Measuring Organizational Character: Leveraging Sentence-BERT and MBTI

Abstract

This study aims to introduce a pioneering approach to measure the organizational character of companies based on the Myers-Briggs Type Indicator (MBTI) employing text analytics, namely Sentence-BERT. Our analysis encompasses a substantial dataset from Glassdoor, comprising 1,329,264 anonymous employee reviews covering 1,147 companies within the S&P 1500 Index. Our findings highlight *ENFJ (Extroversion, Intuitive, Feeling, Judging type)*, *ENTJ (Extroversion, Intuitive, Thinking, Judging type)*, and *ENFP (Extroversion, Intuitive, Feeling, Perceiving type)* as the foremost organizational character types out of 16 types, with *ENFJ* representing 29% of the sample companies. *EJ (Extroverted-Judging type)* behavioral temperament and *NF (Intuitive-Feeling type)* decision-making temperament emerge as prevalent traits within these organizational contexts. Companies operating within the same industry tend to have analogous organizational character. Additionally, our statistical validation highlights that *ENTJ* companies exhibit the highest levels of innovativeness. These findings offer practical insights for organizational diagnostics and strategic formulation while paving the way for prospective empirical inquiries into the broader impact of organizational character.

Keywords

Organizational character, MBTI, Online company review, Text similarity, Sentence-BERT

1. Introduction

An organization is not merely a static group of individuals with a shared objective; it is a dynamic, evolving entity (Morgan, 2006). Like any living organism, it grows, transforms, and interacts with its environment. This dynamic nature fosters the development of a unique personality for the organization, referred to as its organizational character (Levinson, 2009). Within the context of a business entity, which includes physical assets such as property, staff, data, and technology, every company exhibits an evolving organizational character (Yu et al., 2018). The intrinsic, distinctive, and enduring features of an organization are closely intertwined with its identity (Kreutzer & Jäger, 2011), serving as a valuable tool for differentiation (Chun & Davies, 2006). Therefore, exploring organizational character can yield valuable insights into the operational mechanisms of companies and industries.

Understanding a company's organizational character is increasingly crucial as industries evolve and competition intensifies. Organizational character, while morally neutral, varies in its suitability for adaptation or competition within specific environments, industries, and cultures, akin to advantageous DNA for survival (Bridges, 1992). Furthermore, as consumer consumption patterns increasingly value a corporation's status, reputation, and characteristics alongside product quality and price, it becomes imperative for companies to cultivate a positive organizational character that resonates with both consumers and employees (Yu et al., 2018). Therefore, companies must prioritize developing and managing their organizational character and product competitiveness to remain viable and attract talent. Consequently, a thorough investigation of organizational character is a critical first step for companies seeking to survive and secure a competitive advantage.

Previous studies have suggested that organizations, including groups, companies, societies, and countries, exhibit shared character patterns among their members stemming from everyday experiences (Levinson, 2009). To assess this organizational character, researchers have primarily relied on tools targeting individual members, given their belief in its close association with individual character (Davies et al., 2004; Gorbaniuk et al., 2017; Otto et al., 2011; Yu et al., 2018). However, these tools are limited as they often depend on questionnaire surveys, restricting the number of respondents and companies that can be included in a study. Consequently, this study explores text analytics using online reviews as an alternative approach to overcome these limitations.

Traditionally, online reviews have significantly influenced users seeking information on specific subjects and exhibit two essential characteristics: First, review platforms in online environments facilitate the collection of large volumes of online reviews, offering flexibility in terms of time and space. In the business realm, the wealth of consumer feedback inherent in online reviews of products or services has long assisted other consumers' decision-making processes, both offline and online. Second, online reviews often provide insights into the subject matter without reservations. In recent years, online company reviews, in which employees directly assess their employers, have garnered significant interest from job seekers. This is attributed to reviewers' tendency to offer sincere opinions or information on companies, facilitated by the anonymity afforded by online platforms (Evans & Mathur, 2005). Furthermore, the rapid advancement of text analysis techniques has enabled the extraction of nuanced information from these reviews, allowing numerous studies to address existing methodological challenges and achieve reliable results (Farhadi & Nanda, 2021; Swain et al., 2020; Symitsi & Stawmolampros, 2021).

This study is designed to fulfill three primary research objectives. The first objective of this study is to elucidate the terminology and concepts associated with the organizational character. By carefully considering and synthesizing concepts related to organizational attributes—such as climate, culture, and characteristics, as examined in previous studies—these elements are collectively captured under the term 'organizational character.' Furthermore, the study adopts the MBTI (Myers-Briggs Type Indicator) as a metric for quantifying aspects of organizational character. The second objective is to introduce a novel methodology for measuring the organizational character across companies, achieved through the application of text similarity analysis using Sentence-BERT, departing from the predominantly survey-dependent methods utilized in prior research. The third objective is to establish the reliability and validity in measuring organizational character through the analysis of a substantial volume of online company review data. Leveraging Glassdoor as our primary data source, which offers textual reviews and ratings from both former and current employees, we assess companies' character by evaluating the text similarity between descriptions of organizational character types and online company reviews.

The remainder of this paper is organized as follows. Section 2 reviews the literature on organizational character, online company reviews, and text similarity analyses. Section 3 describes our research method, including the research process, dataset, and character measurement. Section 4 presents the experimental results, including the distribution of company character types, behavioral and decision-making temperament types, and company positioning maps. In Section 5, the significance of the proposed methodology is statistically validated through a post-hoc analysis. Section 6 discusses our results and those of previous studies, which have several implications. Finally, Section 7 concludes the paper by suggesting future research paths and presenting this study's limitations.

2. Literature Review

2.1. Organizational Character

As the business environment changes rapidly, all organizations must adapt, develop, and interact with the external environment (Morgan, 2006). Organizations adjust and evolve in response to the surrounding environment to survive and overcome the functional limitations of traditional organizational structures, management policies, and systems in an era marked by rapid political, social, and economic change (Katz & Kahn, 1978). Through this process, unique characteristics, such as distinctive organizational structures and consistent behavioral styles, are formed, resembling those of a living organism (Nonaka & Toyama, 2003). Previous studies have explored organizational climate, culture, and character.

Organizational climate, also referred to as organizational atmosphere, was formally introduced based on Lewin's (1951) academic concepts and defined as an objective trait of the working environment that is distinct from other organizations and continuously influences members' behavior (Forehand & Gilmer, 1964; Stern, 1970). Moran and Volkwein (1992) stated that organizational climate comprises essential characteristics within the work environment that directly or indirectly influence members' behavior. By contrast, Schneider et al. (2013) defined it as a shared experience or perception of an organization's routines, tasks, events, or practices.

Organizational culture, a concept that is more macroscopic and complex than climate, is defined as the basic assumption or pattern that the organization learns through resolving internal integration and external adaptation issues (Schein, 2010). Additionally, organizational culture is described as a property of an organization that forms over time, is difficult to change once established, and is more stable than the organizational climate (Paais & Pattiruhu, 2020).

Finally, organizational character is used interchangeably with the aforementioned terms. Forehand and Gilmer (1964) suggested that organizational climate implies organizational character. Furthermore, Kim and Yoo (2008) stated that organizational character can be synonymous with culture and climate, whereas Nazari et al. (2011) introduced organizational characteristics based on the concepts of culture and climate. Considering previous studies and the modern perspective of an organization as a living organism, organizational character is a more suitable term than the others (Li et al., 2018; Levinson, 2009; Yu et al., 2018). Therefore, this study uses this term.

The exploration of organizational characteristics has been a subject of scholarly interest for decades. As one of the pioneers, Kardiner (1945) posited that groups, much like individuals, exhibit distinct personalities. Bois (1944) further elucidated this concept by suggesting that a group's personality not only mirrors the differences between individuals from various groups but also the similarities among its members. Defined by Schneider (1987) at a more expansive group level, organizational character encapsulates the collective experiences of an organization's members, shaping their behaviors. In a similar vein, Shee and Abratt (1989) conceptualized organizational character as the integration of behavioral and intellectual traits that distinguish one organization from another. Slaughter et al. (2004) likened organizational character to an individual's personality traits. Given the frequent foundation of studies on organizational character in the Myers-Briggs Type Indicator (MBTI) framework, a thorough understanding of MBTI is instrumental.

The MBTI is a personality type test developed by Myers and McCaulley (1985) and rooted in Jung's (1971) theory of psychological types. It categorizes individuals into 16 personality types based on four preferences: *Extroversion* (*E*) or *Introversion* (*I*), *Sensing* (*S*) or *Intuition* (*N*), *Thinking* (*T*) or *Feeling* (*F*), and *Judging* (*J*) or *Perceiving* (*P*). For instance, one of the 16 types is *ESTJ*, which indicates preferences for *Extroversion* (*E*), S*ensing* (*S*), T*hinking* (*T*), and J*udging* (*J*). The MBTI has been widely used to assess the characteristics of company stakeholders to gain insights into organizational dynamics. Roberts (1989) explored the personality traits of entrepreneurs in technical organizations using the MBTI. Ginn and Sexton (1990) compared the psychological preferences of the founders and CEOs of fast-growth firms with those of the founders of slow-growth firms, using the MBTI to elucidate differences in information gathering, assimilation, and processing. Similarly, Carland and Carland (1992) analyzed MBTI preferences among small business owners, managers, and executives. Meanwhile, Reynierse (1997) compared MBTI results among similar sample groups, aligning with prior studies.

Some researchers have applied the concept of the MBTI directly at the organizational level. Bridges (1992) proposed that organizational character could be classified into the same 16 types as individuals, encompassing *Extroversion* (*E*) or *Introversion* (*I*), *Sensing* (*S*) or *Intuition* (*N*), *Thinking* (*T*) or *Feeling* (*F*), and *Judging* (*J*) or *Perceiving* (*P*). He detailed the characteristics of each type across these four dimensions. For example, *extroverted* organizations seek external resources through resource acquisition, whereas *introverted* organizations rely on internal sources. Second, regarding information gathering, *Sensing* organizations base their decisions on past experiences or recent cases, whereas *intuitive* organizations prioritize innovative changes by considering both present and future perspectives. Third, *thinking-oriented* organizations emphasize consistency and efficiency in information processing, while *feeling-oriented* organizations prioritize honesty, loyalty, and responsibility. Finally, *judging-oriented* organizations make prompt decisions in their external responses, whereas *perceiving-oriented* organizations engage in open discussions and defer decisions to explore better options.

Furthermore, Park (2015) identified 16 types of organizations classified according to the MBTI, organizing them into two distinct sets of temperaments. Firstly, in terms of behavioral temperament toward the environment, organizations were categorized into four types: *Extroverted-Judging* (*EJ*), *Extroverted-Perceiving* (*EP*), *Introverted-Judging* (*IJ*), and *Introverted-Perceiving* (*IP*). These classifications were based on their preferred sources of energy and methods of external response. Secondly, regarding decision-making temperament, organizations were classified into four types: *Sensing-Thinking* (*ST*), *Sensing-Feeling* (*SF*), *Intuitive-Feeling* (*NF*), and *Intuitive-Thinking* (*NT*). This classification reflects their preferred types of information and methods of information processing.

The estimation of organizational characters typically involves two methods. The first determines the representative character of an organization by identifying the most frequent character type among the individual members. Schneider et al. (1998) assessed the characters of 142 U.S. organizations by analyzing the personalities of 13,000 managers. Similarly, other researchers have examined individual members' characters to infer the organization-level character (Chu et al., 2019; Schneider & Bartram, 2017). The second method involves directly assessing organizational character using scales specifically designed for this purpose. One such scale is the Organizational Character Index (OCI), developed by Bridges (1992). The OCI classifies organizational character into 16 types, aligning with the MBTI classification system, and comprises 36 questions, with nine questions in each of the four dimensions. Krathwohl (1993) utilized the OCI to measure the characters of several organizations, and Sirmans (2002) noted its accuracy in assessing organizational character. Maron and Van Bremen (1999) found the OCI to be a valuable tool for comparing the cultures of different organizations. More recently, the Organizational Climate Index (OCI) has been employed to measure the climate at the organizational level across various research domains (Khan, 2019; Shanker et al., 2017; Tang & Lee, 2021)

Given that founders, managers, and members significantly influence the organizational climate, culture, and character (Levinson, 2009), traditional methods for measuring organizational character generally involve surveying these organizational members, including employees at all levels of management. However, the time and cost constraints associated with these survey-dependent methods frequently result in small sample sizes that may not adequately capture the character of an organization. Consequently, recent studies have highlighted the need for the development of new methods for measuring organizational character (Chu et al., 2019; Gorbaniuk et al., 2017; Li & Yu, 2018).

2.2. Online Company Reviews

With the rapid improvement of computer processing capacity and the considerable development of technology for collecting, processing, and analyzing data, the number of online reviews posted on social media and online spaces, as well as the importance of the information included in them, has increased exponentially (Jiménez & Mendoza, 2013; Yang et al., 2019). Traditionally, online reviews of products and services have played a crucial role in consumer purchase decision-making in both online and offline environments, and previous studies have confirmed the helpfulness of these reviews (Chen & Xie, 2008; Fink et al., 2018; Krishnamoorthy, 2015). Furthermore, online company reviews and employees' direct evaluations of their companies have recently attracted significant attention (Parameswaran et al., 2022). In today's decision-making landscape, online reviews have become a crucial source of information, with company reviews gaining popularity among employees seeking insights into various aspects, such as organizational culture, management, and compensation (Choi et al., 2023). These reviews naturally contain valuable clues that offer insights into an organization's decision-making processes and operational procedures. For example, Glassdoor (http://glassdoor.com) provides various company information, such as ratings and text reviews left by anonymous former and current employees around the world. It has been actively utilized by users interested in job searches or turnover (Luo et al., 2016).

Company review platforms usually guarantee reviewer anonymity. In traditional surveys, respondents tend to be hesitant to reveal the negative aspects of their jobs because of concerns about the possible consequences (DeMaio, 1984). Job reviewers on online platforms are more likely to offer honest information about their jobs owing to their anonymity (Evans & Mathur, 2005). Moreover, job reviewers are motivated to offer honest evaluations because they contribute to the public good (Lerner & Tirole, 2002). Thus, review readers can gather unique information about jobs that corporate disclosure never provides and tend to trust this information more than the official information presented by a company or country (Lakin, 2015). Therefore, online company reviews have drawn the attention of researchers and job seekers.

As online company reviews facilitate easy data acquisition and can efficiently provide a large sample size, many researchers across various fields have increasingly utilized reviews from online platforms such as Glassdoor. Schmiedel et al. (2015) analyzed reviews of Fortune 500 companies on Glassdoor, using topic modeling to extract keywords such as “work-life balance,” “flexibility,” and “employee treatment,” which reflects organizational factors valued by employees. Similarly, Swain et al. (2020) developed a methodology to quantify organizational culture based on Glassdoor reviews, validating their approach by demonstrating that the quantified culture correlates with job performance. Moreover, Farhadi and Nanda (2021) conducted a textual analysis of Glassdoor reviews to assess employees’ opinions on private companies, while Symitsi and Stawmolampros (2021) enhanced the predictability of stock returns in their financial models by incorporating employee sentiment derived from reviews. Thus, this study extends these efforts by analyzing online company reviews to understand and measure the organizational character of companies.

2.3. Text Similarity Analysis

In recent years, text processing and analysis technologies have received significant attention for extracting meaningful information from textual data (Abramova et al., 2022; Pejic-Bach et al., 2020). Like traditional data-mining methods, text mining includes document-based frequencies, clustering, and similarity analyses. Text similarity analysis measures the similarity between two or more documents by calculating the distance between two document vectors. Here, cosine similarity, which is based on the cosine of the angle between two vectors, is the most common method for gauging distance and has been used to determine the similarity of documents in previous studies (Benedetti et al., 2018; Gunawan et al., 2018; Park et al., 2020). However, it is essential to convert textual data into 0 or 1 forms that computers understand, along with initial processes such as collection, filtering, and parsing. This process transforms document data with string values into a vector matrix with number values, which is sufficient to determine the analysis results. Many researchers have suggested various methods of interest.

As the most common method of converting text into numbers, the Vector Space Model proposed by Salton et al. (1975) regards a document as a Bag of Words (BoW) and transforms it into a numerical vector containing word-level information. Each document has a vector space equal to the number of words in the entire document, and the frequency information of each word in the document is expressed as a numerical value. Here, as the term weight in the document, the numerical value of each word represents the presence or absence of the word, the frequency of the word's appearance within the document (Term Frequency: TF), or the frequency of the word's appearance within the document considering non-critical words commonly used in all documents (Term Frequency-Inverse Document Frequency: TF-IDF) (Jones, 1972; Salton et al., 1975). These have been consistently used owing to their stable performance and convenience of implementation. Nonetheless, they have a limitation in that each word's word order and semantic information are ignored.

The method proposed to overcome this shortcoming is Doc2Vec, which was developed based on Word2Vec. Word2Vec, proposed by Mikolov et al. (2013), begins with the Distributional Hypothesis that words with similar meanings tend to appear in similar contexts. As a method for converting text composed of multiple sentences into hundreds of vector space dimensions and embedding all the words contained in the text into this space, Word2Vec enables the measurement of semantic relationships between words. Additionally, Doc2Vec, proposed by Le and Mikolov (2014), is an extended form of Word2Vec for expressing one sentence, paragraph, or document as a vector matrix of fixed length using not only the neighboring words but also a document matrix that has the semantic and structural information of the document. Like Word2Vec, Doc2Vec enables the measurement of semantic similarities or contextual relevance between two documents by calculating the distance between their vectors. An et al. (2022) used Doc2Vec to assess the organizational character of Korean companies. They calculated the similarity between online company reviews and documents that describe characteristics at the organizational level. However, these methods are limited in comprehending semantics because of their inability to capture exact word sequences (Rath & Chow, 2022).

Based on deep learning, Devlin et al. (2018) introduced Bidirectional Encoder Representations from Transformers (BERT), a new pre-trained language representation model that demonstrated superior performance across various sentence-pair similarity comparison tasks. BERT consists of multiple transformer encoder layers that facilitate deep language feature extraction at both token and sentence levels, processing information from both forward and backward sequences (Vaswani et al., 2017). Building on this foundation, Reimers and Gurevych (2019) developed Sentence-BERT (SBERT), enhancing BERT's sentence-level performance through the use of a Siamese network architecture. This architecture employs two identical BERT networks running in parallel, which share the same network weights, allowing each network to process an input sentence, map it onto a high-dimensional feature space, and produce a fixed-size sentence representation. SBERT calculates sentence similarity by measuring the distances between these representations. The utility of SBERT has been confirmed in a variety of textual analysis applications across multiple domains, as evidenced by recent studies conducted by Garcia and Berton (2020), Rath and Chow (2022), and Wang et al. (2021, 2022).

Recently, various large language models (LLMs) such as GPT (Brown et al., 2020), PaLM (Chowdhery et al., 2022), and LLaMA (Touvron et al., 2023) have been introduced. Research comparing their performance with existing models across various natural language tasks have been actively conducted. For instance, Kim et al. (2024) quantitatively compared the performance of BERT-based and ChatGPT-based models. Their results showed that ChatGPT outperformed BERT-based models in inference tasks, while BERT-based models exhibited better performance in similarity tasks (Kim et al., 2024). Additionally, Freestone and Santu (2024) conducted a performance comparison study involving three LLM-based models (LLaMA2, PaLM 2 and ADA-002) and classical models such as SBERT. Their experiments showed that while LLM-based models typically surpassed classical models in analogy tests, they did not always excel in capturing semantic similarity, as demonstrated by SBERT outperforming LLaMA (Freestone and Santu, 2024). ADA and PaLM exhibited high accuracy among LLMs and showed significant agreement with SBERT, suggesting SBERT could be a suitable alternative (Freestone and Santu, 2024). Therefore, this study leverages SBERT to measure the organizational character of companies, capitalizing on its proven capability to capture semantic similarity in complex language data.

3. Research Method

3.1. Overall Process

This study measures the organizational character of companies and classifies them according to their organizational character. To this end, we prepare two types of text: (1) company reviews collected from Glassdoor (http://glassdoor.com) and (2) descriptions of the eight preferences extracted from the related literature (Bridges, 1992; Myers & McCaulley, 1985). All sentences in these texts are vectorized respectively using the SBERT model. Then, we calculate the similarity between each of the company review vectors and each of the eight preference vectors using vector similarity analysis. The similarity results are averaged by review, preference, and company in order. Then, we obtain eight average similarity results for each company. As we are aiming to measure four dimensions of each company's character, similarity differences in each pair of two preferences in four dimensions are calculated. Finally, depending on the similarity difference results, each company is classified into one of the sixteen types. The overall process is shown in Figure 1.

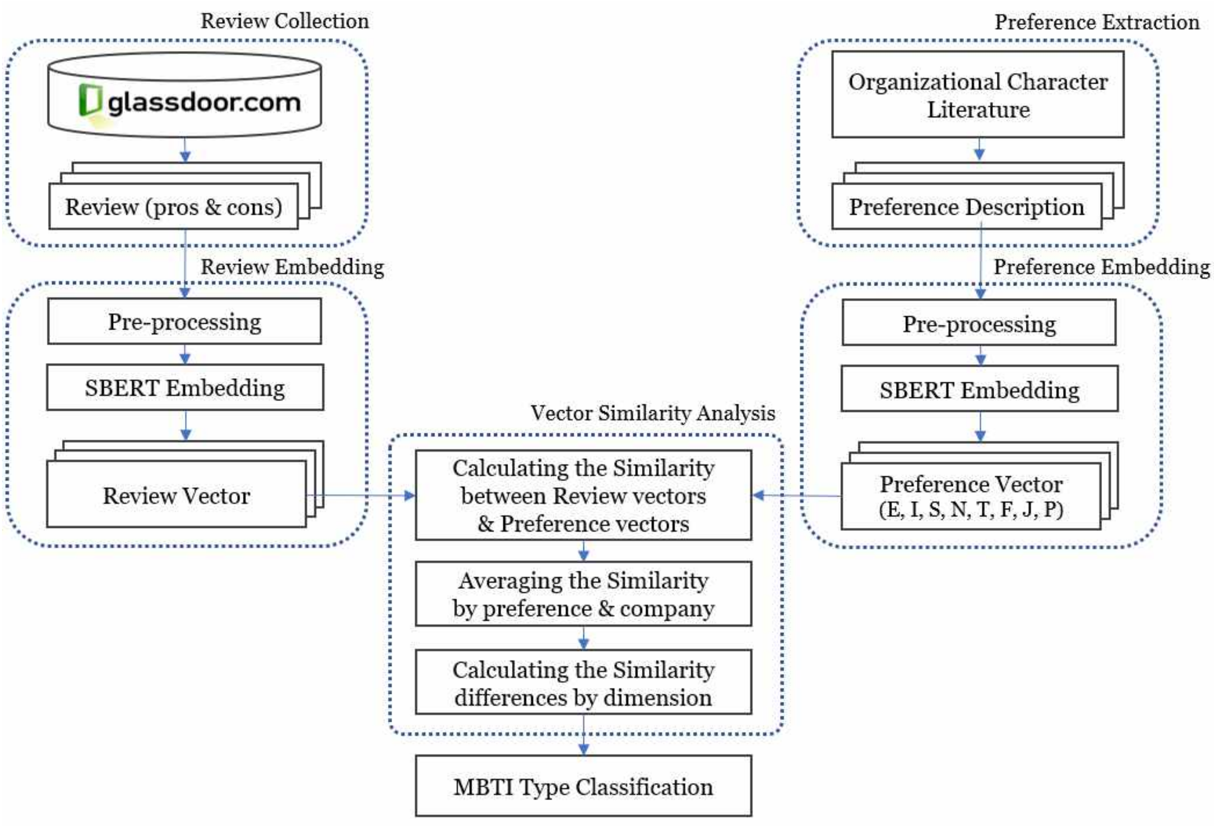

Figure 1. Overall Research Process

3.2. Company Review Collection

This study analyzes company reviews collected from Glassdoor, the most globally popular company review site. Glassdoor was launched in 2008 and currently contains about a million companies with more than 50 million reviews, company ratings, salary reports, and CEO approval ratings from worldwide locations. The employment positions of reviewers are varied, and they are former or current employees of the company they reviewed. Each of the reviews provides numeric ratings, including overall rating and five criteria ratings, and textual contents, including pros, cons, and advice to management. Figure 2 shows an example of reviews in Glassdoor.

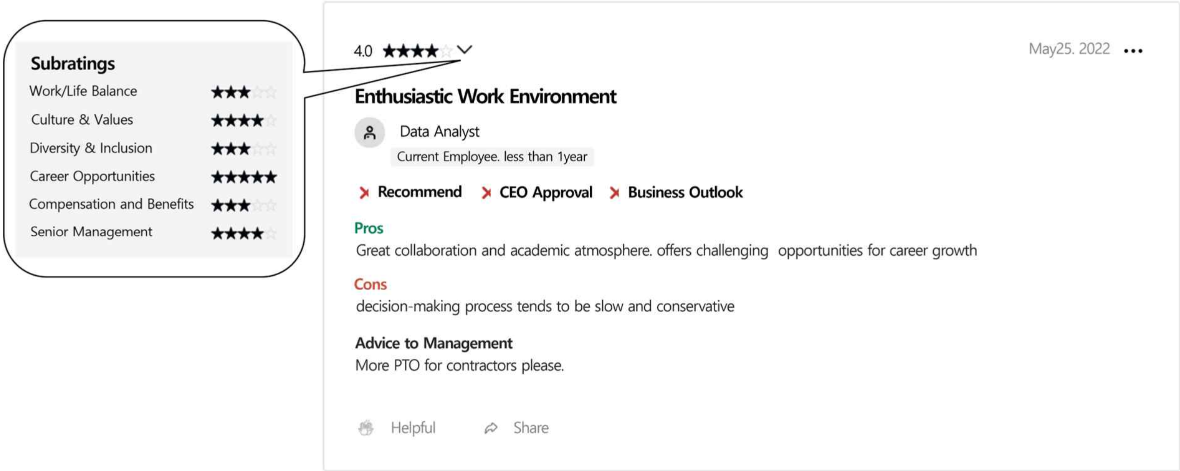

Figure 2. An Example from Glassdoor Reviews

We assume that a pros and cons text in reviews can offer clues to infer the character of companies. Thus, we developed a Python web crawler to collect pros and cons text in reviews of companies that belong to S&P 1500. Then, we eliminate non-English reviews and redundant reviews. Reviews that consist of less than ten words are discarded since they are considered not to contain sufficient information. Finally, our dataset consists of 1,329,264 reviews from 1,147 companies, including company name, posted date, pros, and cons.

3.3. Preference Extraction

Prior studies discussed traits of each of the eight preferences and the differences between two preferences in each pair of four dimensions (Bridges, 1992; Myers & McCaulley, 1985). Based on these studies, we summarize each of the eight preferences, as shown in Table 1. Sentences belong to each of both preference descriptions of each pair are the same in number and symmetric to each other.

***Extroversion* (*E*)**	***Introversion* (*I*)**
· Have open boundaries	· Have closed boundaries
· Allow access to decision-making	· Prevent access to decision-making
· Trust oral communication	· Trust written communication
· Encourage inter-departmental cooperation	· Experience inter-departmental mistrust
· Seek resources from the outside	· Seek resources from the inside
· Collaborate a lot	· Collaborate rarely
***Sensing* (*S*)**	***Intuition* (*N*)**
· Are at their best with detail	· Are at their best with big pictures
· Prefer incremental change	· Prefer transformational change
· Make improvements	· Change paradigms
· Trust experience and authority	· Trust insight and creativity
· Emphasize targets and plans	· Emphasize purposes and vision
· Make decisions with masses of information	· Make decisions with the overall trend
· Prefer solid routines	· Are careless about routines
***Thinking* (*T*)**	***Feeling* (*F*)**
· Make decisions based on principles	· Make decisions based on human values
· Think in terms of rules and exceptions	· Think in terms of particular human situations
· Are goal-oriented	· Are people-oriented
· Emphasize efficiency	· Emphasize harmony
· Value what is logical	· Value what we care about
· Encourage employees to achieve their goals	· Encourage employees to do their best
· Are social machines	· Are social communities
***Judging* (*J*)**	***Perceiving* (*P*)**
· Set clear, specific standards	· Set general standards
· Define things clearly and in detail	· Leave things unclear and vague
· Are tight and strict	· Are loose and tolerant
· Emphasize the speed of decision-making	· Emphasize the quality of decision-making
· Decide quickly	· Decide slowly
· Drive toward decisions	· Delay decisions for a better choice

Table 1. Descriptions of Eight Preferences

3.4. Review Embedding and Preference Embedding

Firstly, both the pros and cons of each review text are merged. Then, non-alphabet characters such as exclamation marks, asterisks, or parentheses were eliminated using Natural Language Toolkit libraries. Then, using the SentenceTransformer package, we vectorize each review in sentence-level text using SBERT.

Preference descriptions are embedded as well. Non-alphabet characters are removed in eight preference texts. Then, each sentence is vectorized with SBERT using the SentenceTransformer package.

3.5. Vector Similarity Analysis

As both reviews and preference descriptions are vectorized, the similarity between both can be measured using vector similarity analysis. The most widely used simple metric to determine the similarity between two vectors is cosine similarity. The calculation of cosine similarity between two vectors, *v* and *s*, can be seen in Equation 1.

$$Similarity_{cos}(v,s) = \frac{v \cdot s}{|v| \cdot |s|} = \frac{\sum_{i=1}^{n} v_i \cdot s_i}{\sqrt{\sum_{i=1}^{n} v_i^2} \cdot \sqrt{\sum_{i=1}^{n} s_i^2}} \quad (1)$$

Using this equation, the similarities between each vectorized sentence in company reviews and each vectorized sentence in eight preferences are calculated.

4. Experimental results

We evaluate similarities between each review and each of the eight preference descriptions at the sentence level. The results are averaged by review and preference. Examples of several reviews posted on Glassdoor and eight similarity evaluation results of each review are shown in Table 2. For instance, the review written as “Project based, communicate with a lot of stakeholders from various companies, internal alignment is also strong. Time management is crucial as workload is project-based” is evaluated as 1.358 of *Extroversion* (*E*), 1.250 of *Introversion* (*I*), and 1.329 of *Sensing* (*S*).

Review (pros and cons are merged)	**Similarity**			
"Project based, communicate with a lot of stakeholders from various companies, internal alignment is also strong." "Time management is crucial as workload is project based."	***E***	***S***	***T***	***J***
	1.358	**1.329**	**1.257**	**1.171**
	I	*N*	*F*	*P*
	1.250	1.327	1.219	1.111
"Supportive culture, innovative, strong leadership, benefits, parental leave, community volunteer time off, unlimited vacation, learning resources, high performance culture, design thinking, green company, diversity and inclusion practices and policies." "Mergers and acquisitions are exciting, but lead to constant change. Agility is required here! :)"	***E***	*S*	***T***	***J***
	1.170	1.290	**1.313**	**1.153**
	I	***N***	*F*	*P*
	1.145	**1.406**	1.262	1.091
"Collaborative, Smart people that like to do great work and have fun doing it." "Change happens a lot and can be frustrating."	***E***	*S*	*T*	***J***
	1.352	1.294	1.309	**1.217**
	I	***N***	***F***	*P*
	1.269	**1.342**	**1.408**	1.137
"Great opportunities to develop and grow." "Decisions processes are sometimes slow."	***E***	*S*	***T***	*J*
	1.370	1.322	**1.280**	1.325
	I	***N***	*F*	***P***
	1.267	**1.416**	1.269	**1.404**

Table 2. Review Examples and Evaluation Results of Similarities with Eight Preferences

The similarity values, as presented in Table 2, are averaged for each company to determine the company-level similarity between reviews and the eight MBTI preferences. Differences between the preferences within each dimension are then calculated by subtracting *Introversion* (*I*) from *Extroversion* (*E*), *Intuition* (*N*) from *Sensing* (*S*), *Feeling* (*F*) from *Thinking* (*T*), and *Perceiving* (*P*) from *Judging* (*J*). If the result of subtracting I from E is positive, the company's character is classified as *Extroversion* (*E*) rather than *Introversion* (*I*). The other three dimensions are determined using the same method. Thus, this approach allows us to determine the MBTI type for each company.

To investigate the distribution of the whole companies' character, we average the 1,147 companies' similarities between reviews and eight preferences and their differences. Table 3 shows the descriptive statistics. Table 4 describes the correlations among the four variables.

	EI			***SN***			***TF***			***JP***		
	E	***I***	***E-I***	***S***	***N***	***S-N***	***T***	***F***	***T-F***	***J***	***P***	***J-P***
Mean	0.177	0.171	0.006	0.189	0.192	-0.002	0.180	0.182	-0.002	0.136	0.133	0.003
Std	0.007	0.009	0.006	0.082	0.012	0.006	0.008	0.007	0.003	0.007	0.007	0.006
Min	0.141	0.133	-0.013	0.152	0.145	-0.023	0.139	0.148	-0.018	0.098	0.092	-0.050
25%	0.172	0.167	0.018	0.184	0.183	-0.007	0.174	0.177	-0.003	0.132	0.130	-0.002
50%	0.178	0.172	0.061	0.189	0.192	-0.003	0.180	0.182	-0.001	0.137	0.134	0.003
75%	0.182	0.177	0.010	0.194	0.201	0.001	0.185	0.187	0.0001	0.141	0.137	0.007
Max	0.219	0.207	0.042	0.230	0.232	0.019	0.211	0.212	0.017	0.173	0.185	0.027

Table 3. Descriptive Statistics of Similarity Differences of Four Dimensions (N = 1,147)

	E-I	***S-N***	***T-F***	***J-P***
E-I	1.000	-0.296	0.241	-0.076
S-N	-0.296	1.000	-0.298	-0.232
T-F	0.241	-0.298	1.000	0.352
J-P	-0.076	-0.232	0.352	1.000

Table 4. Correlation Matrix of Variables

Using the results obtained from the similarity difference calculation, we categorize each of the 1,147 companies into one of the 16 types. The distribution of the companies' types is shown in Figure 3. *ENFJ* is dominant and occupies 29.21%, followed by *ENTJ*, *ENFP,* and *ESFJ*, respectively. The companies of these four types occupy almost 70%.

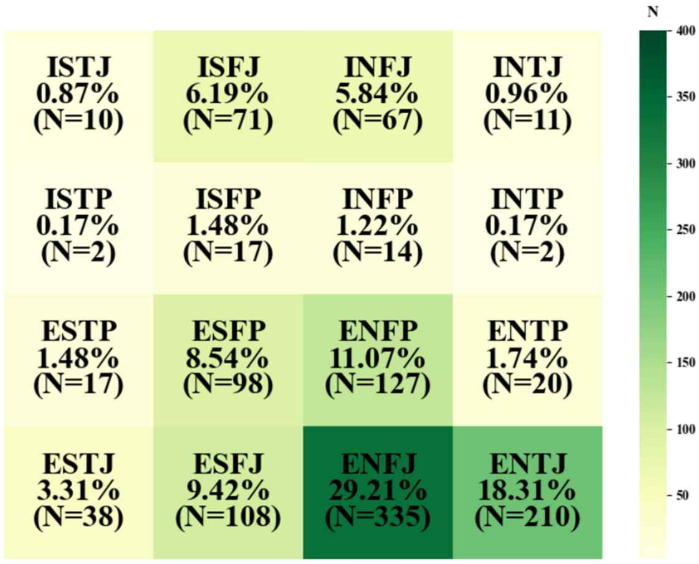

Figure 3. Distribution of Company Character Type (N=1,147)

In this study, companies are also categorized based on behavioral temperament types by combining *Extroversion-Introversion* (*E-I*) with *Judging-Perceiving* (*J-P*) dimensions and decision-making temperament types by combining *Sensing-Intuition* (*S-N*) with *Thinking-Feeling* (*T-F*) dimensions. Figure 4 illustrates the grouping results for the behavioral and decision-making temperament types among the 1,147 companies analyzed. The *Extroverted-Judging* (*EJ*) behavioral type and the *Intuitive-Feeling* (*NF*) decision-making type are the most prevalent, representing 60.24% and 47.34% of the companies, respectively.

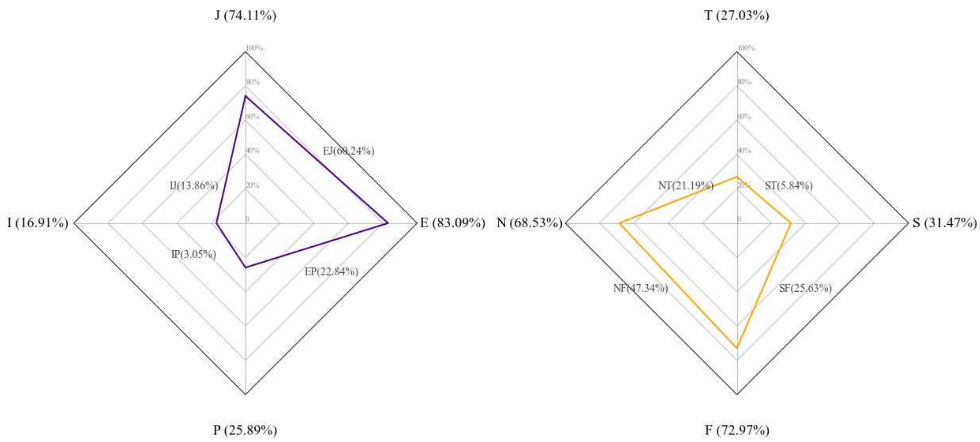

Figure 4. Behavioral and Decision-making Temperament Types of the Companies

As the previous studies have argued, we also assume that companies in the same industry tend to have similar organizational character. To test our assumption, we generate two-dimensional positioning maps of industries, respectively. For this purpose, we first examine the distribution of the total of 1,147 companies' industrial sectors. They belong to a total of 99 industrial sectors, and the industries with more than ten companies and the number of companies in those industries are shown in Table 5. Then, we conduct dimensionality reduction aiming to reduce behavioral temperament, i.e., both *I*-*E* and *T*-*F* dimensions, into a single dimension, and decision-making temperament, i.e., both *T*-*F* and *S*-*N* dimensions, into another dimension based on principal component analysis using the sklearn package.

Sector	**#**	**Sector**	**#**	**Sector**	**#**
Industrial Manufacturing	80	Food & Beverage Manufacturing	34	Construction	21
Biotech & Pharmaceuticals	77	Health Care Services & Hospitals	31	Aerospace & Defense	20
Computer Hardware & Software	58	Health Care Products Manufacturing	31	Wholesale	18
Electrical & Electronic Manufacturing	57	Department, Clothing, & Shoe Stores	29	IT Services	17
Consumer Products Manufacturing	43	Enterprise Software & Network Solutions	26	Miscellaneous Manufacturing	16
Insurance Carriers	38	Investment Banking & Asset Management	26	Internet	15
Chemical Manufacturing	35	Transportation Equipment Manufacturing	23	Metal & Mineral Manufacturing	13
Oil & Gas Exploration & Production	34	Oil & Gas Services	22	Telecommunications Services	11

Table 5. Industrial Sector Distribution of Companies (N=1,147)

Figure 5 shows positioning maps of the 24 industrial sectors listed in Table 5. The *x*-axis indicates behavioral temperament, and the *y*-axis indicates decision-making temperament. The distributions of companies in each map show that, to some extent, there exists a tendency among companies to be positioned closely to each other in the same industrial sectors. Furthermore, companies in similar industrial sectors are positioned in regions on the map that are similar. For example, companies in IT-related industries, including Computer Hardware and Software (3^{rd}), Enterprise Software and Network Solutions (13^{th}), IT Services (20^{th}), and the Internet (22^{nd}), are located in the lower region of the map. Such results imply that the character of companies might have an association with the industry of the companies.

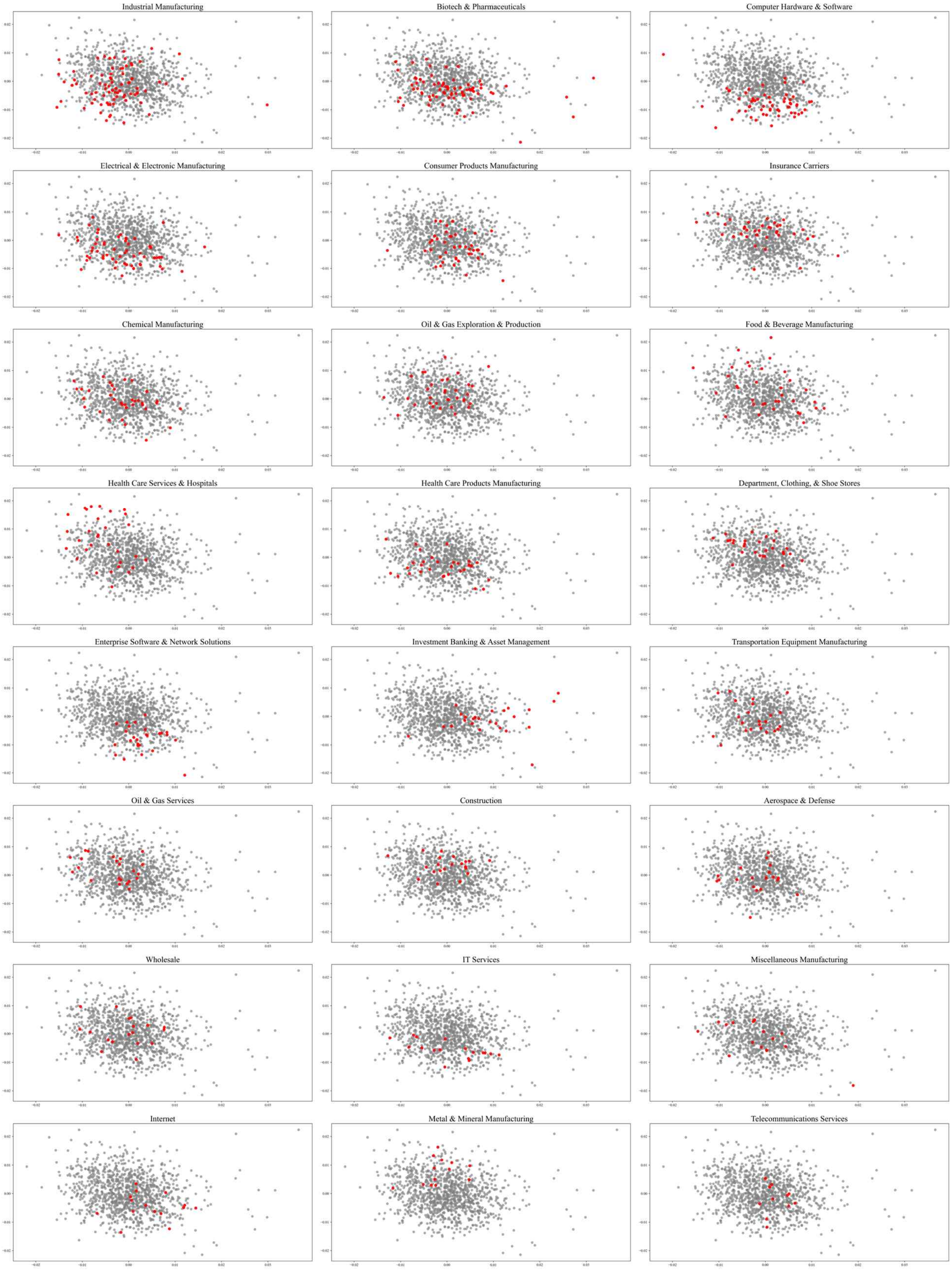

Figure 5. Positioning Map of Industrial Sectors

5. Post-hoc Analysis

Additional statistical verification is required to validate the results' significance. Based on existing studies on firm characteristics and innovativeness (Chen et al., 2010; Dolfsma & Van der Velde, 2014), this study assumes that if our measurement of organizational character is significant, the relevance of companies' organizational characters to their innovativeness might be confirmed. To test this assumption, we use the variables *lnpat* and *lnpcw* from the number of patents held by a firm as indicators of the firm's innovativeness. $lnpat_{t}$ is the natural logarithm of the number of patents filed by firm *i* in year *t*:

$$lnpat_{t} = \ln(1 + P_t),$$

where P_t is the number of patents filed by firm *i* in year *t*. Meanwhile, $lnpcw_{t}$ is the natural logarithm of patents weighted by the number of citations:

$$lnpcw_{t} = \ln\left[1 + \sum_{j=1}^{P_t}\left(1 + \frac{C_j}{AC_t}\right)\right],$$

where C_j is the number of citations for patent *j*, and AC_t is the average number of citations for patents in year *t*. Thus, *lnpat* measures the simple quantity of patents that a company produces, while *lnpcw* measures the quality of patents proxied by the number of citations. We exploit the type classifications and measures of the organizational characters of 1,147 firms. Our dataset is converted into a panel dataset by year, resulting in 4,804 observations.

First, the influence of organizational character type on innovativeness is tested using a t-test. Table 6 presents the results. This table reports the mean differences in innovativeness among firms with different organizational characters. The results indicate that the *Extroversion* (*E*), *Intuition* (*N*), *Thinking* (*T*), and *Judging* (*J*) types are more innovative than *Introversion* (*I*), *Sensing* (*S*), *Feeling* (*F*), and *Perceiving* (*P*) types, respectively, with statistical significance at the 5% level.

Panel A. *Extroversion* (*E*) vs. *Introversion* (*I*)

	E		*I*		Diff.	
	Obs.	Mean	Obs.	Mean	Mean	Std. Err.
lnpat	3318	2.913	1486	2.448	0.465***	0.047
lnpcw	3318	3.375	1486	2.893	0.482***	0.055

Panel B. *Sensing* (*S*) vs. *Intuition* (*N*)

	S		*N*		Diff.	
	Obs.	Mean	Obs.	Mean	Mean	Std. Err.
lnpat	884	2.238	3920	2.889	-0.651***	0.053
lnpcw	884	2.690	3920	3.347	-0.657***	0.062

Panel C. *Thinking* (*T*) vs. *Feeling* (*F*)

	T		*F*		Diff.	
	Obs.	Mean	Obs.	Mean	Mean	Std. Err.
lnpat	2074	2.895	2730	2.673	0.222***	0.048
lnpcw	2074	3.327	2730	3.150	0.177**	0.055

Panel D. *Judging* (*J*) vs. *Perceiving* (*P*)

	J		*P*		Diff.	
	Obs.	Mean	Obs.	Mean	Mean	Std. Err.
lnpat	3171	2.902	1633	2.512	0.390***	0.047
lnpcw	3171	3.352	1633	2.983	0.369***	0.055

Note: *, **, and *** indicate statistical significance at 10%, 5%, and 1%, respectively.

Table 6. Organizational Character Types and Innovativeness

Second, we regress the innovativeness measures on the measures of organizational characters as well as employees' ratings of various aspects of the company. The control variables include *Ratings*, where the subscripts *Overall, C&V, D&I, WLB, SM, C&B,* and *CO* denote the overall rating, culture and values, diversity and inclusion, work/life balance, senior management, compensation and benefits, and career opportunities, respectively. Industry fixed effects are included in all specifications to alleviate the impact of similarities between organizational characters within industries. The regression analysis estimates are listed in Table 7. In the analyses of (1) and (4), we use the *E-I*, *S-N*, *T-F*, and *J-P* measures. Among the different dimensions of organizational characters, the *Intuition* (*N*) type has the most substantial impact on firm innovativeness. The analyses in (2) and (5) confirm the effects of behavioral and decision-making temperaments, respectively. Although the dimensionality of temperament limits direct interpretation, the more negative the behavioral temperament and the more positive the decision-making temperament, the more innovative the firm. Finally, in the analyses of (3) and (6), the four dimensions are reduced to one through principal component analysis, and the result shows that the more negative the value, the higher the innovativeness.

	(1) *lnpat*	(2) *lnpat*	(3) *lnpat*	(4) *lnpcw*	(5) *lnpcw*	(6) *lnpcw*
E-I	1.862			1.535		
	(1.198)			(1.375)		
S-N	-4.118***			-4.990***		
	(1.464)			(1.681)		
T-F	2.734			1.903		
	(1.729)			(1.984)		
J-P	-1.181			-2.608**		
	(0.942)			(1.081)		
Behavior Temperament		-1.625*			-2.936***	
		(0.886)			(1.016)	
Decision-making Temperament		4.864***			5.375***	
		(1.445)			(1.658)	
$MBTI_{PC}$			-1.932**			-3.275***
			(0.882)			(1.012)
$Rating_{Overall}$	1.360***	1.375***	1.354***	1.525***	1.530***	1.507***
	(0.193)	(0.192)	(0.192)	(0.221)	(0.220)	(0.221)
$Rating_{C\&V}$	0.476***	0.480***	0.525***	0.439***	0.441***	0.490***
	(0.147)	(0.146)	(0.146)	(0.168)	(0.168)	(0.167)
$Rating_{D\&I}$	0.703***	0.701***	0.677***	0.729***	0.728***	0.701***
	(0.082)	(0.082)	(0.082)	(0.094)	(0.094)	(0.094)
$Rating_{WLB}$	-0.845***	-0.844***	-0.803***	-1.051***	-1.051***	-1.005***
	(0.091)	(0.090)	(0.090)	(0.104)	(0.104)	(0.103)
$Rating_{SM}$	-1.548***	-1.563***	-1.577***	-1.619***	-1.624***	-1.640***
	(0.155)	(0.154)	(0.155)	(0.178)	(0.177)	(0.177)
$Rating_{C\&B}$	-0.134	-0.146*	-0.138	-0.042	-0.046	-0.037
	(0.089)	(0.089)	(0.089)	(0.102)	(0.102)	(0.102)
$Rating_{CO}$	1.278***	1.291***	1.287***	1.425***	1.429***	1.425***
	(0.128)	(0.128)	(0.128)	(0.147)	(0.146)	(0.147)
Industry-Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	4799	4799	4799	4799	4799	4799
R^2	0.310	0.310	0.308	0.304	0.304	0.302
Adj. R^2	0.299	0.299	0.297	0.292	0.293	0.291

Note: *, **, and *** indicate statistical significance at 10%, 5%, and 1%, respectively. Standard errors are in parentheses.

Table 7. Measures of Organizational Character and Innovativeness

Overall, the significance of our post hoc analysis results suggests that the types and measures of organizational character that we propose have meaningful explanatory power for company characteristics, particularly innovativeness.

6. Discussion

This study presents a research framework and results that are consistent with contemporary studies across various disciplines focused on organizational character. Firstly, our research explores the relationship between organizational character and performance, aligning with investigations in multiple domains. Chu et al. (2019) examined the relationship between organization-level personality and individual-level safety performance in the high-speed rail industry, revealing significantly positive effects of certain personality traits on safety compliance and safety participation. Similarly, Li and Yu (2018) investigated the mediating effects of organizational character on the relationship between intellectual capital and technological innovation. Furthermore, our analysis reveals a significant correlation between the organizational character types of companies and their capacity for innovation. Specifically, companies characterized as *ENTJ* types are most likely to exhibit innovative behaviors. Moreover, within the spectrum of personality traits, the preference for *Intuition* (*N*) is most strongly associated with a propensity for innovation. In a related study, Theil et al. (2022) found that *intuitive* communication by CEOs, as analyzed through their formal speeches, is significantly associated with a decreased risk profile for their companies.

Secondly, our research further inspects the similarities in organizational character among companies within the same industry. The positioning map presented above illustrates that companies operating in the same industry sector tend to exhibit similar organizational characters. This result is consistent with Bridges' (1992) study, which stated that the organization-level characters of companies within a group of similar industries tend to be analogous. Our results also show that the characters of companies in IT-related industries tend to differ from those of companies in other industries, such as construction and metal and mineral manufacturing. This observation aligns with the findings of Woodruff (1980), who demonstrated that IT-related workers, including data analysts, system analysts, and programmers, tend to exhibit personality profiles that differ from those of the general working population.

The results, pertaining to detailed aspects of organizational character, are compared with existing literature as follows: First, among the 16-character types of the MBTI, the *ENFJ*, *ENTJ*, and *ENFP* types are identified as the most prevalent among companies listed in the S&P 1500. This finding resonates with Reynierse's (1997) observation that entrepreneurs, small business owners, and managers often exhibit these three character types. Additionally, the prominence of the *ENTJ* type is further substantiated by Roberts (1989), who noted its prevalence among technical entrepreneurs, and by Theil et al. (2022), who found this type to be shared among top executives based on an analysis of CEOs' speeches.

Second, a prominent finding from our sample is the prevalence of the *Extroversion* (*E*) trait among companies. This aligns with Carland and Carland (1992), who observed that entrepreneurs, business owners, and managers of small companies tend to be more *extroverted*. Similarly, Reynierse (1997) found that both lower-level managers and executives commonly exhibit *extroverted* traits. Moreover, while Ginn and Sexton (1990) reported that approximately 87% of Inc. 500 founders are predominantly *thinking-oriented*, and subsequent studies by Carland and Carland (1992) and Reynierse (1997) also identified *Thinking* (*T*) as a dominant trait among various officers, our study presents a contrasting trend where companies are more likely to be f*eeling-oriented* rather than *thinking-oriented*.

Third, our study identifies that approximately 60.24% of the companies exhibit the *EJ* behavioral temperament, a combination of *Extroversion* (*E*) and *Judging* (*J*) preferences. This finding correlates with Reynierse's (1997) observation that lower-level managers show a preference for *EJ* over *Introverted-Judging* (*IJ*), *Introverted-Perceiving* (*IP*), and *Extroverted-Perceiving* (*EP*). Additionally, 47.34% of the companies in our study are characterized by an *NF* decision-making temperament, favoring *Intuition* (*N*) and *Feeling* (*F*). This presents a contrast to the findings of Ginn and Sexton (1990), who reported that a majority of CEOs possess an *Intuitive-Thinking* (*NT*) temperament, characterized by a future-oriented approach to information gathering and an objective decision-making style.

7. Implications

The findings of the present study have several academic implications. First, this study's careful synthesis of organizational attributes, such as organizational climate, culture, and characteristics, into the concept of organizational character provides a robust framework for advancing research on organizational behavior and culture. In this process, utilizing the MBTI as a new metric for measuring organizational character also provides an innovative method that connects individual personalities with organizational attributes, fostering new research opportunities.

Second, this study introduces a novel method that leverages text analytics applied to a substantial corpus of online company reviews for determining a company's character. This provides academic researchers in organization-related research fields with a new methodology, enabling empirical studies that have thus far been difficult to perform.

Third, this study expands the research stream on organizational character. Unlike previous studies conducted primarily at the individual level, we present our research findings at the organizational level and statistically examine the relationship between organizational character and innovativeness.

Lastly, this study is a good case study for research utilizing the text similarity analysis method. Although text similarity analysis has proven highly valuable across various domains, its application within the business sector remains limited, with few research cases. Therefore, the methodology of this study can be utilized to explain various phenomena or solve problems in business administration.

This study also provides two practical implications for understanding organizational states, tendencies, and features in terms of organizational diagnosis by introducing a valuable tool for measuring organizational characteristics. Firstly, by utilizing the proposed method, decision-makers and human resource managers can swiftly and accurately identify the organizational traits of their company. This enables them to develop theories addressing various situations and issues that the company may face and to establish proper strategies for effective operation and development.

The second practical implication concerns job seekers, who can leverage the measured organizational characters of companies, as identified in this study. Chun and Davies (2006) noted that the specific character of an organization might affect employees who share a similar individual character, thereby enhancing their performance and suitability. Consequently, job seekers might expect better performance and a greater sense of fit when they join a company whose organizational character aligns with their own.

8. Conclusions

We measured the characters of companies listed in the S&P 1500 based on the classification of organizational character types. In this process, we proposed a novel approach to quantitatively measure organizational character and classify it into 16 MBTI types by calculating the similarity between online company reviews and descriptions of organizational character. Consequently, the primary organizational character of each company and the differences in character between industrial groups were identified through visualization based on their characters. Additionally, the proposed measurement of organizational character was tested by examining the relationship between companies' organizational characters and their innovativeness.

This study has some limitations. First, while we presented a new method for identifying and classifying company characters, an inherent challenge in categorizing organizational characters was confirmed. Companies often exhibit continuity across various aspects, which may blur the distinctions when divided into 16 types of character, potentially leading to the loss of nuance. Nonetheless, the significance of this study should not be underestimated. Categorizing companies into a limited number of types offers significant advantages by providing a consistent perspective that simplifies their complex characteristics. However, future studies should statistically confirm the relationship between the continuous values of organizational character and financial performance. Second, this study utilized a sufficient number of online company reviews to analyze company character, albeit with potential biases owing to collection from a single data source. However, Glassdoor, the largest online platform for company reviews worldwide, provides a substantial volume of reviews from former and current employees across diverse companies, industries, and countries, rendering the results relatively reliable. Nevertheless, future research may benefit from incorporating data from other platforms, such as Indeed, LinkedIn, and Blind, which could enhance the trustworthiness of the findings.

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