell, 2017, p.169).

CEOs' Strategic Decision Choices

Management research and practice will benefit from research into hubristic leadership as follows. First, hubristic leadership research can help to explain recent and significant 'performance shocks', such as those emanating from flawed strategic decision-making leading-up to the financial crisis, poor M&A decisions (for example, Hewlett Packard and Compaq). Second, hubristic leadership research can explain flawed executive judgements and how these are related to psychological antecedents (for example, self-concept) and biases in strategic decision-making (for example, over-confidence). Third, hubristic leadership research bridges the reductionist (focus on individual managers' decision-making biases such as 'unbridled intuition', Claxton et al., 2015) and 'pluralist' behavioural strategy schools of thought (Powell et al., 2011) by focusing on hubris within the power dynamics of TMT contexts (Padilla et al., 2007).

Normatively, hubristic leadership research seeks to counter decision biases and negative, unintended consequences accruing from executive overreach (Taleb et al., 2009), see Figure 1. It treats CEO hubris as another category of risk to be managed alongside conduct, credit risk, liquidity risk, and market risk[1]. Vigilance and early diagnosis of its emergence can contribute to better design of the 'psychological architecture', due diligence and governance structures of firms (Powell et al., 2011; Tang et al., 2018). Finally, our research contributes to the methodological diversity in improving behavioural strategy research (Hambrick and Crossland, 2018; Powell, 2017).

CEO hubristic leadership has negative consequences that are not accidental, but this is not because there is some provable causal link between hubris and destructive outcomes, rather there are emergent effects/unintended consequences that hubris invites in the complex social settings of business organisations. These processes need to be identified as early as possible and guarded against through appropriate governance and other measures. Therefore, our research contributes to destructive leadership research using a novel technique for generating early warnings of flawed and incompetent decision-making associated with hubris.

[1] These are the categories of risk identified by the new Governor of the Bank of England, Andrew Bailey. https://www.bankofengland.co.uk/speech/2016/culture-in-financial-services-a-regulators-perspective

Computational linguistics

Language plays a vital role in business management and leadership. How CEOs' leadership is/will be performed is evidenced, 'to a substantial extent', in the language (Craig and Amernic, 2011, p.563). Leaders are required to verbally interact with colleagues, subordinates and stakeholders for the projection of image and influence (Amernic et al., 2010). CEO language, therefore, is a potentially fertile resource for the study of leaders' cognitions/behaviours and their impact on strategic decision choices. Moreover, in recent years, the availability of large bodies of data in digital format provides both an opportunity and a challenge for leadership and management researchers.

Previous research in this field has used traditional computational linguistics techniques to identify 'linguistic markers' of hubris (Akstinaite et al, 2019; Amernic et al., 2010). Such approaches are highly deductive and theory-driven (essentially using word counts and classifications into predetermined theoretical categories of 'natural language use', see Pennebaker et al., 2003). Standard methods for analysing linguistic data (e.g., close-reading of texts) are a way of accessing CEO intentions and behaviours as expressed in language, but are slow, time-consuming, and hard-to-perform on large datasets (Basit, 2003). This necessitates more efficient data analysis methods to cope with the volumes of data involved.

ML approaches are one such technique (Batistič and van der Laken, 2019) which is now applied widely in areas such as text classification, analysis and portfolio optimisation (Ikonomakis et al., 2005; Sena et al., 2019). ML algorithms can be trained on a set of pre-classified written texts to categorise new unseen texts into categories of interest, such as the site of a neurological lesion (Garrard et al., 2014b). According to Sebastiani (2005, p.2), 'the accuracy of classifiers (i.e., their capability to make the right classification decisions) built by ML methods now rivals that of human professionals and usually exceeds that of classifiers built by knowledge engineering methods'. Initially, classifiers used to be built manually, based on knowledge of engineering techniques (building a system that emulates the behaviour of a human expert when making a judgement on a specific topic), however recent advances in ML enable automatic construction of the classifier (Krabben, 2010). Such classifiers have potential for management research. A recent study by Spisak, van der Laken and Doornenbal (2019) found that ML algorithms could predict leader effectiveness through Big Five personality traits. In addition, ML has been used to successfully predict employee turnover (Punnoose and Ajit, 2016) and detect leadership cues through text mining (Xie et al., 2018).

Our research contributes to the application of computational linguistics in management. It does so by using machine learning techniques for the automatic identification of linguistic markers of hubristic speech which could then be used for early warning and intervention. To the best of our knowledge, this never been attempted before. Whilst the modelling technique used in our research is exploratory, it demonstrates the potential for the use of data mining of language in future research in other aspects of behaviours over-and-above the specific application to CEO hubris.

Aim and Method

We used ML techniques to identify linguistic attributes of CEO hubris by classifying transcribed interview samples of textual data into hubristic or non-hubristic utterances and identify the features on which the model relied to make the classification.

Analysis software

We used the Waikato Environment for Knowledge Analysis (WEKA) data mining platform (Witten et al., 2016). WEKA was chosen for the following reasons: (1) provides access to a collection of ML algorithms that can be applied for a variety of data mining tasks; (2) has been used extensively and successfully in similar research studies (Garrard et al., 2014b; Williams et al., 2020).

Basic principles

WEKA's main working principle is based on 'supervised learning'. A researcher provides a classified example for the software ('training dataset'), which may consist of the instances of a certain word in a text and/or other features ('attributes') associated with a phenomenon of interest. Based on these initial data, the software identifies patterns for the specified category ('class'). To accomplish this, a ML classifier algorithm is used, which outputs the 'class' value: in this case 'hubristic' or 'non-hubristic'. This process is depicted in Figure 2.

[INSERT FIGURE 2 HERE]

Method

Our method can be summarised in five steps: (1) prepare sample and data to be used in the study; (2) extract relevant attributes; (3) build classifier to identify hubristic vs. non-hubristic speech; (4) refine attribute list if required; (5) test and compare models. The following sections describe each of these steps.

We conducted two studies. Study A used scores for Linguistic Inquiry and Word Count (LIWC) categories (i.e., predefined dimensions as specified by Pennebaker et al (2003) in LIWC software based on theory of 'natural language use') as attributes. Study B used raw data (i.e., spoken utterances produced by hubristic and non-hubristic CEOs) as attributes. The full list of LIWC categories and its examples are available from the authors upon request.

Sample and Data

A non-probability purposive sampling strategy was used to categorise CEOs into hubristic or non-hubristic samples. This selection was based on the assessment of observers (hubris researchers and media assessments) that judged CEOs as hubristic or non-hubristic and who were independent of our own assessment and consistent with sampling methods used in prior research (Akstinaite et al., 2019; Craig and Amernic, 2018).

Sample 1: Hubristic CEOs

A three-stage sampling process was employed: (1) systematic review of relevant articles in Business Source Complete (BSC) database pertaining to CEO hubris; (2) review of relevant media articles (outputs of the search engine query) pertaining to CEO hubris; (3) comparison of the results from outputs (1) and (2) to identify overlapping categorisations. To reduce the impact of potential mistakes in English grammar and syntax made by non-native speakers, only native English language speakers were included. This exercise resulted in five CEOs that were included in the final sample: Steve Jobs (Apple), Howard Schultz (Starbucks), Elon Musk (Tesla, SpaceX), Jamie Dimon (JP Morgan), and Travis Kalanick (formerly of Uber).

Sample 2: Non-hubristic CEOs

Given that existing leadership literature lacks established criteria or specific attributes for a ‘non-hubristic leader’, for the purpose of this research, ‘non-hubristic CEOs’ were shortlisted based on publicly available information from well-established rankings that list CEOs based on their financial, social and inter-personal performance. After a review of existing CEO rankings, the following rankings (years 2015–2017, dates of when this research has been conducted) were deemed appropriate for the purposes of this research: *Harvard Business Review*’s (*HBR*) annual ranking of ‘The Best-Performing CEOs in the World’, Glassdoor’s annual ranking of ‘Highest Rated CEOs’, Richtopia’s ‘Philanthropists and Social Entrepreneurs Top 200’ and *Fortune* magazine’s ‘The World’s Greatest Leaders’. When sampling for non-hubristic CEOs, the following process was used: (1) review of four above-mentioned annual rankings; (2) comparison of the outputs from four rankings to identify CEOs that appeared in several rankings. The full list of shortlisted non-hubristic CEOs is available from the authors. A given CEO has been added as non-hubristic if his/her name appeared in at least two different rankings. As above, only native English language speakers were included. This process resulted in five CEOs included in the final sample: Jeff Bezos (Amazon), Mark Parker (NIKE), Robert Iger (Walt Disney), Mike Bloomberg (Bloomberg) and John Chambers (formerly of Cisco). As a final step, both samples were cross-checked for potential CEO overlap; however, none of the shortlisted CEOs appeared in both samples.

Data

Secondary data in the form of interviews with media were used for text mining. All available interviews with the above-mentioned CEOs were retrieved using search engines and then used in the analysis (see Study A and B below). The secondary data materials used for each of these CEOs are available from the authors.

Study A Results – LIWC scores

Step 1 - Attribute selection

An ‘attribute’ is a linguistic feature that is potentially associated with a phenomenon of interest. Normally the attributes used have been described in previous research that has revealed correlations between measurable linguistic factors and the classification for which the researchers are creating a ML model (Mairesse et al., 2007). In the present case, the classification is between hubristic and non-hubristic CEOs. In this research, attributes therefore relate to the linguistic cues that might identify hubris. In this study, we used LIWC scores identified as being potential indicators of hubris in the recent publication by Akstinaite et al. (2019). The full attribute list is provided in Table 1.

[INSERT TABLE 1 HERE]

Step 2 – Building a classifier

To build a classifier that determines whether an individual CEO's language is hubristic or not based on the set of attributes listed in Table 1, scores for each of these attributes obtained by LIWC were used as input data for the classifier ('training set'). Appendix 1 contains the full set of input data that were used to build the baseline classifier. As ML has not previously been applied to destructive leadership research, there is no *a priori* reason for favouring any specific classification model. This study therefore compares and contrasts five different learning algorithms from WEKA's toolbox: (1) C4.5 decision tree learning (J48); (2) Random Tree (RT); (3) Instance-based learning (IBk); (4) Naïve Bayes (NB); (5) Support Vector Machines (SVM). These algorithms have been used previously in similar research where textual data was used to identify various personality components (Schöch et al., 2016; Spisak et al., 2019).

Step 3 – Refinement of the attribute list

The third step is reducing the attribute list decrementally (by removing the attribute that had the most similar score in hubristic and non-hubristic class) from 17 to five attributes to improve the model's accuracy in distinguishing hubristic from non-hubristic CEOs based on their LIWC scores.

Step 4 – Model testing

One of the requirements for the creation of a successful model is its testing (Witten et al., 2016). The models presented in this study were trained and tested by applying a 10-fold cross-validation option in WEKA. This step allows the model to be sequentially evaluated on ten different subsets of the training data and tested on the remaining data. Identification accuracy is calculated by taking the average accuracy over the ten validation cycles.

Step 5 – Results of Study A

Prediction accuracy describes the percentage of correctly classified instances for each of the classifiers. For example, in Table 2 below, the accuracy of 20% means that the classifier predicted eight out of 10 instances incorrectly. Prediction accuracy results obtained after the first run of all five classifiers are summarised in Table 2. Accuracy for the classifier with all 17 attributes ranged from 10% to 50%, indicating that the ML algorithm needed refinement. Although there is no unequivocal agreement among researchers as to what classifies as a 'good' prediction accuracy, the overall prediction accuracy reported in Table 2 can be considered to be unsatisfactory—the best accuracy (50%) is no better than flipping a coin. To improve the prediction accuracy, the attributes for which a difference between hubristic and non-hubristic sample score averages was minimal (or there was no difference at all) were removed from the attribute list. The classifiers seemed to perform best with five attributes (see Table 2).

[INSERT TABLE 2 HERE]

The following five attributes were found to best predict the hubristic versus non-hubristic language use: (1) Total count of pronouns; (2) Impersonal pronouns; (3) Auxiliary verbs; (4) Common verbs; (5) Tentative tone.

Study B Results – Data-driven analysis

A novel ML approach based on the same underlying textual data was implemented in Study B. Such strategy was more inductive and shifted the approach used from a theory-driven to an atheoretical, exploratory one. All the collected data was used to build a model based on the most promising words as attributes to identify hubris.

Step 1 - Attribute selection

The entire set of spoken utterances produced by hubristic and non-hubristic CEOs (see 'Sample and Data' section) were used to generate attributes in Study B. In other words, every word, rather than theoretically pre-specified LIWC dimensions, from the 'hubristic' and 'non-hubristic' texts became an attribute for the model.

Step 2 – Building a classifier

Text mining is a process of deriving meaningful patterns from textual data using ML algorithms. In Study B, text mining refers to running ML algorithms in WEKA on the entire data set and allowing the software to choose freely on the basis of which words are most predictive of hubristic versus non-hubristic categorization. These predictive words (or 'lexical markers' of hubris) operate as attributes for the classification model. However, in this case, they are derived from data as opposed to being manually selected by researchers on the basis of prior analysis/theory. The entire dataset uploaded to WEKA consisted of 40,976 words, which, after checking for the same terms, was composed of 1645 unique words that became baseline attributes for Study B. As in Study A, five different learning algorithms from WEKA's toolbox were used: J48, Random Tree, IBk, Naïve Bayes, and SVM.

Step 3 – Refinement of the Attribute List

After the initial run of the classifiers based on the attribute list consisting of 1645 words, the list was further refined by using the attribute selection filter in WEKA, which helped to evaluate the predictive value of attributes and select those most predictive of CEO hubris. Appendix 2 contains the list of the top 30 attributes. A full list of attributes is available from the authors.

Step 4 – Model testing

To test the classifier's performance, and ensure that the model is performing well, the following testing methods were applied: (1) splitting existing training dataset into 'training' and 'test' parts; (2) choosing a percentage of the sample to be used for training (66%), remainder being used for testing (34%); (3) applying 10-fold cross-validation which allows the model to be sequentially evaluated on ten different subsets of the training data and tested on the remaining data.

Step 5 – Results of Study B

The text mining method described in this study evaluated binary classification models based on word vectors (separate words as attributes). All classifiers were run on the textual data in the following manner: (1) using 10-fold validation; (2) with a specified training versus testing split; (3) with a specified training versus testing split, but customised settings to optimise performance of the classifier.

Once all runs on the entire set of attributes were completed, an attempt was made to improve prediction accuracy results by further refining the attribute list using the Attribute Selection filter in WEKA which automatically refined the attribute list to 'most promising' attributes. Table 3 below summarises the final performance results of all five classifiers in terms of prediction accuracy.

[INSERT TABLE 3 HERE]

Final prediction accuracy results for the classifiers ranged from 63% to 85%, depending on the classifier and its testing method. This means that in most cases, this study was able to categorise between hubristic and non-hubristic CEOs with around 80% accuracy.

Discussion

The aim of our research was to discover if and how machine learning can be used to predict whether a CEO is categorised as hubristic or non-hubristic CEO. It did this through the identification of linguistic markers and the discernment of category membership using a predictive ML analysis of CEO speech. We found that a ML method was able to categorise hubristic and non-hubristic CEOs on the basis of their lexical choices with high levels of accuracy. As such, the method could be developed as a risk management tool for the early identification of CEO hubris and to obviate potentially destructive consequences (Sadler-Smith et al., 2018). In doing so, we have combined together in a novel and practically useful manner the three main threads of our argument, namely: the theory of natural language use and the use of lexical choices (Pennebaker et al., 2003; Pentland, 2010) to allow making better predictions as well as explanations (Yarkoni and Westfall, 2017) of destructive leader behaviours, and specifically hubristic leader behaviours (Sadler-Smith, 2019), given that such behaviours can have potentially dire consequences for individuals, organizations and even wider society (Padilla et al., 2007; Schyns and Schilling, 2013). In summary, we have woven together three theoretical threads into a novel theoretical and methodological contribution to business management research.

Data mining is an innovative approach to the study of the relationship between hubristic leadership and language. The use of ML to distinguish hubristic from non-hubristic speech, has to the best of our knowledge, never been used in management research before, and is, therefore, a novel approach for research in leadership, TMTs, strategic management and related areas. As such, the study represents a practical introduction of the methodology and application of ML to a management research community that still has limited familiarity with it. As our results show, there are a number of ways in which data mining can be used to distinguish between hubristic and non-hubristic language. For reasons outlined below under ‘Limitations and Future Directions’, we suggest that the results of the present study, while being far from definitive, nonetheless represent an important exemplar study, on which future research can usefully build.

Study A used theoretically predetermined LIWC categories as attributes for ML classifiers. Results obtained by using this method identified a link between hubristic speech and higher frequency of impersonal pronouns. Other categories identified that were used to distinguish between hubristic and non-hubristic speech were total counts of pronouns, auxiliary verbs, and verbs and the adoption of a tentative tone. In most cases, these categories have also been classed as markers of hubristic speech, however, findings are not conclusive.

Study B took a data-driven approach, using the words in each sample of text as attributes, and compared the classification accuracies achieved by five different algorithms. All produced higher prediction accuracies than Study A: mean prediction accuracy of the five classifiers in Study A was 60% (range 50-80%) whilst those obtained in Study B averaged 65% (range 57-81%) with the full dataset and 74% (range 63-85%) after feature selection.

The data-driven method also enabled identification of words with greatest potential to distinguish hubristic from non-hubristic language. Results from Study B complemented, and thus validated, the findings from Study A: personal (i.e., use of 'I', 'we') and impersonal pronouns (i.e., use of 'it'), as well as verbs (i.e., 'don't', 'doesn't'), were identified as potential linguistic markers of hubris. Attribute selection identified more words that could help to distinguish between hubristic and non-hubristic language (i.e., 'million', 'creative', 'possible', 'money'). Some words relate to hubristic features ('symptoms') proposed by Owen and Davidson (2009). For example, words 'million' and 'money' could be lexical representations of the symptom 2 (enhancing self-image) or 3 (disproportionate concern with presentation). Similarly, 'know' (IG 0.01606[2]) may index symptom 7 (excessive confidence in one's own judgement) and 'possible' (IG 0.02561) symptom 8 (exaggerated self-belief).

In contrast, the large number of negative words identified by the data-driven approach (e.g., 'can't', 'doesn't, and 'haven't') is a new discovery, not covered by previous studies (Garrard et al., 2014a). It may be that what these items are marking is the start of the negative part of the cycle or overconfidence, derailment and destruction. This interpretation could potentially be tested in a larger, longitudinal sample that allowed comparisons between lexical

[2] IG refers to 'Information Gain Score', see Appendix 2.

choices at different stages of the process. Future research should also seek to consolidate the positive links between the Owen and Davidson's (2009) criteria for 'hubris syndrome' and lexical choices using similar hypothesis-driven methodologies to those used by Garrard et al. (2014a) on a fresh corpus of language samples.

One contribution of this study is providing foundations for future studies for ML applications in management. In practical terms markers of speech pattern, such as the relative rate of occurrence of specific lexical items could be used as 'honest signals' (Pentland, 2010) of change in leaders' states of mind, giving a longer time-window in which measures to mitigate the impact of destructive behaviour, to be implemented (Sadler-Smith et al., 2018).

Limitations and Future Directions

This research is subject to a number of limitations. First, the availability of CEO text is (for reasons discussed in the 'Introduction') limited, yielding a relatively small sample size. Secondly, the fact that the data is representative of just business leadership domain, raises the possibility that the findings may not generalise to other spheres, such as politics. Therefore, future research should apply a similar methodological approach to larger and more diverse samples. Finally, although cross-validation (training and testing the model on different combinations of training and hold-out subsets of the data) was used to ensure that the model was learning from, rather than simply describing, the data (the problem of 'overfitting'), the gold standard verification of any model's accuracy is to expose it to an unseen set of data (Witten et al., 2016), a test that the scarcity of data made impossible. It is likely that more abundant data will become increasingly available to researchers as sources and usage of digital data (such as social media platforms) and their usage expands. Such sources will arguably be associated with greater spontaneity of expression, enhancing their status as 'honest signals' of psychological states.

Not necessarily a limitation as such, however Study A depended on LIWC and its underlying theoretical precepts. This method required an intermediate step - calculating scores for various categories using LIWC - and only then inputting them into WEKA. Study B aimed to address this limitation by exploring a method for the direct investigation of the data.

The use of secondary data in such research raises several methodological questions concerning the extent to which a leader's interview or speech is representative of their true personality characteristics and belief system. However, the use of secondary data is based on the assumption that 'a leader's public behaviour is constrained by his public image and that, over time, his public actions will consistently match his public beliefs' (Walker et al., 2003, p.223). This assumption has been validated in studies that have used the 'at-a-distance' approach analyses (Akstinaite et al., 2019; Craig and Amernic, 2018; Garrard et al., 2014a).

This indicates a need to analyse the variety of classifiers further to identify the most optimal classifier(s) for hubris research. Although the present study compared five different classifiers, future research should investigate other classifier categories (i.e., meta-classifiers or classifiers based on rules) as well as aim to improve prediction accuracies produced by classifiers used in the present study.

Theoretical and Practical Implications

Our research has several theoretical implications. First, given that hubristic leadership is a type of destructive leadership, our research contributes to theories of destructive leadership (Einarsen et al., 2007; Krasikova et al., 2013) because we have shown empirically that the categories of hubristic and non-hubristic CEO can be discerned automatically using ML-based assessment of CEO utterances. This is an important finding using a novel method for management research offering support for the theory that leaders' lexical choices are associated with hubris (Akstinaite, 2019; Garrard et al., 2014a, 2014b). Second, researchers have made appeals for the development of objective measures of CEO hubris, for example, through the use of psychometrics (Asad and Sadler-Smith, 2020). Hiller and Hambrick's (2005) theoretical proposal for measuring hubris using hyper Core Self-Evaluation (hCSE) was a significant step forward. Nonetheless, previous efforts have focused largely on the possibilities for self-report assessment and subjective ratings. Our research overcomes this fundamental limitation of traditional psychometrics, subjective ratings and self-report by providing an objective method for identifying or categorising *ex ante* CEOs who are generally agreed to be hubristic. Third, further work is now required to validate the markers that we have discovered in this exploratory study and develop a theoretical model that explains how the linguistic markers that ML discerned are explicable in terms of CEO self-concept and strategic cognition. Fourth, we suggest that a ML linguistic markers discerned by an algorithm could with further refinement be trained to discern linguistic markers for the theoretical attributes of self-concept and self-evaluation that prior research has proposed such as exaggerated perceptions of status, self-worth, freedom from anxiety, over-precision, self-efficacy, ability to control events, and expectations of success (Hiller and Hambrick, 2005; Picone et al., 2014). The approach could also be used to generate theoretical models inductively without necessarily recourse, or reference to, established theory.

There are also broader theoretical and methodological implications of our research. CEOs' utterances that identify them as hubristic are 'honest signals' that reflect underlying psychological variables, including aspects of personality and cognition. An intriguing possibility is that if machine learning can identify hubrists, it may also have the potential to identify not only other aspects of destructive leadership but wider aspects of CEO personality and provide an alternative to psychometric and self-report assessments. The method is not applicable only to CEOs' utterances; other aspects of their digital profile and footprint could be analysed using similar techniques. In this respect, our research contributes to wider developments in the application of ML as an assessment tool that can ‘powerfully predict’ not only personality (machine learning personality assessment, MLPA) and cognition but also human behaviour (Bleidorn and Hopwood, 2019, p.190). Use of computational techniques for automated data extraction, analysis, validation and prediction of CEOs’, and other employees’, category membership, intentions and behaviour raise scientific, practical and ethical questions. The potency and perils of algorithms that can learn from digital data and make predictions without being pre-programmed to do so are only just beginning to be explored in business and management studies and are worthy of further investigation and critical scrutiny.

Turning to practical issues, the capability of the ML approach to predict category membership offers stakeholders a component of an ‘early warning system’ for CEOs’ decision-making behaviours that could ultimately imperil the interests of an organisation and its stakeholders. In the conceptual framework diagnosis of category membership (hubristic CEO or non-hubristic CEO) by ML analysis of spoken utterances is proposed as a basis for intervention. What form such interventions take is likely to depend on local circumstances, but could include strategies, that: (1) alert stakeholders to the possibility that the CEO’s vision may be unfeasible; (2) encourage CEOs and boards to develop multiple scenarios rather than following a hubristic CEO’s single, grandiose vision; (3) making CEOs themselves conscious of competing priorities and alternative strategies through a trusted confidante such as chairman, executive coach or mentor, trusted colleague or ‘toe holder’; (4) de-centralising strategic decision making away from a hubristic CEO; (5) constraining CEO power through active boards, interventions by non-executive directors, splitting the role of chairman and CEO, curtailment of remuneration for high-risk decision making, diluting ownership concentration, having fixed / flexible CEO tenures; (6) the organisation consciously attempting to learn from failures or instigating pre-mortems in a process of scenario planning for alternative futures (Li and Tang, 2010).

Conclusion

Language is an important component of the leadership process and CEOs express their leadership through their verbal and written discourse (Amernic and Craig, 2018). Although researchers have sought previously to uncover linguistic markers associated with hubris (Akstinaite et al., 2019) and hubristic leadership, only recently have they begun to explore hubris using machine learning, thereby enabling less subjectivity and greater efficiency in analysing large amounts of data (Garrard et al., 2014a, 2014b; Sheng et al., 2019). Data mining has significant but yet under-explored potential in management research, particularly as it lends itself to the development of systems that are automatic, scalable and free of researcher bias. Since most research on hubris is based on secondary data especially with senior leaders such as CEOs and political leaders (Akstinaite et al., 2019; Garrard et al., 2014a), ML holds real potential here, allowing for the creation of a completely automatic analytical process for distinguishing hubristic and non-hubristic language. In line with previous research on hubris and language, our research confirmed that linguistic markers hold considerable promise to reveal CEO hubris through subtle differences in language use and showcased possibilities for using data mining in future research, as an 'early warning' for an incipient and emergent hubristic 'tone at the top' of organisations. Moreover, wider applications of ML methods for predicting employees' category membership, intentions and behaviours on the basis of records of individuals' utterances or other aspects of their digital profiles and footprints raises a variety of important questions not only for business and management studies but society more generally.

Compliance with Ethical Standards

The authors did not receive any funding in the conduct of this research.

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Table 1. Linguistic features used as attributes in Study A

Linguistic Feature	Abbreviation
Pronouns	Pronoun
Pronoun ‘We’ and its derivatives	We
Pronoun ‘You’ and its derivatives	You
Pronoun ‘They’ and its derivatives	They
Impersonal pronouns	Ipron
Auxiliary verbs	Auxverb
Negations	Negate
Common verbs	Verb
Common adjectives	Adj
Interrogatives	Interrog
Quantifiers	Quant
Discrepancy words	Discrep
Tentative tone	Tentat
Certainty tone	Certain
Power related words	Power
Reward related words	Rewards
Money related words	Money

Table 2. Classification results in Study A

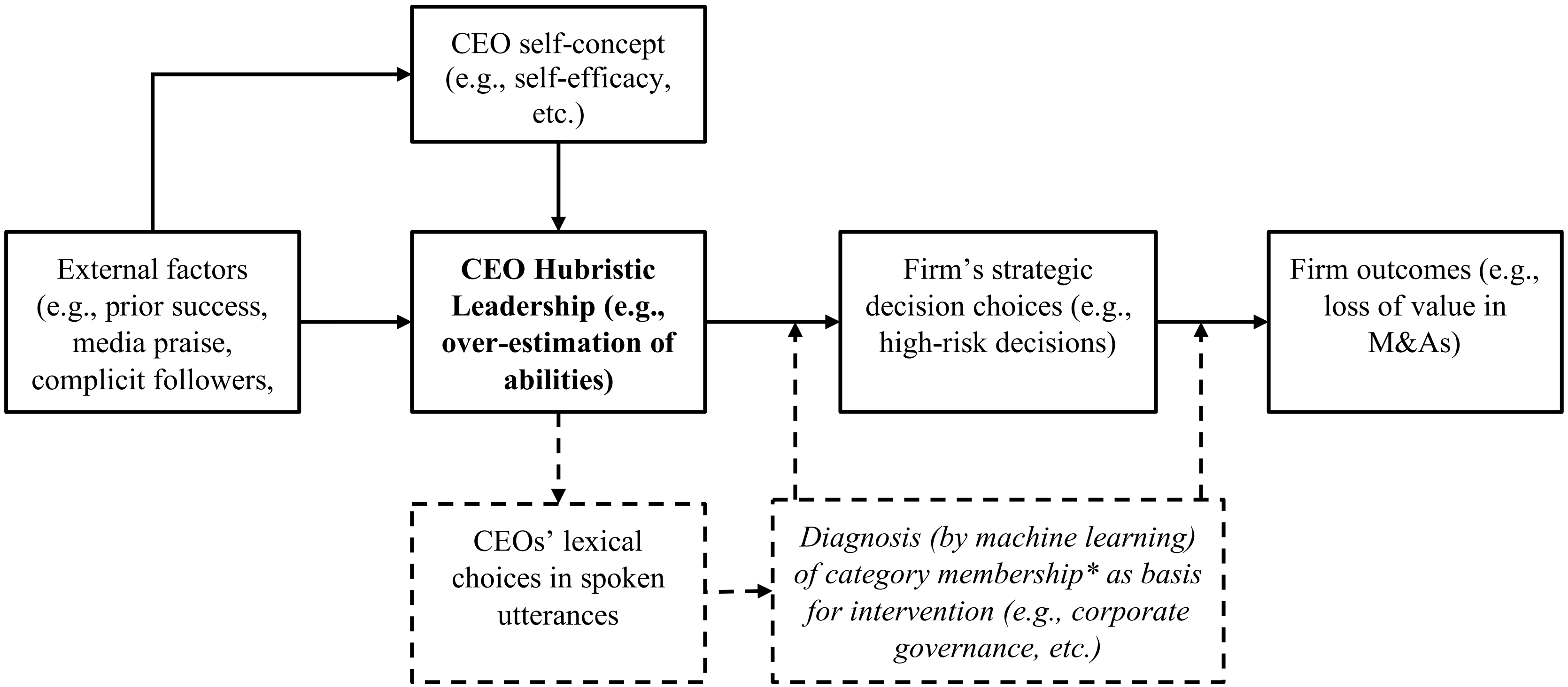
Classifier	Prediction accuracy (17 attributes)	Prediction accuracy (5 best attributes)
Random Tree	50%	80%
J48	50%	60%
Naïve Bayes	30%	50%
SVM	10%	50%
IBk	20%	60%
Average	**30%**	**60%**

Table 3. Final prediction accuracy results

Classifier	Prediction accuracy		
	Using 10-fold cross-validation	With specified training vs testing split	With specified training vs testing split and customisations
Random Tree	73%	77%	72%
J48	70%	64%	66%
Naïve Bayes	78%	73%	85%
SVM	84%	82%	82%

IBk	65%	64%	63%
Average	**74%**	**72%**	**73.6%**

Figure 1. Conceptual framework



Notes: * categories hubristic CEO and non-hubristic CEO; solid lines, causal paths; dashed lines, diagnostic and interventional paths

Figure 2. Classification process in a supervised ML model