Essays on the Strategic Role of Message Consistency in Employer Branding and Omni-Channel-Recruiting

Inauguraldissertation zur Erlangung des akademischen Grades

Doktor der Wirtschaftswissenschaften der Universität Mannheim

Vorgelegt von

Ben Moradi, M.Sc.

Sindelfingen

Mannheim, im August 2025

Dekan: Joachim Lutz

Erster Gutachter: Prof. Dr. Florian Stahl

Zweiter Gutachter: Prof. Dr. Florian Kraus

Tag der mündlichen Prüfung: 23. September 2025

Contents

List of Figures

List of Tables

1 General Introduction

The global labor market is under considerable pressure. In the US, around 74% of employers reported that they were facing difficulties in recruiting skilled staff (The Conference Board, 2024). Europe is also affected by a growing shortage of skilled workers. In 2023, approximately 75% of companies in European countries were unable to find employees with the qualifications they were looking for, representing an increase of more than 30 percentage points compared to 2018. The situation is particularly dramatic in the IT sector: 57.5% of EU companies were unable to find suitable candidates, and in Germany the figure was over 70% (European Commission, 2024).

The labor market in Germany is undergoing structural change: demographic shifts, technological progress, and changing values among younger generations are forcing companies to face fundamental challenges in attracting and retaining qualified skilled workers. The Federal Employment Agency predicts that by 2035 more than 7 million employees will leave the labor market due to age. Already today, nearly half of all shortage positions remain unfilled, especially in healthcare, technology, and finance, with the latter two being central to this dissertation (Bundesagentur für Arbeit, 2023; Institut der deutschen Wirtschaft, 2024).

This shortage of skilled employees is not only a problem in terms of quantity, but also fundamentally changes the balance of power in the labor market. Whereas applicants used to compete for attractive jobs, many companies today find themselves forced to actively and credibly position themselves as attractive employers. As a result, employer branding, the strategic positioning of a company as an attractive place to work, has moved to the center of human resources and communication strategies.

This is not purely an HR-driven issue. Rather, employer branding lies at the interface between human resources management, marketing, and strategic communication. Today, employer brand is a key differentiator in the competition for talent, and its design requires interdisciplinary thinking (Backhaus & Tikoo, 2004; Lievens & Slaughter, 2016; Theurer et al., 2018).

In light of the challenges outlined above, companies need to distinguish themselves more clearly from competitors in attracting employees. Research has identified a number of possible areas of differentiation, ranging from monetary incentives and cultural values to meaningfulness and purpose.

These areas of differentiation can be structured effectively within the framework of the functional-symbolic employer branding approach (Lievens & Highhouse, 2003). Functional characteristics include objective value propositions such as salary, benefits, job security, and development opportunities. They address the rational considerations of applicants. Symbolic characteristics, on the other hand, relate to the emotional, identity-related significance that applicants associate with a company, such as innovativeness or prestige.

Building an attractive employer brand therefore requires a combination of functional offerings and authentic symbolic positioning. However, both dimensions are only effective if they are communicated credibly and consistently to the outside world. Potential applicants need to not only know what a company offers, but also perceive it as authentic, relevant, and trustworthy.

Nowadays, this occurs through a variety of channels: company websites, career portals, social media, online review platforms, as well as traditional job advertisements. This omni-channel-reality presents a significant opportunity to raise the visibility of the employer brand, but it also poses a risk, as every communication measure contributes to the overall perception (Cloos, 2021). The complexity of managing these channels increases exponentially with each additional channel, creating major challenges for companies (Lee & Chung, 2023). Today's applicants have more transparency and opportunities for comparison than ever before. They research, compare employers, read reviews, and check statements for contradictions (Ingrassia, 2017). Especially younger generations like Millennials emphasize authenticity and internal communication culture over the mere channel being used (Völker, 2018).

The perception of employer attractiveness is therefore not only shaped by content – functional or symbolic – but also to a large extent by the way in which this content is communicated. Communication is thus more than a tool for sharing brand promises, it is an independent strategic pillar of employer branding.

This dissertation examines this interface by analyzing how the consistency of communication across different channels influences the perception of employer attractiveness. This emphasizes an aspect that has long been underestimated, namely the role of message consistency in connecting strategic brand management with authentic employer positioning.

However, consistency does not happen automatically. It requires conscious control. Studies in brand research and perception psychology show that inconsistencies in communication can undermine trust, trigger doubts, and create cognitive friction (Fiske & Taylor, 1991; Keller, 1993). Especially in decision-making situations, such as choosing a potential employer, contradictory signals can complicate or negatively influence the process.

The employer's perception is formed in the applicant's mind as a subjective overall picture that is shaped by many individual pieces of information, such as texts on the career page, comments on Glassdoor, and posts on social media. If this information is inconsistent, for instance when a company promises innovation on LinkedIn but highlights traditional tasks on the career website, a disconnect arises that casts doubt on its authenticity.

Message consistency thus becomes a decisive perception filter. It determines whether individual signals have their intended effect or are neutralized by contradictions. Given its potential influence on trust and decision-making, message consistency warrants closer theoretical and empirical examination.

The theoretical applicability of the concept of message consistency is multifaceted. Signaling theory, for example, assumes that applicants infer a company's quality and suitability from the information they receive (Spence, 1973). In this context, inconsistent signals are considered weak, untrustworthy, or even deterrent. Consistency is also considered essential for building strong brands in brand management (Keller, 2009).

Despite its theoretical relevance, the concept has hardly been systematically researched in the context of employer branding. There is a lack of empirical studies that not only describe consistency but also causally examine its influence on perception dimensions such as employer image or attractiveness. In particular, experimental designs that specifically analyze applicant reactions to consistent versus inconsistent communication are rare.

At the organizational level, empirical evidence on the link between consistent communication and behavioral recruitment outcomes, such as application likelihood or time-to-hire, remains scarce. In addition, there is a methodological gap regarding the measurement of consistency: scalable, data-driven approaches for operationalizing message consistency in digital touchpoints are still lacking.

This dissertation addresses the outlined research gap with two complementary essays that examine the influence of message consistency on perception and behavior in the application process from different methodological perspectives.

The first essay answers the following research questions in particular:

- **RQ1:** How consistent are companies' communication strategies across different recruitment channels?
- **RQ2:** To what extent and in what patterns do cultural dimensions become visible in employer communication – and how does this relate to consistency?

The essay follows a descriptive-analytical approach and examines the strategic relevance and content characteristics of message consistency in combination with cultural signals in corporate communication. Based on a large-scale content analysis of the online communication of 118 companies from five industries, including companies from the Forbes Top 100 Employers, both message consistency and the cultural values communicated are analyzed using transformer-based language models. The aim is to gain a differentiated picture of how employer communication is structured in practice and what patterns emerge in terms of consistency and cultural orientation. The second essay examines the following questions:

- **RQ3:** How does the consistency of employer communication influence the perception of the symbolic employer brand image and perceived employer attractiveness?
- **RQ4:** How does the semantic consistency of job advertisements relate to the application process, measured by time-to-hire?

The second essay combines an experimental and a field analytical approach. An online experiment with 510 participants examines how different manifestations of consistency and cultural signals (e.g., integrity, innovativeness) influence the perception of the symbolic employer brand image and perceived employer attractiveness. In addition, a message consistency measure based on over 1 million real online job advertisements is developed and linked to application and hiring data to analyze the relationship between message consistency and time-to-hire.

Both essays address message consistency from complementary perspectives: one focuses on companies' communication practices in the competition for talent, the other on the cognitive and behavioral effects on potential applicants. The dissertation thus makes an evidence-based contribution to interdisciplinary research at the intersection of employer branding, communication science, and strategic marketing.

The dissertation is divided into two empirical essays that examine the phenomenon of message consistency from different methodological perspectives. Chapter 2 is devoted to a descriptive analysis of the communicative practices of leading employers. Chapter 3 takes up these findings and analyzes the effect of consistent versus inconsistent communication. Chapter 4 discusses the implications of the results, summarizes key findings, and offers an outlook on future research.

2 Essay 1: Omni-Channel-Recruiting: A Descriptive Study on the Role of Message Consistency and Cultural Dimensions

2.1 Introduction

Vacant positions have been placing a significant burden on companies, especially since the COVID-19 crisis. In 2022, the number of vacant positions in the US reached a record high of over 12 million, the highest since the JOLTS (Job Openings and Labor Turnover Survey) of the US Bureau of Labor Statistics began recording data in 2000. As of early 2024, still about 9 million positions remained vacant, representing about 5% of all jobs (US Bureau of Labor Statistics, 2024). Similar trends can be observed worldwide: e.g., in Europe, around 3% of all positions were vacant at the start of 2024, equivalent to approximately 4 million vacant positions (European Commission, 2024).

Vacant positions can lead to substantial losses for companies, impacting overall productivity. In addition to financial implications, staff shortages often affect the satisfaction of existing employees, who may be required to assume additional responsibilities. The resulting increase in workload can, in turn, lead to elevated stress levels and a heightened risk of burnout. In industries that are heavily reliant on specialized knowledge, such as pharmaceuticals and information technology, these unfilled positions can significantly hinder a company's ability to innovate and remain competitive.

However, the challenge for companies is not only to fill the millions of vacant positions but also to find talent with the necessary skills to drive the company's innovation. The quality of employees, their creativity, and their ability to innovate are crucial competitive advantages in today's economy.

While finding skilled talent and filling vacant positions has become a competitive advantage for companies in today's business world, there has been a shift in the balance of power between companies and applicants. This shift is primarily driven by the high number of job vacancies and the resulting shortage of skilled workers. Applicants today often have multiple job offers and are in greater demand than in the past when companies had more control over the recruitment process. As a result, applicants can afford to be more selective and conduct thorough research before deciding to apply. According to Kristia (2023) and Ahmed et al. (2016), applicants today use a variety of channels, including official career websites, social media, and review platforms, to gather information about potential employers. Studies show that up to 79% of job seekers are likely to use social media in their job search, highlighting not only the growing importance of social media platforms in the recruitment process but also the significance of a multi-channel-approach, where job seekers consider multiple sources before deciding to apply for a position (Skaggs, 2018).

In light of the trend that potential applicants use a variety of channels to gather comprehensive information about employers, many companies have significantly expanded their recruitment activities to new channels in recent years. The goal is to be present on all channels that applicants prefer to use. This is increasingly leading to an *omni-channel-recruiting* approach, which is analogous to omni-channel-marketing often used in retail. However, the focus here is not on selling a product but on attracting applications. While this approach increases the company's visibility, it also significantly raises the complexity of maintaining and coordinating these numerous channels (Bijmolt et al., 2019). The growing complexity of omni-channel recruiting arises mainly from two key challenges, which will be examined in the course of this study: first, conveying the consistency of messages across all channels used, and second, ensuring that the communicated content, especially the core dimensions of corporate culture, is targeted and expressed clearly.

The aim of this study is to examine the two mentioned key challenges of omni-channel-recruiting in greater detail as part of a descriptive study. First, the current status quo of companies' communication strategies with regard to message consistency is analyzed. Second, the core dimensions of corporate culture communicated by companies across various recruitment platforms are examined.

To address these challenges, this study seeks to answer the following research questions:

- **RQ1:** How consistent are companies' communication strategies across different recruitment channels?
- **RQ2:** To what extent and in what patterns do cultural dimensions become visible in employer communication – and how does this relate to consistency?

Through this study, companies are expected to gain valuable insights into how they can successfully address current risks, including the large number of unfilled positions, the shift in power towards applicants, and the increased use of multiple information channels by potential talent. The findings will not only help improve the effectiveness of recruitment strategies but also support companies in achieving a sustainable competitive advantage in the war for top talent through a well-coordinated omni-channel-recruiting approach. Additionally, this study contributes to the theoretical understanding of employer branding and omni-channel-communication by addressing the underexplored relationships between message consistency, cultural communication, and employer brand perception.

2.2 Background

The objective of this chapter is to lay the theoretical foundations for two central concepts that are the focus of this study: message consistency and communicated cultural dimensions.

The focus here is not on the effect of the two constructs in employer communication on applicants, which will be addressed in later studies, but on a descriptive analysis of communicative practice in relation to these constructs. To concretize this question, two central lines of research are taken up, namely theoretical perspectives from communication psychology as well as empirical work on message consistency and the communication of corporate cultural dimensions.

The following sub-chapters are structured as follows: 2.2.1 presents the theoretical frame of reference, 2.2.2 places the topic in the context of employer branding, 2.2.3 is dedicated to the concept of message consistency in detail and sub-chapter 2.2.4 is dedicated to the concept of corporate cultural dimensions in detail.

2.2.1 Theoretical Frame of Reference: Signals, Dissonance and Identity

Signaling Theory

Signaling theory (Spence, 1973) describes how actors in markets with incomplete information (e.g. applicants versus companies) try to reduce uncertainty through signals. In an organizational context, this means that companies send targeted messages via websites or social media in order to create a certain image. These signals can relate to values, culture, benefits or general employer attributes.

In the context of this study, signaling theory helps to explain why the consistency of messages is relevant for recipients, since the clearer and more consistent a signal is across different channels, the more likely it is to be interpreted as credible and trustworthy (Celani & Singh, 2011).

Cognitive Dissonance

According to the cognitive dissonance theory (Festinger, 1957), people strive for consistency between their perceptions, beliefs and actions. When they are confronted with contradictory information, for instance if a company presents itself as innovative on its careers page but as conservative on LinkedIn, cognitive dissonance arises. This can lead to a loss of trust or even to rejection.

For the analysis of organizational communication, this means that inconsistency is not just a stylistic problem, but a potential risk for the connectivity and acceptance of the message.

Social Identity Theory & Attraction-Selection-Attrition Framework

Social identity theory (Tajfel & Turner, 1979) emphasizes that people establish social affiliation by identifying with organizations. If a company is perceived as credible, attractive and consistent, this potentially promotes identification with its values.

The Attraction-Selection-Attrition framework (Schneider, 1987) complements this perspective: people apply to organizations that match their own values. Cultural communication of values is therefore not just image cultivation, but also relevant for the perception of fit.

2.2.2 The Role of Employer Branding in Omni-Channel-Recruiting

Although this study does not primarily examine the effect of message consistency and communicated cultural dimensions on applicants, it is part of the context of employer branding. Employer branding refers to the strategic positioning of a company as an attractive employer through internal and external communication. This communication is increasingly taking place via various platforms, which makes questions of consistency and content central.

As part of omni-channel-recruiting, organizations deliberately use several channels simultaneously to reach different target groups. This increases reach and enables a targeted approach, but also increases the complexity of communication management. Employer branding has a key role in this context: it has a decisive influence on how potential applicants perceive a company. A strong and authentic employer brand is crucial for attracting talent, and it is created through the consistent communication of central corporate values and cultural characteristics across all recruitment channels (Backhaus & Tikoo, 2004). Research shows that the consistency of messages is a key success factor, especially in the context of an omni-channel approach. This relationship has already been extensively researched in product branding and is also receiving increasing attention in employer branding.

Individual studies show that inconsistent brand communication across channels reduces trust and recognition, effects that can also be transferred to the employer brand. Recruitment research has also begun to investigate how consistent communication across multiple channels influences employer perception. For example, the study by Barbaros (2020) provides evidence that employer branding can only be successful if there is a consistent, coordinated communication strategy between HR, marketing and communication, an aspect that becomes particularly relevant in omni-channel-processes. Backhaus & Tikoo (2004) emphasize that the consistency between internal brand promise and external communication is essential for the success of employer branding. This internal–external fit forms the basis for consistent messages to the outside world to be credible. It is conceptually related to the across-channel message consistency examined here, but has not yet been studied on a theory-driven basis across different platforms.

Based on this research situation, the comprehensive framework by Theurer et al. (2018) provides a suitable theoretical foundation. This model integrates findings from brand management, organizational psychology and HR practice and differentiates employer branding along three central levels: (1) strategic employer branding inputs (e.g. corporate culture, HR practices, symbolic and functional benefits), (2) communicative touchpoints and channels (e.g. website, social media, job portals) and (3) target group perception and employer image.

Particularly relevant for this study: Theurer et al. (2018) point out the central importance of consistent messages across channels, but do not operationalize this aspect theoretically or empirically. It also remains unclear which cultural content is conveyed via these channels.

This conceptual extension forms the fundamental basis for the empirical study carried out later in the study. The aim is to systematically record whether and how consistently organizations communicate across different platforms, and which cultural values they convey in the process. The resulting framework thus represents an innovative contribution to the theory-based analysis of organizational communication in the context of employer branding and omni-channel-recruiting.

2.2.3 Message Consistency in Employer Communication

As explained in chapter 2.2.1, psychological approaches such as Festinger's cognitive dissonance theory (1957) show that people perceive inconsistent information as cognitively unpleasant and therefore prefer consistent messages. Similarly, signaling theory (Spence, 1973) emphasizes that every communication act sends signals about a company's identity and attractiveness. Inconsistent signals can create doubts about authenticity, reinforcing the notion that people prefer consistent communication. This theoretical foundation forms the basis for the assumption that applicants respond particularly sensitively to the consistency of employer communication.

The relevance of consistent messaging is well documented in traditional brand research: consistent communication strengthens brand trust, enhances recognition, and improves brand perception (Navarro-Bailón, 2011). However, these insights from product branding have rarely been systematically transferred to the employer brand context. While consistency in product marketing has been studied at the message level, especially with regard to core statements, values, and meanings (Castañeda-García et al., 2020), it remains largely unclear whether companies in the context of employer branding actually ensure such message consistency across platforms. In particular, it is not empirically evident how consistent employer messages really are in practice, or whether organizations deliberately manage this aspect of their communication strategy.

Research on employer branding is increasingly recognizing that not only the content of the employer brand, but also its consistent communication across different channels plays a central role in brand perception. While studies such as that by Deepa & Baral (2021) identify integrated communication as a success factor for employer attractiveness, there is still a lack of systematic research on semantic message consistency across platforms.

In contrast, in the domain of product branding, it is well established that inconsistent messages across channels can harm brand loyalty and trust (Navarro-Bailón, 2011). Applied to employer branding, this highlights a central research gap: There is no established conceptual or empirical framework for operationalizing message consistency in recruitment communication.

Even though Backhaus & Tikoo (2004) emphasize the importance of consistent communication, they focus on the consistency between internal value proposition and external communication without differentiating between channel- or platform-related aspects. Initial indications are provided by an HR-specific study by Barbaros (2020), which shows that a lack of coordination between HR and marketing communication can lead to contradictory perceptions of the employer brand. Nevertheless, the systematic measurement of message consistency in the context of employer branding remains a research gap.

This study focuses explicitly on message consistency, meaning consistency in the content of messages, as opposed to stylistic (e.g., tone of voice) or visual (e.g., design) consistency. This distinction is crucial, as applicants primarily compare content-related statements on values, company culture, and employer promises. The aim of the study is to examine whether, and to what extent, semantic consistency exists across different digital communication channels.

This study extends the framework of Theurer et al. (2018) to include an explicit dimension of message consistency and develops a theory-based grid for evaluating semantic consistency in employer branding. In doing so, it addresses a double research gap: On the one hand, there is a lack of a theoretically sound concept for cross-channel consistency in the recruiting context, and on the other hand, there is a lack of empirical operationalization that makes the status quo in organizations visible. The findings offer important impulses for both science and practice in order to strategically align employer communication more coherently.

2.2.4 Core Corporate Culture Dimensions

In addition to the consistency of employer communication, its cultural value is also becoming increasingly important. In practice, applicants increasingly expect insights into the values, attitudes and cultural influences of a company. Studies show that perceived cultural fit can have a decisive influence on employer attractiveness and application motivation (Lievens et al., 2005; Kristof-Brown et al., 2005). However, it remains empirically unclear which specific cultural values companies communicate as part of their employer branding and through which channels these messages are conveyed.

Research on organizational culture offers a variety of established frameworks for structuring cultural characteristics, such as Hofstede, Schein or the GLOBE model. These differ in their analytical focus and objectives: while Hofstede looks at national cultural dimensions (Hofstede, 2011), Schein focuses on the levels of organizational culture (artefacts, values, basic assumptions) (Westover, 2024). The GLOBE model, on the other hand, extends Hofstede's approach to include leadership styles and cultural practices in organizations (House et al., 2002).

Despite their theoretical value, the direct application of these models to digital organizational communication content is limited. Hofstede and GLOBE were developed to analyze cultural differences at the country level and are less suitable for capturing company-specific communication (Dorfman et al., 2012). Schein's approach, on the other hand, focuses on internal cultural processes and less on external, publicly communicated values (Hogan & Coote, 2014).

The present study therefore deliberately builds on the empirically based model by Guiso, Sapienza, & Zingales (2015), which operationalizes nine central cultural values (see Table 1) that were systematically coded in mission statements and corporate presentations of over 600 US companies. Due to its explicit reference to external communication, this model is particularly suitable for analyzing values communicated by companies in the digital space.

Despite the relevance of cultural content in employer branding, very little research has been conducted into how often and in what way these values are actually communicated via different platforms. Comparisons between platforms or the question of whether cultural priorities vary depending on the channel have also hardly been examined to date.

Table 1: Description of the nine cultural dimensions (Essay 1)

Dimension	Description
Integrity	This dimension refers to the promotion of honesty and ethical behavior within the company. Companies that highly value integrity tend to develop a strong foundation of trust between employees and leadership, which leads to sustainable success in the long run.
Teamwork	This dimension emphasizes the importance of collaboration and cooperation among employees. A culture that fosters teamwork often results in stronger integration of ideas and better outcomes, especially in complex projects.
Innovation	Companies that cultivate a culture of innovation are capable of continuously developing and implementing new ideas. This enhances their competitiveness and adaptability in a constantly changing market environment.
Respect	Respect in corporate culture refers to the appreciation and recognition of employees. This dimension strengthens the work climate and fosters employee loyalty to the company.
Quality	This dimension focuses on the continuous maintenance and improvement of product and service quality, which is considered essential for a company's long-term success.
Safety	Workplace safety is one of the fundamental requirements of corporate culture, protecting both the physical and mental health of employees and thereby increasing the stability and efficiency of the company.
Community	This dimension highlights the company's responsibility towards the community, both within and outside the organization. Companies with a strong community culture often engage in social and environmental causes, thereby enhancing their reputation and loyalty.
Communication	Effective communication is crucial to a company's success. This dimension promotes openness and clarity in the exchange of information and prevents misunderstandings that could negatively affect the company's performance.
Hard Work	This dimension focuses on the dedication and hard work of employees, which are seen as critical to achieving the company's goals.

2.3 Method

The aim of this descriptive study is to analyze the current status quo of corporate communication in omni-channel-recruiting. The focus is on measuring message consistency and the communicated core corporate culture dimensions. The study exclusively uses quantitative methods and is based on data collected through data scraping.

2.3.1 Data Collection

The data basis for this study consists of a sample of 118 companies, 59 of which are among the Forbes Top 100 World's Best Employers 2023. The selection of the Forbes Top 100 companies is based on their repeated use in numerous scientific studies (Dikkatwar & De, 2023; Miles & Angelis, 2021). The study focuses on five industries: Aerospace & Defense, Automotive, Financial Services & Insurance, Information Technology, and Retail & Wholesale. These industries are most frequently represented in the Forbes Top 100 World's Best Employers 2023 list.

To avoid potential biases that could arise from exclusively considering top employers, a matched-pairs design was implemented. Each of the 59 Top 100 companies was paired with a comparable company from the same industry. These matched companies were selected based on criteria such as similar geographic origin and company size (measured by number of employees). For example, the Top 100 employer Mastercard was matched with the non-Top 100 company Visa. This results in a sample of 118 companies from five industries, divided into two groups (Top 100 vs. non-Top 100).

The sample includes 40 companies from the Information Technology sector, 24 from Financial Services & Insurance, 20 from the Automotive industry, 18 from Aerospace & Defense, and 16 from Retail & Wholesale. Regarding their business models, 57% of the companies operate in B2C (Business to Consumer), 35% in B2B (Business to Business), and 8% in both B2B & B2C. The sample also includes a diverse range of founding years, with the majority (51%) of companies founded before 1950, followed by 27% between 1975 and 1999, 14% between 1950 and 1974, and a smaller portion (8%) founded after 2000.

As part of the study, data were collected via data scraping from the following sources: (1) Facebook posts, (2) LinkedIn posts, (3) career websites, (4) Glassdoor reviews, and (5) Glassdoor descriptions. In cases where companies operated several country-specific channels in a given source, the home-country official channel was used for analysis. For instance, among Microsoft's various national Facebook pages, the United States page was selected. In addition, platform-specific career subpages were included when available, but such dedicated career presences were observed exclusively on Facebook.

For Facebook, LinkedIn, and Glassdoor reviews, the most recent 50 posts and reviews were scraped. This limit is based on the assumption that potential applicants typically only look at the most recent posts and do not delve far into the past, as older posts are often no longer relevant and may be several years old. For career websites and Glassdoor company descriptions, all texts available at the time of data collection were captured. Graphical elements were not included to focus solely on the textual content. The data scraping was conducted in strict compliance with data protection regulations and platform policies. No personal data, such as names, email addresses, or phone numbers, were collected; the focus was exclusively on publicly accessible, company-related information and anonymized reviews. To ensure data quality, extensive quality control measures were implemented, with irrelevant or redundant content being manually identified and removed. Random checks were conducted to ensure the completeness of the data collection and to verify that the dataset was representative of the companies' communication channels under investigation. Since the models used for analysis were primarily developed for English-language texts, all non-English texts were translated into English to ensure consistent and reliable data processing. These translations were also randomly checked to ensure content accuracy and maintain the quality of the analysis.

2.3.2 Data Analysis

The data analysis in this study was conducted in two steps: first, by measuring message consistency, and second, by analyzing the communicated corporate culture dimensions.

For measuring message consistency, two dimensions were considered: within-channel consistency and across-channel consistency. Within-channel consistency refers to the degree of alignment of messages within a single channel, while across-channel consistency measures the alignment of messages across different channels. A total of 14 consistency measurements were conducted for each company (as shown in Table 2 (within-channel consistency) and Table 3 (across-channel consistency).

Operational definitions

Within-channel consistency.

For company f and channel c, let texts $x_1^{(c)}, \dots, x_{n_c}^{(c)}$ have unit-normalized embeddings $\mathbf{e}_1^{(c)}, \dots, \mathbf{e}_{n_c}^{(c)} \in \mathbb{R}^d$.

$$\text{Consistency}_c^{\text{within-channel}}(f) = \frac{2}{n_c(n_c-1)} \sum_{1 \le i < j \le n_c} \cos\big(\mathbf{e}_i^{(c)}, \mathbf{e}_j^{(c)}\big), \qquad \cos(\mathbf{u}, \mathbf{v}) = \mathbf{u}^\top \mathbf{v}. \tag{1}$$

Within-channel consistency averages pairwise similarities among texts on one platform; higher scores indicate stronger alignment.

Across-channel consistency.

For a channel pair (c, c') with $n_c, n_{c'} \ge 1$:

$$\text{Consistency}_{c,c'}^{\text{across-channel}}(f) = \frac{1}{n_c n_{c'}} \sum_{i=1}^{n_c} \sum_{j=1}^{n_{c'}} \cos\big(\mathbf{e}_i^{(c)}, \mathbf{e}_j^{(c')}\big). \tag{2}$$

Across-channel consistency averages similarities across two platforms; higher scores indicate stronger alignment.

Notes. Channels with fewer than two texts are not used for (1).

Within-channel consistency: examples

Low: Some LinkedIn posts promise hybrid work, others require five days on site.

High: All posts repeat the same hybrid policy and similar core responsibilities.

Across-channel consistency: examples

Low: The career site lists flexible hours, LinkedIn lists fixed shifts.

High: The career site and Glassdoor use the same job titles, benefits, and policy wording.

Within-Channel Message Consistency:

Table 2: Within-channel message consistency measures (Essay 1)

Consistency Measure	Definition
IS_F	Within-Channel Consistency within the Facebook channel
IS_L	Within-Channel Consistency within the LinkedIn channel
IS_W	Within-Channel Consistency within the career website
IS_GR	Within-Channel Consistency within the Glassdoor reviews

Consistency within the Glassdoor company description was not considered, as each company had only a single text in this category.

Across-Channel Message Consistency:

Table 3: Across-channel message consistency measures (Essay 1)

Consistency Measure	Definition
ES_FL	Across-Channel Consistency between Facebook and LinkedIn channels
ES_FGG	Across-Channel Consistency between the Facebook channel and the Glassdoor company description
ES_FGR	Across-Channel Consistency between the Facebook channel and Glassdoor reviews
ES_FW	Across-Channel Consistency between the Facebook channel and the career website
ES_LGG	Across-Channel Consistency between the LinkedIn channel and the Glassdoor company description
ES_LGR	Across-Channel Consistency between the LinkedIn channel and Glassdoor reviews
ES_LW	Across-Channel Consistency between the LinkedIn channel and the career website
ES_GGGR	Across-Channel Consistency between the Glassdoor company description and Glassdoor reviews
ES_WGR	Across-Channel Consistency between the career website and Glassdoor reviews
ES_WGG	Across-Channel Consistency between the career website and Glassdoor company description

To measure the semantic consistency between texts, this study used a Sentence Similarity Transformer. Transformer models are widely recognized as some of the most effective methods for capturing semantic consistency in current research, due to their ability to process deeper semantic and syntactic information compared to traditional approaches such as word- or n-gram models. Studies have shown that transformer-based models generally achieve superior performance in measuring text similarities across various benchmarks while operating more efficiently than traditional methods (Wang & Kuo, 2020; Yu, Su, & Luo, 2019).

In this study, multiple Sentence Transformers were evaluated, including "all-MiniLM-L6-v2" and "all-mpnet-base-v2". While "all-MiniLM-L6-v2" provided strong results in terms of efficiency, the "all-mpnet-base-v2" model was ultimately selected for its superior accuracy in processing semantic and syntactic information, particularly in the context of HR and recruiting. MPNet combines word and sentence representations with attention mechanisms, allowing for precise calculation of sentence similarities. Studies confirm that MPNet ranks among the most accurate and robust models in benchmarks like the STS-Benchmark and the SICK dataset, surpassing traditional methods in accuracy and efficiency (Xu et al., 2020).

In the present study, approximately 20,000 texts from the dataset were converted into vectors with the help of the Sentence Transformers to calculate their similarities. This was done by computing the cosine similarity between the vectors, resulting in over 2 million cosine similarities being determined. These data were used to calculate four within-channel (Table 2) and 10 across-channel consistency metrics (Table 3). For each company, the average value of the consistency metrics was then calculated to ensure consistent processing of the dataset.

For the classification of the approximately 20,000 texts according to communicated corporate culture dimensions, the model by Guiso, Sapienza, & Zingales (2015) was used, which defines nine core culture dimensions.

For text classification, the RoBERTa-large-MNLI Transformer was used, as it is considered particularly powerful for classification tasks in research. RoBERTa (Robustly Optimized BERT Approach), a further development of BERT (Bidirectional Encoder Representations from Transformers), uses optimized training procedures that enhance sensitivity to semantic nuances. Across many text-classification tasks, it often surpasses support vector machines (SVMs), long short-term memory networks (LSTMs), and other traditional baselines in accuracy (Liu et al., 2019; Devlin et al., 2019; Galke et al., 2025). For example, a study by Imran et al. (2023) demonstrated that RoBERTa outperformed other transformer-based models in classifying legal documents, achieving high precision, recall, and F1 scores.

Another study by Qin (2023) utilized RoBERTa for classifying problematic text data in a technical domain, showing that it achieved superior results compared to other models (Qin, 2023). These findings are consistent with the performance of RoBERTa in various applications, including complex texts as used in this study, covering both company-generated content (e.g., Facebook posts, career websites) and user-generated texts (e.g., Glassdoor reviews), since the model better captures and generalizes semantic subtleties. As a result of the classification, each text was assigned a probability from 0 to 100% for each of the nine cultural dimensions, indicating how strongly the respective dimension is represented in the text. Since these are relative probabilities, the values for each dimension of a text sum to 100%.

After calculating the consistency metrics using the MPNet Transformer and cosine similarity, as well as assigning the probabilities for the communicated core corporate culture dimensions through RoBERTa, various statistical methods were applied to test the hypotheses. In the first step, the distributions of the consistency metrics and probabilities were examined. For normally distributed data, t-tests, paired t-tests, and ANOVA were conducted; for non-normally distributed data, Mann-Whitney U-tests and Kruskal-Wallis tests were employed. Additionally, multivariate regression analyses were performed. A p-value threshold of 0.05 was set for statistical significance.

2.4 Hypotheses

To achieve the outlined goal of this study, 10 hypotheses were developed at the start of the study and tested throughout the investigation. Five of the hypotheses focus exclusively on the construct of message consistency, three on core corporate culture dimensions, and two examine the interaction of both phenomena as well as their effects.

H1a: There is a significant difference between companies in within-channel consistency.

H1b: There is a significant difference between companies in across-channel message consistency.

Building on cognitive dissonance theory (Festinger, 1957), this study assumes that inconsistencies in communication can create psychological discomfort among recipients, potentially undermining trust in the employer brand. Within-channel consistency may vary significantly between companies due to multiple organizational and structural factors. Limited resources, decentralized team structures, and simultaneous targeting of multiple stakeholder groups (e.g., customers and job seekers) can complicate the alignment of messaging within a platform. Moreover, seasonal recruitment campaigns or reactive communication strategies in response to current events can further affect the uniformity of messages.

Across-channel consistency is subject not only to the same internal factors but also to platform-specific constraints. Different platforms serve distinct audiences and operate under different content norms and technical formats, requiring tailored communication strategies. While such tailoring may enhance local effectiveness, it also increases the risk of brand fragmentation. From a signaling perspective (Spence, 1973), inconsistent messaging across platforms may weaken the credibility of the employer brand, as job seekers perceive conflicting signals about company values and identity.

H2: Within-channel message consistency is generally higher than across-channel message consistency

From a structural and process-oriented perspective, it is assumed that companies find it easier to maintain consistent messaging within a single channel than across multiple platforms. Within-channel consistency benefits from uniform technical constraints (e.g., character limits, content formats) and is often managed by the same content teams, reducing the risk of misalignment. Furthermore, content within a given platform is frequently repurposed and reused, aiming at a consistent audience with shared communication goals.

In contrast, across-channel consistency poses greater challenges. Different channels (e.g., LinkedIn vs. Facebook vs. Glassdoor) target distinct audiences, follow different interaction norms, and are often handled by separate teams.

H3a: There is a significant difference in within-channel message consistency between Top 100 and non-Top 100 employers.

H3b: There is a significant difference in across-channel message consistency between Top 100 and non-Top 100 employers.

We hypothesize that companies listed among the Top 100 employers exhibit significantly higher levels of both within-channel and across-channel message consistency compared to their non-Top 100 counterparts. This assumption is grounded in the strategic importance of employer branding for leading organizations, which often face intense competition for top talent. Consistent communication across platforms acts as a signal of organizational reliability and professionalism (Spence, 1973), reinforcing brand credibility and applicant trust.

Furthermore, Top 100 employers typically benefit from more mature employer branding processes, dedicated communication teams, and higher resource availability. These factors facilitate tighter coordination and enable the deployment of standardized messaging across platforms. In contrast, smaller or less brand-focused companies may lack the structural integration necessary to maintain coherence across departments and communication outlets.

H4a: There is a significant difference between industries in within-channel message consistency.

H4b: There is a significant difference between industries in across-channel message consistency.

We assume that message consistency varies across industries due to differences in recruitment intensity, communication strategy, and budgetary constraints. Industries such as Information Technology and Automotive, where competition for talent is high, are more likely to invest in coherent communication to signal credibility and build employer trust (Spence, 1973; Deutsch, 1958). In contrast, sectors like Retail & Wholesale, which rely on dynamic and seasonal messaging, may exhibit lower consistency due to frequent content adjustments and multi-purpose channel use. Cost-sensitive sectors may also deprioritize consistency due to limited resources, while industries such as Financial Services & Insurance or Aerospace & Defense often emphasize consistent messaging to reinforce perceptions of stability and security.

H5: Companies that maintain a dedicated Facebook career page exhibit higher consistency within the Facebook channel.

This hypothesis draws on principles from Media Richness Theory (Daft & Lengel, 1986) and Stakeholder Theory (Freeman, 1984). A dedicated Facebook career page allows for the reduction of message complexity by targeting a specific audience, namely prospective employees, within a high-interaction medium. This segmentation enables more focused, relevant, and coherent messaging, enhancing within-channel consistency.

Such dedicated communication structures reflect a more mature and deliberate communication strategy, allowing companies to align their employer branding efforts with audience expectations without diluting other corporate messages. While this hypothesis focuses on Facebook, the underlying logic suggests that content segmentation within a channel, regardless of platform, may generally enhance message consistency and signal a well-organized approach to corporate communication.

H6: There is a significant difference in the communicated core corporate culture dimensions across different platforms.

This hypothesis builds on the assumption that companies strategically adapt the communication of their cultural values to the specific characteristics and audience expectations of each platform. According to audience design theory (Bell, 1984), communicators tailor messages to resonate with the anticipated recipient group. Similarly, framing theory (Entman, 1993) suggests that organizations emphasize certain value dimensions over others depending on the context in which the message is delivered.

On professional networks, companies may be more inclined to emphasize values such as integrity, respect, or hard work in order to convey a credible and professional employer image. Conversely, on more informal social platforms like Facebook, organizations might choose to highlight values such as teamwork, innovation, or community to foster relatability and emotional appeal.

H7: There is a significant difference in the communicated culture dimensions between Top 100 and non-Top 100 employers.

This hypothesis is based on the assumption that companies with strong employer brands, such as those ranked among the Top 100, may communicate their corporate values more strategically than non-Top 100 employers. From a strategic branding perspective (Backhaus & Tikoo, 2004), such organizations are more likely to align their cultural messaging with their employer value proposition (EVP) to reinforce their market positioning and attract high-quality talent.

Top 100 employers might place greater emphasis on cultural dimensions such as innovation, integrity, or teamwork, as these are frequently associated with leadership, trust, and high performance. In contrast, non-Top 100 employers may adopt a more reactive or ad hoc communication style, potentially highlighting values that reflect operational priorities or industry-specific concerns.

H8: There is a significant difference in the distribution of culture dimensions between different industries.

It is assumed that different industries emphasize different culture dimensions to meet their specific needs. In highly regulated industries such as Financial Services and Aerospace & Defense, integrity, safety, and quality may be prioritized to ensure trust and compliance. Technology-driven industries such as Information Technology and Automotive may place more emphasis on innovation, teamwork, and hard work to promote adaptability. In the Retail & Wholesale industry, respect, community, and communication may be emphasized to strengthen customer proximity and service.

H9: There is a significant correlation between the communicated culture dimensions and the average consistency of messages with the overall company rating on Glassdoor.

H10: There is a significant correlation between the communicated culture dimensions and the average consistency of messages with the culture rating of the company on Glassdoor.

We hypothesize that the consistent communication of certain culture dimensions may be associated with more favorable employer ratings on platforms like Glassdoor. While such ratings primarily reflect the perceptions of current or former employees, these individuals also perceive and interpret external employer communication. Although such communication is primarily directed at potential applicants, its effects may extend internally, shaping employee expectations and perceived organizational authenticity.

Drawing on signaling theory (Spence, 1973), consistent cultural messaging, especially around values like integrity, teamwork, or innovation, can serve as a credibility signal. Over time, this may foster trust and reinforce alignment between communicated values and actual employee experiences. In addition, the Attraction–Selection–Attrition (ASA) framework (Schneider, 1987) suggests that value-consistent communication may attract individuals whose personal values align with the organization's, potentially leading to higher person–organization fit and more favorable evaluations.

Conversely, inconsistent or ambiguous cultural communication could create dissonance and mistrust, both among current employees and new hires, which may in turn be reflected in lower general or culture-specific Glassdoor ratings.

2.5 Results

Hypothesis 1

The first hypothesis (H1a) posited that within-channel message consistency varies significantly between companies. As shown in Table 4, this assumption is supported by the data. Group comparisons based on raw pairwise similarity scores were conducted using ANOVA or Kruskal-Wallis tests, depending on distributional assumptions. All within-channel consistency types, Facebook (IS_F), LinkedIn (IS_L), Website (IS_W), and Glassdoor Reviews (IS_GR), yielded $p < .001$, indicating significant differences between companies.

The highest within-channel consistency was found on career websites (IS_W, $M = 0.5991$), followed by Glassdoor Reviews (IS_GR, $M = 0.4197$), LinkedIn (IS_L, $M = 0.3677$), and Facebook (IS_F, $M = 0.3496$). This suggests that company-controlled content is more internally consistent than social media or review platforms. Notably, within-channel consistency in user-generated Glassdoor Reviews was relatively high compared to Facebook and LinkedIn.

With consistency values between 35-42$\%$ on social platforms and review sites, overall within-channel consistency remains modest. Such inconsistencies may lead to cognitive dissonance among applicants, reducing trust and potentially deterring talent (Festinger, 1957).

To explore which company characteristics influence consistency, several differentiators were examined: industry, continent, business model, founding year, revenue, and number of employees. However, only industry showed a statistically significant effect, which is further discussed under Hypothesis 4.

Hypothesis H1b assumed that across-channel message consistency also differs across companies. As Table 4 shows, this assumption is supported. Again, either ANOVA or Kruskal-Wallis tests were applied.

The highest across-channel consistency was found between Website and Glassdoor company descriptions (ES_WGG, $M = 0.5011$), followed by LinkedIn and Glassdoor company descriptions (ES_LGG, $M = 0.4091$), Facebook and Glassdoor company descriptions (ES_FGG, $M = 0.3578$), and LinkedIn and Website (ES_LW, $M = 0.3445$). The lowest values occurred between Facebook and Glassdoor Reviews (ES_FGR, $M = 0.1527$) and LinkedIn and Glassdoor Reviews (ES_LGR, $M = 0.1782$).

Across-channel consistencies involving Glassdoor Reviews were consistently the lowest, suggesting a gap between controlled employer messaging (e.g., LinkedIn, Facebook, Website) and employee-generated content. This misalignment may undermine perceived authenticity and employer credibility.

Table 4: Statistical comparison of similarity scores by type of metric (Essay 1)

Similarity Type	n	Mean	Median	SD	p-Value	Test	Significant
IS_F	124827	0.3496	0.3415	0.1880	$< .001^{***}$	ANOVA	true
IS_L	123813	0.3677	0.3619	0.1708	$< .001^{***}$	Kruskal-Wallis	true
IS_W	103952	0.5991	0.6024	0.1811	$< .001^{***}$	Kruskal-Wallis	true
IS_GR	137506	0.4197	0.4177	0.1596	$< .001^{***}$	Kruskal-Wallis	true
ES_FL	239442	0.3011	0.2913	0.1679	$< .001^{***}$	ANOVA	true
ES_FW	141060	0.3198	0.3140	0.1712	$< .001^{***}$	Kruskal-Wallis	true
ES_FGR	256638	0.1527	0.1314	0.1209	$< .001^{***}$	ANOVA	true
ES_FGG	4775	0.3578	0.3662	0.1853	$< .001^{***}$	Kruskal-Wallis	true
ES_LW	141728	0.3445	0.3394	0.1581	$< .001^{***}$	Kruskal-Wallis	true
ES_LGG	4704	0.4091	0.4248	0.1655	$< .001^{***}$	Kruskal-Wallis	true
ES_LGR	247660	0.1782	0.1643	0.1189	$< .001^{***}$	ANOVA	true
ES_WGG	2799	0.5011	0.5142	0.1706	$< .001^{***}$	Kruskal-Wallis	true
ES_WGR	151548	0.2901	0.2848	0.1228	$< .001^{***}$	ANOVA	true
ES_GGGR	5181	0.2456	0.2216	0.1508	$< .001^{***}$	Kruskal-Wallis	true

Note. All comparisons yielded statistically significant results ($p < .001$). Significance levels: $p < .05$ (*), $p < .01$ (**), $p < .001$ (***).

Hypothesis 2

Hypothesis 2 stated that within-channel message consistency is higher than across-channel consistency. For this analysis, all four within-channel consistency measures were combined into a single aggregated score, and all 10 across-channel consistency measures were likewise aggregated. As shown in Table 5, this assumption was confirmed by the paired t-test (p-value $< .001$). The average within-channel consistency was 0.4428, and the average across-channel consistency was 0.3119. These results indicate that companies can convey more consistent messages within a single channel, likely because the content is often created by the same teams and follows uniform communication standards.

Table 5: Comparison of within-channel vs. across-channel consistency (Essay 1)

Comparison	Mean (Within-Channel)	Mean (Across-Channel)	p-Value	Test	Result
Within-Channel > Across-Channel	0.4428	0.3119	$< .001^{***}$	paired t-test (one-sided)	true

Note. Significance levels: $p < .05$ (*), $p < .01$ (**), $p < .001$ (***).

Hypothesis 3

Hypotheses 3a and 3b examined whether there are significant differences in within-channel message consistency (H3a) and across-channel message consistency (H3b) between Top 100 and non-Top 100 companies.

To test these hypotheses, matched company pairs, each consisting of one Top 100 and one non-Top 100 firm, were compared using one-sided paired t-tests on the company-level average similarity scores. As shown in *Table 6*, the vast majority of comparisons yielded non-significant results ($p > .05$), indicating no systematic difference in message consistency between the two groups.

In within-channel consistency, all metrics showed no statistically significant differences. Likewise, across-channel consistency metrics showed no significant differences between Top 100 and non-Top 100 firms, with the only exception being ES_FGR (Facebook–Glassdoor Reviews), where a statistically significant difference was found ($p < .01$).

Overall, the results suggest that message consistency does not systematically distinguish Top 100 employers from others. Thus, consistency alone does not appear to be a defining characteristic of companies ranked among the most attractive employers.

Table 6: Comparison of similarity metrics across samples (Essay 1)

Similarity Metric	Mean Top 100	Mean non-Top 100	Mean (Total)	Median	SD	p-Value	Test	Result
IS_W	0.6410	0.6328	0.6369	0.6417	0.1330	.7411	paired t-test	false
IS_GR	0.4236	0.4133	0.4184	0.4193	0.0458	.1748	paired t-test	false
IS_L	0.3785	0.3791	0.3788	0.3668	0.0946	.9691	paired t-test	false
IS_F	0.3528	0.3475	0.3501	0.3438	0.1115	.7850	paired t-test	false
ES_WGG	0.5479	0.5782	0.5630	0.5666	0.1095	.1953	paired t-test	false
ES_LGG	0.4086	0.4180	0.4133	0.4172	0.0939	.6150	paired t-test	false
ES_LW	0.3867	0.3819	0.3843	0.3780	0.0861	.7769	paired t-test	false
ES_FGG	0.3700	0.3641	0.3670	0.3812	0.1254	.7915	paired t-test	false
ES_FW	0.3467	0.3195	0.3331	0.3205	0.1106	.1526	paired t-test	false
ES_FL	0.2986	0.3088	0.3037	0.2995	0.0933	.4693	paired t-test	false
ES_WGR	0.2886	0.2807	0.2846	0.2869	0.0485	.3709	paired t-test	false
ES_GGGR	0.2414	0.2423	0.2418	0.2367	0.0841	.9513	paired t-test	false
ES_LGR	0.1776	0.1767	0.1771	0.1810	0.0441	.9063	paired t-test	false
ES_FGR	0.1672	0.1367	0.1519	0.1470	0.0613	$< .01^{**}$	paired t-test	true

Note. Significance levels: $p < .05$ (*), $p < .01$ (**), $p < .001$ (***).

Hypothesis 4

Hypotheses 4a and 4b examined whether within-channel message consistency (4a) and across-channel message consistency (4b) varies significantly between industries. As shown in Table 7, significant differences in consistency were identified across several similarity metrics. For instance, significant differences were observed in the consistency metrics for LinkedIn (IS_L: $p < .01$), Facebook (IS_F: $p < .001$), and various across-channel consistency measures, such as ES_FW ($p < .001$) and ES_FGR ($p < .01$).

To assess these differences, industry-specific group comparisons were conducted using ANOVA or Kruskal-Wallis tests on the company-level average similarity scores. The choice of test was based on the distributional properties of the similarity values within each group.

As expected, industries like Automotive, which compete heavily for qualified employees, place greater emphasis on consistent messaging to foster trust and enhance their employer image. This is reflected in higher consistency scores on LinkedIn (IS_L: Automotive 0.4279) and Facebook (IS_F: Automotive 0.4144), as visualized in Figure 1, which shows a heatmap for all significant similarity dimensions.

In contrast, industries like Retail & Wholesale, which rely more on seasonal offerings, show weaker consistency as their messages are more frequently adjusted to changing market conditions. This is highlighted by lower consistency scores on Facebook (IS_F: 0.2769) and in across-channel consistency (ES_FGR: 0.0967).

Similarly, Financial Services & Insurance and Aerospace & Defense, whose success heavily depends on a stable and trustworthy brand image, exhibit stronger consistency, particularly in across-channel consistency (e.g., ES_FW: Aerospace & Defense 0.3702, Financial Services & Insurance 0.3120).

Table 7: Comparison of similarity metrics across groups (Essay 1)

Similarity Metric	Mean	Median	SD	p-Value	Test	Result
IS_W	0.6288	0.6461	0.1210	.6586	Kruskal-Wallis	false
IS_GR	0.4155	0.4193	0.0443	.7278	Kruskal-Wallis	false
IS_L	0.3830	0.3580	0.0886	$< .01^{**}$	Kruskal-Wallis	true
IS_F	0.3504	0.3234	0.1041	$< .001^{***}$	Kruskal-Wallis	true
ES_WGG	0.5580	0.5515	0.1102	.7633	Kruskal-Wallis	false
ES_LGG	0.4137	0.4029	0.0896	$< .05^{*}$	Kruskal-Wallis	true
ES_LW	0.3833	0.3773	0.0829	.0660	ANOVA	false
ES_FGG	0.3499	0.3896	0.1163	$< .01^{**}$	ANOVA	true
ES_FW	0.3222	0.3118	0.1014	$< .001^{***}$	ANOVA	true
ES_FL	0.3030	0.2786	0.0855	$< .001^{***}$	ANOVA	true
ES_WGR	0.2842	0.2911	0.0434	$< .05^{*}$	ANOVA	true
ES_GGGR	0.2424	0.2366	0.0786	.1709	ANOVA	false
ES_LGR	0.1774	0.1884	0.0424	$< .01^{**}$	ANOVA	true
ES_FGR	0.1446	0.1463	0.0590	$< .01^{**}$	Kruskal-Wallis	true

Note. Significance levels: $p < .05$ (*), $p < .01$ (**), $p < .001$ (***). Statistical tests are based on group comparisons using ANOVA or Kruskal-Wallis, depending on distributional assumptions.

Hypothesis 5

Hypothesis 5 posited that companies with a dedicated Facebook career page exhibit higher within-channel message consistency on Facebook than companies without such a page. As shown in Table 8, the data support this assumption.

Out of 113 companies included in the Facebook sample, 27 maintained a dedicated Facebook career page, while 86 did not. Companies with a dedicated page achieved a significantly higher average within-channel consistency (Mean = 0.427) compared to companies without a dedicated page (Mean = 0.326). The independent t-test yielded a statistically significant result ($p < .001$), confirming the hypothesis.

Despite the fact that only about one in four companies operate a dedicated Facebook career page, the findings suggest that such a focused communication channel contributes substantially to greater within-channel message consistency on Facebook.

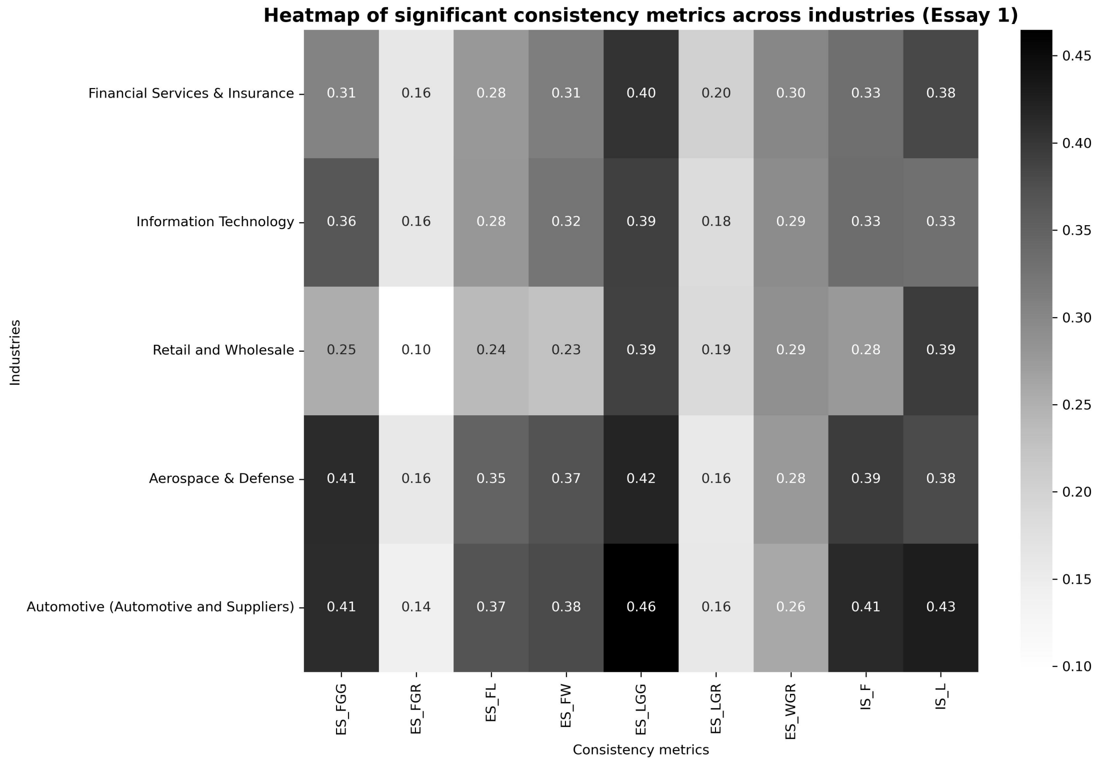


Figure 1: Heatmap of consistency metrics across industries (Essay 1)

Table 8: Comparison of within-channel consistency by Facebook page (Essay 1)

Group	n	Mean	Median	SD	p-Value	Test	Result
Dedicated Facebook career page (Yes)	27	0.427	0.409	0.109			
Dedicated Facebook career page (No)	86	0.326	0.305	0.105			
Significance Test					$< .001^{***}$	independent t-test	true

Note. Significance levels: $p < .05$ (*), $p < .01$ (**), $p < .001$ (***).

Hypothesis 6

Hypothesis 6 posited that there are significant differences in the communicated cultural dimensions across different channels.

To test Hypothesis 6, as shown in Table 9 a one-way ANOVA was conducted for each of the nine cultural dimensions in order to assess whether there are statistically significant differences in the expression of these dimensions across communication platforms. Since each group contained more than 30 observations and the assumptions for ANOVA were met, this parametric test was used consistently. All nine ANOVAs yielded statistically significant results with $p < .001$, indicating that the communicated emphasis of cultural dimensions differs systematically between platforms.

To further explore these differences, a 100% stacked bar chart was created (see Figure 2), visualizing the relative share of each dimension in the overall cultural profile per channel. The results reveal clear platform-specific emphases.

Across all channels, quality appears most frequently among the top cultural values. On Glassdoor Reviews (GR), quality (31.1%), hard work (17.0%), and teamwork (12.2%) are most prominent. Company websites (W) emphasize quality (12.6%), communication (12.2%), and community (12.0%). LinkedIn (L) highlights quality (19.3%), community (14.2%), and hard work (12.2%), while Facebook (F) shows a similar pattern with quality (22.5%), community (14.3%), and communication (9.9%). In Glassdoor company descriptions (CG), quality (15.2%), innovation (12.3%), and community (12.3%) dominate the cultural profile.

Overall, while quality is a consistent theme, other dimensions such as hard work, community, and communication vary considerably depending on the communication channel.

Taken together, these findings support Hypothesis 6. They indicate that companies adapt the relative weighting of cultural dimensions in response to the platform context, likely reflecting both audience expectations and the strategic framing of their employer image.

Table 9: Comparison of cultural dimensions across platforms (Essay 1)

Dimension	Mean	Median	SD	p-Value	Test	Result
Quality	0.229	0.225	0.034	$< .001^{***}$	ANOVA	true
Hard Work	0.132	0.130	0.019	$< .001^{***}$	ANOVA	true
Community	0.127	0.126	0.012	$< .001^{***}$	ANOVA	true
Teamwork	0.113	0.113	0.013	$< .001^{***}$	ANOVA	true
Communication	0.093	0.092	0.012	$< .001^{***}$	ANOVA	true
Integrity	0.082	0.081	0.009	$< .001^{***}$	ANOVA	true
Innovation	0.078	0.075	0.020	$< .001^{***}$	ANOVA	true
Respect	0.077	0.076	0.008	$< .001^{***}$	ANOVA	true
Safety	0.069	0.069	0.011	$< .001^{***}$	ANOVA	true

Note. Significance levels: $p < .05$ (*), $p < .01$ (**), $p < .001$ (***). All tests conducted using one-way ANOVA. Mean values refer to the relative share of each cultural dimension across platforms.

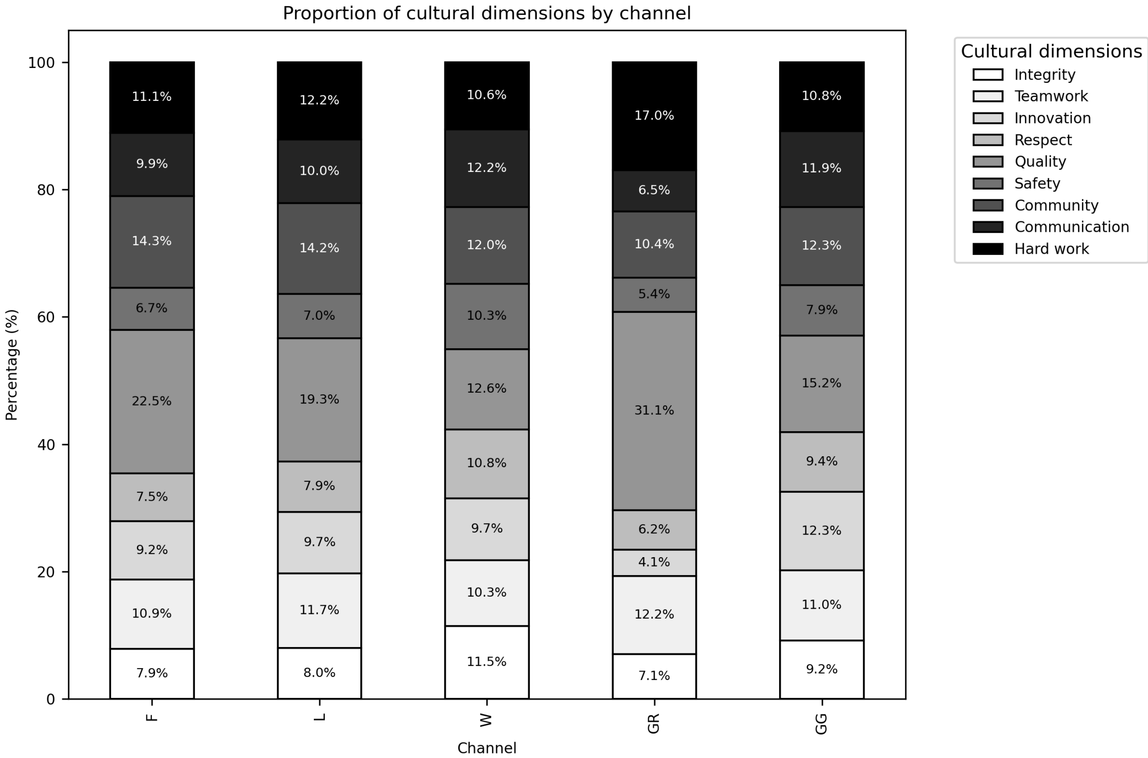


Figure 2: Proportion of cultural dimensions by channel (Essay 1)

Hypothesis 7

Hypothesis 7 examined whether there are systematic differences in the communication of cultural values between Top 100 and non-Top 100 employers. To test this hypothesis, company-level values for nine cultural dimensions were compared across matched company pairs. Each pair consisted of one Top 100 and one non-Top 100 company operating in a similar industry. Based on these pairings, one-sided paired t-tests were conducted to assess whether Top 100 employers systematically differ in their cultural emphasis. The results are presented in Table 10.

The majority of comparisons yielded non-significant results ($p > .05$), suggesting that most cultural values are communicated with comparable intensity across both groups.

However, significant differences emerged in three dimensions. Hard work was more strongly emphasized by non-Top 100 companies (13.6% vs. 12.9%; $p < .05$). In contrast, Top 100 firms placed greater focus on integrity (8.4% vs. 8.0%; $p < .01$) and respect (7.9% vs. 7.5%; $p < .05$). These findings suggest that while both groups share similar cultural narratives, Top 100 employers may invest more in promoting values associated with ethical behavior and interpersonal conduct, whereas non-Top 100 companies slightly emphasize effort and performance orientation.

Overall, the paired comparison design strengthens the validity of these results. The evidence indicates that although most cultural values are similarly emphasized, selected differences exist, particularly in the communication of integrity, respect, and hard work.

Table 10: Cultural dimensions: top 100 vs. non-top 100 (Essay 1)

Cultural Dimension	M Top 100	M non-Top 100	M (Total)	Median	SD	p-Value
Quality	0.226	0.234	0.230	0.229	0.034	.162
Hard Work	0.129	0.136	0.132	0.130	0.019	$< .05^{*}$
Community	0.128	0.125	0.127	0.125	0.012	.103
Teamwork	0.112	0.113	0.113	0.112	0.013	.677
Communication	0.093	0.092	0.093	0.091	0.012	.776
Integrity	0.084	0.080	0.082	0.082	0.009	$< .01^{**}$
Innovation	0.080	0.078	0.079	0.078	0.020	.610
Respect	0.079	0.075	0.077	0.076	0.008	$< .05^{*}$
Safety	0.070	0.067	0.068	0.069	0.011	.072

Note. Significance levels: $p < .05$ (*), $p < .01$ (**), $p < .001$ (***).

Hypothesis 8

Hypothesis 8 examined whether the relative importance of cultural values differs significantly across industries. As shown in Table 11, significant differences were identified for multiple cultural dimensions, including teamwork ($p < .01$), innovation ($p < .001$), quality ($p < .05$), safety ($p < .01$), community ($p < .001$), and communication ($p < .01$).

To evaluate these differences, industry-specific group comparisons were conducted using ANOVA or Kruskal-Wallis tests, depending on the distributional properties and sample sizes within each group. The heatmap in Figure 3 visualizes the distribution of cultural values across industries for all and only significant dimensions, respectively.

The results indicate that cultural values are not evenly emphasized across industries. For instance, innovation is particularly prominent in Information Technology (mean = 0.090) and Aerospace & Defense (mean = 0.082), both of which are known for their focus on technological advancement. In contrast, quality is emphasized more strongly in Automotive (mean = 0.25) and Retail & Wholesale (mean = 0.23), where product reliability and customer satisfaction are critical.

Similarly, safety plays a greater role in Aerospace & Defense (mean = 0.070) and Financial Services & Insurance (mean = 0.075), reflecting the strict regulatory environments in these sectors. Teamwork is highlighted in Retail & Wholesale (mean = 0.12) and Aerospace & Defense (mean = 0.12), suggesting the importance of collaboration in customer-facing and high-stakes operational contexts.

The community dimension, often linked to social responsibility and internal cohesion, is most pronounced in Retail & Wholesale (mean = 0.14) and Financial Services & Insurance (mean = 0.13). Likewise, communication is emphasized in Retail & Wholesale (mean = 0.10) and Automotive (mean = 0.097), industries where clarity, coordination, and stakeholder communication are critical.

In summary, the findings support Hypothesis 8: the relative emphasis on specific cultural dimensions varies significantly between industries. Technology-driven and safety-critical industries focus more on innovation and safety, while consumer-oriented sectors emphasize values like quality, teamwork, and communication.

Table 11: Comparison of cultural dimensions across industries (Essay 1)

Cultural Dimension	Mean	Median	SD	p-Value	Test	Result
Integrity	0.082	0.081	0.001	.115	Kruskal-Wallis	false
Teamwork	0.114	0.113	0.003	$< .01^{**}$	Kruskal-Wallis	true
Innovation	0.076	0.076	0.003	$< .001^{***}$	Kruskal-Wallis	true
Respect	0.077	0.075	0.001	.325	ANOVA	false
Quality	0.229	0.225	0.007	$< .05^{*}$	ANOVA	true
Safety	0.069	0.066	0.001	$< .01^{**}$	ANOVA	true
Community	0.128	0.125	0.003	$< .001^{***}$	Kruskal-Wallis	true
Communication	0.093	0.091	0.002	$< .01^{**}$	Kruskal-Wallis	true
Hard Work	0.132	0.130	0.004	.357	Kruskal-Wallis	false

Note. Significance levels: $p < .05$ (*), $p < .01$ (**), $p < .001$ (***). Test selection based on group size and distribution: ANOVA for normally distributed groups with $n > 30$, otherwise Kruskal-Wallis. Mean values refer to the relative share of each cultural dimension across industries.

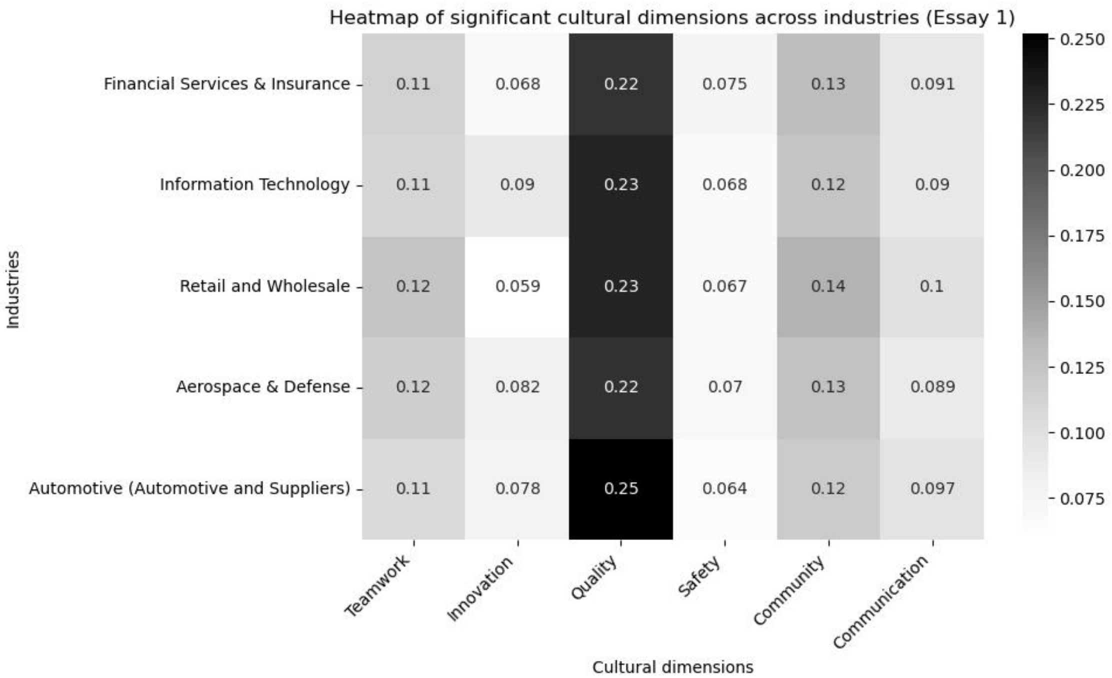


Figure 3: Heatmap of significant cultural dimensions across industries (Essay 1)

Hypothesis 9

Hypothesis 9 examined the relationship between the consistency of the communicated cultural dimensions and the overall rating of a company. The multiple regression analysis, as evidenced in Table 12, shows that only two variables yielded significant results: innovation and the interaction between avg_consistency and community.

Innovation has a positive impact on the overall rating with a coefficient of approximately 2.7361 ($p < .05$), indicating that communication of innovation leads to higher ratings.

The interaction between avg_consistency and community shows an even stronger effect with a coefficient of 83.8617. This suggests that an emphasis on community values, combined with overall message consistency, has a much greater impact on the overall rating than innovation alone.

The interaction between avg_consistency and community has a much stronger impact on the rating than innovation. The combination of these factors significantly improves the overall rating.

Table 12: Regression results with interaction terms for overall Glassdoor review (Essay 1)

Variable	Coeff.	Std. Error	t-Value	p-Value	Result
Avg_Consistency	0.2520	0.4975	0.5064	.614	false
Teamwork	-3.6416	1.8785	-1.9385	.055	false
Hard Work	-2.2291	1.3147	-1.6955	.093	false
Innovation	2.7361	1.2433	2.2007	$< .05^{*}$	true
Respect	4.1861	2.9611	1.4137	.160	false
Quality	0.9067	0.7436	1.2193	.225	false
Safety	-1.2351	2.3496	-0.5257	.600	false
Community	-3.1811	2.1280	-1.4949	.138	false
Communication	-3.1689	2.0952	-1.5125	.133	false
Integrity	0.7736	2.9136	0.2655	.791	false
Avg_Consistency × Teamwork	-19.4166	36.7539	-0.5283	.598	false
Avg_Consistency × Hard Work	-24.3451	22.2021	-1.0965	.275	false
Avg_Consistency × Innovation	18.5352	25.2094	0.7353	.464	false
Avg_Consistency × Respect	-55.7144	58.4917	-0.9525	.343	false
Avg_Consistency × Quality	3.4438	12.1427	0.2836	.777	false
Avg_Consistency × Safety	-59.4350	41.7198	-1.4246	.157	false
Avg_Consistency × Community	83.8617	39.3867	2.1287	$< .05^{*}$	true
Avg_Consistency × Communication	65.7046	41.9274	1.5671	.120	false
Avg_Consistency × Integrity	-85.2289	62.6963	-1.3594	.177	false

Note. Significance levels: $p < .05$ (*), $p < .01$ (**), $p < .001$ (***). All coefficients stem from a linear regression with interaction terms between average consistency and cultural dimensions.

Hypothesis 10

Hypothesis 10 examined the relationship between the consistency of the communicated cultural dimensions and the culture rating of a company. The multiple regression analysis, as evidenced in Table 13, shows that some variables yielded significant results.

Innovation shows a positive and significant impact on the culture rating with a coefficient of 3.3728 ($p < .05$). This suggests that communication of innovation positively influences the culture rating of a company.

Also significant is the negative impact of hard work on the culture rating (coefficient = -3.6672, ($p < .05$)). This may suggest that an emphasis on hard work is perceived more negatively, possibly because it is seen as burdensome or stressful, thereby lowering the culture rating.

Particularly noteworthy is the significant interaction between avg_consistency and community, which has an extraordinarily strong positive impact on the culture rating with a coefficient of 119.3981 ($p = .05$). This combination shows that the consistent emphasis on community values, in conjunction with an overall coherent message, has a much larger effect on the culture rating than individual dimensions like innovation or hard work. This demonstrates that communicating community values within a consistent framework can have a particularly strong impact on the perception of corporate culture.

In conclusion, the results show that consistent communication of community values, combined with overall message consistency, can significantly enhance the culture rating. This underscores the importance of a holistic and consistent communication strategy for positively shaping the perception of corporate culture.

Table 13: Regression results with interaction terms for cultural Glassdoor review (Essay 1)

Variable	Coeff.	Std. Error	t-Value	p-Value	Result
Teamwork	-1.1735	2.4250	-0.4839	.629	false
Hard Work	-3.6672	1.6580	-2.2118	$< .05^{*}$	true
Innovation	3.3728	1.5832	2.1304	$< .05^{*}$	true
Respect	3.6501	3.7830	0.9649	.337	false
Quality	1.0677	0.9466	1.1279	.262	false
Safety	-2.4899	2.9828	-0.8348	.406	false
Community	-1.2158	2.7300	-0.4454	.657	false
Communication	-5.1398	2.6481	-1.9410	.055	false
Integrity	-1.3244	3.7045	-0.3575	.721	false
Avg_Consistency × Teamwork	-18.1499	47.4902	-0.3822	.703	false
Avg_Consistency × Hard Work	-25.4989	28.0637	-0.9086	.366	false
Avg_Consistency × Innovation	56.3738	31.7441	1.7759	.078	false
Avg_Consistency × Respect	-62.1353	74.8323	-0.8303	.408	false
Avg_Consistency × Quality	-5.9578	15.4673	-0.3852	.701	false
Avg_Consistency × Safety	-52.6464	53.2427	-0.9888	.325	false
Avg_Consistency × Community	119.3981	50.3005	2.3737	$< .05^{*}$	true
Avg_Consistency × Communication	47.4374	53.4056	0.8882	.376	false
Avg_Consistency × Integrity	-82.3303	80.0532	-1.0284	.306	false

Note. Significance levels: $p < .05$ (*), $p < .01$ (**), $p < .001$ (***). All coefficients stem from a linear regression with interaction terms between average consistency and cultural dimensions.

2.6 Discussion

The findings of this study have meaningful theoretical implications in the field of corporate communication, particularly in the context of employer branding and omni-channel-recruiting. The study reveals significant differences in the consistency of corporate messaging, both within individual communication channels (e.g., Facebook or LinkedIn) and across different channels (e.g., between social media and career websites). This suggests that potential applicants could encounter inconsistent messages when gathering information about a company from various sources.

Drawing on Festinger's (1957) theory of cognitive dissonance, one could theoretically infer that such inconsistencies might lead to cognitive dissonance. While the career website of a tech company focused heavily on innovation, agility, and modern technologies, the Facebook page of the same company emphasized community, stability, and local roots. These differences in content can cause dissonance among applicants seeking information, especially those with a high need for cognitive closure. Festinger's theory posits that individuals have an inherent need for consistency in their beliefs, attitudes, and perceptions. When confronted with contradictory information, they experience an uncomfortable state known as cognitive dissonance. People then strive to reduce this dissonance by either changing their beliefs or ignoring or avoiding the inconsistent information. Applied to the results of this study, this means that inconsistent messages could theoretically cause applicants to experience dissonance. This, in turn, could lead to a loss of trust in the employer brand, as the conflicting information undermines the coherence and credibility of the brand. However, this is a theoretical conclusion based on existing psychological theories.

It is crucial to emphasize that the present study does not directly examine these effects. As this is a more descriptive study, it primarily highlights differences in message consistency. Whether and how these differences actually affect applicants' trust or behavior has not been empirically tested in this study. Nonetheless, these theoretical assumptions provide a solid foundation for future research, which could specifically investigate the causal relationship between message consistency, cognitive dissonance, and the perception of the employer brand.

Another theoretically significant aspect of the study is the examination of different dimensions of corporate culture and their communication across various channels. The study draws on the model by Guiso, Sapienza, & Zingales (2015), which identifies nine dimensions of corporate culture. The results show that certain dimensions of corporate culture are emphasized differently on different platforms. For example, innovation is more strongly communicated on platforms like general Glassdoor pages, while values such as community is more prominent on social networks like Facebook.

These varying emphases suggest that a company's communication strategy should not only be consistent but also tailored to the specific requirements and target audiences of each platform. Companies face the challenge of maintaining consistent core messages across multiple channels while also aligning with the specific norms and expectations of each platform. This adaptation is crucial for preserving the consistency of the brand message while maximizing the relevance and appeal of the messages to the respective target audience.

The study also raises important questions for future research. A crucial next step would be to empirically examine the causal relationship between the structured communication of specific cultural dimensions on particular channels and the strengthening of the employer brand. Specifically, research could investigate whether and how the targeted emphasis on dimensions such as innovation on LinkedIn or community on Facebook actually enhances trust in the brand and increases the company's attractiveness as an employer. Such investigations could also explore the interactions between different dimensions of corporate culture and their combined impact on the perception of the employer brand.

In summary, the study shows that differences in message consistency exist and could potentially create dissonance among target audiences, theoretically affecting trust in the employer brand. However, this relationship has not yet been empirically proven and could be the subject of future research. Moreover, the study suggests that the communication of corporate culture is heavily influenced by the communication platform used, highlighting the need for a differentiated and adaptable communication strategy. Future research could also further explore the causal impact of structured communication of cultural dimensions on strengthening the employer brand.

2.6.1 Practical Implications

The practical implications of this study are relevant for companies, particularly in enhancing their recruitment strategies and increasing their attractiveness as employers. The study reveals that the overall level of message consistency in corporate communication across different channels is often lower than expected. There are considerable differences in message consistency both within individual channels and across different platforms. These inconsistencies could undermine the trust of potential applicants if they encounter contradictory information about a company.

One key takeaway from the study is that companies should take proactive measures to improve the consistency of their communication. One concrete step towards higher consistency is the introduction of standardized *employer brand playbooks* and platform-specific style guides that outline tone, cultural dimensions, and narrative framing. These could be complemented by quarterly *consistency audits* — cross-functional reviews to align messages across social media, career websites, and third-party platforms. Additionally, establishing clear frameworks and document hierarchies in the form of guidelines and directives can further support the delivery of consistent messages across all channels.

While this study does not empirically examine communication team structures, the observed variation in how cultural dimensions are emphasized across platforms suggests that more granular, channel-focused setups could enhance alignment with platform-specific expectations. Rather than assigning large multifunctional teams to individual channels, companies might benefit from deploying smaller, specialized units that deeply understand the norms, audiences, and affordances of each platform. These units can craft consistent messages tailored to their specific channel while adhering to shared brand guidelines. To ensure overarching consistency, a central coordination team should oversee these decentralized units, acting as a strategic hub that ensures message alignment across all communication touchpoints. This hybrid model, which combines platform sensitivity with centralized brand governance, could help address the inconsistencies identified in this study and improve the overall coherence of employer branding efforts.

Furthermore, the study suggests that companies should clearly segment their target audiences to improve message consistency. For example, the separate use of career pages on platforms like Facebook, as confirmed in hypothesis 6 of the study, can lead to higher consistency in communication on that platform. Companies that operated separate Facebook career pages achieved higher consistency in their communication on this platform. This indicates that segmenting target audiences through specific platforms can be an effective strategy to enhance the clarity and consistency of messages.

The study also shows that the consistency of messages varies by industry. In highly regulated industries such as financial services or defense, it might be particularly important to ensure consistent communication of values like integrity and safety to signal trust and reliability. In other industries, such as IT and technology, a stronger focus on communicating innovation and adaptability could be more appropriate. Tailoring communication strategies to the specific requirements of each industry is crucial for maximizing the credibility and relevance of the brand.

Particularly noteworthy is the study's finding that a combination of generally consistent communication and the targeted emphasis on specific cultural dimensions can significantly amplify the effect on the perception of the employer brand. The examination of Hypotheses 9 and 10 suggests that a consistent emphasis on values like community, combined with a high level of overall message consistency, could have a markedly positive impact on the company's ratings and reputation. Although the study does not establish causal relationships, these findings provide valuable insights into how companies can refine their communication strategies to improve the perception of their corporate culture and thereby strengthen their employer brand.

In conclusion, the study underscores the importance of a well-considered and consistent communication strategy. Companies that can clearly and consistently communicate their cultural values while adapting this communication to the requirements of specific platforms and industries are likely to be more successful in recruiting talent. While the study does not directly demonstrate causal links, the results offer important insights into how companies can optimize their communication strategies to strengthen the trust and loyalty of their target audiences. Future research could focus on validating these theoretical assumptions further and empirically examining the actual impact of communication strategies on the employer brand.

2.6.2 Strengths, Weaknesses, and Potential Biases

This study offers significant strengths, particularly in its comprehensive analysis of message consistency across multiple communication channels within the context of corporate communication and employer branding. By examining a wide range of channels, such as social media platforms and career websites, the study provides valuable insights into how companies communicate their messages and maintain consistency across these platforms. This broad approach is crucial for understanding the challenges that organizations face in omni-channel-recruiting, especially when attempting to deliver consistent and coherent messages to potential applicants.

A key strength of the study is its focus on how different dimensions of corporate culture are communicated across various channels. The study highlights how dimensions such as integrity, teamwork, innovation, and respect are emphasized differently depending on the platform. This nuanced understanding of cultural communication provides a foundation for companies to tailor their messaging strategies to better align with the expectations and norms of each platform, thereby enhancing the overall effectiveness of their employer branding efforts.

However, the study also has some limitations and potential biases. As a descriptive study, it does not establish causal relationships between message consistency and its potential impact on the employer brand or the trust of applicants. The findings suggest theoretical implications based on existing psychological theories, such as cognitive dissonance, but these have not been empirically tested within the scope of this research.

Another limitation is the focus on certain industries, which may restrict the generalizability of the findings. Different industries have unique communication challenges and cultural norms that were not fully explored in this study, potentially limiting the applicability of the results across various sectors. However, the chosen industries represent about 60% of the Top 100 employers, which shows, that these are the most relevant industries. Additionally, the study's reliance on online communication channels may not fully capture the complete landscape of how applicants gather information about potential employers, though it aligns with the current trend of online-based research by job seekers.

3 Essay 2: Strategic Power of Message Consistency: A Mixed-Methods Study on Employer Branding and Recruitment Success

3.1 Introduction

Global competition for qualified talent has intensified substantially in recent years. Companies worldwide are increasingly faced with the challenge of attracting and retaining suitable skilled workers. According to an international survey by ManpowerGroup (2022), around 75% of companies report difficulties in recruiting, a figure that is rising steadily in many OECD countries. While countries such as Germany, the US, and France are particularly affected by the demographic decline in skilled workers, new requirements are also emerging. Knowledge work, technological specialization, and the growing need for purpose-driven work environments are making it even more difficult to match companies and talent (Tsai et al., 2018).

In this environment, employer branding has rapidly gained importance as a strategic field of action. The ability to position oneself as an attractive employer is becoming a decisive differentiating factor in the labor market. Ambler and Barrow (1996) already called for a brand strategy perspective on human resources marketing processes. Backhaus & Tikoo (2004) expanded this understanding with a theoretically sound model that views employer branding as an investment in a differentiating employer brand, with effects on both external recruitment success and internal employee retention.

Building on this relevance, the present study shows that message consistency in employer communication significantly shapes how potential applicants perceive symbolic employer brand image dimensions and organizational attractiveness. In addition, a large-scale field analysis reveals that semantically consistent job advertisements are associated with shorter time-to-hire durations. Interestingly, for certain symbolic dimensions, these effects follow a non-linear pattern.

Numerous studies confirm that strong employer brands attract and retain talent, not only through instrumental benefits such as salary, which tend to be relatively similar within the same industry and therefore offer limited potential for differentiation, but increasingly through symbolic brand associations that reflect cultural identity (Lievens & Slaughter, 2016; Theurer et al., 2018). Lievens & Highhouse (2003) introduced the instrumental-symbolic brand model, which captures employer brand not only on the basis of functional characteristics, but also along attributes such as sincerity, innovativeness, or prestige.

Today, employers communicate their brand through a variety of channels. In addition to traditional media, digital touchpoints play a central role: numerous social media profiles, company websites, review portals (e.g., Kununu, Glassdoor), and specific recruiting platforms form a complex communication space where potential talents come into contact with information about employers. This shift has given rise to what is often referred to as *omni-channel-recruiting*, an approach that leverages multiple, interconnected channels to reach and engage candidates across their entire decision journey. While this media shift offers great opportunities for differentiated target group addressing, it also brings new risks, especially with regard to message consistency. This issue is not unique to employer communication. In the broader marketing literature, scholars emphasize that fragmented customer journeys and media complexity demand coordinated, consistent messages across touchpoints. Verhoef et al. (2015), for instance, highlight the need for integrated communication to prevent confusion and maintain brand trust in omni-channel-environments – a requirement that can be directly applied to employer branding.

Consumer research has repeatedly shown that high message consistency strengthens trust in brands, reduces uncertainty, and facilitates decision-making processes (Šerić, Ozretić-Došen & Skare, 2020). In their empirical study with over 450 respondents, the authors showed that perceived inconsistencies in communication lead to a decline in brand satisfaction and loyalty, regardless of the quality of the individual measures. This perspective is supported by Kannan and Li (2017), who argue that consistency across platforms is essential in the digital era to enable seamless consumer experiences and consistent brand perceptions. Their findings suggest that inconsistent messaging increases cognitive load and may dilute brand meaning.

The dimension of message consistency is also becoming increasingly relevant in employer branding. Deepa & Baral (2021) analyzed the effect of integrated communication on employer brand perception and found that perceived consistency in communication strengthens trust in the employer value proposition (EVP) and leads to higher affective commitment. The authors argue that consistency serves as a signal of professionalism and credibility, an aspect that is particularly important in the early stages of the application process, when formal criteria (e.g., the content of a job advertisement) still need to be supplemented by symbolic cues.

Despite clear findings on the importance of message consistency in product and consumer branding, there has been limited research on how content inconsistencies in employer communication, such as contradictory statements a company makes about itself, shape perceptions of symbolic brand attributes. This essay addresses this gap by focusing specifically on the early stage of the recruitment process, when potential applicants are still deciding whether to engage with an employer at all.

Building on signaling theory (Spence, 1973), this study demonstrates that message consistency, previously established as a key credibility cue in product branding, also plays a crucial role in employer branding. It provides empirical evidence that these effects are not only present but can be systematically quantified across symbolic brand image dimensions and early-stage recruitment outcomes. By transferring and validating these mechanisms, the study extends prior research into a domain where theoretical assumptions have thus far lacked robust empirical support.

In an experimental study design, the study examines how different communicative content sent out by a uniformly identified employer brand influences symbolic associations and perceived organizational attractiveness. The aim is to empirically isolate the effect of inconsistent versus consistent communication under controlled conditions in which other characteristics (such as sender identity, channels, visual design) are kept constant.

The aim of this thesis is to answer the following research questions (RQ):

- **RQ1:** How does the consistency of employer communication influence the perception of the symbolic employer brand image and perceived employer attractiveness?
- **RQ2:** How does the semantic consistency of job advertisements relate to the application process, measured by time-to-hire?

The thesis is structured as follows: Chapter 3.2 presents the theoretical background and preliminary work. Chapter 3.3 describes the conceptual framework and hypotheses. Chapter 3.4 describes the study method, and chapter 3.5 presents the empirical results. Chapter 3.6 discusses these findings in light of existing research, derives practical implications, and outlines future research needs.

3.2 Background

This study examines how message consistency in employer communication influences the perception of the symbolic employer brand image and organizational attractiveness on the one hand and the time-to-hire on the other hand. The theoretical positioning takes place at the intersection of brand perception, psychological information processing and applicant behavior and is based on established concepts of employer branding as well as psychological and communication theory.

3.2.1 Definition of Key Constructs

The employer brand describes the strategically developed identity of a company as an employer. Originally defined by Ambler and Barrow (1996) as "the package of functional, economic and psychological benefits provided by employment and identified with the employing company", the concept today encompasses both instrumental and symbolic attributes (see section 3.2.4 for details).

In contrast, employer branding refers to the strategic process of shaping and communicating this identity to internal and external audiences (Backhaus & Tikoo, 2004). Specific activities and frameworks are discussed in section 3.2.2.

This study focuses on the symbolic employer brand image, that is, personality-related attributes such as sincerity, competence, prestige, innovativeness, and robustness, which act as social signals of value and cultural fit (see section 3.2.4 for theoretical background).

Organizational attractiveness refers to the overall affective-cognitive perception of an organization as a desirable employer (Highhouse et al., 2003). Its key drivers are discussed in section 3.2.5.

This study defines message consistency as the alignment of communicated content across channels, focusing specifically on message consistency rather than stylistic uniformity. Consistent communication is perceived as more credible, clearer and more professional and makes it easier to process complex information (Wilden, Guerdgan & Lings, 2010). In this study, message consistency is conceptualized as a strategically influenceable, independent variable that can influence both the image and the attractiveness of an employer.

Terminology used in this essay: It is distinguished between three levels of message consistency: (1) within-ad consistency: semantic alignment within a single job advertisement; (2) across-ad consistency: alignment between multiple ads from the same company; and (3) across-channel consistency: alignment across platforms (e.g., LinkedIn, career site, Glassdoor).

3.2.2 Employer Branding

In the field of employer branding, there are various established conceptual frameworks that reflect partial aspects of brand perception and the attractiveness of employers.

One influential model comes from Backhaus & Tikoo (2004). It distinguishes between the internal and external effects of employer branding. For external target groups, the model describes a chain from employer brand associations via employer brand image to organizational attractiveness. This model was instrumental in establishing the dual impact of employer branding and in highlighting the role of brand image as a mediating construct. Although this model shows basic structures, it remains abstract at a conceptual level and does not take into account concrete communication strategies such as the consistency of messages.

Also the conceptual framework of Cable & Turban (2001) offers an important contribution to the explanation of cognitive processes in employer perception. It describes employer knowledge as a sequence of familiarity, reputation and image, which are moderated by credibility, source and depth of processing. This framework provides a valuable micro-level perspective on how job seekers perceive and process employer-related information. However, this model also remains at a more information-psychological level and does not consider any operational implications for the strategic communication of employers.

Taken together, both models offer essential theoretical foundations, one from a branding strategy perspective, the other from a cognitive processing angle, but neither addresses the question of how employers can manage content across channels in a consistent way.

This is why this study is conceptually based on the integrative Employer Branding Value Chain framework by Theurer et al. (2018). This model links strategic employer branding activities (e.g. EVP positioning, communication channels) with perceptual (e.g. employer image, attractiveness) and behavioral (e.g. application, retention) outcomes. Particularly relevant for the present study is the explicit differentiation between instrumental and symbolic employer brand image attributes, an aspect that is at the center of the research question. Although this framework does not explicitly take message consistency into account, it does offer a connectable structure for theoretical expansion. This study therefore builds on this model and systematically extends it by integrating message consistency into the framework as an independent variable. In this way, the study not only makes an empirical contribution, but also further develops the theoretical foundation of employer branding, by specifically taking into account the previously neglected consistency of content across communication channels.

To support this conceptual extension, it is essential to review the current empirical evidence on message consistency in the context of employer branding. While the theoretical importance of message consistency has been emphasized in both branding and communication research, there is surprisingly little empirical work that directly quantifies its effect within the context of employer branding. Existing studies often examine perceived credibility, distinctiveness or informativeness of employer brand messages, but rarely isolate consistency as a measurable construct (Zhang & Zhu, 2023; Chang, 2018; Šerić, Ozretić-Došen & Skare, 2020; Navarro-Bailón, 2011). In most cases, consistency is treated as a qualitative attribute embedded within broader evaluations of communication quality. Moreover, empirical research in related domains such as integrated marketing communications has shown that consistent brand messages can increase brand trust, loyalty, and identification (Šerić, Ozretić-Došen & Skare, 2020), yet such findings have not been systematically transferred to employer branding contexts.

Against this backdrop, the present study makes two contributions: First, it introduces a scalable, NLP-based operationalization of message consistency in employer communication, allowing for objective measurement across a large corpus of job-related texts. Second, it empirically tests the causal effect of message consistency on key employer branding outcomes, such as symbolic employer image and organizational attractiveness, within an experimental design. In doing so, this study not only addresses an important empirical gap but also extends current theoretical frameworks by integrating message consistency as a strategic communication variable in employer branding.

3.2.3 Signaling Theory

The effect of consistent communication can be explained according to signaling theory (Spence, 1973). Information asymmetries exist in application processes, as potential applicants have no direct insight into corporate culture or practice. Organizations therefore send signals, e.g. via career pages, social media, job advertisements, etc., to communicate desired values or attributes. Consistent signals are more credible, easier to process and allow clear conclusions to be drawn. In addition, studies show that schema-congruent information strengthens trust, while incongruent content promotes mistrust (Harmon-Kizer, 2017).

Furthermore, psychological theories show that inconsistent communication leads to cognitive dissonance, an unpleasant state of contradictory cognitions that individuals reduce by rejecting or devaluing the source of information (Festinger, 1957).

This is further supported by psychological evidence showing that consistency in communication fosters trust. Inconsistent or contradictory messages are often interpreted as indicators of inauthenticity or a lack of transparency, thereby undermining confidence in the organization. Recent research demonstrates that subjective consistency, understood as the perceived coherence between communicated elements, significantly increases trust even when the individual messages themselves are neutral in tone. This effect holds true not only in interpersonal communication but also in broader decision-making contexts such as economic exchanges (Nowak et al., 2023). For employer branding, this implies that a consistently conveyed identity across all touchpoints enhances credibility, reduces cognitive friction, and makes it easier for applicants to identify and evaluate the employer.

3.2.4 Symbolic Employer Brand Image

According to the Instrumental-Symbolic framework (Lievens & Highhouse, 2003), employer brand image encompasses both functional and symbolic attributes. Symbolic attributes, such as sincerity, competence, prestige, innovativeness and robustness, reflect how the organization is perceived as a *person* and have a particularly strong effect on people with a high need for cultural fit.

The selection of these symbolic dimensions is based on established concepts from brand personality research. With the Brand Personality framework, Aaker (1997) developed a widely recognized model for describing brands along five personality dimensions (sincerity, excitement, competence, sophistication, ruggedness). Building on this approach, the dimensions were transferred to employer brands in later research (Slaughter et al., 2004) and further developed.

This study examines a contextualized, empirically supported adaptation of this model. The selection of the symbolic dimensions is also based on empirical findings that employers within the same industry can be distinguished from one another more by symbolic than by functional characteristics. Symbolic image dimensions show a higher variance than functional ones, such as pay or job security, which are typically similar within an industry (Van Hoye et al., 2013).

It is assumed that a higher perceived consistency in communication leads to clearer and more positive evaluations of the symbolic image dimensions.

3.2.5 Organizational Attractiveness

Organizational attractiveness describes the overall affective-cognitive perception of a company as a desirable employer (Highhouse et al., 2003). It is a central predictor of application intentions and is influenced by image perception, trust level and communicative quality (Hoppe, 2018).

This study assumes that, in addition to influencing employer image, message consistency also has a direct effect on attractiveness itself, for example through higher credibility, coherence, and perceived professionalism.

3.3 Conceptual Framework and Hypotheses

This study develops an extended conceptual framework model that integrates message consistency as a central, strategically influenceable factor in employer communication. It builds on the integrative Employer Branding Value Chain framework by Theurer et al. (2018) and supplements it with consistency-related influencing factors that have so far been insufficiently considered.

Figure 4 illustrates the underlying model and the derived hypotheses. It shows how different forms of consistency (within-ad and across-ad as well as across- channel) can affect the perception of the employer brand, the attractiveness of the employer and ultimately the behavior of potential applicants (especially time-to-hire).

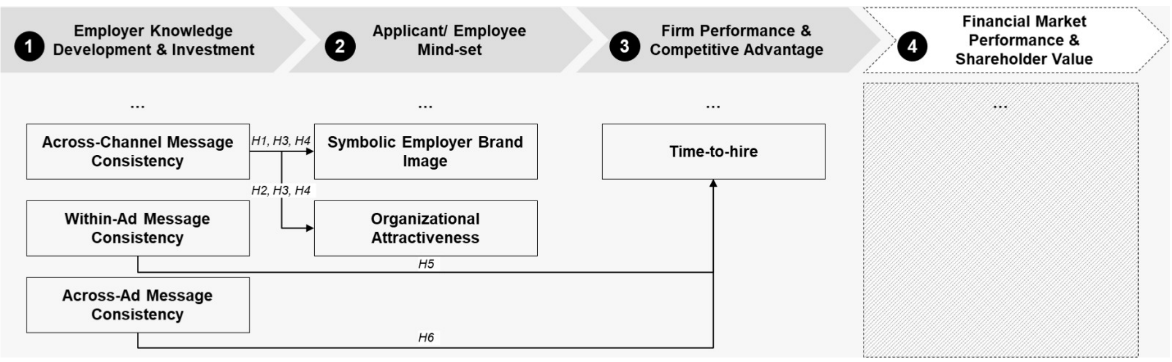


Figure 4: Conceptual framework message consistency and employer brand (Essay 2)

3.3.1 Conceptual Framework

Building on the integrative Employer Branding Value Chain framework by Theurer et al. (2018), this study develops an extended conceptual model that explicitly integrates message consistency as a central, strategically influenceable variable of employer communication. While the original model links strategic branding activities (e.g. EVP development, choice of communication channels) with perceptual and behavioral outcomes (e.g. employer image, attractiveness, application or retention behavior), it remains abstract with regard to the content consistency of communication.

This study expands the model to include three different levels of consistency:

- **Across-Channel Message Consistency:** consistency of content across different channels.
- **Within-Ad Message Consistency:** consistency of content within a single job advertisement.
- **Across-Ad Message Consistency:** consistency of content across different job advertisements of a company.

These three consistency measures are conceived as independent, strategically controllable influencing variables that can influence both the perception of symbolic brand image attributes and perceived organizational attractiveness. These perceptions in turn affect behavioral outcome variables such as time-to-hire, that is, the time it takes to fill an advertised position.

The extended framework thus understands employer branding as a signaling process in which the consistency of the signals (messages) conveyed are decisive for the effect on potential applicants. It combines theoretical elements from signaling theory, schema theory and the theory of cognitive dissonance with practical key figures on the effectiveness of employer branding and recruiting.

3.3.2 Hypotheses

Based on the theoretical foundation, the following hypotheses are derived:

H1: The perception of symbolic dimensions of the employer brand image changes between pre- and post-measurement depending on the degree of across-channel consistency of the communication:

(a) With high consistency, perception increases significantly.

(b) With medium consistency it remains unchanged.

(c) It decreases significantly with low consistency.

The hypothesis assumes that symbolic employer brand image perceptions are particularly sensitive to the consistency of external communication. These traits, adapted from Aaker's (1997) brand personality framework and applied to the employer context by Slaughter et al. (2004), serve as important signals for applicants. Prior research shows that consistent communication across channels enhances the credibility and clarity of these symbolic cues, thereby strengthening employer image (Hoppe, 2018). In contrast, inconsistencies may dilute or contradict brand signals, leading to a deterioration of symbolic perceptions.

H2: Perceived organizational attractiveness changes between pre- and post-measurement depending on the degree of across-channel consistency of the communication:

(a) It increases significantly with high consistency.

(b) With medium consistency, it remains stable.

(c) It decreases significantly with low consistency.

Organizational attractiveness refers to the extent to which a company is perceived as a desirable place to work (Highhouse et al., 2003). Prior research highlights that consistent communication across channels enhances credibility and reinforces the employer's value proposition (Hoppe, 2018; Deepa & Baral, 2021). In contrast, contradictory messages can undermine trust and create cognitive dissonance (Fiske & Taylor, 1991), reducing the likelihood that applicants consider the company attractive, even if individual brand attributes are positive.

H3: The negative effect of low across-channel consistency on symbolic employer brand image and organizational attractiveness is more pronounced than the positive effect of high consistency.

This hypothesis is grounded in the principle of expectancy asymmetry: while consistent communication is expected, inconsistencies are perceived as norm violations and evaluated disproportionately negatively. This is supported by cognitive dissonance theory (Festinger, 1957). Empirical research confirms this pattern: communication consistency has a negatively asymmetric effect on brand perceptions, with inconsistencies damaging trust and image more than consistency improves them (Šerić, Ozretić-Došen & Skare, 2020).

H4: Demographic characteristics (e.g. age, gender, education, professional experience) influence the change in the perception of employer brand image and organizational attractiveness.

The hypothesis draws on consumer behavior research, which shows that demographic factors such as age, gender, and education influence how individuals process brand communication. For example, older or more experienced individuals often rely more on consistency and emotional coherence when evaluating brands (Cole et al., 2008), while gender and cognitive style affect the sensitivity to message contradictions (Meyers-Levy & Loken, 1995). It is therefore plausible that applicant subgroups also differ in how strongly they react to consistent or inconsistent employer branding messages.

H5: The higher the within-ad consistency, the shorter the time it takes to fill the advertised position.

This hypothesis can be theoretically grounded in signaling theory (Spence, 1973). A consistent presentation in job advertisements may enhance perceived professionalism and clarity, thereby reducing uncertainty for applicants and increasing their intention to apply. While prior research shows that message specificity in job ads positively affects ad perception, job fit evaluations, and application intentions (Feldman, Bearden & Hardesty, 2006), this relates to message quality rather than consistency per se. Thus, the hypothesis introduces a novel assumption that warrants further empirical examination.

H6: The higher the across-ad consistency between several job advertisements of a company, the shorter the time it takes to fill these positions.

This hypothesis draws on signaling theory (Spence, 1973) and uncertainty reduction theory, which propose that consistent communication across multiple touchpoints increases trust, clarity, and perceived reliability, factors that may accelerate application behavior (Berger & Calabrese, 1975). It builds on evidence that consistent communication across multiple job advertisements strengthens brand recognition, reduces information uncertainty, and increases trust and applicant clarity (Šerić, Ozretić-Došen & Skare, 2020). While these mechanisms may plausibly accelerate application decisions and reduce time-to-hire, no direct empirical link has yet been established. Therefore, this hypothesis is framed as requiring future empirical investigation.

3.4 Method

The overall aim of the study is to measure the effect of message consistency in corporate communication on recruitment success. Two studies were carried out for this purpose. In a first research project (Project A), the effect of message consistency between different channels (career website, LinkedIn posts, Glassdoor reviews) on the perception of a company's symbolic employer brand image and organizational attractiveness was investigated using an online study. As part of a second research project (Project B), message consistency in corporate communication was examined with a focus on advertised job descriptions. Project B analyzes within-ad and across-ad consistency in job advertisements. In both cases, the influence of the respective form of consistency on the hiring duration of advertised job vacancies was analyzed. Section 3.4.1 examines project A, while section 3.4.2 examines project B.

3.4.1 Online Study

The design of Project A builds on findings from a prior descriptive study (Essay 1), which revealed considerable variation in communication consistency across companies and channels, specifically career websites, Facebook, LinkedIn, and Glassdoor. On average, communication was found to be relatively inconsistent, with statistically significant discrepancies that may negatively affect employer brand perceptions.

Project A picks up on these results and aims to make the influence of such inconsistencies empirically measurable by conducting realistic communication experiments with potential applicants in order to quantify the influence on symbolic employer brand image as well as on organizational attractiveness. Based on pretest results, the career website, LinkedIn, and Glassdoor were selected as more relevant channels than Facebook.

Sample

A total of 510 people took part in the study. An overview of the sample and structure of the online study is provided in Figure 5. At the beginning, participants were asked to choose the company they would be most likely to apply to from three well-known companies from three different industries – Microsoft, BMW, and Airbus. The company selection introduced a realistic decision-making context and accounted for brand familiarity. Prior research highlights that such familiarity strongly shapes perceptions of employer attractiveness (Theurer et al., 2018).

The resulting distribution shows a clear preference for Microsoft (n = 238), followed by BMW (n = 194) and Airbus (n = 78). Participants were then randomly assigned to one of three experimental groups that differed in terms of the level of across-channel consistency in corporate communication (low, medium, high). The allocation was almost evenly distributed (n1 = 170, n2 = 168, n3 = 172).

In terms of professional status, the sample consisted largely of students (n = 302). In addition, early career professionals (n = 101), mid-level professionals (n = 65), and smaller groups of senior professionals (n = 22), trainees (n = 13), and other professionals (n = 7) participated. In line with the target group, the age distribution was heavily concentrated among young adults. The majority of participants were between 18 and 24 years old (n = 256) or between 25 and 34 years old (n = 226). Only a small proportion were between 35 and 44 years old (n = 16), 45 years or older (n = 9), or under 18 years of age (n = 3). The gender distribution was also largely balanced: 299 participants identified as female, 208 as male, 2 as diverse, and 1 person did not specify.

In terms of educational attainment, the majority of participants had a bachelor's degree (n = 276) or a general university entrance qualification (n = 123). Other educational qualifications included vocational training (n = 71), a master's degree (n = 13), an intermediate school leaving certificate (n = 13), a doctorate (n = 10), and other or no formal qualifications (n = 4). Students were also asked about their current progress in their studies. The largest group was in their first year of study (n = 84), followed by participants in their fourth (n = 54), fifth (n = 49), second (n = 49), third (n = 42), and sixth year or later (n = 24).

The majority of the sample came from the field of economics (n = 349). Other fields represented included engineering/IT (n = 48), social sciences/humanities (n = 39), law (n = 15), medicine/health sciences (n = 8), and natural sciences (n = 4).

With regard to the timing of their last application, 220 people stated that they had applied in the last 6 months. A further 152 had applied between 1 and 5 years ago, 96 within the last 6 to 12 months, 34 more than 5 years ago, while 8 people stated that they had never submitted an application.

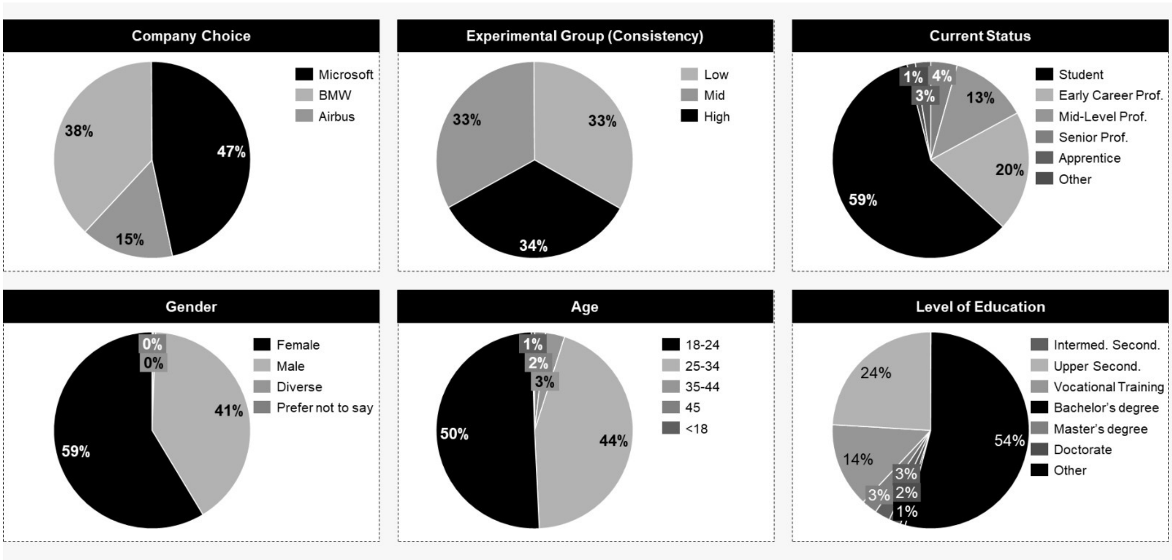


Figure 5: Sample online experiment (Essay 2)

Design and Procedure

The online study was conducted using SoSci Survey between January and April 2025. The aim was to simulate as realistic a job applicant scenario as possible in order to investigate the influence of across-channel message consistency on the perception of employer brand image and organizational attractiveness.

The underlying study design combines elements of an experimental between-subjects design with a repeated measurement (pre-post design). Participants were randomly assigned to one of three experimental groups that differed only in terms of the degree of across-channel message consistency:

- **low consistency** (contradictory values across channels),
- **medium consistency** (partially consistent content),
- **high consistency** (consistent communication across all channels).

After selecting a company, the participants' initial perceptions of the employer brand image and organizational attractiveness were recorded. Texts from three digital communication channels of the selected company were then presented: the career website, the LinkedIn page, and selected reviews on Glassdoor. The texts shown were systematically manipulated to represent one of three predefined levels of message consistency across the selected communication channels. Immediately after the content was received, the two central constructs were measured again. To avoid response bias, items that were slightly varied in form but equivalent in content were used.

The stimuli were based on authentic communication material from real recruiting and image texts from companies. The original texts were systematically extracted from publicly available sources on the three channels and prepared for use in the experiment. Each of the three channels comprised five texts, each of which specifically addressed one of the five dimensions of the symbolic employer brand image (sincerity, innovativeness, competence, prestige, and robustness). This resulted in a total of 15 base texts, which were then varied in the next step according to the experimental conditions.

The texts were converted into the three experimental consistency levels using a two-stage semantic process based on modern natural language processing models (transformers). The aim was to assign the texts to image dimensions on the one hand and to ensure the semantic consistency of the content on the other in an objective, traceable, and data-based manner.

(1) Dimension assignment with RoBERTa-large-MNLI

In the first step, all source texts were assigned to one of the five dimensions of the symbolic employer brand image. The underlying text base consisted of over 20,000 real communication texts that had previously been extracted from various digital employer communication channels, including career websites, LinkedIn company profiles, Facebook pages, and Glassdoor reviews. These texts were collected as part of Essay 1.

The *RoBERTa-large-MNLI* model was used for classification, a variant based on the RoBERTa architecture that was fine-tuned to the MNLI corpus (Multi-Genre Natural Language Inference). It was chosen because it is particularly effective at recognizing semantic relations between hypotheses and premises — i.e., assessing whether a text supports the statement "This text communicates competence." This method has already been used successfully for dimension assignment in comparable studies (see Imran et al., 2023).

(2) Consistency assessment with all-mpnet-base-v2

In the second step, the semantic consistency of company-related communication was calculated within each image dimension. For this purpose, the *Sentence Transformer all-mpnet-base-v2* was used, which is based on the MPNet architecture (Xu et al., 2020). This model combines Masked Language Modeling (MLM) with Permuted Language Modeling (PLM), thereby achieving particularly accurate detection of semantic differences in meaning. MPNet is one of the most powerful models for calculating semantic similarity between sentences and has received multiple awards in benchmarks such as the *STS benchmark* and *SICK*.

Until recently, research on message consistency has primarily relied on more traditional methods such as TF-IDF, n-gram overlap, Latent Semantic Analysis (LSA), or topic modeling (e.g., LDA). While these approaches offer useful approximations of lexical or thematic similarity, they fall short in capturing contextual nuance, paraphrased meaning, and sentence-level semantics, particularly in natural, varied employer communication. The transformer-based approach used in this study addresses these limitations by generating dense, contextualized sentence embeddings and comparing them via cosine similarity. This enables a more robust, semantically valid, and scalable quantification of message consistency across different communication formats and platforms.

The classified texts were converted into embeddings, i.e., high-dimensional vector representations. The mean cosine similarity value between the texts from LinkedIn, the career website, and Glassdoor was then calculated for each company and each dimension. This value reflects how similar a company's content is across different channels within an image dimension.

The similarity values calculated in this way were converted into a distribution for each dimension and then divided into three empirically based levels:

- **Low consistency**: lower 33% of cosine similarity values
- **Medium consistency**: middle 34% (34th to 66th percentile
- **High consistency**: upper 33%

This distribution resulted in specific thresholds for low, medium, and high consistency in communication for each of the five dimensions.

In a next step, these consistency scores were used to manually generate varied text versions based on real corporate communications that corresponded to the respective consistency levels. The classification is therefore empirically based, data-supported, and calibrated for each dimension.

The final stimulus material thus comprised 135 texts (15 combinations of channel and image dimension $\times$ 3 consistency levels $\times$ 3 companies).

Pretest

Following the automated classification of the source texts, a pretest was conducted to empirically validate the content-based assignment of the texts to the five dimensions of the symbolic employer brand image. At the same time, the aim was to check whether the texts were suitable for use in the main experiment in terms of comprehensibility and plausibility.

To this end, 15 sample texts were selected, one text per channel and dimension, which served as basic material for the subsequent consistency manipulation. The participants in the pretest received the texts in random order and were asked to assign each text to exactly one of the five dimensions. This was a forced-choice categorization task in which the most appropriate dimension had to be selected for each text.

The criterion for a valid assignment was an agreement rate of at least 65%, i.e., at least two-thirds of the participants had to assign the same text to the same dimension as the transformer model had done in advance. A total of 13 out of 15 texts met this requirement, with 9 texts achieving agreement rates of well over 70%. The 2 texts that fell below the threshold were subsequently revised to make the intended dimension clearer. Only the successfully validated texts were included in the main experiment.

29 people took part in the pretest, 20 of whom were female and 9 male. 12 of the participants were between 18 and 24 years old, 17 between 25 and 34 years old. In terms of highest level of education, 5 people stated “high school diploma or equivalent”, 20 stated a bachelor’s degree, and 4 stated a master’s degree. Details on the pretest and its sample are shown in Figure 6.

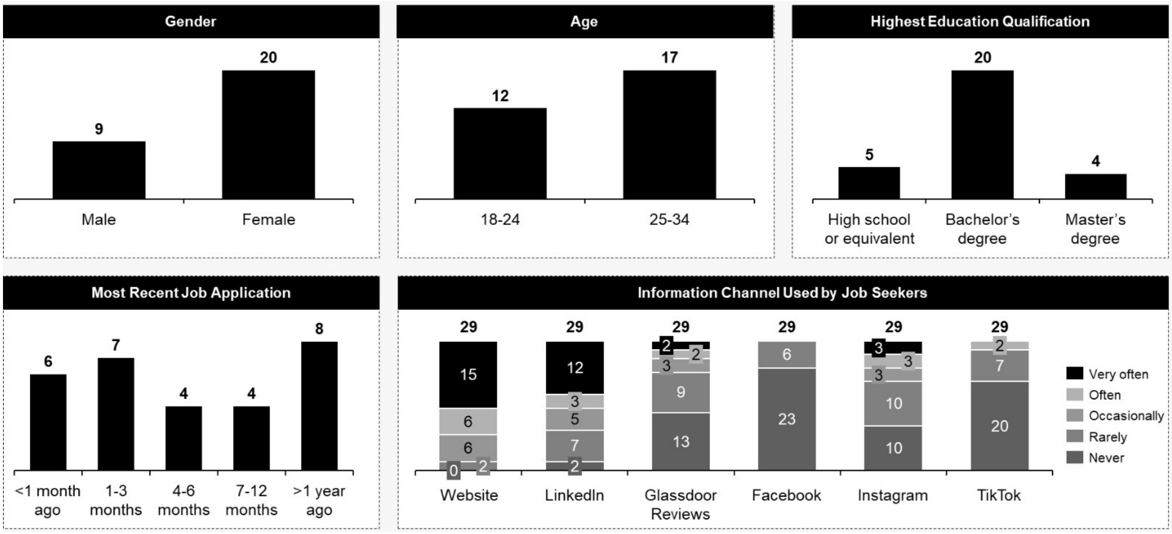


Figure 6: Sample pretest (Essay 2)

There was a wide range of application behavior: 6 participants had applied for a job in the last 4 weeks, 7 in the last 1–3 months, 4 in the last 4–6 months, another 4 in the last 7–12 months, and 8 people said they had last applied more than 1 year ago.

The frequency of use of relevant information channels for employer research was also recorded. The career website (15 times “very frequently”) and LinkedIn (12 times “very frequently”) were particularly frequently mentioned as central sources. Glassdoor reviews and Instagram were mentioned less frequently, while Facebook and TikTok were not identified by participants as channels they used regularly at all. These results support the decision to specifically use the three channels career website, LinkedIn, and Glassdoor in the main experiment.

Measures

The study focused on two central dependent constructs: the symbolic employer brand image and perceived organizational attractiveness. The symbolic employer brand image was differentiated along five dimensions that have been identified in previous research as particularly relevant for the perception of employers (see Lievens & Highhouse, 2003; Van Hoye et al., 2013; Hoppe, 2018). Organizational attractiveness was operationalized as an overall assessment of the attractiveness of the company as a potential employer (Highhouse et al., 2003).

The measurement was carried out using several validated items for symbolic employer brand image and organizational attractiveness from the relevant literature. All items were recorded on a 5-point Likert scale (1 = strongly disagree; 5 = strongly agree). The five dimensions of employer brand image were each operationalized using three semantically related items. These items were selected based on established literature (including Lievens & Highhouse, 2003; Van Hoye et al., 2013; Hoppe, 2018). Three items were also used for organizational attractiveness (e.g., “A job at the company is very appealing to me,” (Lievens, 2007).

To capture potential effects of the experimental stimuli, both a pre- and post-measurement of the employer brand image were conducted. In the pre-measurement, participants were asked to give their initial assessment of the selected company before reading the manipulated communication texts (stimuli). To avoid post-treatment bias (Coppock, 2019) and automated response tendencies, linguistically differentiated but semantically equivalent items were used in the post-measurement. The scale structure remained identical to the pre-measurement. This approach follows recommendations from experimental methodology and is intended in particular to reduce reactance effects.

In addition, attention tests in the form of negated items (e.g., “The employer is deceptive”) were integrated to ensure response quality. Negatively formulated items were recoded accordingly before evaluation.

To empirically verify the reliability of the scales, Cronbach’s alpha was calculated for each dimension of employer brand image and organizational attractiveness, both before and after the stimuli were received. The calculation was based on the items applicable to the selected company, so that internal consistency was aggregated on a person-specific but cross-company basis.

The results show that all scales exhibit good to very good internal consistency in the pre-measurement. Prestige ($\alpha = .843$), robustness ($\alpha = .824$), and attractiveness ($\alpha = .865$) in particular achieve very high values. Sincerity also shows stable consistency before stimulus reception with $\alpha = .797$. In the post-measurement, the high values are confirmed in most dimensions, especially for prestige ($\alpha = .833$) and innovativeness ($\alpha = .718$). However, there is a noticeable decline in the dimension sincerity ($\alpha = .376$). This slump could indicate semantic ambiguities in the stimuli, response-related variation, or reactance effects in particularly sensitive aspects such as authenticity and trustworthiness.

In addition to the central dependent variables, sociodemographic characteristics and professional/application-related background information were also collected in order to take potential control or moderator variables into account. These included:

- Age
- Gender
- Highest level of education
- Current professional status
- Professional field / field of study
- Time of last application

3.4.2 Job Ads

To answer the research questions in Project B, we used a big secondary data set with over 1 million job ads. Due to their structured form, their widespread distribution via digital channels, and their central importance in the application process, job advertisements are particularly suitable for analyzing communicative features such as consistency, language, and target group appeal.

The aim of the studies described below was to investigate how differences in the content consistency of job advertisements, both between several advertisements from the same company (Project B-1) and within individual advertisements (Project B-2), affect the time it takes to fill a position (days_to_hire). Both analyses are based on the same data set, which is described below and then explained in terms of design, procedure, and metrics used.

Sample

The research project for Project B was based on a data set consisting of 1,056,696 job advertisements collected from a total of 215 sources between January 2023 and January 2025. The data set covers a total of 44 countries, with the majority of ads originating from Germany (49.1%), France (10.3%), and the United Kingdom (7.1%). The ads are available in a total of 54 different languages, with English (42.1%) and German (40.3%) dominating.

The data contains information on the following variables:

- Job title
- Company name
- Location
- Language of the job advertisement
- Publication and deactivation date (for calculating *days_to_hire*)
- Seniority
- Job group
- (Estimated) salary

Some variables have missing values. For example, approximately 12.8% of the ads do not include information on the duration of the job posting (*days_to_hire*). These ads were excluded from the analysis. The variable (estimated) salary has a very high rate of missing values (97.7%) and was completely excluded from the analysis due to the low data quality.

In terms of company distribution, there is a strong concentration on a few corporations. A total of 42 aggregated company groups were formed. Most of the ads come from Deutsche Post (11.5%), Siemens (11.4%), and Airbus (6.9%). In terms of seniority level, the proportion of entry-level positions dominates, with Associate roles (62.1%) being the most common, followed by Senior positions (17.6%) and Internships (10.1%). The job advertisements can be assigned to a total of 461 different job sub-groups. The most common groups are Business Administration Support (6.04%), Distribution and Delivery (5.49%), and Software Engineering (3.87%). The top sources of the dataset are Eurojobs (10.2%), Dejobs (7.1%), and Xing (6.7%).

The target variable for the investigations in Project B is *days_to_hire*, defined as the number of days between the publication date and the removal of the advertisement. The average value is 68.4 days, the median is 35 days.

Design and Procedure

For both subprojects (B-1 and B-2), only English-language job advertisements were considered. The reason for this is the use of a semantic sentence transformer for consistency measurement, which is optimized for English texts in particular.

Specifically, as in section 3.4.1, the model all-mpnet-base-v2 from the SentenceTransformer library was used.

Project B-1: Message consistency between job advertisements (across-ad)

The aim of the research project is to analyze the effect of across-ad message consistency or inconsistency between different job advertisements of a company on days_to_hire.

The preparatory steps included:

- Exclusion of all advertisements with a *days_to_hire* value below seven days in order to eliminate purely formal or internally already filled positions (e.g., for compliance reasons).
- Inclusion of only those job advertisements for which there was at least two other advertisements with related content. Ads were considered related if they:
  - originated from the same company,
  - were online at the same time on at least one day,
  - were assigned to the same job sub-group, and
  - were located within a maximum distance of 15 kilometers from each other.

These restrictions are based on the realistic search behavior of applicants, who usually search within a specific job category and region and consider several ads from the same company. The aim was to map a realistic applicant scenario and ensure comparability. After filtering, 214,672 observations remained.

Vectors were calculated for each advertisement using the all-mpnet-base-v2 model. The mean cosine similarity to all content-related advertisements was then determined in order to calculate a consistency score per advertisement.

Operational definition: across-ad consistency.

For a focal ad A and a set of related ads $\mathcal{R}(A)$, define ad-level embeddings as the mean of sentence embeddings: $\mathbf{e}_A = \frac{1}{n_A}\sum_{i=1}^{n_A} \mathbf{e}_{A,i}$ and $\mathbf{e}_B = \frac{1}{n_B}\sum_{i=1}^{n_B} \mathbf{e}_{B,i}$ for $B \in \mathcal{R}(A)$. Focal-level across-ad consistency is

$$\text{Consistency}_{\text{across-ad}}(A \mid \mathcal{R}(A)) = \frac{1}{|\mathcal{R}(A)|}\sum_{B\in\mathcal{R}(A)} \cos\big(\mathbf{e}_A, \mathbf{e}_B\big), \qquad \cos(\mathbf{u},\mathbf{v}) = \mathbf{u}^\top\mathbf{v}. \tag{3}$$

Set-level across-ad consistency for a set $\mathcal{S}$ of m related ads is

$$\text{Consistency}_{\text{across-ad}}(\mathcal{S}) = \frac{2}{m(m-1)}\sum_{\substack{A,B\in\mathcal{S}\\ A<B}} \cos\big(\mathbf{e}_A, \mathbf{e}_B\big). \tag{4}$$

Notes. Related ads are defined by the same company and role within a fixed time and geography window; near duplicates are excluded. Higher scores indicate stronger semantic alignment between related ads.

Across-ad consistency — examples

Low: Two "Sales Manager" ads (same company, same week): one offers hybrid and flexible hours; the other demands full on-site and fixed hours; titles and salary bands differ.

High: Several "Software Engineer" ads share the same title taxonomy, repeat core tasks (code reviews, customer demos), state the same hybrid policy, and list matching benefits.

In addition, the following features were collected and integrated into the analysis for both subprojects:

- Number of sentences per advertisement
- Total number of words
- Average number of words per sentence
- Seniority level
- Company group
- Country code

Project B-2: Message consistency within job advertisements (within-ad)

This research project investigates the effect of within-ad message consistency or inconsistency within individual job advertisements on days_to_hire.

The approach comprised the following steps:

- Segmentation of the advertisement descriptions into individual sentences, each treated as a separate text element.
- Calculation of sentence embeddings using the all-mpnet-base-v2 transformer.
- Calculation of the average cosine similarity between all sentence pairs to determine a consistency score per advertisement.

Operational definition: within-ad consistency.

Let a job ad A be segmented into n sentences $s_1, \ldots, s_n$ with sentence embeddings $\mathbf{e}_1, \ldots, \mathbf{e}_n \in \mathbb{R}^d$ (unit-normalized). Within-ad consistency is the mean pairwise cosine similarity among all sentences:

$$\text{Consistency}_{\text{within-ad}}(A) = \frac{2}{n(n-1)} \sum_{1 \leq i < j \leq n} \cos\bigl(\mathbf{e}_i, \mathbf{e}_j\bigr), \qquad \cos(\mathbf{u}, \mathbf{v}) = \mathbf{u}^\top \mathbf{v}. \quad (5)$$

Notes. Ads with fewer than 10 sentences ($n < 10$) are excluded. Higher scores indicate stronger semantic alignment within the ad.

Within-ad consistency — examples

Low: Intro promises creativity and autonomy; tasks require fixed procedures and frequent approvals; requirements say "follow instructions only."

High: Intro stresses teamwork; tasks include client contact and team reviews; requirements ask for collaboration skills; benefits mention mentoring.

After data cleaning and segmentation, the final dataset comprised n = 345,090 observations.

3.5 Results

This section presents the empirical findings of the two-part study. The first part is based on an online study that investigates how different levels of message consistency and various initial symbolic employer images affect the perception of employer brand image and organizational attractiveness (Hypotheses 1–4). The second part is based on a large-scale dataset of real job advertisements and examines whether higher within-ad and across-ad message consistency in job advertisements is associated with faster recruitment success (Hypotheses 5–6). In the following, the results of both components are presented in detail.

3.5.1 Online Study

In the first part of the study, participants were randomly assigned to different conditions and asked to evaluate the company before and after exposure to a fictitious employer campaign. In addition to main effects of consistency, interaction effects with the initial image of the employer and moderating effects of demographic characteristics were analyzed (Hypotheses 1–4).

Hypothesis 1

A two-factor ANOVA tested H1 for each of the five symbolic dimensions with the factors degree of consistency and initial image. Table 14 summarizes the results of the two-factor ANOVA. All five dimensions showed significant main effects of consistency (all $p < .01$) and of initial image (all $p < .001$). Significant interaction effects emerged for sincerity, innovativeness, and competence (all $p < .05$). Complementary one-sample tests are reported in Table 16.

Normal distribution was tested using the Shapiro-Wilk test. Parametric tests were used when $n \geq 30$ or normality was present; Wilcoxon tests were applied otherwise. Groups with $n < 10$ were excluded from hypothesis testing.

To test H1a–H1c, one-sample tests against zero were conducted within each consistency × initial image group. Results support H1c: At low consistency ($Z001 = 1$), a significant decline in employer brand image was observed in all five dimensions in the groups with a sufficient number of cases ($n \geq 10$) (all $p < .001$). H1b is partially supported: In groups with a neutral image, medium consistency led to no significant changes in sincerity, competence, and robustness. However, several negative or positive initial image groups showed significant increases (e.g., prestige × medium: $\Delta = 0.339$, $p < .001$). H1a is not supported overall: Although high across-channel consistency increased image perception in several neutral groups (e.g., innovativeness × medium: $p < .001$), effects in groups with a positive initial image were mostly absent or negative (e.g., sincerity × good: $\Delta = -0.667$, $p < .001$).

Given the limited support for H1a, we explored a potential non-linear (inverted U-shaped) relationship, where the effect of consistency peaks at medium levels. Linear and quadratic regressions were performed (consistency coded as low = 1, medium = 2, high = 3); an inverted U was assumed if the squared term was negative and significant with a turning point in [1–3].

Linear models confirmed a general positive effect of consistency on all dimensions ($p < .05$). Quadratic models showed a significant inverted U-shape for innovativeness and prestige, peaking at medium consistency. No such pattern emerged for sincerity or robustness; for competence, the turning point lay outside the range between low and high consistency.

These results suggest diminishing or negative returns of excessive consistency, particularly for innovativeness and prestige (see Table 15).

Table 14: Results of the two-factor ANOVA for symbolic employer brand image (Essay 2)

Dimension	F (Consistency)	p (Consistency)	η^2	F (Initial Image)	p (Initial Image)	η^2	F (Interaction)	p (Interaction)	η^2
Sincerity	27.9	$< .001^{***}$	0.100	91.0	$< .001^{***}$	0.266	3.28	$.011^{*}$	0.026
Innovativeness	46.1	$< .001^{***}$	0.155	33.5	$< .001^{***}$	0.118	24.8	$< .001^{***}$	0.165
Competence	47.3	$< .001^{***}$	0.159	38.9	$< .001^{***}$	0.134	18.7	$< .001^{***}$	0.130
Prestige	55.3	$< .001^{***}$	0.181	100.0	$< .001^{***}$	0.286	0.72	$.577$	0.006
Robustness	4.89	$.008^{**}$	0.019	112.0	$< .001^{***}$	0.309	0.96	$.431$	0.008

Note. Significance levels: $p < .05$ (*), $p < .01$ (**), $p < .001$ (***). Partial η^2 represents the proportion of variance explained by each factor or interaction.

Table 15: Quadratic regression analysis for symbolic employer brand image (Essay 2)

Dimension	R^2 (quad)	β (Consistency)	β (Consistency^2)	p (Consistency^2)	Turning Point x	Inverted U-Shape?
Sincerity	0.076	0.659	-0.105	.113	–	–
Innovativeness	0.113	1.028	-0.183	.007**	2.807	yes
Competence	0.133	0.859	-0.137	.031*	–	–
Prestige	0.153	1.309	-0.248	$< .001^{***}$	2.645	yes
Robustness	0.013	0.395	-0.072	.340	–	–

Note. Significance levels: $p < .05$ (*), $p < .01$ (**), $p < .001$ (***). The turning point x is calculated as $-\beta_1/2\beta_2$ when the quadratic term is significant and negative.

Table 16: One-sample tests of change in symbolic employer brand image (Essay 2)

Dimension	Consistency	Initial Image	n	Δ	Test	Test Statistic	Cohen's d	p
Sincerity	low	good	27	-1.272	t-Test	-10.894	-2.10	$< .001^{***}$
	low	medium	140	-0.376	t-Test	-8.210	-0.69	$< .001^{***}$
	medium	good	29	-0.701	t-Test	-5.973	-1.11	$< .001^{***}$
	high	good	31	-0.667	t-Test	-5.712	-1.03	$< .001^{***}$
	high	medium	135	0.111	t-Test	2.142	0.18	$.034^{*}$
Innovativeness	low	good	61	-0.869	t-Test	-8.835	-1.13	$< .001^{***}$
	low	medium	109	-0.254	t-Test	-4.320	-0.41	$< .001^{***}$
	medium	good	64	-0.333	t-Test	-4.446	-0.56	$< .001^{***}$
	medium	medium	100	0.183	t-Test	2.805	0.28	$.0061^{**}$
	high	good	63	-0.328	t-Test	-4.731	-0.60	$< .001^{***}$
	high	medium	101	0.261	t-Test	5.104	0.51	$< .001^{***}$
Competence	low	good	126	-0.841	t-Test	-13.562	-1.21	$< .001^{***}$
	low	medium	44	-0.280	t-Test	-3.398	-0.51	$.0015^{**}$
	medium	good	117	-0.425	t-Test	-7.939	-0.73	$< .001^{***}$
	medium	medium	50	0.120	t-Test	1.361	0.19	$.180$
	high	good	118	-0.282	t-Test	-6.091	-0.56	$< .001^{***}$
	high	medium	50	0.253	t-Test	3.418	0.48	$.0013^{**}$
Prestige	low	good	115	-0.707	t-Test	-10.432	-0.97	$< .001^{***}$
	low	medium	54	-0.284	t-Test	-3.639	-0.50	$.0006^{***}$
	medium	good	107	-0.209	t-Test	-4.876	-0.47	$< .001^{***}$
	medium	medium	60	0.339	t-Test	5.094	0.66	$< .001^{***}$
	high	good	113	-0.142	t-Test	-3.113	-0.29	$.0023^{**}$
	high	medium	54	0.321	t-Test	4.294	0.59	$.0001^{***}$
Robustness	low	good	71	-0.967	t-Test	-10.776	-1.28	$< .001^{***}$
	low	medium	98	-0.248	t-Test	-4.217	-0.43	$.0001^{***}$
	medium	good	68	-0.882	t-Test	-11.048	-1.34	$< .001^{***}$
	medium	medium	98	-0.044	t-Test	-0.748	-0.08	$.4565$
	high	good	76	-0.798	t-Test	-9.397	-1.08	$< .001^{***}$
	high	medium	94	0.028	t-Test	0.390	0.04	$.6971$

Hypothesis 2

A two-factor ANOVA tested changes in attractiveness across consistency levels and initial image (see Table 17). Significant main effects were found for both across-channel consistency and initial image (both $p < .001$), while the interaction was not significant ($p = .243$).

H2a–H2c were further examined via one-sample t-tests within each consistency $\times$ initial image group (see Table 18). Groups with $n < 10$ were excluded from inferential analysis due to insufficient statistical power. The following results emerged:

H2c is confirmed: Low across-channel consistency led to significant declines in attractiveness for participants with a positive ($\Delta = -0.745$) and a neutral initial image ($\Delta = -0.174$; both $p < .01$).

H2b is not supported: Medium across-channel consistency increased attractiveness among participants with a neutral image ($\Delta = 0.280$, $p < .001$), but decreased it among those with a positive image ($\Delta = -0.208$, $p = .003$).

H2a is partially supported High across-channel consistency significantly increased attractiveness in the neutral group ($\Delta = 0.304$, $p < .001$), but had no effect in the positive image group ($p = .165$).

To explore potential non-linearity, a quadratic regression (consistency coded as low = 1, medium = 2, high = 3) was conducted to test for an inverted U-shaped relationship. The squared term was negative and statistically significant ($\beta = -0.217$, $p = .0006$), and the turning point at $x = 2.68$ falls within the observed range. This supports the assumption of an inverted U-shape: attractiveness perceptions increase with across-channel consistency up to a moderate-to-high level, but overly polished or rigid communication may reduce perceived credibility or authenticity.

Table 17: Effect of consistency and initial image on organizational attractiveness (Essay 2)

	Two-way ANOVA							**Quadratic Regression**					
Dimension	F (Cons.)	p (Cons.)	η^2 (Cons.)	F (Init.)	p (Init.)	F (Int.)	p (Int.)	R^2	β_1	β_2	$p(\beta_2)$	Turning Pt.	Inv. U?
Attractiveness	43.30	< 0.01	0.147	45.54	< 0.01	1.37	0.243	0.135	1.164	-0.217	0.0006	2.682	yes

Table 18: Change in organizational attractiveness (Essay 2)

Consistency	Initial Image	n	Δ	Test	Statistic	Cohen's d	p
Low	Good	72	-0.745	t-Test	$t = -7.85$	-0.93	$< .001^{***}$
Low	Medium	94	-0.174	t-Test	$t = -2.68$	-0.28	$.009^{**}$
Medium	Good	64	-0.208	t-Test	$t = -3.09$	-0.39	$.003^{**}$
Medium	Medium	94	0.280	t-Test	$t = 5.20$	0.54	$< .001^{***}$
Medium	Poor	10	0.400	t-Test	$t = 1.45$	0.46	.181
High	Good	72	-0.079	t-Test	$t = -1.40$	-0.17	.165
High	Medium	91	0.304	t-Test	$t = 4.90$	0.51	$< .001^{***}$

Note. Cohen's d calculated as $t/\sqrt{n}$. Groups with $n < 10$ were not statistically tested due to low power. Reported values are descriptive only. Significance levels: $p < .05$ (*), $p < .01$ (**), $p < .001$ (***). Groups with $n < 10$ were excluded.

Hypothesis 3

To test hypothesis 3, a group comparison was carried out between low ($Z001 = 1$) and high across-channel consistency ($Z001 = 3$), based on the change values (post–pre) in the dimensions of employer brand image and organizational attractiveness. A detailed breakdown is given in Table 19.

The results show consistent significant differences between the two groups in all dimensions examined (all $p < .05$). The change values were always more negative for low consistency than for high consistency. The differences were particularly pronounced in the symbolic dimensions of sincerity, innovativeness, competence, and prestige (all $p < .001$). The difference for robustness was also significant ($p = .016$), albeit with a lower effect size. Organizational attractiveness likewise showed a strong significant difference in favor of the group with high consistency ($\Delta = 0{,}180$ vs. $\Delta = -0{,}412$, $p < .001$).

These results support Hypothesis H3 and thus the assumption of an asymmetric effect of across-channel consistency: While high consistency only leads to moderate improvements in employer brand image, low levels of consistency lead to significantly stronger negative effects. This pattern is consistent with theoretical considerations on expectation disconfirmation (Festinger, 1957).

Table 19: Comparison of change values between low and high consistency (Essay 2)

Dimension	n_{low}	Δ_{low}	n_{high}	Δ_{high}	Test	Cohen's d	p
Sincerity	170	−0.486	172	−0.010	$t = -6.326$	−0.68	$< .001^{***}$
Innovativeness	170	−0.475	172	0.116	$t = -7.434$	−0.80	$< .001^{***}$
Competence	170	−0.696	172	−0.074	$t = -8.507$	−0.91	$< .001^{***}$
Prestige	170	−0.561	172	0.078	$t = -8.282$	−0.88	$< .001^{***}$
Robustness	170	−0.535	172	−0.324	$t = -2.413$	−0.26	$.016^{*}$
Attractiveness	170	−0.412	172	0.180	$t = -7.869$	−0.84	$< .001^{***}$

Note. Cohen's d calculated as $t/\sqrt{n_{\text{eff}}}$, where $n_{\text{eff}} = \frac{n_1 \cdot n_2}{n_1 + n_2}$. Significance levels: $p < .05$ (*), $p < .01$ (**), $p < .001$ (***).

Hypothesis 4

To test Hypothesis 4, separate linear regression models were estimated for each symbolic dimension and for employer attractiveness. In each model, consistency and one demographic characteristic (e.g., age, gender) were entered together as categorical predictors, and the interaction term tested whether the effect of across-channel consistency differed across demographic groups. This approach was preferred over a multivariate model (e.g., MANOVA) because it enables dimension-specific interpretation, is less affected by violations of multivariate normality, and avoids sparse category combinations in moderators.

Although prior analyses indicated an inverted U-shape relationship between across-channel consistency and three outcome dimensions (innovativeness, prestige, and attractiveness), consistency was treated as a categorical factor here to allow comparison across the three consistency levels within demographic subgroups, without assuming a specific functional form.

Given partly small subgroup sizes, results should be interpreted as indicative rather than conclusive. Age (PD02) and level of education (PD04) emerged as potential moderators in several dimensions, while current status (PD01) and professional field (PD07) showed effects in isolated cases. Gender (PD03) and date of last application (PD08) were included but showed no significant moderation.

A review of mean patterns suggests:

- **Age (PD02):** Older respondents appeared more sensitive to inconsistent communication. Low consistency led to larger declines in ratings, whereas high consistency produced above-average gains in attractiveness, competence, and prestige.
- **Level of education (PD04):** Lower and higher education levels tended to show stronger reactions, both negative under low consistency and positive under high consistency, compared to medium levels.
- **Occupational field (PD07):** Moderation was most visible for attractiveness, with some fields reacting more positively under high consistency and more negatively under low consistency.
- **Current status (PD01):** Effects for robustness suggest young professionals reacted more positively than students under high consistency, but more negatively under low consistency.

Overall, these patterns provide initial evidence that demographic characteristics may influence how message consistency affects employer brand perception, particularly for age and education.

Table 20: Significant moderation effects — interaction (Essay 2)

Moderator	**Dimension**	p	**partial** η^2
Age (PD02)	Sincerity	$.001^{**}$	.050
Education (PD04)	Sincerity	$.002^{**}$	.067
Age (PD02)	Innovativeness	$< .001^{***}$	.088
Education (PD04)	Innovativeness	$< .001^{***}$	.124
Age (PD02)	Competence	$< .001^{***}$	.089
Education (PD04)	Competence	$< .001^{***}$	.122
Age (PD02)	Prestige	$< .001^{***}$	.122
Education (PD04)	Prestige	$< .001^{***}$	.128
Current status (PD01)	Robustness	$.013^{*}$	.044
Education (PD04)	Robustness	$.039^{*}$	.049
Age (PD02)	Attractiveness	$< .001^{***}$	.101
Education (PD04)	Attractiveness	$< .001^{***}$	.113
Occupational field (PD07)	Attractiveness	$.025^{*}$	.046

Note. Significance levels: $p < .05$ (*), $p < .01$ (**), $p < .001$ (***). Partial η^2 indicates the proportion of variance in the dependent variable explained by the interaction effect, calculated as: $\eta^2_{\text{partial}} = \frac{\text{SS}_{\text{effect}}}{\text{SS}_{\text{effect}}+\text{SS}_{\text{error}}}$.

3.5.2 Job Ads

The second part of the study analyzes a large-scale dataset of job advertisements from various companies across countries and industries. The aim is to investigate whether the message consistency of communication within and across job ads influences the time-to-hire i.e., how quickly a position is filled after publication. Two types of consistency are considered: (1) within-ad consistency, which refers to consistency within a single advertisement, and (2) across-ad consistency, which captures how consistently a company presents itself across multiple job ads. Regression analyses with extensive control variables test the hypotheses derived from communication and employer branding theory (Hypotheses 5–6).

Hypothesis 5

To test hypothesis 5, we analyzed whether greater within-ad message consistency is associated with a shorter time-to-hire. The dependent variable days_to_hire has a strongly right-skewed distribution, which is why it was log-transformed (log_days_to_hire) to minimize distortions caused by outliers and to better reflect linear relationships. The previously calculated consistency_score was used as the central independent variable. In addition, structural characteristics were controlled: seniority, country_code, company_grouped, and linguistic characteristics of the advertisement (sentence_count, total_word_count, avg_words_per_sentence). Categories with low frequency were grouped together to ensure robust estimates.

Table 21: Change in employer brand image by consistency and moderator group (Essay 2)

Dimension	Moderator group	Δ_1 (low)	Δ_2 (medium)	Δ_3 (high)
Attractiveness	18–24	-0.395	0.034	0.093
Attractiveness	25–34	-0.452	0.169	0.282
Attractiveness	Bachelor's degree	-0.436	0.059	0.187
Attractiveness	Master's/Diploma/Magister	-0.353	0.185	0.280
Attractiveness	Upper secondary education	-0.522	0.100	0.095
Attractiveness	Business/Economics	-0.417	0.111	0.230
Attractiveness	Engineering/IT	-0.167	0.062	-0.333
Attractiveness	Other	-0.356	-0.044	0.294
Attractiveness	Social Sciences/Humanities	-0.510	0.028	0.400
Competence	18–24	-0.598	-0.232	-0.137
Competence	25–34	-0.798	-0.262	-0.066
Competence	Bachelor's degree	-0.640	-0.304	-0.099
Competence	Master's/Diploma/Magister	-0.873	-0.178	-0.061
Competence	Upper secondary education	-0.855	-0.200	-0.048
Innovativeness	18–24	-0.483	-0.008	-0.056
Innovativeness	25–34	-0.518	-0.008	0.282
Innovativeness	Bachelor's degree	-0.479	0.033	0.095
Innovativeness	Master's/Diploma/Magister	-0.500	0.030	0.318
Innovativeness	Upper secondary education	-0.536	-0.133	-0.107
Prestige	18–24	-0.510	-0.021	0.007
Prestige	25–34	-0.601	0.034	0.141
Prestige	Bachelor's degree	-0.528	-0.037	0.135
Prestige	Master's/Diploma/Magister	-0.529	0.096	0.038
Prestige	Upper secondary education	-0.754	0.033	-0.012
Robustness	Bachelor's degree	-0.479	-0.458	-0.381
Robustness	Master's/Diploma/Magister	-0.588	-0.319	-0.311
Robustness	Upper secondary education	-0.609	-0.333	-0.607
Sincerity	18–24	-0.502	-0.215	-0.174
Sincerity	25–34	-0.461	-0.084	0.141
Sincerity	Bachelor's degree	-0.475	-0.168	-0.099
Sincerity	Master's/Diploma/Magister	-0.657	-0.126	0.106
Sincerity	Upper secondary education	-0.464	0.000	0.060

Note. Groups with $n < 10$ were excluded.

Table 22 shows the regression results supporting Hypothesis 5. The multiple linear regression model shows a significant negative correlation between the within-ad message consistency score and the logarithmic time-to-hire ($\beta = -0.1897$, $p < .001$). This means that as content consistency increases, time-to-hire decreases significantly. With an average time-to-hire of 68.4 days, an increase in the consistency score from zero to one corresponds to a reduction in time-to-hire of approximately 17.3%, specifically around 11.8 days.

The explained variance of the model is $R^2 = 0.061$, which is not unusual in large-scale field studies given the large number of unobserved influencing factors, such as internal processes or regional market conditions (Gupta et al., 2024). Studies from similar fields of application show that even R^2 values below 10% can represent meaningful correlations if they are theoretically sound and statistically significant (Miles, 2005).

In addition to consistency, the length of the advertisement (measured in sentence_count) also proves to be a significant predictor ($\beta = +0.007$, $p < .001$). Longer ads tend to be associated with slightly longer filling times, possibly because they describe more complex roles or processes. In contrast, total_word_count and avg_words_per_sentence showed no significant effects.

Systematic patterns also emerge for the control variables: Higher positions (e.g., seniority_director) tend to be associated with longer filling times, while entry-level and internship positions are filled significantly faster (seniority_entry_level and intern: both negative, $p < .001$). As expected, country and company dummies reveal clear differences, which are likely to reflect country-specific labor market conditions and internal processes.

The results show that consistent within-ad communication can not only improve the perception of the employer brand, but also has a directly measurable impact on the time it takes to fill a position. In practice, this means that a professionally structured, consistent presentation of content can not only strengthen employer branding, but also increase the efficiency of recruiting – an observation that is clearly supported by recent research (Jones et al., 2006; Allen, Scotter & Otondo, 2004; Feldman et al., 2006).

Table 22: Regression results on the effect of within-ad consistency (Essay 2)

Variable	**Coefficient (β)**	**Std. Error**	**p-Value**	
Content Consistency (within single ad)				
Consistency Score	**-0.1897**	0.041	$< .001^{***}$	
Linguistic Control Variables				
Sentence Count	0.0072	0.000	$< .001^{***}$	
Total Word Count	0.000009	0.000017	.576	
Avg. Words per Sentence	0.0003	0.0002	.214	
Structural Control Variables				
Seniority: Director	0.0231	0.007	$.001^{**}$	
Seniority: Entry Level	-0.0925	0.007	$< .001^{***}$	
Seniority: Executive	-0.0928	0.016	$< .001^{***}$	
Seniority: Intern	-0.0523	0.006	$< .001^{***}$	
Seniority: Senior	0.0170	0.004	$< .001^{***}$	
Model Fit				
n				345,090
R^2				0.061
Adjusted R^2				0.060
Note:	Robust standard errors. Additional control variables (e.g., country and company dummies) included in the model but not displayed for space reasons. Significance levels: $p < .05$ (*), $p < .01$ (**), $p < .001$ (***)			

Hypothesis 6

To test hypothesis 6, we analyzed whether a higher across-ad message consistency between job advertisements from the same company was associated with a shorter time-to-hire. The dependent variable days_to_hire was logarithmized due to its strong skewness in order to mitigate outliers and better reflect linear relationships (as in hypothesis 5).

Regression results testing Hypothesis 6 are reported in Table 23. The multiple linear regression model shows a highly significant negative correlation between across-ad message_consistency_score and the logarithmic time-to-hire ($\beta = -0.6915$, $p < .001$). Specifically, this means that a 0.1-point increase in the across-ad consistency score leads to a reduction in time-to-hire of approximately 5%. With an average time-to-hire of 68.4 days, this corresponds to a reduction of around 3.4 days. This clearly confirms hypothesis 6.

The explained variance of the model is $R^2 = 0.067$. Although this value appears moderate at first glance, such effect sizes are not uncommon in the context of real-world field data with numerous unobserved influencing factors, such as internal processes or seasonal effects (Gupta, 2024). Studies from similar fields of application show that even R^2 values below 10% can represent meaningful correlations if they are theoretically sound and statistically significant (Miles, 2005).

The results underscore the importance of a consistent employer presence across various touchpoints. Consistent and reliable communication across multiple ads not only pays off in employer branding, but also measurably shortens the time-to-hire, thereby increasing operational efficiency in the recruiting process.

3.6 Discussion

This study examined the effect of message consistency in employer communications on symbolic employer brand dimensions and the time it takes to fill advertised positions. Two complementary studies, an online experiment (Project A) and a large-scale field analysis of more than 1 million real job advertisements (Project B), show that consistent messages are a key lever for the perception and effectiveness of employer messages in terms of the perception of the employer brand image, organizational attractiveness and behavioral recruitment metrics.

Table 23: Regression results on the effect of across-channel consistency (Essay 2)

Variable	Coefficient (β)	Std. Error	p-Value	
Content Consistency (across multiple ads)				
Message Consistency Score	**-0.6915**	0.015	$< .001^{***}$	
Linguistic Control Variables				
Sentence Count	0.0065	0.0004	$< .001^{***}$	
Total Word Count	-0.00008	0.00002	$< .001^{***}$	
Avg. Words per Sentence	0.0019	0.0003	$< .001^{***}$	
Structural Control Variables				
Seniority: Director	0.0346	0.008	$< .001^{***}$	
Seniority: Entry Level	-0.1144	0.008	$< .001^{***}$	
Seniority: Executive	-0.1102	0.018	$< .001^{***}$	
Seniority: Intern	-0.1168	0.006	$< .001^{***}$	
Seniority: Senior	0.0249	0.005	$< .001^{***}$	
Model Fit				
n				214,774
R^2				0.067
Adjusted R^2				0.067
Note:	Robust standard errors. Additional control variables (e.g., country and company dummies) included in the model but not displayed for space reasons. Significance levels: $p < .05$ (*), $p < .01$ (**), $p < .001$ (***).			

In Project A, an online experiment with 510 participants examined the influence of different levels of across-channel consistency on changes in the symbolic employer brand image and on organizational attractiveness. The findings show that low consistency systematically leads to negative shifts in symbolic employer brand image perception across all dimensions and also regarding organizational attractiveness. While high consistency does not always yield significant improvements, it becomes evident that inconsistency is clearly detrimental, whereas high consistency shows diminishing returns beyond a certain point.

These results indicate that more consistency is not always better. Instead, there appears to be a *sweet spot* at which consistency exerts its optimal effect. Excessive repetition or perfect uniformity may not be interpreted as professional or trustworthy, but rather as calculated, inauthentic, or even manipulative. In such cases, consistency can lead to cognitive reactance or perceived blandness. This effect is especially relevant for symbolic dimensions such as prestige, where uniform, over-standardized messages may be perceived as presumptuous or hollow (“they always say the same thing”).

Furthermore, it becomes clear that the effect of across-channel consistency is not independent of the initial perception of the company. If the pre-image is already positive, a low level of across-channel consistency leads to particularly strong image losses, especially in the dimensions of prestige and robustness. This finding is surprising, as it contrasts with earlier studies suggesting that a strong brand can buffer negative effects (e.g., Stockman et al., 2019). The present results suggest that high expectations from a strong brand image may actually amplify the disappointment triggered by inconsistent messaging. Conversely, if the pre-image is rather weak, consistent communication can contribute particularly strongly to improving the image. A similar pattern can also be seen in organizational attractiveness: for companies with a negative initial image, consistent communication significantly increases perceived attractiveness, while companies that are already perceived positively see little additional gain. These patterns point to the central role of expectation congruence: applicants seem to assume a high degree of consistency in content from well-known and positively rated employers. If this expectation is disappointed, there is a disproportionate loss of trust. If it is fulfilled, the image stabilizes without improving significantly. In contrast, consistent communication can be an important signal for repositioning in the case of a negative pre-image.

A methodological added value of Project A lies in the combination of theory-based scale measurement, realistic experimental design, and statistical modeling of interactive effects. By using real communication texts and integrating individual pre-scores of employer brands, a high degree of ecological validity was achieved while maintaining internal validity through randomization and targeted manipulation of consistency levels.

Project B complements these findings with a large-scale analysis of over 1 million real online job advertisements. Using sentence embeddings from the all-mpnet-base-v2 Transformer model, a measure of semantic consistency between the central text components was developed. The results show that higher semantic within-ad and across-ad consistency is significantly associated with a shorter time-to-hire, even when controlling for numerous covariates such as company size, industry, position type, and country. This confirms the importance of consistent communication not only at the perception level, but also through observable behavior in the recruitment process.

The combination of both studies provides a consistent overall finding: consistency acts as a psychological signal in the sense of signaling theory, reducing uncertainty, conveying professionalism, and positively influencing the decision-making processes of potential applicants, both in terms of brand perception and concrete application decisions.

3.6.1 Practical Implications

The results of both studies show that message consistency is a key success factor in employer communication, both in terms of perception and concrete recruitment results. In practice, this means that employers should ensure that key text elements in job advertisements are consistent. Inconsistent statements (e.g., innovative tasks combined with a traditional corporate culture) can cause confusion among potential applicants and lead to negative brand associations.

In addition, companies should take into account existing perceptions of their employer brand: If an employer's image is weak or unclear, consistent communication offers the opportunity for targeted (re)positioning. Conversely, brands that are perceived very positively should avoid jeopardizing this trust by inconsistent communication.

A noteworthy insight from both studies is that consistency is not a cost-free optimization variable. It requires coordination across communication teams, standardized templates, potentially algorithmic support, and continuous review. Managers should therefore not treat consistency as a dogma, where "more" automatically means "better". Instead, strategic communication must balance recognizability with content freshness. For example, overly consistent social media posts or campaigns may come across as inflexible or empty – especially in fast-changing markets or among young applicants who value authenticity.

This also implies that employer branding activities should be accompanied by well-defined, but not overly rigid, consistency guidelines – such as editorial style guides, semantic quality checks, or automated NLP-based tools. The results of Project B also show that the use of modern NLP methods for analyzing and controlling consistent communication is scalable and can contribute to optimizing recruitment processes in practice. Nevertheless, these mechanisms require organizational resources. Not every company can or should aim for maximum consistency across all channels and formats. Consistency is therefore not only a question of strategic alignment, but also of operational feasibility and cost-effectiveness.

Overall, the findings provide employers with a clear, evidence-based rationale to invest in consistency, but with nuance. Rather than pursuing maximal uniformity, organizations should treat consistency as a flexible instrument: one that can stabilize a positive image, enable strategic repositioning, and strengthen applicant trust – as long as it does not come at the cost of authenticity or relevance.

3.6.2 Limitations and Directions for Future Research

Despite the contributions outlined above, there are methodological and content-related limitations. Project A attempted to replicate the real-world situation as closely as possible, among other things by using real communication texts, individual pre-image measurements, and the targeted variation of consistency while maintaining controlled presentation. In addition, the possibility of choosing between different employers integrated another element of realistic decision-making logic: the selection implicitly reflects individual brand familiarity and enables a situational examination of a credibly chosen employer alternative. Nevertheless, it remains unclear to what extent the perceptions measured in the experiment translate into actual application decisions – for example, when applicants compare several offers at the same time under time pressure, resort to external advisors (e.g., Kununu, friends, social media), or simultaneously view and evaluate additional information on career pages and job portals. Another methodological limitation concerns the reliability of the innovativeness scale in Project A, which showed a relatively low Cronbach's alpha (α = .61). This suggests that findings related to this dimension should be interpreted with some caution, as measurement reliability may be limited.

Project B is based on observed data and does not allow causal conclusions to be drawn. Although many confounding variables were controlled for, it remains unclear whether time-to-hire is actually attributable to applicant decisions or is influenced by internal company processes. In addition, although the semantic consistency metric used reflects content consistency between text modules, it does not capture formal or visual aspects of communication that may also be relevant.

Moreover, consistency was operationalized based on semantic similarity using sentence embeddings. While this offers a scalable and objective measure, it may not capture subtler forms of consistency such as tone, brand voice, or narrative coherence. Future work could explore multimodal consistency metrics that integrate textual, visual, and structural alignment across communication formats.

Another limitation is the assumption that higher consistency is inherently desirable. As the results suggest, the relationship between consistency and perception is not strictly linear: overly consistent communication may lead to perceived inauthenticity or message fatigue. For example, our data show that high consistency does not always lead to improved perceptions, and that a strong pre-image can even amplify negative reactions to inconsistency. This nonlinear effect warrants further investigation, both conceptually and in terms of measurement. Follow-up studies could test for potential *tipping points* or threshold effects using non-parametric or nonlinear modeling approaches.

In addition, the sample is skewed toward younger individuals under the age of 35 and predominantly consists of business students. While this reflects a key demographic within early-career applicant pools, it limits the generalizability of the findings to more experienced professionals or individuals from other academic or vocational backgrounds. Future research should examine whether the observed effects hold across more diverse age groups and fields of study.

Future research should investigate the cross-channel impact of consistent communication, e.g., how job ad texts interact with content on career pages or social media. The development of valid measurement tools for the automated evaluation of consistency in multimodal communication would also be a valuable step forward. Furthermore, experimental field studies could help to understand how consistency works under real selection conditions – for example, through A/B testing of ad variants with a view to application submissions, quality, and conversion rates.

4 General Conclusion

This dissertation examined employer communication as a strategic lever of employer branding and recruiting outcomes across channels and methods. Against the backdrop of intensifying competition for talent, the work brought together large-scale, AI-based text analytics with controlled experimentation to understand when and how consistent messaging shapes perceptions and behavior in the labor market.

Essay 1 – *Omni-Channel-Recruiting: A Descriptive Study on the Role of Message Consistency and Cultural Dimensions* mapped the omni-channel-landscape. Using Transformer-based measures, it quantified message consistency and cultural signaling across corporate websites, career pages, and social platforms for 118 companies in five industries, contrasting firms named in the 2023 Forbes Top 100 Employers with closely matched peers. The analysis revealed substantial within- and cross-channel inconsistencies, with systematic variation by industry and platform. Sectors under tight skill pressure (e.g., IT, automotive) displayed higher internal alignment, providing evidence that consistency is used deliberately to build trust, reduce uncertainty, and strengthen the employer brand. The results further suggest that consistency is most effective when it aligns the expression of culturally salient values, such as innovation or community, with audience expectations on each platform. In short, Essay 1 established both the prevalence of inconsistency and the strategic value of targeted, culturally coherent communication at scale.

Essay 2 – *Strategic Power of Message Consistency: A Mixed-Methods Study on Employer Branding and Recruitment Success* turned from mapping to consequences. Combining an online experiment (N = 510) with a dataset of more than 1 million job ads, it showed that message consistency improves symbolic employer brand dimensions (especially sincerity and competence), raises perceived organizational attractiveness, and predicts shorter time-to-hire, even after accounting for job characteristics and seniority. The effects are nuanced: for innovativeness, prestige, and competence, the relationship is non-linear, such that very low and very high consistency can depress evaluations. Brand context matters as well: inconsistent messaging harms already well-regarded employers disproportionately, while consistent messaging helps weaker brands reposition. These results recast consistency from a hygiene factor into a context-dependent, strategic tool whose payoffs hinge on calibration rather than maximization.

Together, the essays advance theory and practice in three ways. Conceptually, they frame semantic consistency as a market signal with both linear and non-linear effects, embedded in brand strength and audience context. Methodologically, they introduce scalable Transformer pipelines to quantify consistency and cultural content across channels and link those measures to perceptual and behavioral outcomes. Managerially, the findings translate into three key recommendations for practice: (1) establish a consistent omni-channel-messaging baseline by aligning core employer messages across all relevant platforms to ensure recognizability, reduce uncertainty, and strengthen brand credibility, (2) tune the intensity of consistency to the existing brand strength, avoiding over-promising or brand fatigue for strong brands, while leveraging high consistency as a repositioning tool for weaker brands, and (3) weigh implementation costs, including stakeholder alignment, editorial governance, and semantic quality control, against the measurable gains in attractiveness and recruitment efficiency.

Like all research, this work has boundaries. The consistency metrics, while validated at scale, are text-based and may under-capture visual or experiential cues; platform and industry scope may limit generalizability; and the observed non-linearities call for finer-grained theory on when *variety within consistency* outperforms strict uniformity. Future research could model the dynamics of consistency over time, explore personalized consistency across segments, integrate visual and multimodal signals, and optimize editorial governance as a closed-loop system.

In sum, this dissertation demonstrates that both what employers communicate and how consistently they do so across channels have a measurable impact on their perception and on hiring speed. Consistency proves most effective when it is deliberate, culturally grounded, and balanced with authenticity and adaptability. Under these conditions, consistency evolves from a mere communication principle into a strategic asset for employer branding and recruitment.

References

Jennifer L. Aaker. Dimensions of brand personality. *Journal of Marketing Research*, 34(3):347–356, 1997.

Shibbir Ahmed, Mahamudul Hasan, Md. Nazmul Hoq, and Muhammad Abdullah Adnan. User interaction analysis to recommend suitable jobs in career-oriented social networking sites. In *Proceedings of the IEEE International Conference on Informatics, Electronics and Vision (ICIEV)*, pages 674–679, 2016.

David G. Allen, James R. Van Scotter, and Rodrigo F. Otondo. Recruitment communication media: Impact on prehire outcomes. *Personnel Psychology*, 57(1):143–171, 2004.

Tim Ambler and Simon Barrow. The employer brand. *Journal of Brand Management*, 4(3):185–206, 1996.

Kristina Backhaus and Surinder Tikoo. Conceptualizing and researching employer branding. *Career Development International*, 9(5):501–517, 2004.

Maria C. Barbaros. Does employer branding beat head hunting? the potential of company culture to increase employer attractiveness. *Journal of Entrepreneurship, Management and Innovation*, 16(4):87–112, 2020.

Rajeev Batra and Kevin L. Keller. Integrating marketing communications: New findings, new lessons, and new ideas. *Journal of Marketing*, 80(6):122–145, 2016.

Talya N. Bauer and Berrin Erdogan. The role of technology in organizational communication. *Journal of Applied Psychology*, 96(2):221–231, 2011.

Robert A. Bell and John A. Daly. The affinity-seeking function of communication. *Communication Monographs*, 51:91–115, 1984.

Charles R. Berger and Richard J. Calabrese. Some explorations in initial interaction and beyond: Toward a developmental theory of interpersonal communication. *Human Communication Research*, 1(2):99–112, 1975.

Tammo Bijmolt, Manda Broekhuis, Sander de Leeuw, Christian Hirche, Robert P. Rooderkerk, Rui Sousa, and Stuart X. Zhu. Challenges at the marketing–operations interface in omni-channel retail environments. *Journal of Business Research*, 109:101–116, 2019.

Bundesagentur für Arbeit. Prognose des arbeitskräfteangebots bis 2035. https://www.arbeitsagentur.de, 2023. Accessed: 2025-08-05.

Daniel M. Cable and Daniel B. Turban. Establishing the dimensions, sources and value of job seekers' employer knowledge during recruitment. *Research in Personnel and Human Resources Management*, 20:115–163, 2001.

Marieke Carpentier, Greet Van Hoye, and Bert Weijters. Attracting applicants through the organization's social media page: Signaling employer brand personality. *Journal of Vocational Behavior*, 2019.

José A. Castañeda-García, Salvador Del Barrio-García, and Miguel A. Rodríguez-Molina. The effect of message consistency and destination-positioning brand strategy type on consumer-based destination brand equity. *Journal of Travel Research*, 59(5):947–965, 2020.

Diane Catanzaro, Heather L. Moore, and Timothy R. Marshall. The impact of organizational culture on attraction and recruitment of job applicants. *Journal of Business and Psychology*, 25(4):649–662, 2010.

Anthony Celani and Parbudyal Singh. Signaling theory and applicant attraction outcomes. *Personnel Review*, 40(2):222–238, 2011.

Yuhmiin Chang. Perceived message consistency: Explicating how brand messages being processed across multiple online media. *Computers in Human Behavior*, 85:125–134, 2018.

Janis Cloos. Employer review platforms – do the rating environment and platform design affect the informativeness of reviews? *Management Revue*, 2021.

Catherine A. Cole, Gilles Laurent, and Aimee Drolet. Affect as a decision-making system of the present in consumers: The role of affect in time-based decisions. *Journal of Consumer Research*, 34(5):618–633, 2008.

James S. Coleman. *Foundations of Social Theory*. Harvard University Press, Cambridge, MA, 1990.

Alexander Coppock. Avoiding post-treatment bias in audit experiments. *Journal of Experimental Political Science*, 6:1–4, 2019.

Richard L. Daft and Robert H. Lengel. Organizational information requirements, media richness and structural design. *Management Science*, 32(5):554–571, 1986.

M. Deepa and Rupashree Baral. Is my employee still attracted to me? understanding the role of employer branding attributes and employee experience in nurturing employer attractiveness in indian organizations. *Journal of Brand Management*, 27(1):110–130, 2021.

Institut der deutschen Wirtschaft. Engpassanalyse 2024. https://www.iwkoeln.de/studien/iw-reports/beitrag/engpassberufe.html, 2024. Accessed: 2025-08-05.

Morton Deutsch. Trust and suspicion. *Journal of Conflict Resolution*, 2(4):265–279, 1958.

Jacob Devlin, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova. Bert: Pre-training of deep bidirectional transformers for language understanding. In *Proceedings of the 2019 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies (NAACL-HLT)*, pages 4171–4186, Minneapolis, MN, 2019. Association for Computational Linguistics.

Ramkrishna Dikkatwar and Tanmoy De. Study of mission statement as an antecedent to financial performance of digital firms. *ABAC Journal*, 30(1):45–60, 2023.

Peter Dorfman, Mansour Javidan, Paul Hanges, Ali Dastmalchian, and Robert J. House. Globe: A twenty year journey into the intriguing world of culture and leadership. *Journal of World Business*, 47:504–518, 2012.

Robert M. Entman. Framing: Toward clarification of a fractured paradigm. *Journal of Communication*, 43(4):51–58, 1993.

European Commission. Job vacancy statistics – quarterly data. https://ec.europa.eu/eurostat/statistics-explained/index.php?title=Job_vacancy_statistics, 2024. Accessed: 2025-08-05.

Daniel C. Feldman, William O. Bearden, and David M. Hardesty. Varying the content of job advertisements: The effects of message specificity. *Journal of Advertising*, 35(1):123–141, 2006.

Leon Festinger. *A Theory of Cognitive Dissonance*. Stanford University Press, 1957.

Susan T. Fiske and Shelley E. Taylor. *Social Cognition*. McGraw-Hill, New York, 2nd edition, 1991.

R. Edward Freeman. *Strategic Management: A Stakeholder Approach*. Pitman, Boston, MA, 1984.

Lukas Galke, Ansgar Scherp, Andor Diera, Fabian Karl, Bao Xin Lin, Bhakti Khera, Tim Meuser, and Tushar Singhal. Are we really making much progress in text classification? a comparative review. *arXiv preprint arXiv:2204.03954*, 2025.

Luigi Guiso, Paola Sapienza, and Luigi Zingales. The value of corporate culture. *Journal of Financial Economics*, 117(1):60–76, 2015.

Avi Gupta, Thor S. Stead, and Lantha Ganti. Determining a meaningful r-squared value in clinical medicine. *Academic Medicine & Surgery*, 2024.

Kujtim Hameli. Foundations of organizational culture: A comprehensive review. *Journal of Balkan Economies and Management*, 1(1):53–66, 2024.

Dorothée Hanin, Florence Stinglhamber, and Nathalie Delobbe. The influence of the characteristics of employer branding-messages on employees' attitudes: The mediating role of organizational identification. *Unpublished manuscript*, 2011. Presented at the 16th European Congress of Work and Organizational Psychology, Maastricht.

T. Harmon-Kizer. The effects of schema congruity on consumer response to celebrity advertising. *Journal of Marketing Communications*, 23(3):242–256, 2017.

Fritz Heider. Attitudes and cognitive organization. *The Journal of Psychology*, 21(1):107–112, 1946.

Scott Highhouse, Filip Lievens, and Evan F. Sinar. Measuring attraction to organizations. *Educational and Psychological Measurement*, 63(6):986–1001, 2003.

Geert Hofstede. Dimensionalizing cultures: The hofstede model in context. *International Journal of Behavioral Medicine*, 2011.

Suellen J. Hogan and Leonard Coote. Organizational culture, innovation, and performance: A test of schein's model. *Journal of Business Research*, 67:1609–1621, 2014.

Alexander Hoppe. Linking employer branding and internal branding: establishing perceived employer brand image as an antecedent of favourable employee brand attitudes and behaviours. *Journal of Product & Brand Management*, 27(5):475–486, 2018.

Robert J. House, Mansour Javidan, Paul Hanges, and Peter Dorfman. Understanding cultures and implicit leadership theories across the globe: An introduction to project globe. *Journal of World Business*, 37:3–10, 2002.

Carl I. Hovland, Irving L. Janis, and Harold H. Kelley. *Communication and Persuasion: Psychological Studies of Opinion Change*. Yale University Press, 1953.

Ali S. Imran, Henrik Hodnefjeld, Zenun Kastrati, Noureen Fatima, Sher M. Daudpota, and Mudasir A. Wani. Classifying european court of human rights cases using transformer-based techniques. *IEEE Access*, 11:55664–55676, 2023.

Raimondo Ingrassia. Appearance or reality? monitoring of employer branding in public network space: the glassdoor case. *Impresa Progetto - Electronic Journal of Management*, 2:1–14, 2017.

P. K. Kannan and Hongshuang (Alice) Li. Digital marketing: A framework, review and research agenda. *International Journal of Research in Marketing*, 34(1):22–45, 2017.

Kevin L. Keller. Conceptualizing, measuring, and managing customer-based brand equity. *Journal of Marketing*, 57(1):1–22, 1993.

Kristia Kristia. Connecting with future talent: A review of employer value propositions and digital media channels for sustainable companies targeting generations y and z. *Journal of Theoretical and Applied Management*, 16(2):294–310, 2023.

Amy L. Kristof-Brown, Ryan D. Zimmerman, and Erin C. Johnson. Consequences of individuals' fit at work: A meta-analysis of person-job, person-organization, person-group, and person-supervisor fit. *Personnel Psychology*, 58(2):281–342, 2005.

Angie Lee and Te-Lin D. Chung. Transparency in corporate social responsibility communication on social media. *International Journal of Retail & Distribution Management*, 2023.

Jos Lemmink, Annelien Schuijf, and Sandra Streukens. The role of corporate image and company employment image in explaining application intentions. *Journal of Economic Psychology*, 24(1):1–15, 2003.

Filip Lievens. Employer branding in the belgian army: The importance of instrumental and symbolic beliefs for potential applicants, actual applicants, and military employees. *Human Resource Management*, 46(1):51–69, 2007.

Filip Lievens and Scott Highhouse. The relation of instrumental and symbolic attributes to a company's attractiveness as an employer. *Personnel Psychology*, 56(1):75–102, 2003.

Filip Lievens and Jerel E. Slaughter. Employer image and employer branding: What we know and what we need to know. *Annual Review of Organizational Psychology and Organizational Behavior*, 3:407–440, 2016.

Filip Lievens, Greet Van Hoye, and Bert Schreurs. Examining the relationship between employer knowledge dimensions and organizational attractiveness: An application in a military context. *Journal of Occupational and Organizational Psychology*, 78(4):553–572, 2005.

Yinhan Liu, Myle Ott, Naman Goyal, Jingfei Du, Mandar Joshi, Danqi Chen, Omer Levy, Mike Lewis, Luke Zettlemoyer, and Veselin Stoyanov. Roberta: A robustly optimized bert pretraining approach. *arXiv preprint arXiv:1907.11692*, 2019.

Ning Luo, Yilu Zhou, and John J. Shon. Employee satisfaction and corporate performance: Mining employee reviews on glassdoor.com. *Journal of the European Economic Association*, 14(6):1358–1390, 2016.

ManpowerGroup. Talent shortage 2022: 75% of employers report hiring difficulties, 2022. Accessed: 2025-08-13.

Joan Meyers-Levy and Barbara Loken. Considering the role of gender in consumer behavior and communication. *Journal of Consumer Research*, 22(2):219–251, 1995.

Jeremy Miles. R-squared, adjusted r-squared. In *Encyclopedia of Statistics in Behavioral Science*. John Wiley & Sons, Ltd, 2005.

Patti Miles and John N. Angelis. Untangling innovation: An examination of compensation, corporate social responsibility, and corporate financial performance. *Social Responsibility Journal*, 17(3):361–378, 2021.

Louise Moroko and Mark Uncles. Characteristics of successful employer brands. *Journal of Brand Management*, 16(3):160–175, 2008.

Richard Mosley. Customer experience, organisational culture and the employer brand. *Journal of Brand Management*, 15(2):123–134, 2007.

María A Navarro-Bailón, Elena Delgado Ballester, and María Sicilia Piñero. Strategic consistent messages in cross-tool campaigns: Effects on brand image and brand attitude. *Journal of Marketing Communications*, 18(3):189–202, 2011.

Andrzej Nowak, Mikolaj Biesaga, Karolina Ziembowicz, Tomasz Baran, and Piotr Winkielman. Subjective consistency increases trust. *Scientific Reports*, 13, 2023.

Ning Qin. Research on the classification method of ctc alignment joint-test problems based on roberta-wwm and deep learning integration. *IEEE Access*, 11:139395–139408, 2023.

Benjamin Schneider. The people make the place: A framework for understanding the etiology of organizational behavior. *Personnel Psychology*, 40(3):437–453, 1987.

Maja Šerić, Durdana Ozretić-Došen, and Vatroslav Skare. How can perceived consistency in marketing communications influence customer–brand relationship outcomes? *European Management Journal*, 38(2):335–343, 2020.

Chris Skaggs. Going inbound for talent acquisition. https://www.glassdoor.com/blog/going-inbound-talent-acquisition/, April 2018. Accessed: 2025-08-13.

Jerel E. Slaughter, Michael J. Zickar, Scott Highhouse, and David C. Mohr. Personality traits in applicant pools: Effects on self-selection and hiring decisions. *Journal of Business and Psychology*, 18(3):347–367, 2004.

Michael Spence. Job market signaling. *The Quarterly Journal of Economics*, 87(3):355–374, 1973.

Sara Stockman, Greet Van Hoye, and Serge da Motta Veiga. Negative word-of-mouth and applicant attraction: The role of employer brand equity. *Journal of Vocational Behavior*, 118:103368, 2019.

Henri Tajfel and John C. Turner. An integrative theory of intergroup conflict. In William G. Austin and Stephen Worchel, editors, *The Social Psychology of Intergroup Relations*, pages 33–47. Brooks-Cole, 1979.

The Conference Board. Responding to u.s. labor shortages. https://www.conference-board.org/research/solutions-briefs/responding-to-us-labor-shortages, 2024. Accessed: 2025-08-05.

Christian Theurer, Uta Tumasjan, Isabell Welpe, and Filip Lievens. Employer branding: A brand equity-based literature review and research agenda. *International Journal of Management Reviews*, 20(1):155–179, 2018.

I-Chang Tsai, Hsin-Jung Wu, Chao-Hung Liao, and Chung-Han Yeh. An innovative hybrid model for developing cross domain ict talent in digital economy. In *2018 IEEE International Conference on Teaching, Assessment, and Learning for Engineering (TALE)*, pages 745–750, 2018.

US Bureau of Labor Statistics. Table 1. job openings levels and rates by industry and region, seasonally adjusted. https://www.bls.gov/news.release/jolts.t01.htm, 2024. Accessed: 16 June 2024.

Greet Van Hoye, Theo A. J. Bas, and Stijn Cromheecke. The image of a prospective employer: A study of the mechanisms underlying the formation of expectations during recruitment. *Applied Psychology: An International Review*, 62(2):259–285, 2013.

Peter C. Verhoef, P. K. Kannan, and J. Jeffrey Inman. From multi-channel retailing to omni-channel customer experience. *Journal of Retailing*, 91(2):174–181, 2015.

Lisa Völker. Employer branding in the millennial generation: The role of online-recruitment channels and workplace communication cultures for millennial applicant attraction, 2018.

Bo Wang and C.-C. Jay Kuo. Sbert-wk: A sentence embedding method by dissecting bert-based word models. *IEEE/ACM Transactions on Audio, Speech, and Language Processing*, 28:2146–2157, 2020.

Jonathan Westover. Understanding organizational culture through schein's model. *Human Capital Leadership Review*, 2024.

Ralf Wilden, Sven Gudergan, and Ian Lings. Employer branding: strategic implications for staff recruitment. *Journal of Marketing Management*, 26(1-2):56–73, 2010.

Xun Xu, Tianyu Wang, Yi Yang, Lei Zuo, Fan Shen, and Heng Tao Shen. Cross-modal attention with semantic consistence for image–text matching. *IEEE Transactions on Neural Networks and Learning Systems*, 31(12):5412–5425, 2020.

Shouling Yu, Jialin Su, and Dongxiao Luo. Improving bert-based text classification with auxiliary sentence and domain knowledge. *IEEE Access*, 7:176600–176612, 2019.

H. Zhang and Y. Zhu. A study on the influence of employer branding attributes congruence on employee creativity. In *Academy of Management Proceedings*, 2023.

Appendix A – Related to the First Essay

A-1: Overview of Companies in the Dataset

Company	Top 100	Continent	Business model	Founding year	Industry	Revenue (in M USD)	Employees
Allstate	no	North America	B2C	before 1950	Financial Services & Insurance	57000.0	53400
Accenture	no	North America	B2B	1950-1974	Information Technology	64112.0	733000
Ace Hardware	yes	North America	B2C	before 1950	Retail & Wholesale	9170.0	12500
ADEO	yes	Europe	B2C	before 1950	Retail & Wholesale	25600.0	124000
Adobe	yes	North America	B2B & B2C	1975-1999	Information Technology	15785.0	25988
AIRBUS	yes	Europe	B2B	1950-1974	Aerospace & Defense	65450.0	147893
Alibaba	no	Asia	B2B & B2C	1975-1999	Information Technology	130350.0	204891
Alphabet	yes	North America	B2B & B2C	1975-1999	Information Technology	307400.0	180895
Amazon	yes	North America	B2B & B2C	1975-1999	Information Technology	574800.0	1525000
AMD	no	North America	B2C	1950-1974	Information Technology	93900.0	41802
Apple	yes	North America	B2C	1975-1999	Information Technology	383290.0	161000
Audi	no	Europe	B2C	1950-1974	Automotive	55680.0	90783
Autodesk	no	North America	B2B	1975-1999	Information Technology	5500.0	14100
AXA	no	Europe	B2C	before 1950	Financial Services & Insurance	83627.0	113696
BAE Systems	no	Europe	B2B	1975-1999	Aerospace & Defense	23078.0	93000
Bain Capital Private Equity	yes	North America	B2B	1975-1999	Financial Services & Insurance	180000.0	1200
Bank Millennium	yes	Europe	B2C	1975-1999	Financial Services & Insurance	1470.0	8153
BDO Unibank	no	Asia	B2C	1950-1974	Financial Services & Insurance	14000.0	115661
Bipa	no	Europe	B2C	1975-1999	Retail & Wholesale	828.5	4400
Blackstone	no	North America	B2B	1975-1999	Financial Services & Insurance	8020.0	4735
BMW Group	yes	Europe	B2C	before 1950	Automotive	142610.0	149475
Boeing	yes	North America	B2B	before 1950	Aerospace & Defense	77790.0	170688
Bosch	yes	Europe	B2B	before 1950	Automotive	91590.0	429416
Bridgestone	no	Asia	B2B	before 1950	Automotive	37450.0	129262
Cisco	yes	North America	B2B	1975-1999	Information Technology	56990.0	84900
Continental	no	Europe	B2B & B2C	before 1950	Automotive	41420.0	202763
Costco	yes	North America	B2B	1975-1999	Retail & Wholesale	242300.0	316000
Covea	yes	Europe	B2C	after 2000	Financial Services & Insurance	113.0	23000
Damen	no	Europe	B2C	before 1950	Aerospace & Defense	2500.0	12500
Dassault Group	yes	Europe	B2B	before 1950	Aerospace & Defense	41100.0	23400
DBS Bank	yes	Asia	B2B	1950-1974	Financial Services & Insurance	16500.0	36000
Decathlon	yes	Europe	B2C	1975-1999	Retail & Wholesale	15400.0	105000
Dell	yes	North America	B2C	1975-1999	Information Technology	101600.0	120000
Dick's Sporting Goods	no	North America	B2C	before 1950	Retail & Wholesale	12980.0	55500
Disney	no	North America	B2C	before 1950	Information Technology	88898.0	225000
DM Drogerie Market	yes	Europe	B2C	1950-1974	Retail & Wholesale	15900.0	79745
DXC	no	North America	B2C	after 2000	Information Technology	13700.0	130000
eBay	yes	North America	B2C	1975-1999	Information Technology	10110.0	12300
Embraer	no	South America	B2B	1950-1974	Aerospace & Defense	5270.0	18997
Erste Group Bank	yes	Europe	B2B	before 1950	Financial Services & Insurance	2690.0	45485
Ferrari	yes	Europe	B2C	before 1950	Automotive	5790.0	4988
Fidelity Investments	yes	North America	B2C	1950-1974	Financial Services & Insurance	28200.0	74000
Ford Motor	yes	North America	B2C	before 1950	Automotive	176200.0	177000
Fujitsu	no	Asia	B2C	before 1950	Information Technology	22322.31	124000
General Dynamics	yes	North America	B2B	before 1950	Aerospace & Defense	42300.0	111600
General Motors	no	North America	B2C	before 1950	Automotive	171800.0	163000
Groupama AM	no	Europe	B2C	1950-1974	Financial Services & Insurance	15000.0	31600
H&M	no	Europe	B2C	before 1950	Retail & Wholesale	24800.0	107375
Home Depot	yes	North America	B2C	1975-1999	Retail & Wholesale	152700.0	463100
Honda Motor	yes	Asia	B2C	before 1950	Automotive	93068.98	204035
HP	yes	North America	B2C	before 1950	Information Technology	53720.0	58000

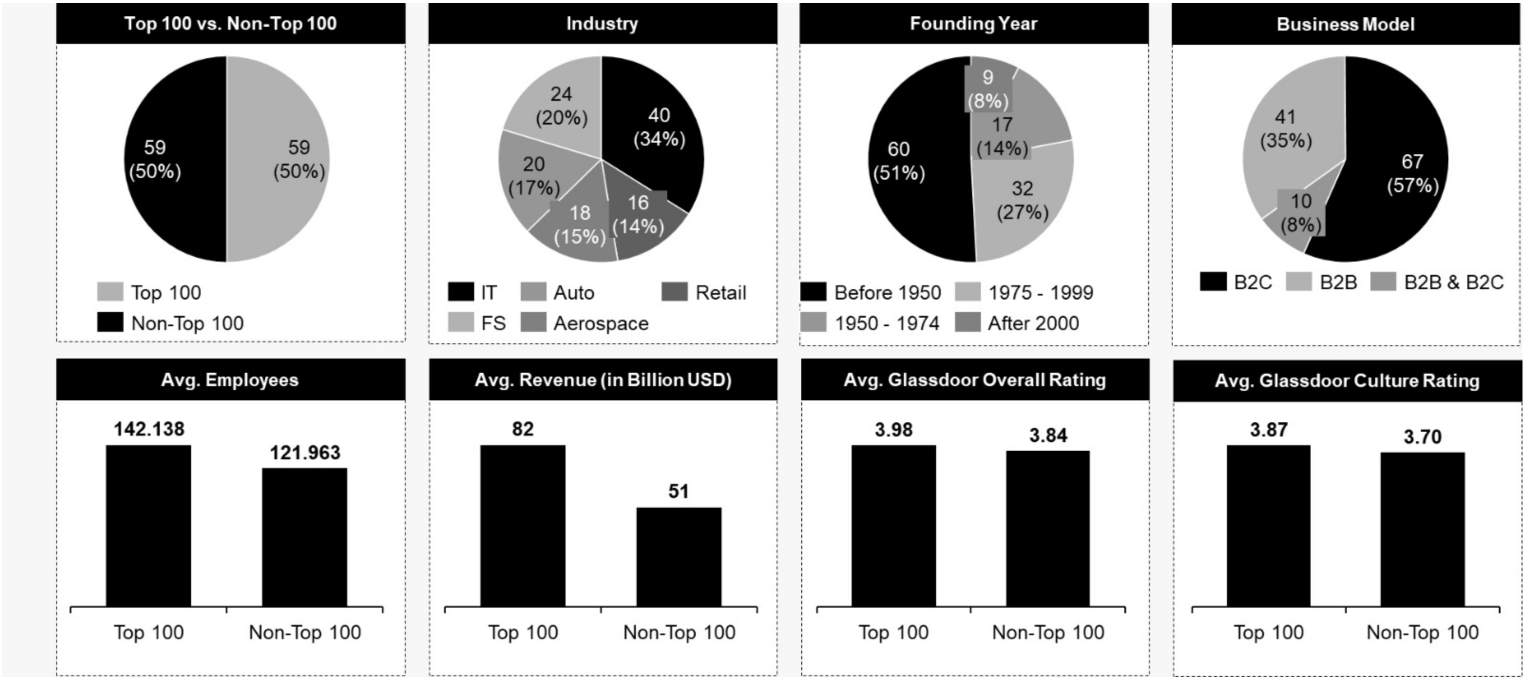
Continued on next page

Company	Top 100	Continent	Business model	Founding year	Industry	Revenue (in M USD)	Employees
Hubspot	no	North America	B2B	after 2000	Information Technology	2170.0	7663
Hyundai	no	Asia	B2C	before 1950	Automotive	84848.97	104731
IBM	yes	North America	B2B	before 1950	Information Technology	61860.0	282200
IKEA	yes	Europe	B2C	before 1950	Retail & Wholesale	44600.0	219000
Infineon	yes	Europe	B2B	1975-1999	Information Technology	16309.0	58600
Intel	yes	North America	B2B	1950-1974	Information Technology	54230.0	124800
Isuzu Motors	yes	Asia	B2C	before 1950	Automotive	23920.0	8056
Juniper Networks	no	North America	B2B	1975-1999	Information Technology	5560.0	11144
KB Financial Group	yes	Asia	B2C	after 2000	Financial Services & Insurance	17200.0	24462
L3Harris	no	North America	B2B	after 2000	Aerospace & Defense	19400.0	50000
Lamborghini	no	Europe	B2C	1950-1974	Automotive	2380.0	11779
Lenovo	no	Asia	B2C	1975-1999	Information Technology	61946.0	77000
Leonardo	no	Europe	B2B	before 1950	Aerospace & Defense	14700.0	50413
Leroy Merlin	no	Europe	B2C	before 1950	Retail & Wholesale	7850.0	164764
LG Electronics	no	Asia	B2C	1950-1974	Information Technology	60207.52	75000
Lockheed Martin	yes	North America	B2B	1975-1999	Aerospace & Defense	67600.0	122000
Lowe's	no	North America	B2C	before 1950	Retail & Wholesale	86380.0	284000
MAIF	yes	Europe	B2C	before 1950	Financial Services & Insurance	3700.0	6000
Mastercard	yes	Europe	B2C	1950-1974	Financial Services & Insurance	25100.0	33400
Mercedes Benz Group	yes	Europe	B2B & B2C	before 1950	Automotive	153200.0	166065
Meta	yes	North America	B2C	after 2000	Information Technology	134900.0	69329
Michelin Group	yes	Europe	B2C	before 1950	Automotive	28590.0	132000
Microsoft	yes	North America	B2B & B2C	1975-1999	Information Technology	211900.0	221000
Mitsubishi Motors	no	Asia	B2C	before 1950	Automotive	17346.68	42625
MTU	no	Europe	B2B	before 1950	Aerospace & Defense	4628.0	10660
Müller	no	Europe	B2C	1950-1974	Retail & Wholesale	4010.0	35000
Naval Group	yes	Europe	B2C	before 1950	Aerospace & Defense	4007.0	14182
Netflix	yes	North America	B2C	1975-1999	Information Technology	33700.0	13000
Nissan	no	Asia	B2C	before 1950	Automotive	3510.0	131461
Northrop Grumman	yes	North America	B2B	before 1950	Aerospace & Defense	39300.0	101000
OCBC	no	Asia	B2C	before 1950	Financial Services & Insurance	13500.0	33000
Oracle	yes	North America	B2B	1975-1999	Information Technology	52960.0	159000
Panasonic	yes	Asia	B2B & B2C	before 1950	Information Technology	45959.57	233391
PayPal	yes	North America	B2C	1975-1999	Financial Services & Insurance	29770.0	27200
Progressive	yes	North America	B2C	before 1950	Financial Services & Insurance	49610.0	55100
Raiffeisen Bank International	no	Europe	B2B	before 1950	Financial Services & Insurance	2140.0	44980
Rakuten	no	Asia	B2C	1975-1999	Information Technology	513620.0	18364
Rolls-Royce Holdings	yes	Europe	B2B	before 1950	Aerospace & Defense	16486.0	50000
Rossmann	yes	Europe	B2C	before 1950	Retail & Wholesale	12150.0	56500
RTX	no	North America	B2B	before 1950	Aerospace & Defense	68920.0	185000
Safran	yes	Europe	B2B	before 1950	Aerospace & Defense	23200.0	92000
Salesforce	yes	North America	B2B	1975-1999	Information Technology	34860.0	72682
Samsung	yes	Asia	B2B & B2C	before 1950	Information Technology	198247.0	270372
Santander Bank	no	Europe	B2C	before 1950	Financial Services & Insurance	43000.0	3401
SAP	no	Europe	B2B	1975-1999	Information Technology	31207.0	106043
Scania	no	Europe	B2C	before 1950	Automotive	16011.39	56927
Security Bank	yes	Asia	B2C	1950-1973	Financial Services & Insurance	735.84	7108
Sharp Electronics	no	Asia	B2B	before 1950	Information Technology	14121.57	46206
Shinhan	no	Asia	B2C	before 1950	Financial Services & Insurance	26691.0	13400
Shopify	yes	North America	B2B	after 2000	Information Technology	7060.0	8300
Sony	yes	Asia	B2C	before 1950	Information Technology	88970.0	113000
Square	no	North America	B2C	1975-1999	Financial Services & Insurance	5960.0	7100
STMicro-electronics	no	Europe	B2B	before 1950	Information Technology	17240.0	51323
Tencent	no	Asia	B2B & B2C	1975-1999	Information Technology	77990.0	112771
Textron	no	North America	B2B	before 1950	Aerospace & Defense	13700.0	35000
Thales Group	no	Europe	B2B	before 1950	Aerospace & Defense	18430.0	81060

Continued on next page

Company	Top 100	Continent	Business model	Founding year	Industry	Revenue (in M USD)	Employees
Toshiba	no	Asia	B2B	before 1950	Information Technology	20740.05	116224
Toyota	no	Asia	B2C	before 1950	Automotive	11070.0	375235
True Value	no	North America	B2C	before 1950	Retail & Wholesale	1488.0	2500
Vanguard	no	North America	B2C	1975-1999	Financial Services & Insurance	6930.0	18800
Visa	no	North America	B2C	1950-1974	Financial Services & Insurance	32700.0	28800
Volkswagen Group	yes	Europe	B2C	before 1950	Automotive	322284.0	667647
Volvo Group	yes	Europe	B2B	before 1950	Automotive	131180.0	104000
Walmart	no	North America	B2C	before 1950	Retail & Wholesale	648120.0	2100000
Woo-Commerce	no	North America	B2B	after 2000	Information Technology	20000.0	434
X	no	North America	B2C	after 2000	Information Technology	5100.0	1000
Xiaomi	no	Asia	B2C	1975-1999	Information Technology	40700.0	32543

A-2: Detailed Data Description



A-3: Overview of Scraped Data

Channel	Number of Companies	Number of Entries	Period
Facebook	113	5,309	July 2013 – March 2024
Glassdoor General	118	118	Scraped March 2024
Glassdoor Review	118	5,696	June 2008 – March 2024
LinkedIn	109	5,141	October 2021 – March 2024
Website	113	3,152	Scraped March 2024
Total	–	**19,416**	**June 2008 – March 2024**

Note: Periods refer to the time span covered by the posts, reviews, or entries in each channel, not the scraping date. All datasets were collected via automated scraping in March 2024, followed by extensive quality checks to remove irrelevant or redundant entries. For Facebook, LinkedIn, and Glassdoor reviews, the most recent 50 entries per company were retrieved; for career websites and Glassdoor company descriptions, all available texts at the time of collection were captured. Only official company channels from the home country were considered, with separate career presences included where applicable.

A-4: Average Consistency Scores by Company

company	IS_F	IS_GR	IS_L	IS_W	ES_FGG	ES_FGR	ES_FL	ES_FW	ES_GGGR	ES_LGG	ES_LGR	ES_LW	ES_WGG	ES_WGR
Allstate	0.4323	0.3834	0.3393	0.5583	0.4216	0.2219	0.3616	0.3834	0.3608	0.3500	0.2049	0.3230	0.5350	0.3163
ACE Hardware	0.2515	0.3942	0.5343	0.7228	0.3085	0.0888	0.1176	0.2785	0.3197	0.2724	0.1735	0.2667	0.7528	0.2811
AMD	0.2819	0.4286	0.3217	0.7378	0.3426	0.0760	0.2451	0.2425	0.2514	0.4602	0.1555	0.3377	0.5515	0.2561
AXA	0.2430	0.3171	NaN	0.6181	0.2136	0.0981	NaN	0.2227	0.2246	NaN	NaN	NaN	0.4343	0.2683
Accenture	0.2656	0.4867	0.3202	0.6150	0.3896	0.1959	0.2765	0.3121	0.4214	0.4224	0.2151	0.3344	0.6730	0.3669
Adobe	0.3449	0.4007	0.3857	0.7965	0.3830	0.1258	0.3267	0.4001	0.2019	0.4031	0.2084	0.4974	0.6882	0.3420
Airbus	0.4840	0.4267	0.5200	0.6557	0.5930	0.2171	0.4891	0.4884	0.3326	0.6444	0.2131	0.5273	0.6736	0.2529
Alibaba	0.3726	0.3395	0.4191	NaN	NaN	0.1541	0.3911	0.4535	NaN	NaN	0.1601	0.4895	NaN	0.2435
Alphabet	0.3452	0.4626	0.3212	0.6919	0.4302	0.2294	0.3335	0.2381	0.4136	0.3900	0.2146	0.2081	0.3360	0.2255
Amazon	0.3008	0.4660	0.3120	0.6492	0.3034	0.2577	0.2396	0.3041	0.3413	0.3787	0.2195	0.3081	0.3308	0.2880
Apple	NaN	0.4918	NaN	0.4687	NaN	NaN	NaN	NaN	0.3504	NaN	NaN	NaN	0.5191	0.2809
Audi	0.5282	0.4416	0.4379	0.7664	0.4933	0.1206	0.4746	0.5240	0.1434	0.4534	0.1385	0.5027	0.6956	0.1949
Autodesk	0.3340	0.4705	0.3915	0.6988	0.4899	0.1712	0.3448	0.3976	0.2358	0.5179	0.2233	0.4799	0.6717	0.3204
BAE Systems	0.3275	0.4063	0.3386	0.4635	0.3473	0.1896	0.3336	0.3034	0.2543	0.3694	0.1972	0.3165	0.4612	0.2472
BDO Unibank	0.5193	0.4390	0.6185	0.6867	0.5317	0.1871	0.5316	0.4780	0.1882	0.5843	0.2400	0.5664	0.5546	0.3119
BIPA	0.2612	0.3301	0.3567	0.4301	NaN	0.0453	0.1966	0.1682	NaN	NaN	0.1468	0.3082	NaN	0.2552
BMW Group	0.4592	0.3837	0.4435	0.5369	0.3715	0.2348	0.3654	0.4208	0.1406	0.4230	0.1312	0.3444	0.4165	0.2654
Bain Capital Private Equity	0.3550	0.4793	0.3661	0.7969	0.2473	0.1999	0.2734	0.3041	0.1404	0.3921	0.1957	0.4586	0.6435	0.2469
Bank Millennium	0.2094	0.4763	0.3031	0.7079	0.2043	0.1099	0.2222	0.1951	0.2366	0.3178	0.1882	0.2870	0.5131	0.3706

Continued on next page

company	IS_F	IS_GR	IS_L	IS_W	ES_FGG	ES_FGR	ES_FL	ES_FW	ES_GGGR	ES_LGG	ES_LGR	ES_LW	ES_WGG	ES_WGR
Blackstone	0.4060	0.4452	0.3827	0.6707	0.4803	0.1702	0.3941	0.4150	0.1982	0.4411	0.1663	0.4018	0.6293	0.3304
Boeing	0.4466	0.4340	0.2729	0.6449	0.4328	0.2270	0.3227	0.4353	0.3203	0.2954	0.1455	0.3079	0.5111	0.3214
Bosch	0.3995	0.4491	0.4589	0.7612	0.5106	0.2053	0.4222	0.4993	0.2641	0.5336	0.2227	0.5523	0.7044	0.3222
Bridgestone	0.1946	0.3947	NaN	0.6951	0.1964	0.0894	NaN	0.2053	0.1628	NaN	NaN	NaN	0.6679	0.2971
Cisco	0.3675	0.4308	0.2716	0.9356	0.4367	0.1652	0.2786	0.4129	0.3655	0.4051	0.1749	0.3629	0.6737	0.3469
Continental	0.3453	0.4105	0.2936	0.5876	0.4164	0.1323	0.3033	0.3110	0.2438	0.4262	0.1701	0.3313	0.5458	0.3160
Costco	NaN	0.4695	0.6475	0.7872	NaN	NaN	NaN	NaN	0.2882	0.4111	0.3134	0.4701	0.5623	0.3345
Covea	0.2710	0.4343	0.3056	0.6351	NaN	0.1700	0.2904	0.3302	NaN	NaN	0.1970	0.3792	NaN	0.3101
DBS Bank	0.5436	0.3864	0.3074	0.5915	0.5705	0.3149	0.3348	0.5041	0.2660	0.4482	0.1787	0.3282	0.5706	0.3049
DM Drogerie Market	0.2334	0.4633	0.3560	0.4864	NaN	0.0697	0.1601	0.1310	NaN	NaN	0.2371	0.3653	NaN	0.3144
DXC	0.3921	0.3960	0.3805	0.6521	0.5356	0.2046	0.3663	0.4319	0.3546	0.4900	0.1730	0.4110	0.6728	0.2585
Damen	0.4788	0.3852	0.4425	0.8822	0.5201	0.1290	0.4644	0.4540	0.1704	0.4870	0.1235	0.4239	0.5639	0.3258
Dassault Group	0.4541	0.4844	0.3057	0.6875	0.3001	0.1453	0.2584	0.3445	0.1943	0.3661	0.1517	0.2160	0.3881	0.1806
Decathlon	0.2665	0.3797	NaN	NaN	0.1858	0.0596	0.2257	0.1562	0.1668	0.5985	0.0632	0.5498	0.7103	0.2857
Dell	0.4431	0.5148	0.3351	0.6271	0.5694	0.3165	0.3513	0.4394	0.4062	0.4229	0.2616	0.3690	0.5399	0.3894
Dick's Sporting Goods	0.1900	0.4430	0.3473	0.7238	0.1823	0.0674	0.2001	0.2289	0.1521	0.3742	0.1531	0.3838	0.6220	0.2217
Disney	0.3413	0.3655	0.3581	0.5032	0.3318	0.1668	0.3506	0.3685	0.1342	0.3389	0.1531	0.3755	0.4776	0.2449
Ebay	0.7165	0.3811	0.3599	0.5075	0.5056	0.2504	0.3571	0.4473	0.2013	0.4680	0.1557	0.3186	0.4481	0.2492
Embraer	0.5556	0.4044	0.5343	0.6472	0.4749	0.1603	0.5316	0.4354	0.1952	0.5089	0.1626	0.4501	0.6885	0.2710
Erste Group Bank	0.2061	0.3918	0.2843	0.6773	0.1355	0.1305	0.2007	0.2161	0.1457	0.2185	0.1849	0.3388	0.5667	0.2557
Ferrari	0.5655	0.3486	0.6159	0.7978	0.4912	0.1497	0.5646	0.5723	0.1671	0.5288	0.1635	0.5976	0.5923	0.2423

Continued on next page

company	IS_F	IS_GR	IS_L	IS_W	ES_FGG	ES_FGR	ES_FL	ES_FW	ES_GGGR	ES_LGG	ES_LGR	ES_LW	ES_WGG	ES_WGR
Fidelity Investments	0.3838	0.4491	0.1865	0.7517	0.3962	0.2430	0.1763	0.3520	0.3403	0.2685	0.1352	0.1759	0.4817	0.3008
Ford Motor	0.3867	0.4434	0.4615	0.5268	0.4728	0.2043	0.4170	0.3997	0.3245	0.5344	0.2522	0.4500	0.5286	0.2646
Fujitsu	0.3437	0.4106	0.3147	0.7050	0.3923	0.2010	0.3125	0.3731	0.3513	0.4053	0.2041	0.3716	0.6874	0.2994
General Dynamics	0.3797	0.4160	0.3707	0.4775	0.3971	0.1199	0.3708	0.3222	0.2336	0.5224	0.1263	0.3765	0.5556	0.2473
General Motors	0.2998	0.4699	0.3042	0.6100	0.4303	0.1898	0.2986	0.3415	0.3417	0.4498	0.1851	0.3303	0.6249	0.3692
Groupama AM	0.2185	0.4201	0.4799	0.8367	0.1836	0.0768	0.2319	0.1787	0.1337	0.4029	0.2536	0.4208	0.5891	0.2556
H&M	0.4609	0.4393	0.4246	0.5315	0.4639	0.1562	0.4360	0.3677	0.3829	0.4293	0.1270	0.3343	0.5365	0.2835
HP	0.5473	0.3882	0.2866	0.7742	0.5325	0.2864	0.3739	0.5946	0.3036	0.3911	0.1878	0.4219	0.6835	0.3343
Home Depot	0.3519	0.4524	0.3464	0.4979	0.2882	0.2133	0.3538	0.2860	0.2452	0.2881	0.2177	0.2930	0.2955	0.2668
Honda Motor	0.3562	0.3627	0.3640	0.5082	0.3676	0.0536	0.3349	0.2853	0.0679	0.4009	0.0953	0.3506	0.4716	0.1674
Hubspot	0.2888	0.4985	0.1570	0.7175	0.2357	0.2043	0.1388	0.2680	0.3284	0.0870	0.1204	0.1663	0.6136	0.3313
Hyundai	0.3787	0.4234	0.3901	0.6441	0.3847	0.1008	0.3301	0.3190	0.2522	0.4989	0.1587	0.4144	0.6414	0.2961
IBM	0.2538	0.4557	0.3493	0.7036	0.3955	0.1537	0.2726	0.3010	0.3901	0.4879	0.2275	0.4099	0.6947	0.3904
IKEA	0.2753	0.4547	0.3967	0.5653	0.3075	0.1067	0.2724	0.2787	0.2063	0.4541	0.2058	0.4236	0.5391	0.3107
Infineon	0.2731	0.4144	0.3476	0.5880	0.2613	0.1582	0.2993	0.2880	0.1419	0.3555	0.1946	0.3815	0.3841	0.2733
Intel	0.3127	0.4014	0.4017	0.6488	0.4351	0.1465	0.3370	0.3139	0.2618	0.5143	0.1947	0.4054	0.5494	0.3158
Isuzu Motors	0.3826	0.4221	0.6126	0.3943	0.4055	0.1000	0.3809	0.2464	0.2057	0.5019	0.1540	0.3342	0.5337	0.2995
Juniper Networks	0.4154	0.4423	0.3039	0.5169	0.4958	0.1453	0.3417	0.2757	0.3185	0.4717	0.1633	0.2930	0.5947	0.2825
L3Harris	0.2941	0.3860	0.3173	0.6568	0.3108	0.1115	0.3007	0.3293	0.2220	0.3284	0.1179	0.3403	0.6638	0.2729
LG Electronics	0.4261	0.3995	0.4042	0.5476	0.4133	0.1048	0.3355	0.3118	0.1164	0.3043	0.1527	0.2647	0.3646	0.2335

Continued on next page

company	IS_F	IS_GR	IS_L	IS_W	ES_FGG	ES_FGR	ES_FL	ES_FW	ES_GGGR	ES_LGG	ES_LGR	ES_LW	ES_WGG	ES_WGR
Lamborghini	0.4362	0.3549	0.5763	0.3835	0.4725	0.1275	0.4542	0.3796	0.1759	0.5962	0.1761	0.5195	0.6188	0.2708
Lenovo	0.4087	0.4127	NaN	0.6563	0.4968	0.2043	NaN	0.4348	0.2923	NaN	NaN	NaN	0.7213	0.3127
Leonardo	0.6369	0.4825	0.3983	0.6385	0.7184	0.1629	0.3919	0.5469	0.2357	0.4465	0.1845	0.4564	0.6334	0.2471
Leroy Merlin	0.2007	0.3485	0.2962	0.5176	0.0956	0.0578	0.1365	0.1359	0.1336	0.2224	0.1901	0.3333	0.3814	0.2982
Lockheed Martin	0.3023	0.4382	0.2973	0.6016	0.3453	0.1755	0.2715	0.3011	0.2449	0.3488	0.1458	0.3365	0.5027	0.2443
Lowe’s	0.3764	0.4961	0.3101	0.5972	0.3587	0.2311	0.3378	0.3187	0.2918	0.3204	0.2168	0.3088	0.4525	0.3091
MAIF	0.1449	0.2666	0.4074	0.7401	0.2499	0.1009	0.1962	0.2362	0.2143	0.4415	0.2201	0.5020	0.6254	0.2831
MTU	0.2692	0.4299	0.4687	0.6579	0.3085	0.1737	0.2858	0.3200	0.2491	0.3573	0.2018	0.3795	0.4614	0.3349
Mastercard	0.1913	0.4117	0.4162	0.6643	0.1425	0.1025	0.1905	0.1613	0.2224	0.3517	0.2367	0.4442	0.4622	0.2893
Mercedes Benz Group	0.6165	0.4198	0.3779	0.6277	0.4732	0.2799	0.3209	0.5296	0.1984	0.3873	0.0952	0.3909	0.6518	0.1946
Meta	0.2013	0.4411	0.2619	0.6160	0.2538	0.0987	0.1877	0.2088	0.2037	0.3145	0.2037	0.3016	0.3673	0.3164
Michelin Group	0.5195	0.4154	0.3909	0.7788	0.5200	0.2444	0.3795	0.5259	0.2082	0.5484	0.1403	0.4704	0.7130	0.2463
Microsoft	0.2685	0.4437	0.2092	0.5326	NaN	0.1647	0.1980	0.2772	NaN	NaN	0.1506	0.2240	NaN	0.3311
Mitsubishi Motors	0.4711	0.3765	0.4378	0.7522	0.3382	0.0891	0.3981	0.3356	0.1277	0.3544	0.1237	0.4004	0.6340	0.2017
Müller	0.2775	0.3872	0.3773	0.6708	NaN	0.0513	0.2500	0.1727	NaN	NaN	0.1334	0.3795	NaN	0.2654
Naval Group	0.3908	0.3553	0.4307	0.7812	0.4153	0.1527	0.4034	0.4561	0.2360	0.4184	0.1474	0.4427	0.5129	0.2959
Netflix	0.1384	0.4121	0.2826	0.4693	0.0882	0.0336	0.1434	0.1051	0.0732	0.3280	0.0827	0.2669	0.3130	0.2228
Nissan	0.3972	0.4344	0.3643	0.6680	0.3685	0.0605	0.3425	0.3902	0.3477	0.4618	0.1178	0.4576	0.6754	0.2299
Northrop Grumman	0.3312	0.3752	0.3563	0.7163	0.3329	0.1957	0.2628	0.3572	0.3349	0.3541	0.1504	0.3887	0.7143	0.3321
OCBC	0.4666	0.3900	0.3517	0.6207	0.3361	0.2603	0.3879	0.4763	0.2508	0.3807	0.2261	0.4259	0.5039	0.2912
Oracle	0.3947	0.4343	0.3232	0.7214	0.4250	0.2555	0.3039	0.4431	0.3036	0.3615	0.2044	0.3533	0.6297	0.3669
Panasonic	0.2543	0.3776	0.2760	0.5430	0.2822	0.1249	0.2508	0.3044	0.1623	0.2628	0.1480	0.3047	0.4501	0.2538

Continued on next page

company	IS_F	IS_GR	IS_L	IS_W	ES_FGG	ES_FGR	ES_FL	ES_FW	ES_GGGR	ES_LGG	ES_LGR	ES_LW	ES_WGG	ES_WGR
PayPal	0.5759	0.3776	0.3860	0.5380	0.6436	0.2197	0.4312	0.5439	0.3064	0.5106	0.1421	0.4101	0.6334	0.2393
RTX	0.2746	0.3931	0.3464	0.5972	0.3849	0.1033	0.2938	0.2693	0.1672	0.4296	0.1232	0.2901	0.3988	0.2845
Raiffeisen Bank International	0.3108	0.4153	0.3572	0.6272	0.3161	0.1133	0.2024	0.1607	0.3928	0.4907	0.2051	0.3866	0.6298	0.3126
Rakuten	0.1988	0.4388	0.2788	0.5070	0.0882	0.0592	0.1428	0.0888	0.2980	0.3853	0.1699	0.2943	0.5148	0.3057
Rolls-Royce Holdings	0.4215	0.4279	0.3597	0.5665	0.5234	0.1260	0.3871	0.3907	0.1971	0.4495	0.1123	0.3506	0.5427	0.2851
Rossmann	0.3385	0.3327	0.3655	0.6706	NaN	0.0771	0.2736	0.3003	NaN	NaN	0.1959	0.4420	NaN	0.2966
SAP	0.2651	0.3987	0.2867	NaN	NaN	0.2150	0.2776	NaN	NaN	NaN	0.2326	NaN	NaN	NaN
STMicro-electronics	0.2091	0.4253	0.2468	0.5671	0.2470	0.0796	0.2162	0.2413	0.1454	0.3238	0.1113	0.3058	0.4865	0.3065
Safran	0.2974	0.4020	0.3198	0.4476	0.3422	0.1057	0.2957	0.2981	0.1478	0.4074	0.1133	0.3262	0.5270	0.2102
Salesforce	0.2749	0.5271	0.3116	0.6434	0.2125	0.2243	0.2314	0.2819	0.3520	0.2317	0.1784	0.2547	0.3415	0.3133
Samsung	0.3533	0.4271	0.3832	0.8440	0.4518	0.1355	0.3041	0.3917	0.3192	0.5110	0.1990	0.4880	0.7227	0.4035
Santander Bank	0.2992	0.4026	0.4383	NaN	0.2909	0.1463	0.2958	NaN	0.1679	0.4257	0.1963	NaN	NaN	NaN
Scania	0.3988	0.4312	0.4647	0.6179	0.3778	0.0838	0.2838	0.3176	0.1468	0.4621	0.2149	0.4779	0.5556	0.2298
Security Bank	0.3116	0.4037	0.6784	0.6654	0.2770	0.2218	0.3575	0.3685	0.2280	0.4609	0.3085	0.5518	0.7148	0.3416
Sharp Electronics	0.2966	0.3683	0.3736	0.6233	0.3082	0.1479	0.2522	0.3141	0.1519	0.2749	0.1878	0.3615	0.6706	0.2411
Shinhan	0.5492	0.4302	NaN	0.6113	NaN	0.1976	NaN	0.3934	NaN	NaN	NaN	NaN	NaN	0.2675
Shopify	0.2870	0.5287	0.3610	0.5987	0.3028	0.1691	0.2786	0.2749	0.2663	0.4826	0.1966	0.3691	0.4836	0.3268
Sony	0.2724	0.4420	0.4763	0.6757	0.2961	0.0820	0.2694	0.2562	0.2795	0.4489	0.1890	0.4557	0.6146	0.3350
Square	NaN	0.3828	NaN	0.5175	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	0.3000
Tencent	0.3473	0.3892	0.4769	0.8310	0.4166	0.1786	0.3641	0.4177	0.2373	0.4906	0.2037	0.4948	0.7229	0.3104

Continued on next page

company	IS_F	IS_GR	IS_L	IS_W	ES_FGG	ES_FGR	ES_FL	ES_FW	ES_GGGR	ES_LGG	ES_LGR	ES_LW	ES_WGG	ES_WGR
Textron	0.3799	0.4174	0.3322	0.7122	0.2511	0.1568	0.2347	0.2404	0.1618	0.3537	0.1910	0.4236	0.5538	0.3485
Thales Group	0.3849	0.3790	0.4191	0.4712	0.4269	0.2101	0.3846	0.3704	0.2624	0.4763	0.2069	0.3781	0.5480	0.2911
Toshiba	0.4579	0.3615	0.3463	0.8771	0.2763	0.0875	0.2576	0.3890	0.1481	0.3623	0.1239	0.4423	0.5853	0.2276
Toyota	0.4827	0.3530	0.4105	0.5647	0.4306	0.1326	0.3238	0.2763	0.3842	0.4836	0.2097	0.3300	0.4559	0.2251
True Value	0.1773	0.4320	0.5098	NaN	0.2069	0.0662	0.2009	NaN	0.2934	0.5634	0.1996	NaN	NaN	NaN
Vanguard	0.2970	0.4269	0.3932	0.5866	0.2801	0.1262	0.2339	0.2802	0.2415	0.3859	0.2080	0.3865	0.4769	0.3204
Visa	0.1675	0.4691	0.3287	0.8699	0.0919	0.0630	0.0938	0.0809	0.2658	0.4819	0.1465	0.4100	0.7690	0.3406
Volkswagen Group	0.2566	0.4188	0.3869	0.5543	0.2545	0.0839	0.2510	0.2508	0.2016	0.3756	0.1183	0.3432	0.6027	0.2464
Volvo Group	0.4132	0.4358	0.3387	0.7059	0.4529	0.1833	0.3596	0.4410	0.1682	0.4106	0.1594	0.3886	0.4512	0.3218
Walmart	0.2158	0.4771	0.3310	0.5292	0.1509	0.0632	0.1732	0.1212	0.4155	0.4038	0.2236	0.3015	0.5015	0.3231
Woo-Commerce	0.2779	0.5082	0.2685	0.3611	NaN	0.1173	0.1547	0.1498	NaN	NaN	0.1948	0.2676	NaN	0.2505
X	NaN	0.3087	NaN	1.0000	NaN	NaN	NaN	NaN	0.2438	NaN	NaN	NaN	0.4748	0.2643
Xiaomi	0.4213	0.3881	NaN	0.0541	NaN	0.0908	NaN	0.2326	NaN	NaN	NaN	NaN	NaN	0.1352

A-5: Influence of Structural Company Characteristics on Consistency Scores

The table reports the results of two OLS-based regression models using Type II ANOVA to identify structural company characteristics associated with within-channel and across-channel consistency. Both models include the same set of categorical controls (industry, business model, founding year, continent) and continuous firm-level indicators (revenue and number of employees).

To reduce skewness and improve model fit, revenue and employees were log-transformed. This transformation also supports interpretation of coefficients in terms of relative changes.

The models are based on 118 complete observations, with 103 residual degrees of freedom each.

Predictor†	Within-Channel consistency			Across-Channel consistency		
	F	p	n	F	p	n
Industry	2.01	.099	118	3.30	.014*	118
Business model	0.01	.988	118	0.07	.937	118
Continent	0.58	.630	118	0.75	.523	118
Founding year	0.91	.438	118	0.41	.743	118
Revenue (log)	0.00	.949	118	0.47	.493	118
Employees (log)	0.17	.681	118	0.45	.506	118
Residual	—	—	103	—	—	103

Note. OLS-based ANOVA with Type II sum of squares. Significance levels: $p < .05$ (*), $p < .01$ (**), $p < .001$ (***). n indicates the number of valid observations for each predictor (not dummies).

† Categorical predictors: – Industry (5 categories: Aerospace and Defense, Automotive, Financial Services, Information Technology, Retail) – Business model (3 categories: B2B, B2C, both) – Continent (4 categories: Asia, Europe, North America, South America) – Founding year (4 categories: before 1950, 1950–1974, 1975–1999, after 2000)

Numerical predictors (log-transformed): – Revenue (annual company revenue) – Employees (number of employees)

A-6: Code for Measuring Message Consistency

Listing 1: Preparation and embedding calculation using SentenceTransformer

```
# Install and import dependencies
!pip install sentence-transformers
import pandas as pd, os, pickle
from tqdm.auto import tqdm
from sklearn.preprocessing import normalize
from sentence_transformers import SentenceTransformer

# Load SentenceTransformer (all-mpnet-base-v2 for final accuracy)
model = SentenceTransformer('all-mpnet-base-v2')

# Function: compute normalized sentence embedding
def get_embedding(text):
    embedding = model.encode(text, show_progress_bar=False)
    return normalize([embedding])[0]

# Load dataset (id, source, text, company info)
df = pd.read_excel("data.xlsx", usecols=["id","source","text","
   sample","compid","company"])

# Calculate embeddings if not cached
file_embeddings = "embeddings.pkl"
if os.path.exists(file_embeddings):
    with open(file_embeddings, 'rb') as f:
        df = pickle.load(f)
else:
    df['embedding'] = df['text'].astype(str).progress_apply(
   get_embedding)
    with open(file_embeddings, 'wb') as f:
        pickle.dump(df, f)
```

Listing 2: Batch calculation of cosine similarity matrix

```
from sklearn.metrics.pairwise import cosine_similarity
from scipy.sparse import lil_matrix, vstack, save_npz, load_npz

# Function: calculate sparse cosine similarity matrix in batches
def batch_cosine_similarity(embedding_matrix, batch_size=700):
    n = embedding_matrix.shape[0]
    sim_sparse = lil_matrix((n, n), dtype=np.float32)
    for start in tqdm(range(0, n, batch_size)):
        end = min(start + batch_size, n)
        batch_sim = cosine_similarity(embedding_matrix[start:end],
    embedding_matrix).astype(np.float32)
        for i in range(batch_sim.shape[0]):
            for j in range(batch_sim.shape[1]):
                if batch_sim[i, j] > 0:
                    sim_sparse[start + i, j] = batch_sim[i, j]
    return sim_sparse.tocsr()

file_sim_matrix = "simMatrix.npz"
if os.path.exists(file_sim_matrix):
    similarity_matrix_sparse = load_npz(file_sim_matrix)
else:
    emb_matrix = vstack(df['embedding'].values)
    similarity_matrix_sparse = batch_cosine_similarity(emb_matrix)
    save_npz(file_sim_matrix, similarity_matrix_sparse)
```

Listing 3: Extracting pairwise similarities and saving results

```
import pickle

results = []
calculated_pairs = set()
ids, sources, companies, compids = df.index.values, df['source'],
   df['company'], df['compid']

# Compare only texts from the same company
for i in tqdm(range(len(df))):
    for j in range(i+1, len(df)):
        if companies[i] != companies[j]: continue
        if (ids[i], ids[j]) in calculated_pairs: continue
        sim_score = similarity_matrix_sparse[i, j]
        results.append({
            'company': companies[i],
            'id1': ids[i], 'id2': ids[j],
            'source1': sources[i], 'source2': sources[j],
            'companyid1': compids[i], 'companyid2': compids[j],
            'similarity': sim_score
        })
        calculated_pairs.add((ids[i], ids[j]))

# Save results
file_results = "final_results.pkl"
with open(file_results, 'wb') as f: pickle.dump(results, f)

# Export in 3 sheets for Excel
df_results = pd.DataFrame(results)
with pd.ExcelWriter("output.xlsx") as writer:
    for idx, split_df in enumerate([df_results.iloc[i::3] for i in
    range(3)]):
        split_df.to_excel(writer, sheet_name=f"Sheet{idx+1}", index
   =False)
```

A-7: Code for Classification of Culture Dimensions

Listing 4: Python code for classifying texts into nine cultural dimensions using RoBERTa-large-MNLI

```
# Install required packages
!pip install pandas transformers tqdm openpyxl datasets

import pandas as pd
from transformers import pipeline
from datasets import Dataset
from google.colab import files
import os

# Upload input file with texts
uploaded = files.upload()
input_file_path = list(uploaded.keys())[0]

# Initialize RoBERTa-large-MNLI for zero-shot classification (GPU-
   enabled)
classifier = pipeline('zero-shot-classification', model='roberta-
   large-MNLI', device=0)

# Nine cultural dimensions (Guiso, Sapienza & Zingales, 2015)
topics = ['Integrity', 'Teamwork', 'Respect', 'Quality', '
   Innovation',
          'Safety', 'Community', 'Communication', 'Hard Work']

# Read Excel file and prepare columns
df = pd.read_excel(input_file_path, engine='openpyxl')
for t in topics:
    df[t] = 0.0

# Convert to HuggingFace Dataset for batch processing
dataset = Dataset.from_pandas(df)

# Classification function
def classify_text(batch):
    results = classifier(batch['text'], topics)
    scores = {t: [0.0] * len(batch['text']) for t in topics}
    for i, r in enumerate(results):
        for t in topics:
            if t in r['labels']:
                scores[t][i] = r['scores'][r['labels'].index(t)]
    return scores

# Apply classification in batches
dataset = dataset.map(classify_text, batched=True, batch_size=128)
df = dataset.to_pandas()
```

Appendix B – Related to the Second Essay

B-1: Pre-Test: Questionnaire

Age

How old are you?
Please select your age group.

- Under 18
- 18–24
- 25–34
- 35–44
- 45 or older

Gender

What is your gender?
Please select your gender.

- Male
- Female
- Diverse
- Prefer not to say

Field of Study

What is your field of study?
Please select the field of study that best matches your current or previous studies.

- Business Administration
- Engineering/Technology
- Social Sciences
- Natural Sciences
- Arts/Humanities
- Medicine/Health Sciences
- Law
- Other

Education

What is your highest educational qualification?
Please select your highest level of education.

- High school or equivalent
- Bachelor's degree
- Master's degree
- Doctorate
- Other

Current Year of Study

What is your current year of study?
Please select your year of study.

- ○ 1st Year Bachelor (Semesters 1 & 2)
- ○ 2nd Year Bachelor (Semesters 3 & 4)
- ○ 3rd Year Bachelor (Semesters 5 & 6)
- ○ 4th Year Bachelor (Semesters 7 & 8)
- ○ 1st Year Master (Semesters 1 & 2)
- ○ 2nd Year Master (Semesters 3 & 4)
- ○ 3rd Year Master (Semesters 5 & 6)
- ○ None

Job Application

When did you last apply for a job?
Please select the time period that best matches your most recent job application.

- ○ Less than 1 month ago
- ○ 1–3 months ago
- ○ 4–6 months ago
- ○ 7–12 months ago
- ○ More than 1 year ago
- ○ I have never applied for a job

Number of Jobs

How many jobs have you had so far?
Please include internships or part-time jobs.

- ○ None
- ○ 1–2
- ○ 3–5
- ○ 6–10
- ○ More than 10

Use of Channels to Gather Information About Potential Employers

How often do you use the following channels to gather information about potential employers?
Please rate how often you use each channel on a scale from 1 (Never) to 5 (Very Often).

	1 *Never*	2	3	4	5 *Very Often*
Company websites	○	○	○	○	○
LinkedIn	○	○	○	○	○
Glassdoor	○	○	○	○	○
Facebook	○	○	○	○	○
Instagram	○	○	○	○	○
TikTok	○	○	○	○	○
Job boards (e.g., Indeed, Monster)	○	○	○	○	○
University career services	○	○	○	○	○

Categorization

Please assign the following text to one of the categories.
Read the text carefully and select the category it best represents.

People working here are smart and have great expertise.

- ○ Sincerity
- ○ Competence
- ○ Prestige
- ○ Innovativeness
- ○ Robustness
- ○ None

Categorization

Please assign the following text to one of the categories.
Read the text carefully and select the category it best represents.

Strong parent company. Job security.

- ○ Sincerity
- ○ Competence
- ○ Prestige
- ○ Innovativeness
- ○ Robustness
- ○ None

Categorization

Please assign the following text to one of the categories.
Read the text carefully and select the category it best represents.

After 11 years at LG, Life's Good has become a deeply meaningful part of my life. It means waking up each day with a sense of fulfillment and joy, knowing that my work is valued and makes a difference.

- ○ Sincerity
- ○ Competence
- ○ Prestige
- ○ Innovativeness
- ○ Robustness
- ○ None

Categorization

Please assign the following text to one of the categories.
Read the text carefully and select the category it best represents.

I love working at LG because of our innovation, not only innovation of our products but our people and the culture that we create. I like the investments that LG makes into keeping up with technology, making sure that the best of the best are hired to support that technology. From our OLED unit to our wall paper unit, from our remote call services to our five star service, from beginning to end, LG has it all and that's why I love working at LG and that's why Life is Good.

- ○ Sincerity
- ○ Competence
- ○ Prestige
- ○ Innovativeness
- ○ Robustness
- ○ None

Categorization

Please assign the following text to one of the categories.
Read the text carefully and select the category it best represents.

At LG Electronics, we take pride in the expertise and precision of our teams, who consistently deliver outstanding results.

- Sincerity
- Competence
- Prestige
- Innovativeness
- Robustness
- None

Categorization

Please assign the following text to one of the categories.
Read the text carefully and select the category it best represents.

At LG Electronics, we take immense pride in being recognized as a global leader with a legacy of excellence that spans decades. LG is more than a workplace—it's a brand that inspires trust and admiration worldwide.

- Sincerity
- Competence
- Prestige
- Innovativeness
- Robustness
- None

Categorization

Please assign the following text to one of the categories.
Read the text carefully and select the category it best represents.

Step into the future of smart living with LG Electronics. Our leadership team unveils the cutting-edge innovations that are transforming technology and redefining modern lifestyles. Discover how LG's commitment to forward-thinking solutions is shaping the way we live, work, and connect.

- Sincerity
- Competence
- Prestige
- Innovativeness
- Robustness
- None

Categorization

Please assign the following text to one of the categories.
Read the text carefully and select the category it best represents.

#LifesGood at LG: We asked colleagues what the phrase means to them. Here's what Jordan Goodness, SEO Manager, had to say... "I think life's good when you're sharing it with people you love. I have a book club with some of my best girlfriends and we meet at different restaurants around the city. It's really casual and a good opportunity to catch up and bond over things that are going on or what we're interested in."

- Sincerity
- Competence
- Prestige
- Innovativeness
- Robustness
- None

Categorization

Please assign the following text to one of the categories.
Read the text carefully and select the category it best represents.

Fast digital transformation, lots of exciting projects.

- Sincerity
- Competence
- Prestige
- Innovativeness
- Robustness
- None

Categorization

Please assign the following text to one of the categories.
Read the text carefully and select the category it best represents.

For decades, LG Electronics has demonstrated unmatched resilience and reliability, thriving in a fast-changing world. Our strong foundation is built on a global presence, advanced infrastructure, and a commitment to delivering consistent quality—no matter the challenge.

- Sincerity
- Competence
- Prestige
- Innovativeness
- Robustness
- None

Categorization

Please assign the following text to one of the categories.
Read the text carefully and select the category it best represents.

At LG Electronics, we foster a culture of continuous improvement and professional development. Employees have access to personalized Career Development Programs (CDP) and over 800 courses across 14 business functions, ensuring they build the skills needed to excel and drive industry standards.

- Sincerity
- Competence
- Prestige
- Innovativeness
- Robustness
- None

Categorization

Please assign the following text to one of the categories.
Read the text carefully and select the category it best represents.

At LG Electronics, we are committed to being recognized as a global leader in innovation and excellence. Our dedication to quality and cutting-edge technology has earned us numerous awards and accolades, reflecting our esteemed position in the industry. We take pride in our rich history and the trust we have built with customers worldwide. Our global operations span multiple countries, showcasing our expansive reach and influence. By upholding the highest standards and continuously striving for excellence, we reinforce our reputation as a prestigious and respected brand on the international stage.

- ○ Sincerity
- ○ Competence
- ○ Prestige
- ○ Innovativeness
- ○ Robustness
- ○ None

Categorization

Please assign the following text to one of the categories.
Read the text carefully and select the category it best represents.

The brand is top notch and clients really need LG solutions. Many of the products sold are must haves.

- ○ Sincerity
- ○ Competence
- ○ Prestige
- ○ Innovativeness
- ○ Robustness
- ○ None

Categorization

Please assign the following text to one of the categories.
Read the text carefully and select the category it best represents.

At LG Electronics, resilience and reliability are at the core of our global operations. With decades of experience, we have built a solid foundation that allows us to thrive in an ever-changing market. Our commitment to stability ensures that we deliver consistent quality and performance, even in challenging times.

- ○ Sincerity
- ○ Competence
- ○ Prestige
- ○ Innovativeness
- ○ Robustness
- ○ None

Categorization

Please assign the following text to one of the categories.
Read the text carefully and select the category it best represents.

The pool of talent and the diversity is great. LG sincerely believes in diversity and inclusion and has created a nurturing environment for employees. The benefits and perks are also good and management works hard to be a competitive employer.

- ○ Sincerity
- ○ Competence
- ○ Prestige
- ○ Innovativeness
- ○ Robustness
- ○ None

B-2: Pre-Test: Details about Survey Respondents

Survey Funnel	
Clicked on survey link	74
Started survey	32
Completed survey	29
Completed survey (after quality exclusions and de-duplication)	29

Age	
18–24 years	41.4%
25–34 years	58.6%

Gender	
Male	31.0%
Female	69.0%

Year of Study	
2nd year Bachelor	10.3%
4th year Bachelor	10.3%
1st year Master	10.3%
2nd year Master	31.0%
3rd year Master	37.9%

Highest Educational Qualification	
High school or equivalent	17.2%
Bachelor’s degree	69.0%
Master’s degree	13.8%

Job Application Timeline	
Less than 1 month ago	20.7%
1–3 months ago	24.1%
4–6 months ago	13.8%
7–12 months ago	13.8%
More than 1 year ago	27.6%

Field of Study/ Profession	
Business Administration	75.9%
Engineering/Technology	6.9%
Social Sciences	3.4%
Natural Sciences	3.4%
Arts/ Humanities	3.4%

Number of Jobs	
1–2	20.7%
3–5	44.8%
6–10	31.0%
More than 10	3.4%

B-3: Online Experiment: Threshold Values for Stimulus

The Table presents the dimension-specific threshold values derived from the percentile-based classification of cosine similarity scores. These thresholds served as the basis for assigning each observation to the categories of low, medium, or high communication consistency.

Dimension	**Low Consistency** ($\leq$ 1/3 percentile)	**Mid Consistency** (mean)	**High Consistency** ($\geq$ 2/3 percentile)
Sincerity	36%	52%	67%
Competence	31%	45%	56%
Prestige	40%	54%	67%
Innovativeness	29%	43%	55%
Robustness	33%	44%	55%

B-4: Online Experiment: Stimulus Texts (Example Competence)

The final stimulus material thus comprised **135 texts** (15 combinations of channel and image dimension $\times$ 3 consistency levels $\times$ 3 companies). An example of the implementation of the 3 consistency levels in the *competence* dimension for Microsoft can be found in the Table.

Example of message consistency manipulation for the dimension *Competence* across three communication channels (Microsoft)

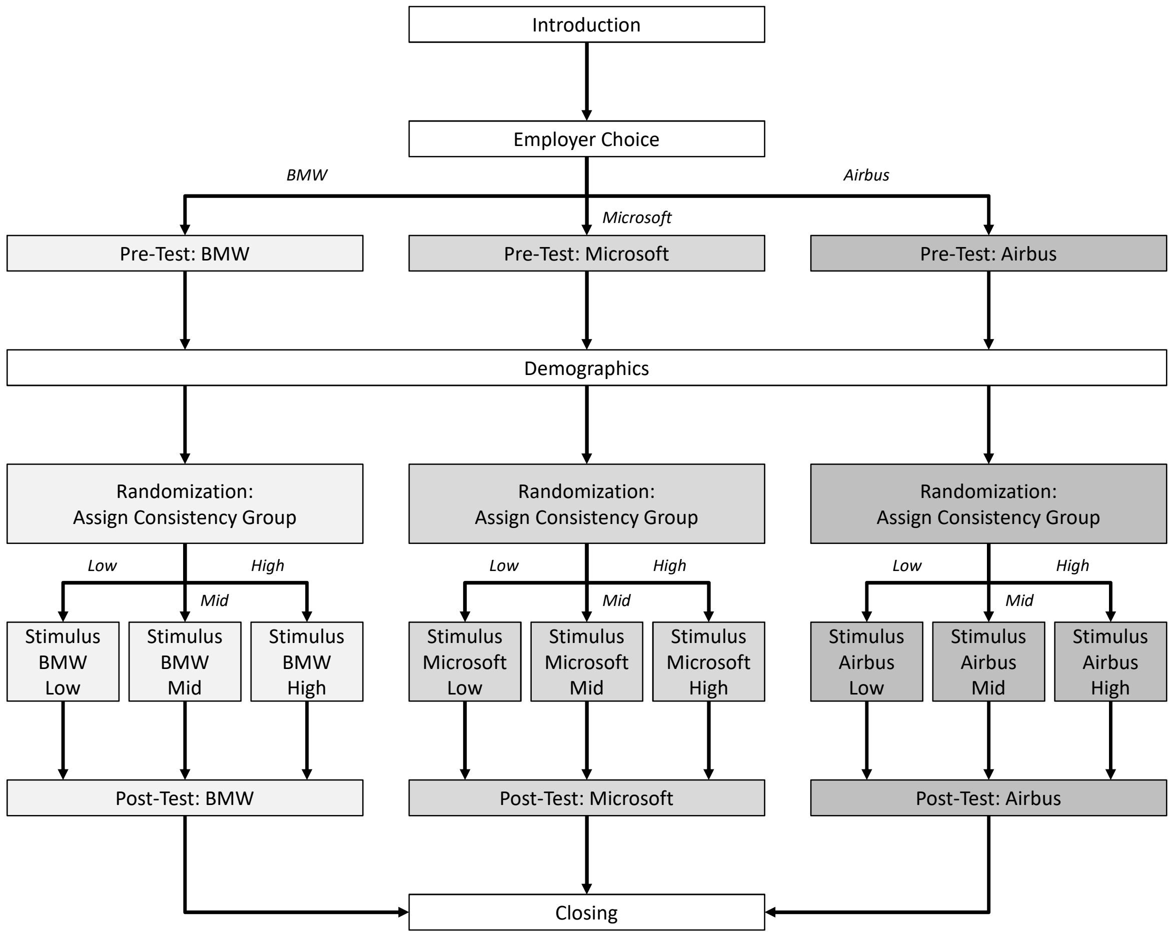
Consistency Level	Website	Glassdoor	LinkedIn
Low	At Microsoft, we foster a culture of continuous improvement and professional development. Employees have access to personalized Career Development Programs and over 800 courses across 14 business functions.	Employees are left to figure things out on their own, with no support for skill-building or career growth.	Our colleagues follow defined workflows to ensure consistency. Development opportunities are unusual and standardized.
Mid	At Microsoft, we support employees' development. Many pursue opportunities to expand their skills. While structured programs exist, employees often rely on their own initiative.	People here are trying to extend their expertise.	Colleagues are motivated to adapt to everyday challenges. Skill-building often depends on individual initiative.
High	We foster a culture of continuous development. Employees have access to structured programs and over 800 courses. Our high-potential program prepares future leaders.	People working here are smart and skilled.	Our teams deliver outstanding results through structured development programs and over 800 training courses.

B-5: Online Experiment: Items for Symbolic Employer Brand Image & Organizational Attractiveness

Dimension	Pre-Measurement Item	Post-Measurement Item
Sincerity	*In my perception, the employer is:* • Honest • Sincere • Authentic	*In my perception, the employer is:* • Deceptive • Trustworthy • Down-to-earth
Innovativeness	*In my perception, the employer is:* • Modern • Daring • Exciting	*In my perception, the employer is:* • Up-to-date • Contemporary • Trendy
Competence	*In my perception, the employer is:* • Successful • A leading company in the industry • Reliable	*In my perception, the employer is:* • Incompetent • Intelligent • Capable
Prestige	*In my perception, the employer is:* • A highly respected organization • High status • Prestigious	*In my perception, the employer is:* • A company that has high standards • Well-respected • Reputable
Robustness	*In my perception, the employer is:* • Strong • Robust • Tough	*In my perception, the employer is:* • Rugged • Resilient • Enduring
Organizational Attractiveness	For me, the employer would be a good place to work A job at the employer is very appealing to me I am interested in learning more about this company as an employer	The employer is attractive to me as a place for employment I would consider applying for a job at this company I would not be interested in this company except as a last resort

Note: Items adapted from Hoppe (2018), Lievens (2007), Lievens & Highhouse (2003), Van Hoye (2013).

B-6: Online Experiment: Questionnaire Structure



B-7: Online Experiment: Questionnaire (Choice: Microsoft, Student, Low Consistency)

Welcome to the survey!

Thank you for participating in this survey. In today's competitive job market, employer branding plays an increasingly important role in attracting top talent. This study, conducted as part of my PhD at the University of Mannheim under the supervision of Prof. Dr. Florian Stahl at the Chair of Quantitative Marketing, aims to explore the relationship between corporate communication and employer brand.

Survey Details
Duration: The survey will take approximately 8–12 minutes to complete.
Deadline: The survey will be open until April 30, 2025.

Anonymity and Confidentiality
Your participation in this study is completely anonymous. No personal information will be collected, and your responses will not be linked to your identity. All responses will be treated confidentially and used solely for the purpose of this research. Results will only be presented in aggregate form, ensuring that individual responses cannot be identified.

Voluntary Participation
Participation in this survey is entirely voluntary. You may choose to exit the survey at any time without any consequences.

Raffle
If you would like to enter our raffle to win one of three vouchers for a hotel stay for two people, including breakfast, at the 4-star Hotel Diehlberg in Olpe, please provide your email address. Your email address will be used exclusively for the raffle and will not be connected to your survey responses.
Please note: Participation in the raffle is only possible after completing the survey.

Receive Study Results
If you are interested in receiving the results of this study, you can also provide your email address. Your email will be used solely for sharing the study findings and will not be linked to your survey responses.

Contact Information
If you have any questions or encounter any issues during the survey, feel free to contact me:

Ben Moradi
PhD Candidate
University of Mannheim, Chair of Quantitative Marketing
bmoradi@mail.uni-mannheim.de

Thank you again for your participation! Your feedback is valuable and will help us gain meaningful insights.

Current Status

What is your current status?
Consider only full-time professional experience.
- ○ Apprentice
- ○ Student
- ○ Early Career Professional (up to 3 years)
- ○ Mid-Level Professional (4–10 years)
- ○ Senior Professional (more than 10 years)
- ○ Other

Age

How old are you?
Please select your age group.

- ○ Under 18
- ○ 18–24
- ○ 25–34
- ○ 35–44
- ○ 45 or older

Gender

Which gender do you identify with?
Please select your gender.

- ○ Male
- ○ Female
- ○ Diverse
- ○ Prefer not to say

Education

What is your highest level of education completed?
Please select the highest education you have completed. Only include completed qualifications, not those you are currently pursuing.

- ○ No formal qualification
- ○ Lower secondary education (e.g., Hauptschule)
- ○ Intermediate secondary education (e.g., Realschule)
- ○ Upper secondary education (e.g., Hochschulreife)
- ○ Vocational training
- ○ Bachelor's degree
- ○ Master's/Diploma/Magister
- ○ Doctorate
- ○ Postdoctoral qualification
- ○ Other

Full-time Work Experience (Only Students)

How much full-time work experience have you gained before or alongside your studies?
Please select the option that best describes the amount of full-time work experience you have gained before or alongside your studies.

- ○ No full-time work experience at all
- ○ Less than 1 year
- ○ 1–3 years
- ○ More than 3 years

Current Year of Study (Only Students)

What is your current year of study?
Please select the total number of years you have spent in your academic studies, including all degrees or programs you have pursued

- ○ First year (Semesters 1–2)
- ○ Second year (Semesters 3–4)
- ○ Third year (Semesters 5–6)
- ○ Fourth year (Semesters 7–8)
- ○ Fifth year (Semesters 9–10)
- ○ Sixth year (Semesters 11–12) or more

Field of Study / Profession

What is your current occupation or professional field?
Please select your current occupation or professional field. If you are not currently employed, choose the highest level of education or vocational training you have completed.

- ○ Business / Economics
- ○ Engineering / IT
- ○ Social Sciences / Humanities
- ○ Natural Sciences
- ○ Law
- ○ Medicine / Health Sciences
- ○ Other

Most Recent Job Application

When was the time period of your most recent job application?
Please select the time period during which you last submitted a job application.

- ○ Within the last 6 months
- ○ 6–12 months ago
- ○ 1–5 years ago
- ○ More than 5 years ago
- ○ I never applied for a job

Microsoft — Initial Rating Symbolic Employer Brand Image

Please rate Microsoft on the following dimensions.
1 = strongly disagree, 5 = strongly agree

	1	2	3	4	5
Honest	○	○	○	○	○
Sincere	○	○	○	○	○
Authentic	○	○	○	○	○
Modern	○	○	○	○	○
Daring	○	○	○	○	○
Exciting	○	○	○	○	○
Successful	○	○	○	○	○
A leading company in the industry	○	○	○	○	○
Reliable	○	○	○	○	○
A highly respected organization	○	○	○	○	○
High status	○	○	○	○	○
Prestigious	○	○	○	○	○
Strong	○	○	○	○	○
Robust	○	○	○	○	○
Tough	○	○	○	○	○

Microsoft — Initial Rating Organizational Attractiveness

Please indicate your agreement.
1 = strongly disagree, 5 = strongly agree

	1	2	3	4	5
For me, Microsoft would be a good place to work	○	○	○	○	○
A job at Microsoft is very appealing to me	○	○	○	○	○
I am interested in learning more about Microsoft as an employer	○	○	○	○	○

Stimulus — Microsoft Career Website (Low Consistency)

Please read carefully.

Text 1. At Microsoft, robustness is the cornerstone of our operations. For decades, we have demonstrated unwavering strength and resilience, enabling us to navigate and excel in an ever-changing global market. Our solid foundation, built on advanced infrastructure and a strong financial backbone, ensures stability and reliability in everything we do. We take pride in our ability to adapt to challenges while maintaining consistent quality and performance. This steadfast approach makes Microsoft a dependable partner for customers, employees, and stakeholders worldwide. Our commitment to durability and trust underscores our mission to deliver solutions that stand the test of time, ensuring long-term success and reliability for all who rely on us.

Text 2. After 11 years at Microsoft, this company has become a deeply meaningful part of my life. It means waking up each day with a sense of fulfillment and joy, knowing that my work is valued and makes a difference. It's about feeling connected to a company that truly supports and celebrates its people. Moments like walking with my son, seeing a Microsoft logo, and hearing him say, "Look, Daddy, it's the smiley face of your company!" remind me of the pride and connection I feel every day. For me, this is what working at Microsoft truly means—belonging, purpose, and shared joy.

Text 3. At Microsoft, we foster a culture of continuous improvement and professional development. Employees have access to personalized Career Development Programs and over 800 courses across 14 business functions, ensuring they build the skills needed to excel and drive industry standards. Our High Potential program identifies and trains future leaders, equipping them with the expertise and knowledge to succeed in their roles. At Microsoft, we are committed to building a workforce defined by skill and performance.

Text 4. At Microsoft, we are committed to being recognized as a global leader in innovation and excellence. Our dedication to quality and cutting-edge technology has earned us numerous awards and accolades, reflecting our esteemed position in the industry. We take pride in our rich history and the trust we have built with customers worldwide. Our global operations span multiple countries, showcasing our expansive reach and influence. By upholding the highest standards and continuously striving for excellence, we reinforce our reputation as a prestigious and respected brand on the international stage.

Text 5. I love working at Microsoft because of our innovation, not only innovation of our products but our people and the culture that we create. I like the investments that Microsoft makes into keeping up with technology, making sure that the best of the best are hired to support that technology. From cloud computing with Azure to innovative tools like Microsoft Teams, from customer support to enterprise solutions, Microsoft has it all and that's why I love working at Microsoft.

Stimulus — Microsoft LinkedIn (Low Consistency)

Please read carefully.

Text 1. In an evolving world, we see change as inevitable and stability as restrictive. Rather than relying on established structures or traditions, we choose to move forward by questioning norms and habits. Our success stems from our willingness to take risks and explore uncharted paths, knowing that true progress often comes from stepping away from the routine. Stability, for us, isn't about staying the same—it's about evolving with purpose and agility to meet the challenges of tomorrow.

Text 2. We asked colleagues what working here means to them. Here's what one of our colleagues said: I feel distant from the company culture. I wish there were more spaces for open dialogue and collaboration. There's a lack of real diversity in thought and background. It's hard to voice new ideas when feedback is rarely encouraged, and leadership seems disconnected from our everyday challenges.

Text 3. Our colleagues follow defined workflows to ensure consistency in organizational tasks. Development opportunities are unusual, but standardized following fixed paths that align with organizational priorities. We focus on systematic processes and company-wide goals.

Text 4. We are proud to be a manufacturer in the US. We are a brand that has started to build a reputation in the region. Our focus on localized strategies has allowed us to strengthen partnerships. Join a team that is working towards long-term success in the US.

Text 5. We recognize the challenges of shaping the future of smart technology. We spend money to explore new approaches, though not every idea leads to immediate success. We continue to refine our methods, striving to create developments that gradually influence the way we live, work, and connect.

Stimulus — Microsoft Glassdoor (Low Consistency)

Please read carefully.

Text 1. Lots of kicked staff. Jobs are not safe.

Text 2. The pool of talent and diversity is not that good. Leadership seems not really valuing diversity and inclusion.

Text 3. Employees are left to figure things out on their own, with no support for skill-building or career growth.

Text 4. The brand is unfamiliar to most potential clients. Some products might be seen as relevant by niche client groups. I worked on projects in my own Country (in the US) no international opportunities.

Text 5. Digital transformation is on the agenda, but is just making slow progress.

Microsoft — Post Rating Symbolic Employer Brand Image

Please rate Microsoft on the following dimensions.
1 = strongly disagree, 5 = strongly agree

	1	2	3	4	5
Deceptive	○	○	○	○	○
Trustworthy	○	○	○	○	○
Down-to-earth	○	○	○	○	○
Up-to-date	○	○	○	○	○
Contemporary	○	○	○	○	○
Trendy	○	○	○	○	○
Incompetent	○	○	○	○	○
Intelligent	○	○	○	○	○
Capable	○	○	○	○	○
A company that has high standards	○	○	○	○	○
Well-respected	○	○	○	○	○
Reputable	○	○	○	○	○
Rugged	○	○	○	○	○
Resilient	○	○	○	○	○
Enduring	○	○	○	○	○

Microsoft — Post Rating Organizational Attractiveness

Please indicate your agreement.
1 = strongly disagree, 5 = strongly agree

	1	2	3	4	5
Microsoft is attractive to me as a place for employment	○	○	○	○	○
I would consider applying for a job at Microsoft	○	○	○	○	○
I would not be interested in Microsoft except as a last resort	○	○	○	○	○

End of Survey

Thank you for your participation! Your time and responses are greatly appreciated.

If you would like to enter the raffle for one of the 3 vouchers for a hotel stay for two people, including breakfast, at the 4-star Hotel Diehlberg in Olpe, please enter your email address below. Your email will be stored separately from your survey responses and used only for the raffle.

If you would like to receive the aggregated results of this study once they are available, please also provide your email address in the field below. Your email will be stored separately and used exclusively to share the results.

Contact Information
For any questions about the study, please contact:

Ben Moradi
PhD Candidate
University of Mannheim, Chair of Quantitative Marketing
bmoradi@mail.uni-mannheim.de

Thank you again for your support and valuable contribution to this research.

B-8: Online Experiment: Details about Survey Respondents

Survey Funnel	
Clicked on survey link	1240
Started survey	660
Completed survey	552
Completed survey (after quality exclusions and de-duplication)	510

Company Choices	
Microsoft	46.7%
BMW	38.0%
Airbus	15.3%

Consistency Groups	
High consistency	33.7%
Mid consistency	32.9%
Low consistency	33.3%

Current Status	
Student	59.2%
Early career professional	19.8%
Mid-level professional	12.7%
Senior professional	4.3%
Apprentice	2.5%
Other	1.4%

Age Groups	
18–24 years	50.2%
25–34 years	44.3%
35–44 years	3.1%
45 or older	1.8%
Under 18	0.6%

Gender	
Female	58.6%
Male	40.8%
Diverse	0.4%
Prefer not to say	0.2%

Education Level	
Bachelor’s degree	54.1%
Master’s degree	24.1%
Upper secondary education	13.9%
Vocational training	2.5%
Intermediate secondary education	2.5%
Doctorate	2.0%
Other qualification	0.6%
No formal qualification	0.2%

Field of Study / Professional Background	
Business / Economics	68.4%
Engineering / IT	9.4%
Other	9.2%
Social Sciences / Humanities	7.6%
Law	2.9%
Medicine / Health Sciences	1.6%
Natural Sciences	0.8%

Job Application Timeline	
Within the last 6 months	43.1%
1–5 years ago	29.8%
6–12 months ago	18.8%
More than 5 years ago	6.7%
Never applied	1.6%

Students Only: Job Experience (n=302)	
Less than 1 year of full-time	42.4%
1–3 years of full-time	36.8%
No full-time at all	15.6%
More than 3 years of full-time	5.3%

Students Only: Year of Study (n=302)	
First year (Sem 1–2)	27.8%
Second year (Sem 3–4)	16.2%
Third year (Sem 5–6)	7.9%
Fourth year (Sem 7–8)	17.9%
Fifth year (Sem 9–10)	16.2%
Sixth year or more (11–12+)	13.9%

B-9: Online Experiment: Codes

Listing 5: Excerpt from Analysis Code for Hypothesis 1[1]

```python
# Categorize pre-image scores into "poor", "medium", "good"
def categorize_pre(value):
    if pd.isna(value):
        return None
    elif value <= 2:
        return 'poor'
    elif value <= 4:
        return 'medium'
    else:
        return 'good'

# Compute partial eta squared for each effect in the ANOVA table
def add_partial_eta_sq(anova_tbl):
    ss_error = anova_tbl.loc["Residual", "sum_sq"]
    anova_tbl["eta2_partial"] = anova_tbl["sum_sq"] / (anova_tbl["
   sum_sq"] + ss_error)
    anova_tbl.loc["Residual", "eta2_partial"] = np.nan
    return anova_tbl

symbolic_dimensions = ["Sincerity", "Innovativeness", "Competence",
    "Prestige", "Robustness"]

anova_results = {}
regression_results = {}
t_test_results = []

for dim in symbolic_dimensions:
    before_col = f"{dim}_Before"
    delta_col = f"{dim}_Delta"

    # Prepare dataset: select relevant columns, create pre-image
   categories
    df = analysis_df[[before_col, delta_col, "Experiment_Group"]].
   copy()
    df = df.rename(columns={"Experiment_Group": "Consistency"})
    df["Pre_Category"] = df[before_col].apply(categorize_pre)
    df = df.dropna(subset=[delta_col, "Pre_Category", "Consistency
   "])
    df["Consistency"] = df["Consistency"].astype("category")
    df["Pre_Category"] = df["Pre_Category"].astype("category")

    # Two-way ANOVA with interaction
    model = ols(f"{delta_col}␣~␣C(Consistency)␣*␣C(Pre_Category)",
    data=df).fit()
    anova_table = sm.stats.anova_lm(model, typ=2)
    anova_table = add_partial_eta_sq(anova_table)
    anova_results[dim] = anova_table
```

```
 # OLS regression with same predictors (for coefficients &
model fit)
 reg_model = smf.ols(f"{delta_col}␣~␣C(Consistency)␣*␣C(
Pre_Category)", data=df).fit()
 regression_results[dim] = reg_model.summary()

 # Cell-wise one-sample tests (per Consistency x Pre_Category
combination)
 for (cons, pre), group in df.groupby(["Consistency", "
Pre_Category"]):
     values = group[delta_col].dropna()
     n = len(values)

     if n < 3:
         # Too few cases for statistical testing
         test_results = {
             "Dimension": dim, "Consistency": cons, "
Pre_Category": pre,
             "n": n, "Mean␣Delta": round(values.mean(), 3) if n
 > 0 else None,
             "Test": "-", "Statistic": "-", "p-Value": "-",
             "Significance": "too␣small"
         }
     elif n < 10:
         # Only descriptive statistics for small sample sizes
         test_results = {
             "Dimension": dim, "Consistency": cons, "
Pre_Category": pre,
             "n": n, "Mean␣Delta": round(values.mean(), 3),
             "Test": "-", "Statistic": "-", "p-Value": "-",
             "Significance": "descriptive␣only"
         }
     else:
         # Check normality for test selection
         mean_delta = round(values.mean(), 3)
         p_norm = shapiro(values)[1]
         if n >= 30 or p_norm > 0.05:
             # Parametric one-sample t-test
             t_stat, p_val = ttest_1samp(values, popmean=0)
             test_used = "t-test"
             stat = round(t_stat, 3)
         else:
             # Non-parametric Wilcoxon signed-rank test
             try:
                 stat, p_val = wilcoxon(values)
                 test_used = "Wilcoxon"
                 stat = round(stat, 3)
             except ValueError:
                 test_used = "-"
                 stat = "-"
```

```
                    p_val = "-"

            test_results = {
                "Dimension": dim, "Consistency": cons, "
   Pre_Category": pre,
                "n": n, "Mean␣Delta": mean_delta,
                "Test": test_used, "Statistic": stat,
                "p-Value": round(p_val, 4) if isinstance(p_val,
   float) else p_val,
                "Significance": (
                    "***" if isinstance(p_val, float) and p_val <
   0.001 else
                    "**"  if isinstance(p_val, float) and p_val <
   0.01  else
                    "*"   if isinstance(p_val, float) and p_val <
   0.05  else
                    "n.s." if isinstance(p_val, float) else "-"
                )
            }

        t_test_results.append(test_results)

# Combine cell-level test results into a DataFrame
t_test_df = pd.DataFrame(t_test_results)
display(t_test_df)

# Combine partial eta squared values from all ANOVAs
eta_summary = (
    pd.concat(anova_results, names=["Dimension"])
    .reset_index()
    .query("index␣!=␣'Residual'")[["Dimension", "index", "
   eta2_partial"]]
    .rename(columns={"index": "Effect"})
)
display(eta_summary.round(3))
```

[1]*Note:* The analysis for Hypothesis 2 follows the same structure, with the only change being the dependent variable (*Organizational Attractiveness*). The code is therefore not reproduced here.

Listing 6: Excerpt from Analysis Code for Hypothesis 3

```
# Compare low (1) vs. high (3) consistency on Delta per symbolic dimension.
# Test choice: independent t-test if both groups ~ normal; otherwise Mann-Whitney U.
# Very small groups (<10) -> descriptive only.

h3_comparison_results = []

for dim in symbolic_dimensions:
    delta_col = f"{dim}_Delta"
    df = analysis_df[[delta_col, "Experiment_Group"]].copy().dropna()
    df = df.rename(columns={"Experiment_Group": "Consistency"})

    group_low = df[df["Consistency"] == 1][delta_col]
    group_high = df[df["Consistency"] == 3][delta_col]

    n_low, n_high = len(group_low), len(group_high)
    mean_low, mean_high = group_low.mean(), group_high.mean()

    # Normality checks (only if n >= 3)
    normal_low = (shapiro(group_low)[1] > 0.05) if n_low >= 3 else False
    normal_high = (shapiro(group_high)[1] > 0.05) if n_high >= 3 else False

    # Test decision
    if n_low < 10 or n_high < 10:
        test = "-"
        stat, p_val = "-", "-"
        note = "too␣small␣groups"
    elif normal_low and normal_high:
        stat, p_val = ttest_ind(group_low, group_high, equal_var=False)
        test = "t-test␣(independent)"
        note = ""
    else:
        stat, p_val = mannwhitneyu(group_low, group_high, alternative="two-sided")
        test = "Mann-Whitney␣U"
        note = ""

    h3_comparison_results.append({
        "Dimension": dim,
        "n_low": n_low,
        "Mean_Delta_low": round(mean_low, 3),
        "n_high": n_high,
        "Mean_Delta_high": round(mean_high, 3),
        "Test": test,
```

```
        "Statistic": round(stat, 3) if isinstance(stat, (int,
   float)) else stat,
        "p_Value": round(p_val, 4) if isinstance(p_val, float)
   else p_val,
        "Significance": (
            "***" if isinstance(p_val, float) and p_val < 0.001
   else
            "**"  if isinstance(p_val, float) and p_val < 0.01
   else
            "*"   if isinstance(p_val, float) and p_val < 0.05
   else
            "n.s." if isinstance(p_val, float) else "-"
        ),
        "Note": note
    })

# Results table
h3_comparison_df = pd.DataFrame(h3_comparison_results)
display(h3_comparison_df)
```

Listing 7: Excerpt from Analysis Code for Hypothesis 4

```
# Dependent variables (change scores)
delta_vars = [
    "Sincerity_Delta", "Innovativeness_Delta", "Competence_Delta",
    "Prestige_Delta", "Robustness_Delta", "Attractiveness_Delta"
]

# Moderators (no PD05 / PD06)
moderators = ["PD01", "PD02", "PD03", "PD04", "PD07", "PD08"]

# Function to return significance stars (APA-style)
def sigstars(p):
    if p is None or not isinstance(p, float):
        return "-"
    return (
        "***" if p < 0.001 else
        "**"  if p < 0.01  else
        "*"   if p < 0.05  else
        "n.s."
    )

results = []

for delta in delta_vars:
    for mod in moderators:
        cols = [delta, "Experiment_Group", mod]
        df_mod = analysis_df[cols].copy()
        df_mod = df_mod.rename(columns={"Experiment_Group": "
   Consistency"})

        # Remove missing values
        df_mod = df_mod.dropna(subset=[delta, "Consistency", mod])

        # Skip if insufficient variance for interaction
        if df_mod["Consistency"].nunique() < 2 or df_mod[mod].
   nunique() < 2:
            p_val = r2_full = delta_r2 = eta_sq = partial_eta_sq =
    None
        else:
            # Full model with interaction
            formula_full = f"{delta}␣~␣C(Consistency)␣*␣C({mod})"
            model_full  = ols(formula=formula_full, data=df_mod).
   fit()
            anova_full  = sm.stats.anova_lm(model_full, typ=2)

            # Reduced model without interaction
            formula_reduced = f"{delta}␣~␣C(Consistency)␣+␣C({mod})
   "
            model_reduced   = ols(formula=formula_reduced, data=
   df_mod).fit()
```

```
            # p-value of interaction
            interaction_term = f"C(Consistency):C({mod})"
            p_val = anova_full.loc[interaction_term, "PR(>F)"]

            # Effect sizes
            ss_total = anova_full["sum_sq"].sum()
            ss_int   = anova_full.loc[interaction_term, "sum_sq"]
            ss_res   = anova_full.loc["Residual",     "sum_sq"]

            eta_sq         = ss_int / ss_total
            partial_eta_sq = ss_int / (ss_int + ss_res)

            # R^2 values
            r2_full    = model_full.rsquared
            r2_reduced = model_reduced.rsquared
            delta_r2   = r2_full - r2_reduced

        results.append({
            "Dimension":      delta.replace("_Delta", ""),
            "Moderator":      mod,
            "p_Value":        p_val,
            "Significance":   sigstars(p_val),
            "R2_full":        r2_full,
            "Delta_R2":       delta_r2,
            "Eta_sq":         eta_sq,
            "Partial_eta_sq": partial_eta_sq
        })

# Results table
moderation_df = pd.DataFrame(results)
display(moderation_df)
```

B-10: Job Ads: Detailed Data Description

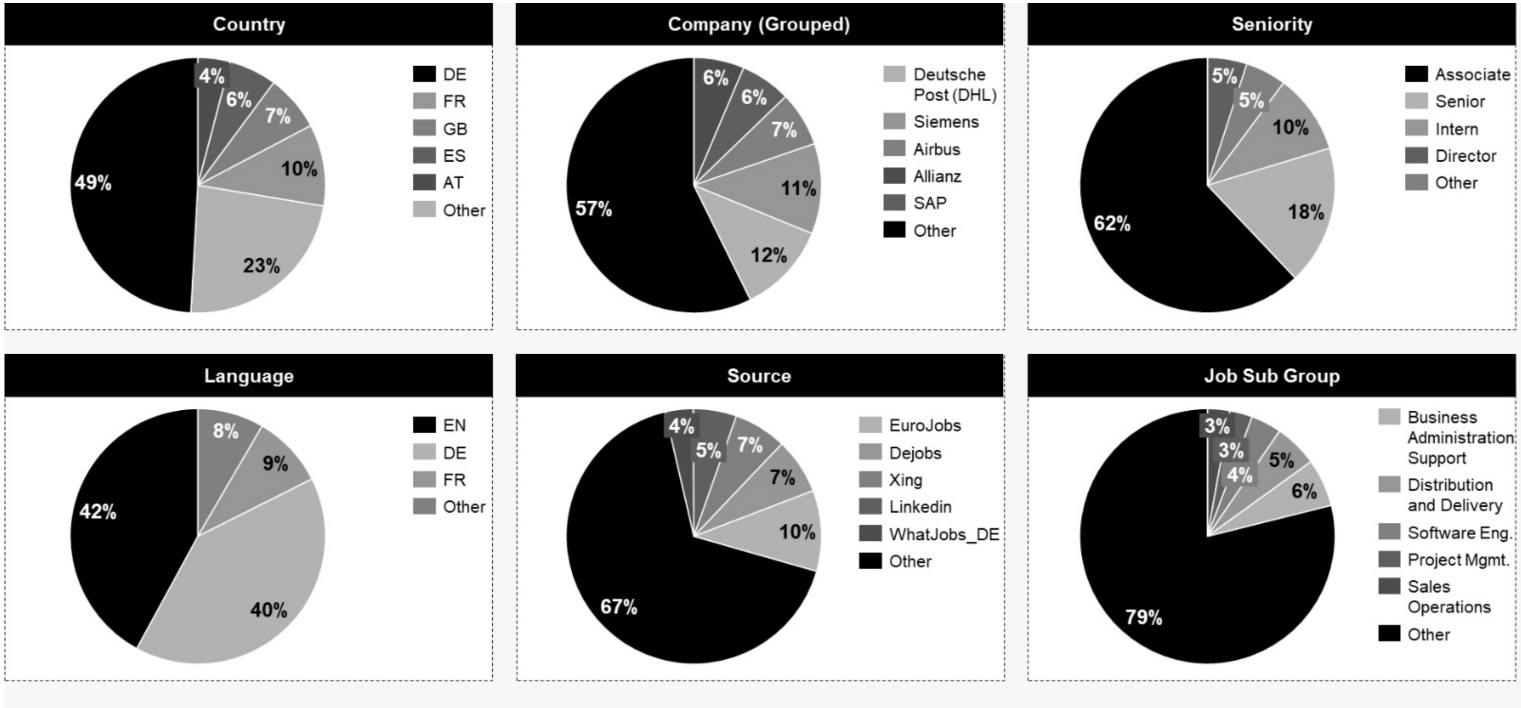
Dataset Overview	
Number of observations	1,056,696
Number of variables	26
Time span	Jan 1, 2023 – Jan 21, 2025
Countries represented	44
Main unit of analysis	Job postings
Target variable	days_to_hire
Key predictors	Consistency measures

days_to_hire Summary	
Mean	68.40
Median	35
Min	0
Max	743
Std. dev	83.82

Missing Data (selected variables)	
location	0.41% (4,333)
job_category	16.47% (173,837)
days_to_hire	12.80% (135,258)
raw_salary	97.68% (1,031,536)
std_title	12.75% (134,699)

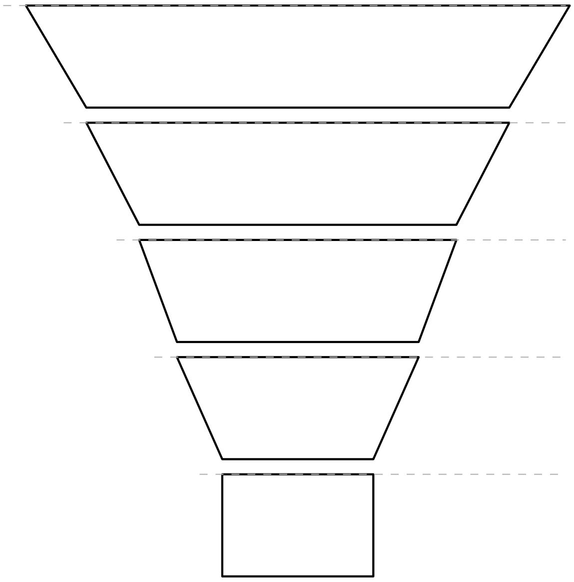
Top 5 Countries	
DE	49.12% (519,168)
FR	10.34% (109,212)
GB	7.12% (75,217)
ES	6.06% (64,012)
AT	4.09% (43,216)

Top 5 Companies (grouped)	
Deutsche Post	11.53% (121,737)
Siemens	11.45% (120,894)
Airbus	6.94% (73,303)
Allianz	6.62% (69,844)
SAP	6.39% (67,471)


Country
DE
FR
GB
ES
AT
Other
49%
23%
10%
7%
6%
4%
Company (Grouped)
Deutsche Post (DHL)
Siemens
Airbus
Allianz
SAP
Other
57%
12%
11%
7%
6%
6%
Seniority
Associate
Senior
Intern
Director
Other
62%
18%
10%
5%
5%
Language
EN
DE
FR
Other
42%
40%
9%
8%
Source
EuroJobs
Dejobs
Xing
Linkedin
WhatJobs_DE
Other
67%
10%
7%
7%
5%
4%
Job Sub Group
Business Administration Support
Distribution and Delivery
Software Eng.
Project Mgmt.
Sales Operations
Other
79%
6%
5%
4%
3%
3%

B-11: Job Ads: Pre-Processing

1,056,696 job ads



Step 1: Filter for English job ads.

Step 2: Filter for days_to_hire > 6.

Step 3: Filter for max. 15 km distance.

Step 4: Filter for min. 3 ads from same company, same job sub-group within same time.

214,774 job ads

B-12: Job Ads: Codes

Listing 8: Excerpt from Analysis Code for Hypothesis 5

```
import os
import pickle
import numpy as np
import pandas as pd
from tqdm import tqdm
from scipy.spatial.distance import cosine
import statsmodels.api as sm

# --- 1. Load list of sentences and group by job_id ---
df = pd.read_csv("segmented_sentences.csv", usecols=["job_id", "
   sentence_number"])
df["sentence_id"] = df.index.astype(str)
job_to_sentences = df.groupby("job_id")["sentence_id"].apply(list).
   to_dict()

# Mapping: sentence_id -> job_id
sentence_to_job = {sid: job_id for job_id, sids in
   job_to_sentences.items() for sid in sids}

# --- 2. Load previous results if available ---
output_file = "job_consistency_scores.pkl"
if os.path.exists(output_file):
    with open(output_file, "rb") as f:
        consistency_scores = pickle.load(f)
else:
    consistency_scores = {}

# --- 3. Compute consistency for a single job_id ---
def compute_consistency_for_job(job_id, sentence_ids,
   embeddings_dict):
    if job_id in consistency_scores:
        return
    embeddings = [embeddings_dict[sid] for sid in sentence_ids if
   sid in embeddings_dict]
    if len(embeddings) < 2:
        consistency_scores[job_id] = None
        return
    similarities = [
        1 - cosine(embeddings[i], embeddings[j])
        for i in range(len(embeddings))
        for j in range(i + 1, len(embeddings))
    ]
    consistency_scores[job_id] = np.mean(similarities) if
   similarities else None

# --- 4. Blockwise processing of embedding files ---
embedding_files = sorted([f for f in os.listdir("embedding_chunks/
   ") if f.endswith(".pkl")])
```

```
BLOCK_SIZE = 25
SAVE_INTERVAL = 200
processed = 0

for i in range(0, len(embedding_files), BLOCK_SIZE):
    block = embedding_files[i:i + BLOCK_SIZE]
    embeddings = {}

    # Load embeddings for current block
    for file in block:
        with open(os.path.join("embedding_chunks/", file), "rb")
   as f:
            part = pickle.load(f)
            embeddings.update({str(k): v for k, v in part.items()})


    # Find all job_ids with sentences in current block
    relevant_jobs = {sentence_to_job[sid] for sid in embeddings if
    sid in sentence_to_job}

    # Compute consistency scores
    for job_id in tqdm(relevant_jobs, desc=f"Block␣{i//BLOCK_SIZE␣+
   ␣1}"):
        compute_consistency_for_job(job_id, job_to_sentences[
   job_id], embeddings)
        processed += 1

        # Save intermediate results
        if processed >= SAVE_INTERVAL:
            with open(output_file, "wb") as f:
                pickle.dump(consistency_scores, f)
            processed = 0

# --- 5. Final save ---
with open(output_file, "wb") as f:
    pickle.dump(consistency_scores, f)

# ======================
# Regression Analysis
# ======================

# 1. Load dataset with consistency scores
df = pd.read_csv("merged_multivariate_base.csv")
df = df.dropna(subset=["days_to_hire", "consistency_score", "
   Company_grouped", "country_code", "seniority"])

# 2. Transform target variable
df["log_days_to_hire"] = np.log1p(df["days_to_hire"])

# 3. Reduce infrequent categories
def reduce_categories(series, min_freq=1000):
```

```
    freq = series.value_counts()
    return series.apply(lambda x: x if freq[x] >= min_freq else "
   OTHER")

df["country_code"] = reduce_categories(df["country_code"])
df["Company_grouped"] = reduce_categories(df["Company_grouped"])

# 4. One-hot encode categorical variables
df_encoded = pd.get_dummies(df, columns=["seniority", "
   country_code", "Company_grouped"], drop_first=True)

# 5. Define features and target
X_cols = [col for col in df_encoded.columns if col not in ["
   days_to_hire", "log_days_to_hire", "job_id"]]
X = sm.add_constant(df_encoded[X_cols].astype(float))
y = df_encoded["log_days_to_hire"]

# 6. Fit OLS model
model = sm.OLS(y, X).fit()
print(model.summary())
```

Listing 9: Excerpt from Analysis Code for Hypothesis 6

```
# --- Great-circle distance (km) between two lat/lon points ---
def haversine(lat1, lon1, lat2, lon2):
    R = 6371
    lat1, lon1, lat2, lon2 = map(radians, [lat1, lon1, lat2, lon2])

    dlat = lat2 - lat1
    dlon = lon2 - lon1
    a = sin(dlat/2)**2 + cos(lat1) * cos(lat2) * sin(dlon/2)**2
    c = 2 * atan2(sqrt(a), sqrt(1 - a))
    return R * c

# --- Build dataset for analysis ---
def build_dataset(jobs_df, titles_df, descriptions_df,
   locations_df):
    # Keep only job_ids with a description
    jobs_df = jobs_df.drop_duplicates(subset=["job_id"])
    titles_df = titles_df.drop_duplicates(subset=["job_id"])
    descriptions_df = descriptions_df.drop_duplicates(subset=["
   job_id"])
    locations_df = locations_df.drop_duplicates(subset=["job_id"])

    jobs_df = jobs_df[jobs_df["job_id"].isin(descriptions_df["
   job_id"])]

    df = pd.merge(jobs_df, titles_df, on="job_id", how="inner")
    df = pd.merge(df, locations_df, on="job_id", how="left")

    # Filter: days_to_hire > 6 and valid coordinates
    df = df[df["days_to_hire"] > 6]
    df = df.dropna(subset=["lat_lon"])

    # Convert dates to UNIX timestamps
    df["posted_date"] = pd.to_datetime(df["posted_date"], errors="
   coerce")
    df["last_updated"] = pd.to_datetime(df["last_updated"], errors
   ="coerce")
    df["posted_timestamp"] = df["posted_date"].view("int64") //
   10**9
    df["last_updated_timestamp"] = df["last_updated"].view("int64")
    // 10**9
    return df

# --- Identify overlapping job postings ---
def find_overlapping_jobs(df, start_jobs=None, max_overlaps=50,
   distance_km=15):
    if start_jobs is None:
        start_jobs = df

    results = []
```

```
    for _, row in start_jobs.iterrows():
        if pd.isna(row["lat_lon"]):
            continue

        lat1, lon1 = map(float, row["lat_lon"].split(",␣"))

        # Candidate pool: same company group, job family, country
        cand = df.query(
            "Company_grouped␣==␣@row.Company_grouped␣"
            "&␣`job_family`␣==␣@row['job_family']␣"
            "&␣country_code␣==␣@row.country_code"
        ).dropna(subset=["lat_lon"]).copy()

        # Spatial filter
        cand["distance_km"] = cand["lat_lon"].apply(
            lambda s: haversine(lat1, lon1, *map(float, s.split(",
  ␣")))
        )
        cand = cand[cand["distance_km"] <= distance_km]

        # Temporal overlap
        overlaps = cand["job_id"][
            (row["posted_timestamp"] <= cand["
  last_updated_timestamp"]) &
            (row["last_updated_timestamp"] >= cand["
  posted_timestamp"])
        ].values

        if len(overlaps) > max_overlaps:
            overlaps = overlaps[:max_overlaps]

        # Only retain focal postings with at least 3 overlaps
        if len(overlaps) > 2:
            results.append([row["job_id"], len(overlaps)] + list(
  overlaps))

    # Normalize columns to widest row
    width = max((len(r) for r in results), default=0)
    cols = ["Job_ID", "n"] + [f"Overlap_{i+1}" for i in range(max
  (0, width - 2))]
    return pd.DataFrame(results, columns=cols)

# --- Regression Analysis ---
# 1. Load datasets
df_base = pd.read_csv("merged_multivariate_base.csv")
df_score = pd.read_pickle("final_results.pkl")

# 2. Keep only required columns from score file and merge
df_score = df_score[["job_id", "message_consistency_score"]]
df = pd.merge(df_base, df_score, on="job_id", how="left")
```

```python
# 3. Filter rows with complete data for relevant variables
df = df.dropna(subset=[
    "days_to_hire",
    "message_consistency_score",
    "Company_grouped",
    "country_code",
    "seniority"
])

# 4. Log-transform target variable
df["log_days_to_hire"] = np.log1p(df["days_to_hire"])

# 5. Collapse infrequent categories into 'OTHER'
def reduce_categories(series, min_freq=1000):
    freq = series.value_counts()
    return series.apply(lambda x: x if freq[x] >= min_freq else "
   OTHER")

df["country_code"] = reduce_categories(df["country_code"])
df["Company_grouped"] = reduce_categories(df["Company_grouped"])

# 6. One-hot encode categorical variables
df_encoded = pd.get_dummies(
    df,
    columns=["seniority", "country_code", "Company_grouped"],
    drop_first=True
)

# 7. Define feature matrix (exclude unwanted variables)
X_cols = [
    col for col in df_encoded.columns
    if col not in [
        "days_to_hire",
        "log_days_to_hire",
        "job_id",
        "job␣sub-group",
        "consistency_score"
    ]
]
X = df_encoded[X_cols].astype(float)
X = sm.add_constant(X)  # add intercept

# 8. Define target variable
y = df_encoded["log_days_to_hire"]

# 9. Fit OLS regression model
model = sm.OLS(y, X).fit()

# 10. Output regression summary
print(model.summary())
```

Reflection on the Use of AI Tools

In the course of this dissertation, AI-supported tools such as ChatGPT, GitHub Copilot, and Grammarly were employed in selected areas. Their use was strictly limited to supportive and technically non-critical functions. Specifically, they served as assistance for text translation, linguistic refinement, grammar and spelling checks, as well as stylistic adjustments. Moreover, they provided technical support in coding with Python and LaTeX, including the identification of errors in data analysis, debugging, and code optimization. In addition, AI tools were used for high-level literature exploration and initial orientation in research fields, for support in structuring arguments, chapters, tables, and headings, and for suggestions regarding formatting, terminology consistency, and adaptation to academic style. Finally, they facilitated routine and repetitive tasks, such as checking references, organizing lists, formatting bibliographies, and similar supportive activities.

The application of AI tools was thus confined to linguistic, technical, and organizational support. All conceptual decisions, the theoretical framing, study design, empirical analyses, and the interpretation of results were carried out independently by the author.

Curriculum Vitae

2023–2025	**Ph.D. in Marketing** (September 23, 2025) *University of Mannheim*, Mannheim, Germany
2018–2020	**Master of Science in Business Administration** (August 12, 2020) *University of Mannheim*, Mannheim, Germany
2015–2018	**Bachelor of Science in Business Administration** (June 16, 2018) *University of Mannheim*, Mannheim, Germany