

PERFORMANCE AND INDUSTRY LEVEL IMPLICATION OF ORGANISATIONS' STRATEGIC PERSONALITY

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Abstract

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This exploratory study investigates how an organisation's strategic personality can be inferred through linguistic and machine learning approaches and its performance and industry-level implications. The study uses 820 chief executive officers' (CEOs) statements published in annual reports of the Australian Stock Exchange (ASX) listed companies in Australia with the personality insight service on the IBM Watson platform to infer the strategic personalities of firms. By applying unsupervised clustering on the extracted values of personality traits, the study found two distinct and reliable clusters of personalities: a bright and a lighter shade of dark personalities, which are differently associated with the indicators of firms' performance and industry categories. While contributing to the advancement of performance-personality research and their measurement at the organisational level, this study opens a new avenue for the adoption of unobtrusive linguistic techniques and data sources for strategic personality-performance research in the corporate governance disciplines. Limitations of the present study and suggestions for future research are also discussed.

Keywords: Organisations' Performance, Strategic Personality, Industry Level, Linguistic Technique; Machine-Learning Approach

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1. INTRODUCTION

Organisational personality or personality inferences about the organisation is a relatively new area of research. Following Aaker's (1997) definition of brand personality, Slaughter et al. (2004) define organisation personality as "a set of human personality characteristics perceived to be associated with an organisation" (p. 86). According

to Slaughter et al. (2004), organisational personality perceptions, or personality characteristics ascribed to organisations, are an example of symbolic characteristics. Lievens and Highhouse (2003) indicate that the symbolic information that describes organisations includes subjective and intangible information such as values, mission, organisational personality, etc. Slaughter et al. (2004) also contended that there may be other

personality traits or dimensions that are relevant to organisation personality but are not relevant to describing brand personality. However, all these researchers and scholars have emphasised the need for both theoretical and methodological development in organisation personality areas due to a lack of a broad and theoretically based taxonomy of organisational personality. In this study, we aim to conduct an exploratory study to contribute to the advancement of theoretical and methodological approaches to measure organisation personality by paying particular attention to strategic and corporate levels and examining its performance and industry-level implications. One of the critical factors that have been reported by previous researchers in organisation personality areas is methodological challenges (Slaughter et al., 2004; Lievens & Highhouse, 2003; Highhouse et al., 2002). In line with these challenges, a new wave of research has emerged recently with a particular focus on methodological advancement in assessing personality profiles and their impact on organisational performance (Lacam & Salvetat, 2023; Howard-Grenville et al., 2019; M.-Y. Chen et al., 2019; T.-H. Chen et al., 2019; Putka et al., 2018; Malhotra et al., 2018; Silberzahn & Menges, 2016). For example, Lacam and Salvetat (2023) and Howard-Grenville et al. (2019) discussed the advancement of methodological approaches as one of the most important aspects of leaders to leverage in management research. T.-H. Chen et al. (2019) applied statistical tests and machine learning algorithms to investigate whether personality plays a significant role in profitability. Malhotra et al. (2018) also adopted a linguistic technique to explore the impact of extraverted chief executive officers (CEOs) on the success of mergers and acquisitions (M&A) as reflected by abnormal returns. Further, while Kobayashi et al. (2018) demonstrated the use of text mining in organisational research, Boyd and Pennebaker (2017) used a language-based personality as a new approach in the digital world. Consistent with this development, IBM¹ (2016) has adopted a machine learning approach to estimate the Big-Five personality scores. Despite the highlighted potential of modern data analytic techniques and machine-learning approaches in organisational research (Howard-Grenville et al., 2019; T.-H. Chen et al., 2019; Putka et al., 2018; Silberzahn & Menges, 2016), the adoption of machine learning in organisation personality and performance research is rather new and scant. In addition, studies that combine both linguistic and machine learning approaches are scarce in personality-performance research. Given this background, we aim to answer the following specific research questions:

RQ1: How can we use linguistic and machine learning approaches to quantitatively estimate the personality traits that are reflected in CEOs' statements in annual reports?

RQ2: Can we reliably identify natural clusters or grouping of personality traits and dimensions by combining such quantitatively and conceptually estimated personality traits through unsupervised clustering?

RQ3: If discrete and natural clusters of personalities are identifiable, do they differ by the levels of firm performance and industry category?

This study is significant for a few reasons. First, it combines trends in both organisation personality-performance research and the advancement in methodological approaches to explore personality traits in organisations using unobtrusive approaches. Second, it will demonstrate how linguistic and machine learning approaches can be used in conjunction with the established statistical methods to quantitatively assess personality traits that reflect in CEOs' statements as they represent strategic and corporate levels of organisations. Third, the findings will contribute to the theory of an organisation's strategic personality, corporate governance, and firm performance, and methodological advancement in the study of unobtrusive organisation personality-performance research under the pressing need for adapting to the heightened technological advancement. Next, we discuss relevant concepts and theories to provide a conceptual background for the study.

2. THEORETICAL FRAMEWORK

2.1. Models of personality

Personality is a complex concept that encompasses behavioural, cognitive, and emotional patterns of people that are shaped by both biological and environmental factors (Cloninger, 2009). Several theories, models, and tests have been developed over the years to understand and estimate personality with varying levels of success. For example, Holland (1973) introduced a typology with 6 personality types: realistic, investigative, artistic, social, enterprising, and conventional. Friedman (1996) proposed a bipolar model called Type A and Type B personality, where Type A people are thought to be intense, competitive, and high achieving, while Type B people are relaxed, less competitive, and transcendent. Another popular typology is the Myers-Briggs Type Indicator (Myers & McCaulley, 1985; Myers & Myers, 1980) where personality is expressed using four bipolar functions, viz. Introversion(I)-Extraversion(E), Sensing(S)-Intuition(N), Thinking(T)-Feeling(F), Judging(J), and Perceiving(P). This theory argues that people tend to be sitting in one of the two extremes of each function, leading to 16 possible personality types in total. Despite the popularity, the Myers-Briggs Type Indicator (MBTI) as well as all foregoing personality typologies have come under strong criticism mainly due to their questionable statistical validity and lack of credible and unbiased empirical evidence for their psychological validity (de Souza & Roazzi, 2017). In this study, we initially utilised the Big-Five personality model (Goldberg, 1990) for several reasons. First, it is one of the most popular personality models in the world (Shang et al., 2016). The Big-Five model, also known as OCEAN, consists of five traits namely, Openness to experience, Conscientiousness, Extraversion, Agreeableness, and Neuroticism. Second, unlike the models discussed earlier, the Big-Five model has proven its validity and reliability in areas such as individual preferences, profitability, mental health monitoring, explaining academic achievement and work success, etc. (T.-H. Chen et al., 2019; de Souza & Roazzi, 2017; Hughes et al., 2012). Third, this model is compatible with the methodological approach, the IBM machine

¹ IBM has discontinued this service since 2021, contact the authors for any further issue.

learning approach in particular that we use in this study to estimate personality scores. The term “strategic personality” seeks to explain the strategic decision-making and behaviour of entities (Ziemke et al., 2001). They note that strategic personalities can be assessed in psychological terms, in a similar way to individuals can be assessed, using typologies to categorise different kinds of personalities and the different behaviour these personalities tend to generate. In this paper, we argue that strategic decision-making and behaviour of firms are reflected in CEO statements in annual reports and thus they might represent the strategic personalities of respective organisations.

2.2. Bright and dark traits of personality

Personality traits placed on a bipolar scale of high and low are often used to identify what are called “bright” and “dark” qualities. Bright traits namely, high emotional stability (low neuroticism), high extraversion, high openness, high agreeableness, and high conscientiousness are typically considered socially desirable, while the opposite dark traits are generally considered socially undesirable (Judge & LePine, 2007). Certain bright traits are associated with high leadership performance. For example, Judge and LePine (2007) note that highly extraverted and conscientious individuals are more likely to excel as leaders. Ciavarella et al. (2004) found that new ventures led by conscientious entrepreneurs are likely to survive in the long run. Zhao et al. (2010) found that bright traits, except agreeableness, are associated with leaders’ performance. However, a substantial body of emerging research points out that there is evidence for the negative impact of certain bright traits and the positive impact of certain dark traits on performance. For example, Hogan and Hogan (2001) found that highly agreeable leaders often fail to resolve conflict and make tough decisions. High emotional stability is usually considered desirable in leaders, but extreme levels could be perceived by followers as a lack of concern about them (Smith et al., 2018). Narcissism is generally considered a dark trait, but narcissistic leaders tend to gain consensus in political processes (Sosik & Dinger, 2007). Chi and Ho (2014) found that a leader’s negative emotional expression is positively correlated with follower performance when followers demonstrate high conscientiousness and agreeableness. Overall, both bright and dark traits seem to benefit organisations in different situations, but when they are not manifested in extremely high or low levels (Smith et al., 2018). In this study, we argue that various personality traits/dimensions do not exist in isolation; rather, they interact with each other and are integrated with the overall orientation and adaptation to issues in real-world situations (Starcevic & Janca, 2022). For example, a combination of prominent agreeableness and conscientiousness has been found to result in socially desirable behaviour (Blagov, 2021). Therefore, it is important to have a better picture of personality traits and facets in relation to a given context to identify natural orientations of behaviours of firms and people. One possibility of having such a combination at the personal or organisational level is the bright and dark clusters of traits. Given the lack of a broad and theoretically based taxonomy of organisation

personality, we pay particular attention to carrying out an exploratory study using linguistic and machine learning approaches to estimate scores for organisation personality. Considering this evidence and the exploratory nature of this study, we establish the following initial hypotheses to design this study.

H1: The Big Five personalities exist as integrated clusters at the organisational level in individual firms.

H2: Integrated personality traits at the corporate/organisational level can have both bright and dark personalities.

H3: Integrated personality traits at the corporate level can have any combination of bright and dark personalities.

H4: The bright personality orientation is associated more positively with firm performance than the dark personality orientation.

H5: Different industries have different bright and dark strategic personality orientations.

3. RESEARCH METHODOLOGY

3.1. Measuring personality

Quantitative measurements of personality traits are often desired, and the default choice of tool for this purpose has traditionally been a questionnaire (Corr & Matthews, 2009). Administering questionnaires to collect personality data from hundreds of top business leaders is unrealistic. An alternative to questionnaire surveying is a novel machine-learning approach, backed by an accepted theory of psychology that suggests the human language reflects one’s personality, thinking style, and emotional status (Boyd & Pennebaker, 2017). International Business Machines Corporation (IBM) operationalised this approach using a machine learning framework. IBM’s work is further inspired by substantial research that found the frequency and variations in word usage in writings can predict aspects of personality (Fast & Funder, 2008; Gill et al., 2009; Golbeck et al., 2011; Hirsh & Peterson, 2009; Yarkoni, 2010).

IBM’s personality insight service follows the open-vocabulary approach (Arnoux et al., 2017; Plank & Hovy, 2015; Schwartz et al., 2013) to infer personality from language. The open vocabulary approach involves identifying words and phrases that characterise certain personality traits using a large volume of data. Machine learning models employed by the personality insight service have been trained using a large volume of text data from one million Twitter users and their known personality traits identified using surveys. The accuracy of the predicted personality score is expressed in terms of Mean Absolute Error (MAE). The MAE is calculated as the average absolute difference between the actual personality trait score obtained from the survey and the predicted score by the machine learning model across one million users. In this study, the MAE for the Big-Five personality traits is 0.12. This gives us confidence to use IBM Watson’s personality insight service to quantify personality traits using CEOs’ communication/statements in annual reports. Full details of the personality insights service can be found in Receptiviti (n.d.).

3.2. Identifying clusters of personality traits

After obtaining a quantified score for personality traits, a natural trend, and a beneficial step is to identify similar patterns of personality in a multi-dimensional personality orientation. For instance, Yukl (2006) suggested that the relationship between personality traits and performance should be more holistically studied, rather than treating one trait at a time. This perspective of research is supported by a growing body of work that investigates cross-interactions of personality traits (Burke & Witt, 2004; Jensen & Patel, 2011). While the traditional approach to identifying sub-groups of personalities in a multi-dimensional personality trait matrix has been manual exploratory analysis and visualisation, it is possible and practical in certain cases, to rely on machine learning algorithms to establish natural sub-groups found in such multi-dimensional planes as demonstrated by Bandiera et al. (2020) and Mumford et al. (2000). This branch of algorithms is commonly known as clustering algorithms that work on a given dataset in an unsupervised manner yet revealing clusters where observations within a cluster are similar and observations between clusters are dissimilar. This study uses the clustering approach due to the large sample size, several independent variables (traits and facets), and our interest in objectively identifying natural groupings of personality traits.

3.3. Data collection

We initially selected the Australian Stock Exchange (ASX) listed top 500 companies. The primary data source was the CEOs' written messages available in annual reports. We downloaded annual reports from company websites for two consecutive years (2016-2017). As a controlling variable, we imposed a condition that a CEO must have served in the concerned company during the entire 2016-2017 period, so we could relate the reflective personality traits with the corresponding years of the firm's performance. To aid impact analysis, we collected company performance data on three indicators, namely, return on assets (ROA), return on equity (ROE), and enterprise value (EV). The ROA and the ROE are both accounting measures that have been used extensively in research that examines firm performance (Cheung et al., 2017; Demerjian et al., 2012). EV is a measure of the wealth (value) of a firm that enhances the shareholders' wealth. Given data covering all the variables of interest were not available in relation to 90 firms, the usable sample was 410 firms (i.e., 820 statements covering two years).

3.4. Quantifying the Big-Five personality traits

For the quantification of personality traits using written language, we used the personality insights service available on the IBM Watson platform. We first copied CEO messages from annual reports into text files. These text files are fed into the personality insights service using a simple Python program that can communicate with this service via the IBM Watson Application Programming Interface (API). The personality insights service calculates trait scores for the given text and returns these scores as a JavaScript Object Notation (JSON) file. These files

are further processed to organize personality trait scores in a spreadsheet format to facilitate further analysis.

In addition to the Big-Five personality traits, the personality insights service also calculates scores for several facets under each personality dimension using separately trained machine learning models. For example, the facets that fall under the trait of Openness are adventurousness, artistic interest, emotionality, imagination, intellect, and liberalism. A complete list of traits and facets that are estimated by the personality insights service can be found in Receptiviti (n.d.). The score for each trait and facet falls in the range of 0 to 1, where any score above 0.5 indicates a greater-than-average tendency for a character. Any score below 0.25 is considered low, while a score above 0.75 is considered high.

3.5. Validity and reliability of measures

The Big-Five personality model consists of acceptable psychometric properties in terms validity of variables, indicators, and their structures as it has been tested globally in more than 70 countries. As a measure of checking the reliability of the data collection method, we performed the IBM mechanism twice for analysing CEOs' statements for two consecutive years (2016-2017), and the reliability/consistency index was found to be 0.78. In addition, Cronbach's alpha coefficients were 0.8 or above for four dimensions: Emotional stability = 0.9, Agreeableness = 0.8, Extraversion = 0.8, and Conscientiousness = 0.8), while it was 0.6 for the Openness dimension. For finalising the cluster scores, we used the average personality scores across the two years.

3.6. Data analysis

3.6.1. Natural clusters of personality traits

As mentioned previously, various personality dimensions do not exist in isolation; rather, they interact with each other, which determine an integrated picture of overall personality orientation (Starcevic & Janca, 2022). Therefore, it is important to have a more realistic and context-specific picture of personality trait distribution in relation to the sample. Simply, after obtaining the scores for the conceptual structure of personality traits and their facets, we aimed to identify natural groupings of personality traits in the dataset. There is a well-established sub-branch in pattern recognition literature called clustering that can be used to fulfil this requirement. Jain (2010) defines clustering as a process by which the k -number of groups is identified given n number of observations such that the difference between observations within a group is minimised, while the difference between observations from distinct groups is maximised. As our clustering algorithm, we used k -means clustering (Nasiri & Khyabani, 2018) in combination with the average silhouette method (Rousseeuw, 1987) that helps determine the optimum number of clusters. Given k groups and n observations, the k -means clustering algorithm aims to minimize the objective function given in eq. (1).

$$J = \sum_{j=1}^k \sum_{i=1}^n \|x_i^{(j)} - c_j\|^2 \quad (1)$$

where, $\|x_i^{(j)} - c_j\|$ is a chosen distance measure between a data point $x_i^{(j)}$ and the cluster centre c_j .

K-means algorithms are implemented as a loop, which consists of the following steps:

1) Randomly select k data points. These points represent the initial cluster centroids.

2) Assign each (remaining) data point to the cluster that has the closest centroid.

3) When all points are assigned, recalculate the cluster centroids (e.g., mean).

4) Repeat steps 2 and 3 until cluster centroids no longer move.

Once observations are clustered into k clusters, it is possible to employ the silhouette method to determine how tight and separate each cluster is. For each observation, a silhouette value measuring how similar a particular object is to its cluster compared to other clusters is calculated. When averaged across all observations, we get the average silhouette width that falls between -1 and +1. The higher the average silhouette value, the better the cluster separation and cluster tightness. We ran the k -means clustering for different k (number of clusters), calculated the average silhouette width under each k , and chose the k that provided the maximum average silhouette width. R open-source statistical software was used for these computations.

3.6.2. Exploring the personality clusters

Once the natural groupings of personality traits are established, we then examined how each personality trait and its facets are represented in each cluster. For this, we used a visualisation-based exploratory analysis where the distribution of values of other

potentially related variables is examined for personality clusters. We could identify distinct distributions of all the Big-Five personality traits and facets for the natural clusters of personalities identified by the k -means clustering. This further confirms the existence of clear personality types/orientations in the dataset. We discuss these findings in detail in the results section.

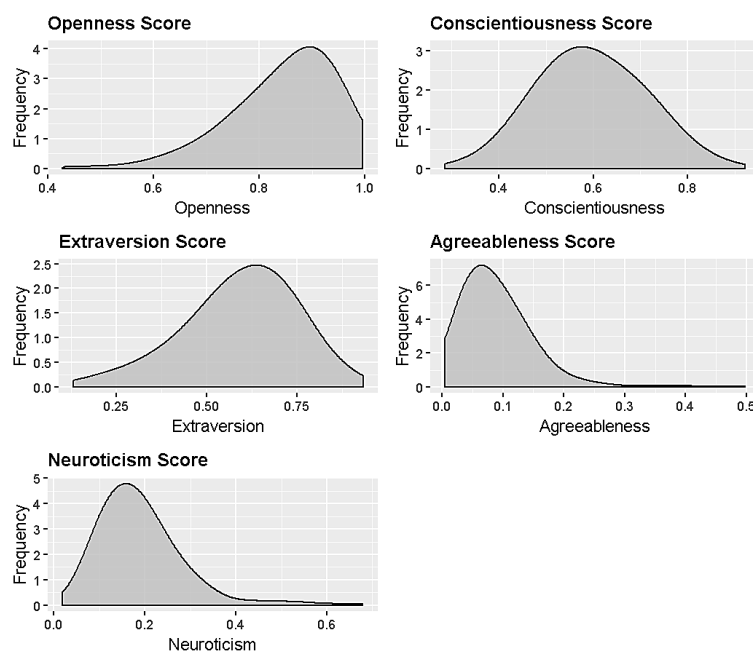
3.6.3. Personality types and performance outcomes

The personality of a firm's leaders has a substantial bearing on firm performance as reported by many researchers (Buyl et al., 2019; de Jong et al., 2013; Ou et al., 2018). In this study, we analysed if the natural personality types identified through the analysis of CEOs' statements are associated with statistically different firm performances. We used three well-known firm performance measures to conduct this comparison (ROA, ROE, and EV). Given that other factors might impact firm performance, it is important that the two personality clusters are first balanced in terms of some observable auxiliary variables, industry category in this case, before evaluating the performance difference between the two clusters. We intend to use the propensity score method (Rosenbaum & Rubin, 1983; Mohr et al., 2020) to extract two samples from the clusters with a balanced covariate structure. The null hypothesis is that there is no difference in firm performance between the two personality clusters that are evaluated using a two-sample t-test.

4. RESULTS AND DISCUSSION

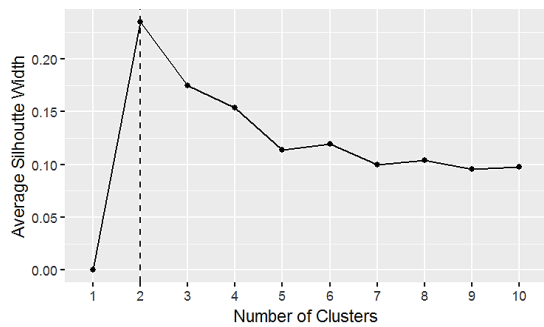
The initial distribution of personality traits reflected in CEOs' statements indicates high openness and extraversion, moderate conscientiousness, and low agreeableness and neuroticism (see Figure 1).

Figure 1. Overall distributions of Big-Five trait scores



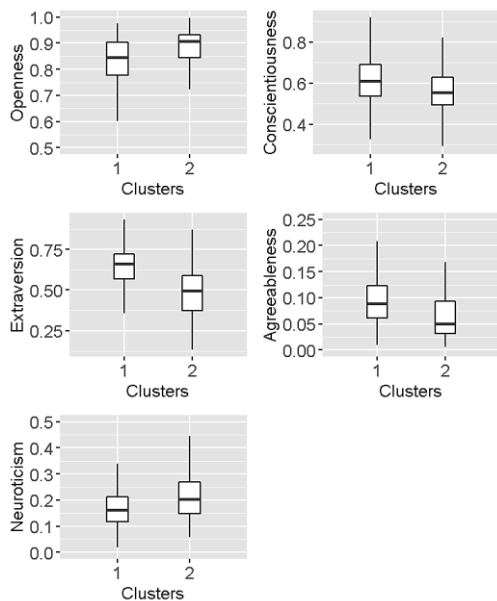
Following the steps mentioned under methodology, we used these Big-Five personality traits, and their component scores to identify natural groupings of personality traits. We combined the *k*-means method with the average silhouette width measure to determine the optimum number of such groups. The highest average silhouette width corresponds to *k* = 2 (see Figure 2), hence we chose two clusters as the optimum number of clusters.

Figure 2. Average silhouette width for different numbers of clusters



At the next stage, these two resulting clusters are separated in relation to each of the Big-Five personality factors (Figure 3). Accordingly, personalities belonging to Cluster 1 show relatively high conscientiousness, extraversion, and agreeableness, and relatively low openness and neuroticism, compared to personalities in Cluster 2. Looking through the lens of bright and dark traits (Judge & LePine, 2007; Smith et al., 2018), Cluster 1 can be considered the brighter cluster, compared to the relatively less bright Cluster 2. This general classification holds except for the bright openness trait, where the Cluster 1 score is relatively low (see Figure 3).

Figure 3. Distribution of personality trait scores for the two clusters



The two clusters are even more discernible in the distributions of component/facet scores. Cluster 1 consistently scores high in the majority of

the brighter facets such as achievement striving, altruism, and cheerfulness. However, it is noteworthy that Cluster 1 scores low for four out of the six facets that fall under the Openness personality trait. These four facets are emotionality, intellect, authority challenging, and imagination. The two facets of openness for which Cluster 1 scores high values are adventurousness and artistic interests. Cluster 1 also records low values for all facets of neuroticism. The distribution of scores for randomly selected sample facets is illustrated in the Appendix. The facets analysis also confirms that Cluster 1 is the brighter one than Cluster 2. In line with the foregoing analysis, from now on we will refer to Cluster 1 as the bright cluster and Cluster 2 as the grey cluster (as it is a lighter shade of dark). We chose the term grey instead of dark to label Cluster 2, as the trait scores of Cluster 2 are not opposite values to those in Cluster 1. In fact, this finding challenges the established terminology, i.e., bright, and dark personality, and thus, a new finding that calls for a new concept such as the one in between bright and dark (might be grey) in future research. In brief, it is important to indicate that the cluster separation could be established using all traits and facets simultaneously in the high dimensional space. This finding confirms our hypothesis *H1* of this study, which is the big-five personalities exist as integrated clusters at the organisation personality level in the sample firms. This finding also supports partially hypothesis *H2* which deals with the proposition that the integrated personality traits at the organisation level can have bright and dark personalities because the unique and innovative second cluster of this study indicates a lighter shade of dark personality. As any combination of bright and dark personalities can exist at the organisational level in practice, this finding, however, confirms our contention in hypothesis *H3* that the integrated personality traits at the organisational level can have any combination of bright and dark personalities.

4.1. Personality clusters and industry category

To examine hypothesis *H5*, we explored if there is evidence to suggest that personality differences can be observed in relation to industrial sector. Table 1 highlights how firms' industry sectors are represented in the two clusters. Compared to the grey cluster, the most dominating industry sectors represented in the bright cluster are consumer discretionary, financial, consumer staples, and information technology. On the other hand, the grey cluster is dominated by industry sectors such as materials, real estate, and healthcare.

Table 1. Industry sector composition of the two personality clusters

Industry sector	Bright cluster, %	Grey cluster, %
Consumer discretionary	19	11
Financial	16	5
Materials	13	28
Industrial	10	12
Information technology	10	6
Consumer staples	7	2
Real estate	6	16
Healthcare	6	11
Energy	5	6
Telecommunication	4	0
Utilities	3	1
Others	0	1

To examine if the two clusters are significantly different in terms of the industrial sector, we ran a chi-square test. In this hypothesis test for contingency tables, our null hypothesis is that the two clusters are not significantly different in relation to the categorical variable — the industrial sector of firms. There is evidence to reject the null hypothesis for the categorical variable such as industry type with 95% confidence ($\chi^2 = 54.5$; $df = 11$; $p = 0.001$). Accordingly, this analysis reveals that the two clusters identified demonstrate differentiable patterns in the type of industry category, which confirms the *H5*.

4.2. Personality traits and firm performance

Bright traits are generally considered desirable as they relate to positive personal and organisational outcomes (Barrick & Mount, 1991; Judge et al., 2002). For example, Ciavarella et al. (2004) found that entrepreneurs' conscientiousness is positively related to a venture's long-term survival, while high openness is negatively related to it. In another study, Zhao et al. (2010) concluded that four of the big five factors, except agreeableness, are directly related to leaders' performance. Following this reasoning, we examined if the two personality clusters, the bright and the grey clusters, are associated with different levels of firm performance (*H4*). Given the unbalanced covariate structure between the two clusters, a propensity score method is first used to match individual cases from the two clusters with similar covariate structures. The two personality cluster samples matched in terms of covariate structures are then compared for performance differences using a t-test, the result of which is given in Table 2.

Table 2. Statistical significance of the performance differences between the two personality clusters

Performance measure	p-value
EV	0.03*
ROA	0.00034*
ROE	0.012*

Note: * significant at $\alpha = 0.05$ level.

Results of the t-test for matched samples (Table 2) reveal that for all the concerned performance indicators, there is statistically significant evidence to reject the null hypothesis with 95% confidence, hence we conclude that the bright and grey personalities are associated with different firm performances. More specifically, confirming hypothesis *H4*, the study found that the bright personality orientation is associated more positively with firm performance than the dark or lighter shade of dark personality orientation. It is important to note that the bright cluster has relatively higher conscientiousness and extraversion, and relatively lower neuroticism and openness, which are proven attributes leading to higher firm performance according to previous research (Barrick & Mount, 1991; Ciavarella et al., 2004; Judge et al., 2002; Zhao et al., 2010).

4.3. Discussion

As an exploratory study on an organisation's strategic personality and its performance and industry-level implication, we examined and

confirmed four out of the five hypotheses. In brief, this study provides evidence to confirm the hypotheses that organisation strategic personality can exist as an integrated bright and dark cluster or any combination between the two at the corporate level in organisations. Further, the bright personality orientation is more positively associated with firm-level performance than that of the grey personality orientation. In addition, the study found that individual firms in the same industry can have both bright and dark strategic personalities or one in between the bright and the dark personalities at the corporate level. Thus, the hypothesis which dealt with having bright and dark organisation personalities at the corporate level was supported partially. Although, conceptually, this (grey cluster) is a unique finding, such scenarios can exist in practice in any organisation as personality represents wholistic human responses in organisations. We discuss below the other theoretical and methodological contributions of these findings.

4.4. Theoretical contributions

Theoretically, this study contributes to the advancement of the strategic personality theory and organisation personality-performance research. Specifically, our findings confirm that certain bright traits such as high conscientiousness, extraversion, and emotional stability (low neuroticism) at the strategic or organisational level are associated with better firm performance as previously supported by individual-level research (Barrick & Mount, 1991; Ciavarella et al., 2004; Judge et al., 2002; Zhao et al., 2010). The findings also indicated that not all bright traits at firm levels are positively correlated with performance. For example, the high-performing cluster of personality exhibits a relatively low openness to experience. This observation supports an emerging area of personality research that explores the dark side of bright traits and the bright side of dark traits (Judge & LePine, 2007; Smith et al., 2018).

Further, the study found significant differences between the two clusters of personality traits in relation to the industry category of the selected firms. Some previous research evidence explains personality differences between industry sectors (Stephan et al., 2023; Judge & Cable, 1997; Schneider et al., 1998). For example, Stephan et al. (2023) found that values of narcissism, psychopathy and psychological capital differed between industries. For example, they found that psychopathy relates significantly to psychological capital in most industries but does not for sectors of architecture, automotive, and consulting. Given this evidence, an important practical implication of the finding of this study is that the extent of assimilation of a person to organisational expectations (e.g., person-organisation-fit, also know P-O fit) is relevant to explaining industry differences as an organisational setting that attracts distinct types of personalities. Similarly, organisations might consider developing existing employees to fit the personalities of organisations. Future research should consider these industry effects and re-examine current understandings of personalities in organisations, leaders, and employees simultaneously.

4.5. Methodological contribution

This study provides evidence regarding how management researchers can use linguistic and machine learning approaches to quantitatively estimate the personality traits that are reflected in CEOs' statements in annual reports to infer organisation personality. It further demonstrated how unsupervised machine learning can be used to identify natural groupings of personality clusters using many variables (traits and facets data) simultaneously. This would open not only new avenues for the quantitative inquiry into personality traits and firm performance but also contribute to the advancement of the recent development in machine learning algorithms to provide better insights into the aspects of the behaviour of firms and people (M.-Y. Chen et al., 2019) and their implications (T.-H. Chen et al., 2019). Overall, the study integrates trends in both personality-performance research in corporate governance and the advancement in methodological approaches to explore personality traits and organisation personality using unobtrusive approaches.

5. CONCLUSION

This exploratory study investigated the organisation and strategic personality by adopting linguistic and machine learning approaches and examined its performance and industry-level implications. The cluster analysis of the Big-Five traits and their dimensions found a bright and a lighter shade of

dark personality, which we interpreted as a grey personality. Further analysis revealed that the brighter personality cluster relates to relatively higher firm performance, consistent with some previous research. Theoretically, the study contributed to the organisation's strategic personality concept, factors affecting firm performance in the corporate governance area, and the bright and dark personality orientations of firms and industries. Methodologically, the reliability of the methods used in this study encourages new avenues for the adoption of machine learning algorithms in organisation personality-performance research. Accordingly, this study serves as an appropriate benchmark against which further research can be assessed. Despite the intriguing findings and their theoretical and practical implications, this study is not free from limitations. It was conducted in Australia, using annual reports data and financial information and therefore, the findings are based on secondary and published data. Further, the findings might not be able to generalise in the context of other countries and stages of the life cycle of firms. Irrespective of the identity of contributors to the annual reports' statements, we assume that annual reports' information is the formal and published data that create company image which is important for all the stakeholders, and that organisation personality can be inferred using that overall image. However, future research might consider the same or different methodologies and perspectives on organisation personality.

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APPENDIX. CLUSTER SEPARATION OBSERVED IN SOME FACETS OF THE BIG FIVE PERSONALITY TRAITS

