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An empirical analysis of linguistic styles in new work services: The case of Fiverr.com

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Abstract

Current online marketplaces, characterized by a high number of sellers and the velocity of offerings, make service differentiation difficult for sellers. One particularly promising avenue for sellers (in this study: individuals) beyond classical demand-side approaches (i.e., prices) is to employ linguistic descriptions of their offerings. Yet, it remains mostly unclear what constitutes “successful” linguistic strategies. To elaborate on this, the current paper mines more than 2000 unique service offerings on [Fiverr.com](https://www.fiverr.com), a leading online marketplace for freelance services. By distinguishing between different service categories (i.e., hedonic and utilitarian services) and other characteristics of individual sellers (e.g., the origin of a seller), the paper analyzes the linguistic service descriptions via the Linguistic Inquirer and Word Counts (LIWC) and provides an empirical taxonomy of linguistic styles among individuals. Although the paper is novel and explorative, a few interesting insights can be obtained. First, there are significant linguistic differences in how sellers describe their service offerings depending on the service category (hedonic/utilitarian). Second, linguistic proxies of complexity, namely, words per sentence, six-letter words, and the overall word count (i.e., increasing informational content) as well as signals of analytical language, appear to be a beneficial strategy for sellers. Third, a linguistic strategy aimed at matching (congruence) of service categories (hedonic/utilitarian) and linguistic styles (analytical/emotional) appears to be beneficial. The results have important implications for creating linguistic strategies in online marketplaces focused on services on the supply side.

KEYWORDS

computer-aided-content-analysis, platforms, signaling, text-mining

INTRODUCTION

The rise of digital platform business models has led to a steady increase in product and service offerings. Digital service providers such as WeWork, Upwork, or Fiverr provide millions of service offerings to customers in a hunch of seconds. In particular, new trends such as the “gig economy,” where workers offer their services outside of a traditional organizational setup, are expected to grow. Referred to as collaborative, sharing, or gig-economy, such platforms already comprise a \$26 billion

market (Burtch et al., 2018). Similarly, traditional organizations show an increased interest in making use of gig workers for sub-contracting tasks, and recent initial public offerings (IPOs) of microservice providers reflect their increasing economic importance. Microservice providers such as Amazon Mechanical Turk, WeWork, or Fiverr facilitate exchange between a party who wish to hire (i.e., requester) and a contractor (i.e., seller). In 2018, approximately 1.6% of US workers reported income from gig platforms, which was comparable with the total size of the information sector in 2017 (JPMorgan

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Chase, 2018). Although demand and transaction volumes are hard to measure (OECD, 2019), both are set to grow significantly in the following years. Kassi and Lehdonvirta (2018) estimated that demand for gig works increased by 20% annually until 2018. Morgan Stanley (2022) estimates that especially younger people (born between 1997 and 2012) earn more per month from online secondary income than any other cohort (about \$300–\$700 per month). These activities pay on average more than low-wage corporate jobs, indicating an increase in value added for sellers themselves as well as rising demand levels.

In this paper, primarily based on signaling theory (Akerlof, 1970; Spence, 1973), I argue that linguistic styles provide important cues of employability that can be used for signaling by sellers as well as a screening device by requesters. By providing textual cues, sellers disclose voluntary private information that shapes the impression of buyers (i.e., requesters), and these cues reflect consciences as well as subconscious choices (e.g., Pennebaker, Mehl, & Niederhoffer, 2003; Pennebaker & Stone, 2003) that requesters can analyze. In addition, language production is associated with low marginal costs, thereby making it cost-efficient and economically interesting. Although correlative in nature, the contribution of the paper is to shift the focus from demand towards supply side approaches that lie under the seller's discretion (i.e., language) as an important ramification of the seller's effort of self-representation. In other words, linguistic strategies provide important prospects for differentiation because many demand factors (e.g., traffic) cannot be amended by individual gig workers.

To test these propositions, I empirically mined the online profiles of one of the largest freelancing platforms, *Fiverr.com*. As one of the most popular digital work platforms, Fiverr lists more than 2.2 million active requesters in Q2 of 2019, according to its annual report, resulting in a major IPO in 2019. Because linguistic styles might be related to meaningful economic consequences, I then link the obtained linguistic profiles with other relevant economic variables for gig workers (e.g., price). Finally, with the use of the linguistic content and style categories that have been validated across contexts such as blogs, newspapers, or homepages (Tausczik & Pennebaker, 2010) via the Linguistic Inquirer and Word Count (LIWC), I provide an empirical taxonomy of linguistic styles based on hedonic versus utilitarian (Overby & Lee, 2006) service categories. I argue that sellers need to carefully adjust their linguistic description to the context of the gig (i.e., captured in this study via the service category) to meet the audience's expectations. Therefore, as a first contribution, I try to make the first few steps towards a better understanding of freelancing platforms by examining specific linguistic determinates of gig offerings and their correlations with economically important outcomes. Empirically, the article is, to my best knowledge, the first

paper to link validated linguistic dimensions to gig-related economic outcomes. Therefore, the article goes beyond easily observable signals of quality in e-commerce (Boulding & Kirmani, 1993; Mavlanova et al., 2012) and extends the scope to textual properties in the signaling theory in the context of platforms.

A second contribution relates to the usage of content analysis in business research. Although classical qualitative content analytical methods have a long history in business research (Duriau et al., 2007; Krippendorff, 1980), non-obtrusive measures in the realm of quantitative content analysis (Morris, 1994) may therefore circumvent traditional low sample sizes for hard-to-access cohorts compared with classical methods such as interviews (e.g., Baruch & Holtom, 2008). Computerized content analysis may complement or substitute other methods because “language people use in their daily lives can reveal important aspects of their social and psychological worlds” (Pennebaker, Mehl, & Niederhoffer, 2003, p. 547). Unfortunately, “only a very few endeavors have been undertaken to exploit the numerous promising advantages offered by (psycho-)linguistic approaches of analysis, such as automated text analysis” (Cho et al., 2014, p. 4). Moreover, Pfarrer et al. (2010) argue that quantitatively analyzing the content of organizational or individual writing can enhance archival research (which fails to provide insights into cognitive processes) while maintaining the advantages of using large samples and mitigating the problems of small sample qualitative work (external validity).

Consequently, “computerized content analysis has the potential to supplement, extend, and qualify existing leadership theory and practice” (Bligh et al., 2004, p. 562). Therefore, utilizing the existing data via text-mining and quantitative content analysis is an important first step towards a better understanding of large amounts of linguistic data, particularly in these newly formed two-sided markets with many linguistic traces. I employ the term “computer-aided text analysis” (CATA) as a word counting technique to operationalize hard-to-measure, latent constructs across micro, meso, or macro levels and across narratives (e.g., Belderbos et al., 2017; Duriau et al., 2007; McKenny et al., 2013; Short et al., 2010). Moreover, the general focus on language and its quantitative measurement provides avenues to link signaling theory and psychological research as requested in the literature (e.g., Boulding & Kirmani, 1993). The paper proceeds as follows. Section II reviews basic signaling approaches and elaborates on empirical findings on the content and style of narratives in various contexts (e.g., Management or Entrepreneurship). In particular, it introduces different kinds of signals (e.g., *signal observability*) and explains the different incentives of sellers to send signals. Subsequently, hypotheses are developed based on service categories. Section III shows the empirical model. Section IV

depicts the operationalization of variables. Section V discusses the results. Section VI discusses managerial implications, limitations and future research.

LITERATURE REVIEW

An overview of signaling and cheap talk theory and its application can be found in the Appendix S1. In the context of gig workers, written, voluntary descriptions are a highly observable signal for requesters (*signal observability*). Higher performing gig workers (e.g., better educated) also have lower signaling costs (*signal costs*). In contexts of gig workers, textual aspects in the service offerings may be the emphasis on educational degrees, certifications, or other things to induce desirable aspects of human interaction (e.g., reliability and trustworthiness). Spence (1973) does not elaborate on how to judge signals or why certain actions are more credible (*signal honesty*); all that matters is the signal. Category membership (here: service category as introduced in the empirical part) may be a credible signal for high productivity sellers, whereas low productivity sellers incur higher costs with “imitating” category membership. Applied articles in the field of e-commerce have classified warranty as a signal of quality (Boulding & Kirmani, 1993) or have classified strategies such as chatbots, third-party seals, or electronic payments as high-cost signals, while at the same time classifying the ease of verification of signals such as the presence of a store locator, contact policy, or secure transaction (Mavlanova et al., 2012). Unfortunately, textual aspects were not explicitly part of this applied research stream.

Theoretically, making no or a low number of textual statements should be regarded as a very bad quality signal, as dishonest signalers would simply keep silent (Lewis, 2011). However, sellers may choose to freeride in the case of signal dishonesty in categories with a high collective reputation. Requesters in gig contexts are unaware of the characteristics and quality of the gig (Akerlof, 1970) and of the behavioral intentions of the seller. Textual disclosure is, therefore, clearly a key mechanism to signal these aspects to requesters. The literature argues that “cheap talk” exists (i.e., unverifiable and costless cues) and that this strategy can be an effective persuasion strategy (e.g., Austen-Smith & Banks, 2000; Crawford & Sobel, 1982; Farrell & Rabin, 1996). Therefore, it is unlikely that cheap talk is absent in gig work in line with literature on eBay showing that cheap talk can be used to trade-off between price and the probability of sale (Backus et al., 2019; Gregg & Walczak, 2008).

However, platforms enable requesters to report sellers that provide “exceedingly low-quality gigs” or who report marketing activities that are “misleading to buyers or others,” as shown in Fiverr’s terms of use. According to Fiverr’s terms of use, a seller account can be terminated at any time if detected by the platform or reported by

members. In conjunction with classical “soft” reputational tools (e.g., number of ratings), it is unlikely that sellers can only send cheap talk in the long term. Other authors (Moss et al., 2015) argue that disclosing cheap talk has high opportunity costs, as sellers do not choose to disclose credible information-adding information in a setting with finite textual space, thereby making these texts a more costly signal. Complementary theoretical explanations for language use on platforms can be found in the online Appendix S2.

Hypothesis development

On the content side, research indicates that text containing elements of charismatic rhetoric (e.g., metaphors and figurative words) is linked with positive attributes such as charisma or creativity attributions from the audience (Baur et al., 2016; Emrich et al., 2001; König et al., 2018). Related changes in language appear to alter an audience’s perception as they respond to an audience’s demands and actively shape the discourse in a field. For instance, positive and confidence-inducing vocabulary increases the likelihood of funding (time and amount) for new ventures (Anglin, Short, et al., 2018; Anglin, Wolfe, et al., 2018). Hence, entrepreneurs tend to employ more positive emotions and less negative emotions than non-entrepreneurs. At the same time, shareholder-orientated words in chief executive officer (CEO) speech contribute to the appearance of conformity to a prevailing norm, thereby enabling CEOs to enforce higher compensation packages (Shin & You, 2017). Carton et al. (2014) find that vision experimentally (imagery) related words in leader communication contribute to a shared sense of organizational goals, enhancing performance via enhanced coordination. Moreover, these studies point to the fact that content-related word choices require different neural processes by the audience (Boroditsky, 2019; Lai et al., 2019; Rapp et al., 2004).

In the entrepreneurial domain, Payne et al. (2013) show that IPO messages containing more words related to organizational virtues (integrity, warmth, and empathy) are suitable to mitigate social stigmas associated with the origin of the new venture. Parhankangas and Ehrlich (2014) argue that moderate levels of positive vocabulary and moderate usage of innovativeness-related vocabulary enhance crowdfunding success. Kim et al. (2016) study crowdfunding texts and show that the language of accountability is less favorable for crowdfunding success than the language of newness. Parhankangas and Renko (2017) find that concrete language is more important for crowdfunding success of social ventures than abstract language, indicating that textual description must adhere to the expectations of the audience within the expected domain.

Therefore, most studies emphasized the role of certain vocabulary (content) and shared narratives that are

congruent with the expectations of the categories that promote understanding of collective targets and therefore contribute to the success of a gig (e.g., Cai et al., 2019; Parhankangas & Renko, 2017). For instance, analyzing emotional experiences by looking at emotion-related words (e.g., “angry,” “sad,” and “happy”) and their change over time is a standard procedure in psycholinguistics (Pennebaker & Francis, 1996). The summary variables of LIWC represent fundamentally different thinking styles. For instance, analytical language represented by greater article and preposition use is more related to complexly organized objects and concepts (i.e., cognitive complexity), whereas verbs, pronouns, adverbs, conjunctions, and negations indicate fewer usage of analytical language (Pennebaker et al., 2014). As a result, it is less likely to resonate with requesters who have different ways of thinking and personalities (e.g., Hellén & Sääksjärvi, 2011).

Using ad hoc word lists to capture these different cognitive states is commonplace in business research (Pan et al., 2017; Patelli & Pedrini, 2014). The methodological rigor of LIWC facilitates its application to large samples and comparability across studies. Given that each service category represents a unique niche with different audience expectations that need to be addressed, it is reasonable to assume that they differ linguistically in the main thinking styles. Style is a term that refers, at the same time, to singular aspects of an individual’s writing habits or a particular document and to aspects that go well beyond the individual writer, such as the adherence to or deviation from social norms or the expression of social identity (Ray, 2014). Beyond the essential elements of spelling, grammar, and punctuation, the writing style is the choice of words, sentence structure, and paragraph structure used to convey the meaning effectively (Sebranek et al., 2006). Essential elements are referred to as rules, elements, essentials, mechanics, or handbooks, whereas writing styles are referred to as style or rhetoric (Crews, 1977). LIWC offers capabilities to analyze both *what* is said and *how* something is said to determine the description of a concept. For instance, punctuation, question, or exclamation marks analyze the adherence to rules and essentials, whereas the dictionary also offers externally validated, subjective dictionaries rated by third parties to make sense of the subjective thinking world (e.g., causal words, thinking words, or temporal references) of the respondent (e.g., Pennebaker & King, 1999). Therefore, I hypothesize the following:

H1. There will be a significant difference between the linguistic styles, as shown by the master vocabulary and the different service categories.

Marketing-orientated scholars argue that online consumer contexts share similar attributes with gig services, altering consumer behavior and preferences (Overby &

Lee, 2006). I use the concept of utilitarian versus hedonic categories to make a distinction between service categories. The concept is used because it represents a key business research construct whereby individuals are more likely to respond differently to these two types of services (Hellén & Sääksjärvi, 2011; Overby & Lee, 2006) and that these two modes need to be described differently (Chaudhuri et al., 2010). Utilitarian value is defined as an overall assessment of functional benefits and sacrifices, including more references and judgments on cognitive aspects of economic value (Overby & Lee, 2006). Hedonic value is defined as an overall assessment of experiential benefits and sacrifices, such as entertainment and escapism, including references to out-of-routine experiences and avoiding task completion (Overby & Lee, 2006). Thereby, these two categories provide simplistic ideal states with distinct underlying cognitive underpinnings and goals they wish to attain, whereby marketers need to address these fundamental differences through product design or textual framing of products (e.g., Chitturi et al., 2008; Kronrod & Danziger, 2013; Roggeveen et al., 2015). Chaudhuri et al. (2010) and Chitturi et al. (2008) find that these product benefit dimensions (hedonic vs. utilitarian) affect different types of emotions as consumers associate different kinds of goals with hedonic versus utilitarian benefits. Utilitarian benefits are perceived as necessities that help fulfill goals such as safety and security, whereas hedonic benefits are viewed as luxuries that fulfill the goals of pleasure and excitement (Chaudhuri, Aboulnasr, & Ligas, 2010). Hence, for instance, concrete language is characterized by the use of verbs, numbers, and past-focused words compared with abstract language (Elliott et al., 2015; Pan et al., 2017; Semin & Fiedler, 1988), and these word categories (e.g., verbs and numbers) are needed to describe the functional and economic benefits of the service.

In contrast, non-functional service categories (i.e., hedonic) may be more suitable for using emotional language to emphasize the experiential and emotional benefits of the category. For instance, painting a picture with words by using word choices such as “dream” instead of “idea” stimulates emotional responses and is related to higher perceived charisma and creativity (Emrich et al., 2001), whereby individuals acknowledge the pleasure and excitement associated with this category. Evidence from entrepreneurship also suggests that ventures emphasizing linguistically single aspects (social or economic benefits) receive more funding as opposed to ventures that emphasize their hybridity (Moss et al., 2018).

Given these fundamental differential goals and values associated with these categories, it is reasonable to assume that a service category will employ language congruent to its domain. In addition, this congruence strategy should increase *signal credibility* and decrease *signal costs*. Therefore, I hypothesize the following.

H2a. A functional service category such as financial consulting will employ more analytic language than a hedonic service category.

H2b. A hedonic service category such as arts and crafts will employ more emotional language than a functional service category.

While the previous arguments have addressed mainly content and its congruence in relation to the service category, structural aspects of language might be beneficial independently of the service category. Concretized language is perceived as more truthful in experimental settings (Hansen & Wänke, 2010). In addition, brain activity shows that nouns and verbs associated with concreteness are easier to revoke and remember (van Hell & de Groot, 1998). Using foreign language learners, concrete words were easier to learn (de Groot & Keijzer, 2000). Miller et al. (2007) find that messages with concrete language receive more attention, are perceived as more important, and receive more positive assessments of the source. Therefore, Barber et al. (2013) argue that concrete words activate regions in the brain relevant for meaning derivation, whereas less concrete words are used for deriving quick decisions. An analysis of more than 50,000 college students indicates that students using more complex and concrete language (i.e., using function words such as verbs to refer to complexly organized objects) receive higher grades (Pennebaker et al., 2014). Experimental economic research shows that concrete language affects investors' feeling of comfort in their ability to evaluate an investment (Elliott et al., 2015), thereby increasing their probability of investing. In the cohort of top executives, CEOs with higher levels of concreteness induce positive investor responses (Pan et al., 2017), thereby increasing the trust in the statement of the person and the organization.

Although Allison et al. (2017) show that emotionally appealing messages increase crowdfunding success, and vivid based language is linked to higher impressions of charisma and creativity (Emrich et al., 2001), a large number of studies emphasize the value of concrete and analytical language as a superior linguistic strategy. Higher performing gig workers (e.g., better educated) also have lower signaling costs (*signal costs*). In the context of the gig workers, textual aspects may be the emphasis of educational degrees, certifications, or other things to induce desirable aspects of human interaction (e.g., reliability and trustworthiness) instead of emotions. In addition, as previously described, higher performing gig workers (e.g., better educated) have lower signaling costs (signal costs), making this strategy more attractive. Therefore, it is reasonable to assume that an analytical style of writing in the absence of costly cues is more likely to induce trust and other desirable aspects in the offering,

thereby resulting in the association with higher average prices. I propose that this effect can be found in each service category.

H3a. The usage of analytical language is related to higher prices.

H3b. The usage of emotional language is related to lower prices.

THE EMPIRICAL CONTEXT: FIVERR

Until 2019, Fiverr Ltd. was thriving with global internet traffic, among the 200 busiest websites in 2019 in the United States, as estimated via the Alexa Rank. Fiverr facilitates the interaction between sellers and requesters. By sellers, I refer to gig workers, defined as short-term independent freelance workers who contract with organizations for specific short or long-term projects without joining the organizations, or freelance workers who sell directly to the market (Petriglieri et al., 2018). Compared with other online gig platforms such as *Upwork*, which charge for requesters for being on the platform and have auction-price styles depending on demand for the seller, Fiverr does not charge for requesters and enables sellers to set their own price, thereby reducing selection biases stemming from high barriers of entry. Another favorable feature of the platform is that micro-tasks are priced at a minimum of five Dollars, enabling me the neglect other market factors that may affect the characteristics of the gig. Some information on Fiverr is standardized; for instance, sellers need to use standardized headlines "I will ...", and some information is automatically tracked the longer the seller is active on the platform (e.g., ratings), but most of the information is disclosed voluntarily. For instance, the content and the amount of text, photos, educational information, or origin enable sellers to create an individual and representative image of their gig.

The web page created by the seller provides the only observable cue for the requester to estimate the quality of the service offering; without previous experience with the seller and the fact that the quality of the service can only be evaluated ex-post, sellers and requesters have a serious asymmetric information problem. To reduce information asymmetry, the seller is incentivized to provide as much textual information as possible as these cues may contain informational content. On the other hand, the sellers may also have an incentive to employ cheap talk to increase the persuasiveness of information, in particular in the absence of other observable cues, thereby trusting the emotional appeal of the message and accepting the obfuscation of informational content. The main reputational mechanism is the ratings that determine whether sellers adhere to the disclosed information.

OPERATIONALIZATION OF INDEPENDENT VARIABLES

Emotional language and analytical language (language characteristics)

To conduct the analysis, I use the LIWC software. The dictionary has been created over the last decades by observing and gathering participants' writing and by collecting psychometrically established scales and via several different kinds of narratives, such as blogs, articles, essays, or homepages (Pennebaker, Mehl, & Niederhoffer, 2003; Tausczik & Pennebaker, 2010). Using these content analytical procedures via standardized psycholinguistic dictionaries remains an important method in business research to analyze conference calls, letters to shareholders, or annual reports (Pan et al., 2017; Patelli & Pedrini, 2014). Similarly, studying language embedded in narratives such as crowdfunding applications via standardized psycholinguistic dictionaries such as LIWC or DICTION has become an established means in entrepreneurship research (e.g., Moss et al., 2015; Parhankangas & Ehrlich, 2014). The methodological rigor of LIWC facilitates its application to large samples and comparability across studies. Each initial list of words was generated by theory, and independent judges rated the appropriateness of the lists (Pennebaker, Mehl, & Niederhoffer, 2003; Tausczik & Pennebaker, 2010); the author also checked reliability by correlating self-reports to LIWC categories while checking reliability across different narratives such as essays or articles (Pennebaker & Francis, 1996; Tausczik & Pennebaker, 2010). The dictionary focuses on content words (e.g., nouns, verbs, and adjectives), describing the substance, and details of a subject matter responsible for conveying meaning to the requester. Besides content words, written language also includes—easy to overlook yet instrumental to effective communication—function words (e.g., pronouns, conjunctions) that indicate the relationships between the content words and develop a deeper understanding of their structure and meaning (Pennebaker, 2013).

Both categories correspond to predictions such as status perception in groups (Kacewicz et al., 2014) or future academic performance (Pennebaker et al., 2014). It shows clear correlations between writing samples and word choice in clinical (Wolf et al., 2007) or non-clinical samples using established theoretical constructs (e.g., Big 5, Hirsh & Peterson, 2009). For instance, high neurotic individuals show more negative emotions, such as anger, anxiety, and sadness-related words (Hirsh & Peterson, 2009). The dictionary comprises more than 2200 words and has been organized into 74 categories by independent judges. The categories include emotional processes (e.g., positive emotions and negative emotions) and temporal dimensions (e.g., future tense and past

tense) as well as grammatical categories (e.g., exclamation mark). The program counts the number of words that belongs to each category and calculates the percentage of total words that they represent in the text. The program creates two master variables that represents two main thinking styles relevant for the study: **Analytic** and **(Emotional) Tone**. Summary variables are percentiles based on standardized categories and therefore have no raw frequencies. In other words, the main dimensions are created by summing up the sub dimensions, which are also standardized for text length. Pennebaker et al. (2014) show that individuals high in analytical language use more articles, more prepositions, fewer auxiliary verbs, fewer adverbs, and fewer negations of the respective LIWC categories. In other words, LIWC will create a function that sums up the sub-dimensions “article” and “preposition” but subtracts the sub-dimensions “auxiliary verb,” “conjunction,” “adverb,” or “negation” to create the master variable Analytical tone (Pennebaker et al., 2014; Tausczik & Pennebaker, 2010).

Similarly, Cohn et al. (2004) show before and after September 11 in diaries of 1084 US citizens that the emotional tone is the subtract of the LIWC categories positive emotions and negative emotions (*Posemo – Negemo*). In other words, positive and negative words may fluctuate, but their sum will show the overall emotionality in the text, leading to the master variable of emotional tone. The two other master variables are **Clout** and **Authentic** (Tausczik & Pennebaker, 2010) that have been used—individually or in conjunction—in several studies (e.g., D'Acunto et al., 2020; D'Acunto & Volo, 2021; Duncan et al., 2019). I also collect the variables **word count** (WC), **words per sentence** (WPS), and **words with more than six letters** (Sixlet) that reflect the quantity of text and cognitive complexity of the text.

Seller characteristics

Status of the seller

Fiverr automatically attributes status to sellers that fulfill financial and nonfinancial conditions. There are three different conditions: “Level 1,” “Level 2,” and “Top-rated.” Level 1 requires sellers to complete at least 10 individual orders (over the course of 60 days); earn at least \$400; maintain a 4.7-star rating over the course of 60 days; a 90% response rate over the course of 60 days; and 90% order completion over the course of 60 days; 90% response rate over the course of 60 days; 90% order completion over the course of 60 days. “Top-rated” sellers have the highest requirements; for instance, they need to earn at least \$20,000. I transform this into an ordinal scale ranging from 0 (no rating) to 3 (top-rated). This is similar to research on market places like eBay (e.g., Lewis, 2011; Song & Baker, 2007).

Origin/cultural dimensions

Sellers can choose to disclose information about their origin. I observe and mine the country of origin, such as “France,” and then match the data set with Hofstede’s cultural dimensions using a tailored Excel command. The data set, therefore, contains the four main dimensions of the Hofstede study that are matched with the country of origin: Power Distance, Uncertainty Avoidance, Individualism, Masculinity, and Long/Short Orientation.

Number of seller reviews

Sellers receive a review by a requester after the order is delivered. More active and mature sellers with several gigs online may receive more reviews. This is a scale variable similar to research on market places like eBay (e.g., Lewis, 2011; Song & Baker, 2007).

Number of stars of the seller

Sellers receive a star rating ranging from 1 to 5 from the platform. Higher-quality gigs may receive higher ratings. The captured values include mean values that range from 1 to 5. Hence, the number of reviews and the number of stars depict central reputational mechanisms on the platform. This is similar to research on market places like eBay (e.g., Lewis, 2011, Song & Baker, 2007).

Several entries

Sellers, particularly full-time sellers, may be incentivized to list several offerings. The dummy variable receives a 1 if the seller’s name appears at least twice in the data set; otherwise, 0. Hence, this may capture imbalances in the activity of the sellers and their number of reviews or stars.

Developed country

This measure is based on the origin variable and assigns dummy variables if the country of origin is based among the seven highest developed countries (G7) Canada, France, Germany, Italy, Japan, the United Kingdom, and the United States. As these countries represent a large share of the world’s gross domestic product, these dummies may be able to capture macro-level economic prosperity. For instance, sellers outside G7 countries may have lower opportunity costs, affecting activity levels and reputational means.

Gig characteristics and outcomes

Price

Sellers may choose a price that reflects the underlying value of their gig. Price is observed as a scale variable in Dollars for a standard gig. The platform offers sellers the ability to provide more sophisticated pricing options, including faster services or more revisions. The price for these offerings is not observed. Although success for gig workers is much more ambiguous and uncertain than traditional work arrangements as they pursue various economic and non-economic goals (Petriglieri, Ashford, & Wrzesniewski, 2018), the price remains an important indicator of economic magnitude (e.g., Lewis, 2011, Song & Baker, 2007).

Delivery

The seller reports the number of days the gig will be delivered. Delivery is a scale variable in days.

Number of revisions

The number of revisions the seller is willing to make in case the buyer wants revisions. The option “unlimited” is for unlimited revisions. All values are mined as scale variables. As the number of revisions is generally low, I recode “unlimited” as a 10, thereby reflecting the discrepancy between low and “unlimited” revisions.

Average response time

Fiverr calculates the average response time by sellers to inquiries of requesters. These can be very detailed. I recorded the values in 1 (days) and 2 (hours). For instance, 14 days or 2 days will be counted as 1, and 2 or 23 h will be counted as 2.

Service categories

The platform has a number of different service categories. To choose categories, I consult the marketing literature (see Hypothesis development section). Most of these studies argue that consumers derive different utilities based on a product category and that different presentation styles affect consumer preferences via a product category (Kronrod & Danziger, 2013; Overby & Lee, 2006; Roggeveen et al., 2015). Although this does not imply that service and product categories are equal, this gives face validity to the choice of service categories. These are Creative writing (1), Digital Marketing/Marketing

Strategy (2), Financial Consulting (3), and Arts& Crafts (4). Arts and Crafts and Creative Writing can be assigned to hedonic categories due to their out-of-routine experience and entertainment purposes (Overby & Lee, 2006).

In contrast, Financial Consulting and Digital Marketing/Marketing Strategy can be assigned to the utilitarian category as they relate to economic value (Overby & Lee, 2006). By selecting two service categories for each hedonic/utilitarian value, I can minimize unobservable biases stemming from the service categories. For instance, based on the data set, sellers in the category Arts and Crafts refer to service titles such as “I will make you a cute paper flower ring” or “I will mail a handwritten letter from Santa with a north pole postmark to someone”; sellers in the Financial Consulting category use service titles such as “I will get you debt financing for projects and business growth” or “I will make profit and loss and income statement for your business.” These examples from the data provide face validity that the gigs are described differently in hedonic and utilitarian categories.

The data gathering process and descriptive results

The main data source is a scraped collection of gig profiles as well as linked seller profiles on [Fiverr.com](https://www.fiverr.com). The scraping is implemented via a commercial text-mining software named *WebHarvey*. Although web scraping can be conducted in freely available software such as *R*, the chosen software was used due to the quickness of its algorithm, usability, and the possibility to export results in machine-readable formats (e.g., Excel) necessary to connect several data sources. The scraping was conducted in one process for each category but at different times across categories and included all the gigs the platform offered in the respective service category at the time of the scraping. These strategies are used (1) to increase the number of cases and, therefore, the explanatory power of the data and (2) to impede the blocking of the IP address by the target server. Although the data are free to users, most servers have mechanisms to detect automated, large data scraping efforts. To mitigate these concerns, further precautionary measures via the software were implemented. Firstly, the option “Inject pauses during mining” was employed to enable random (small and large) breaks to mirror human behavior (e.g., fatigue). Secondly, the option “Disable cookies while mining” was activated to allow the software to delete local cookies on the PC to conceal identity. Thirdly, the option “Scrape via Proxy Server” was enabled to use a single proxy server or a list of proxy servers for web scraping. Taken together, these strategies enable the gathering of larger data sets compared with manual scraping but simultaneously increase the resource intensity (especially time) compared with automated web scraping without these precautionary measures. After finishing the process and receiving results

in machine-readable format (Excel), I drop double entries but retain cases with a dummy variable if a seller offers several gigs simultaneously. I also observe the entire service offerings across a service category as displayed on Fiverr, thereby reducing the possibility of biases through the non-random display of results through the platform. I then select four service categories as described in theory. The original data set contains more than 10,000 observations across the four categories. Because Fiverr and other platforms show anomalies like changing HTML structures to impede large web scraping processes and the list of variables is comprehensive (i.e., sellers are not obligated to disclose all the information captured by the variables), the initial data set contains a significant number of missing values. In other words, the described precautionary measures tend to inflate the number of cases while, simultaneously, the large number of voluntary disclosures of sellers on the platform make missing entries more likely. In addition, algorithmic error leads to incorrect scraping of some cases, such as random strings instead of words. These cases were detected and deleted. Only unique and correct cases with complete disclosures were retained for the analysis. Although this leads to a significant decrease in sample size, this is the most conservative assumption and retains sufficient cases.

After cleaning the data, 2600 observations can be made across four service categories. Table 1 in Appendix S2 summarizes the variables in the data set in a structured way. Each set contains several items attributable to the gig, such as the number of stars, number of reviews, price, or orders in the queue that are not under the seller’s discretion. The main linguistic variable “gig description” is collected in Excel, converted subsequently into text format (.txt), and exported to LIWC. The analyzed linguistic results of LIWC are exported and then matched with the structural results of the sellers in a master file. One can see from these results that the average number of stars is highly right-skewed, with an average number of stars of 4.8, indicating that most sellers receive an average rating of four to 5 stars. Somewhat different is the number of reviews of the gig with an average number of 32.95 but a high standard deviation (108.96), indicating high contrast between “well” and “bad” performing gigs. The average order in the queue is 12.61. The average price of a gig is \$25.42 with a high SD, again showing a high variance of prices across the sample. About 40% of sellers report more than one gig. The average WC is relatively low, with 100.77 with a high SD, indicating considerable differences in how sellers describe their offerings. The descriptive results show the first hints about the differential usage of the language across categories as well as within variance. Whereas both utilitarian categories show similar average WCs, Creative Writing (hedonic) employs almost twice as much information transmission as Arts and Crafts (hedonic). These results also provide hints for considerable within-group variance. The main language variables are scaled and

TABLE 1 Correlative results of the study

Variable	Mean	SD	1	2	3	4	5	6	7	8	9	10	11	12	13	14
1 Number of stars of the gig	4.879	0.376	1	0.036	0.035	0.004	-0.018	0.070	0.765**	0.057	-0.062	-0.003	0.000	-0.016	-0.008	-0.033
2 Number of reviews of the gig	22.601	81.228	0.036	1	0.308**	-0.028	0.050	-0.010	0.048	0.394**	0.051	0.010	0.051	0.009	0.036	-0.001
3 Orders in Queue	12.612	46.922	0.035	0.308**	1	-0.040	-0.024	-0.053	0.053	0.316**	-0.030	0.013	0.008	0.006	0.050	-0.026
4 Price	25.422	57.305	0.004	-0.028	-0.040	1	0.275**	-0.006	0.061	-0.029	0.005	0.107**	0.056	-0.015	-0.010	-0.036
5 Delivery in days	3.017	3.058	-0.018	0.050	-0.024	0.275**	1	-0.039	0.019	0.087	0.024	-0.013	0.000	0.056	0.014	-0.006
6 Revision	4.684	4.038	0.070	-0.010	-0.053	-0.006	-0.039	1	0.035	-0.037	0.013	0.009	-0.034	0.024	0.112	0.053
7 Number of stars of seller	4.729	0.783	0.765**	0.048	0.053	0.061	0.019	0.035	1	0.111**	-0.132	0.065	0.019	-0.048	-0.062	-0.116
8 Number of reviews of the seller	99.003	201.574	0.057	0.394**	0.316**	-0.029	0.087	-0.037	0.111**	1	0.066	0.002	0.033	0.010	-0.016	0.039
9 Recent Delivery Code	1.407	0.491	-0.062	0.051	-0.030	0.005	0.024	0.013	-0.132	0.066	1	-0.063	0.003	0.013	0.020	0.047
10 Analytic	58.230	30.254	-0.003	0.010	0.013	0.107	-0.013	0.009	0.065	0.002	-0.063	1	0.565	0.247	0.530	-0.213
11 Clout	67.133	31.410	0.000	0.051	0.008	0.056	0.000	-0.034	0.019	0.033	0.003	0.565	1	0.190	0.634	-0.236
12 Authentic	28.384	26.052	-0.016	0.009	0.006	-0.015	0.056	0.024	-0.048	0.010	0.013	0.247	0.190	1	0.274	-0.085
13 Tone	66.812	35.465	-0.008	0.036	0.050	-0.010	0.014	0.112	-0.062	-0.016	0.020	0.530	0.634	0.274	1	-0.214
14 Dummy Same seller (1 if the same seller)	0.425	0.494	-0.033	-0.001	-0.026	-0.036	-0.006	0.053	-0.116	0.039	0.047	-0.213	-0.236	-0.085	-0.214	1
15 Average Response Time code	1.767	0.423	0.008	0.058	0.001	0.037	-0.014	-0.033	-0.044	0.103	0.355	-0.037	0.014	-0.017	-0.003	0.043
16 WC	100.765	67.147	0.025	0.109**	0.043	0.110**	0.115	0.096	0.118	0.097	-0.076	0.463	0.530	0.196	0.503	-0.204
17 WPS	16.657	13.076	-0.037	-0.007	-0.005	0.058	-0.071	0.083	0.000	-0.040	-0.025	0.438	0.391	0.194	0.344	-0.139
18 Sixtr	22.129	12.156	0.004	-0.001	-0.014	0.132	-0.090	0.224	0.107	-0.085	-0.036	0.708	0.531	0.250	0.484	-0.224
19 Status of seller	1.389	0.654	0.035	0.267**	0.179	0.113	0.116	0.004	0.093	0.402	0.149	0.001	0.058	0.027	0.081	0.060
20 Power Distance	25.632	28.216	-0.027	-0.011	0.051	0.012	0.015	-0.120	0.017	0.029	0.022	0.281	0.241	0.248	0.160	-0.055
21 Uncertainty Avoidance	26.612	28.563	-0.011	-0.003	0.009	0.029	0.019	-0.077	0.033	0.015	-0.010	0.274	0.233	0.263	0.177	-0.069
22 Individualism (vs. Collectivism)*	29.066	37.344	-0.027	0.042	-0.005	0.114	0.128	-0.252	-0.013	0.035	-0.027	0.207	0.259	0.157	0.163	-0.086
23 Masculinity (vs. Femininity)*	28.319	29.043	-0.028	0.018	0.019	0.063	0.063	-0.181	0.011	0.031	-0.011	0.281	0.276	0.241	0.191	-0.079
24 Long/Short-term Orientation*	11.716	18.548	-0.026	0.012	0.006	0.079**	0.091	-0.215	-0.021	0.065	0.024	0.179	0.224	0.129	0.118	-0.066
25 G7 US	0.159	0.366	0.001	0.072**	-0.017	0.155	0.115	-0.202	0.035	0.009	-0.069	0.133	0.177	0.068	0.104	-0.085
26 G7 France	0.002	0.043	-0.081**	-0.006	-0.005	0.055	0.012	-0.040	0.004	-0.016	0.008	0.042	-0.002	-0.023	-0.008	0.015
27 G7 Italy	0.008	0.090	0.014	-0.008	-0.016	0.048	-0.043	-0.080	0.025	0.011	0.034	0.010	0.028	0.006	-0.006	-0.011
28 G7 Canada	0.014	0.119	0.000	-0.013	-0.009	0.023	0.080	-0.067	0.023	0.003	-0.013	0.046	0.018	0.033	0.024	0.031
29 G7 Germany	0.006	0.080	0.008	0.026	0.036	-0.004	0.000	0.003	0.024	-0.002	0.017	0.014	0.052	-0.010	0.024	-0.050
30 G7 United Kingdom	0.033	0.180	0.016	0.036	0.012	0.064	0.063	0.085	0.044	0.027	-0.005	0.056	0.077	0.019	0.051	-0.025
31 G7 Japan	0.001	0.027	0.008	-0.003	-0.006	0.006	0.006	0.007	0.007	0.067	0.038	0.004	0.014	-0.004	0.007	-0.024
32 Number (LIWC)	3.322	14.309	0.026	-0.024	0.003	-0.016	-0.009	0.019	0.059	-0.054	-0.094	0.069	0.059	-0.018	0.105	-0.134
33 Quant (LIWC)	0.157	1.590	-0.003	0.005	-0.003	-0.017	-0.031	-0.034	0.023	-0.035	-0.036	0.009	0.039	-0.009	0.051	-0.014
34 Posemo (LIWC)	1.612	6.568	0.036	0.098**	0.016	0.001	0.014	0.026	0.065	0.022	0.011	0.068	0.091	-0.036	0.137	-0.059

TABLE 1 (Continued)

Variable	Mean	SD	1	2	3	4	5	6	7	8	9	10	11	12	13	14
35 Negemo (LIWC)	0.064	1.232	0.010	-0.007	-0.002	-0.013	0.040	-0.046	0.018	-0.011	0.021	0.003	-0.002	0.049*	0.033	-0.013
36 Anx (LIWC)	0.015	0.483	-0.013	-0.006	-0.004	-0.010	-0.020	-0.017	0.004	-0.014	-0.010	0.025	0.023	-0.017	0.007	-0.027
37 Anger (LIWC)	0.004	0.215	0.008	0.027	0.051*	0.014	0.012	-0.040	0.008	0.022	-0.019	-0.014	0.019	-0.011	0.018	-0.017
38 Sad (LIWC)	0.019	0.968	0.008	-0.005	-0.005	-0.009	0.060	-0.040	0.008	0.002	0.027	-0.004	-0.025	0.048*	0.018	-0.017

*Cannot be computed because at least one of the variables is constant.

**Correlation is significant at the 0.01 level (two-tailed).

*Correlation is significant at the 0.05 level (two-tailed).

TABLE 1 (Continued)

	15	16	17	18	19	20	21	22	23	24	25	26
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16	0.019	1	0.388**	0.396**	0.092*	0.123**	0.126**	0.177**	0.166**	0.118**	0.190**	-0.011
17	0.009	0.388**	1	0.441**	0.017	0.167**	0.176**	0.092**	0.160**	0.062**	0.064**	0.009
18	-0.056*	0.396**	0.441**	1	-0.017	0.294**	0.306**	0.110**	0.257**	0.110**	0.087**	0.041*
19	0.193**	0.092*	0.017	-0.017	1	0.012	-0.017	-0.067	-0.036	0.028	-0.071	-0.006
20	0.015	0.123**	0.167**	0.294**	0.012	1	0.846**	0.557**	0.882**	0.634**	0.260**	-0.045*
21	0.005	0.126**	0.176**	0.306**	-0.017	0.846**	1	0.596**	0.886**	0.403**	0.347**	-0.046*
22	-0.003	0.177**	0.092**	0.110**	-0.067	0.557**	0.596**	1	0.826**	0.734**	0.848**	-0.039
23	0.001	0.166**	0.160**	0.257**	-0.036	0.882**	0.886**	0.826**	1	0.659**	0.593**	-0.048*
24	0.014	0.118**	0.062**	0.110**	0.028	0.634**	0.403**	0.734**	0.659**	1	0.477**	-0.031
25	-0.039	0.190**	0.064**	0.087**	-0.071	0.260**	0.347**	0.848**	0.593**	0.477**	1	-0.019
26	0.024	-0.011	0.009	0.041*	-0.006	-0.045*	-0.046*	-0.039	-0.048*	-0.031	-0.019	1

TABLE 1 (Continued)

	15	16	17	18	19	20	21	22	23	24	25	26
27	0.022	0.020	0.020	0.002	-0.018	-0.095 ^{**}	-0.097 ^{**}	-0.081 ^{**}	-0.102 ^{**}	-0.066 ^{**}	-0.040 [*]	-0.004
28	-0.021	0.058 ^{**}	0.028	0.050 ^{**}	0.030	0.065 ^{**}	0.103 ^{**}	0.188 ^{**}	0.112 ^{**}	0.084 ^{**}	-0.052 ^{**}	-0.005
29	0.009	0.033	0.005	0.011	-0.061	0.030	0.123 ^{**}	0.093 ^{**}	0.119 ^{**}	0.095 ^{**}	-0.035	-0.003
30	-0.021	0.110 ^{**}	0.022	0.048 [*]	-0.078	-0.194 ^{**}	-0.199 ^{**}	-0.166 ^{**}	-0.208 ^{**}	-0.135 ^{**}	-0.081 ^{**}	-0.008
31	0.017	0.045 [*]	0.004	-0.007	0.010	0.031	0.072 ^{**}	0.014	0.072 ^{**}	0.115 ^{**}	-0.012	-0.001
32	-0.075 ^{**}	0.050 ^{**}	-0.001	0.060 ^{**}	-0.158 ^{**}	-0.007	-0.001	0.090 ^{**}	0.040	0.058 ^{**}	0.128 ^{**}	-0.010
33	-0.022	0.047 [*]	0.005	0.009	-0.012	-0.031	-0.020	-0.007	-0.019	-0.023	0.032	-0.004
34	-0.025	0.186 ^{**}	0.010	0.095 ^{**}	0.069	-0.026	0.002	0.048 [*]	0.014	0.002	0.116 ^{**}	0.042 [*]
35	0.009	0.036	-0.001	0.005	0.023	-0.006	-0.018	-0.023	-0.008	-0.016	-0.013	-0.002
36	-0.022	0.015	0.000	0.022	-0.025	0.015	0.025	0.002	0.016	-0.008	0.010	-0.001
37	0.012	0.013	-0.005	-0.004	0.039	-0.020	-0.021	-0.017	-0.022	-0.014	-0.008	-0.001
38	0.012	0.003	-0.008	-0.003	0.039	-0.020	-0.021	-0.017	-0.022	-0.014	-0.008	-0.001

TABLE 1 (Continued)

	27	28	29	30	31	32	33	34	35	36	37	38
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TABLE 1 (Continued)

	27	28	29	30	31	32	33	34	35	36	37	38
21	-0.097 ^{***}	0.103 ^{***}	0.123 ^{***}	-0.199 ^{***}	0.072 ^{***}							
22	-0.081 ^{***}	0.188 ^{***}	0.093 ^{***}	-0.166 ^{***}	0.014							
23	-0.102 ^{***}	0.112 ^{***}	0.119 ^{***}	-0.208 ^{***}	0.072 ^{***}							
24	-0.066 ^{***}	0.084 ^{***}	0.095 ^{***}	-0.135 ^{***}	0.115 ^{***}							
25	-0.040 [*]	-0.052 ^{***}	-0.035	-0.081 ^{***}	-0.012							
26	-0.004	-0.005	-0.003	-0.008	-0.001							
27	1	-0.011	-0.007	-0.017	-0.002							
28	-0.011	1	-0.010	-0.022	-0.003							
29	-0.007	-0.010	1	-0.015	-0.002							
30	-0.017	-0.022	-0.015	1	-0.005							
31	-0.002	-0.003	-0.002	-0.005	1							
32	0.037	0.019	0.051 ^{***}	-0.004	0.018							
33	-0.009	-0.012	-0.008	0.036	-0.003	-0.016	1	0.101 ^{***}	-0.005	-0.003	-0.002	-0.002
34	-0.007	-0.025	-0.020	0.070 ^{***}	0.019	-0.050 [*]	0.101 ^{***}	1	0.022	0.054 ^{***}	-0.005	-0.005
35	-0.005	-0.006	-0.004	0.073 ^{***}	-0.001	-0.012	-0.005	0.022	1	0.391 ^{***}	0.174 ^{***}	0.785 ^{***}
36	-0.003	-0.004	-0.003	-0.006	-0.001	-0.007	-0.003	0.054 ^{***}	0.391 ^{***}	1	-0.001	-0.001
37	-0.002	-0.002	-0.002	0.104 ^{***}	-0.001	-0.004	-0.002	-0.005	0.174 ^{***}	-0.001	1	0.000
38	-0.002	-0.002	-0.002	-0.004	-0.001	-0.004	-0.002	-0.005	0.785 ^{***}	-0.001	0.000	1

^aCannot be computed because at least one of the variables is constant.

^{**}Correlation is significant at the 0.01 level (two-tailed).

^{*}Correlation is significant at the 0.05 level (two-tailed).

standardized between 0 and 99 and have high standard deviations, indicating that the master variables are used differently across categories. For instance, utilitarian categories appear to use, on average fewer emotions (65.56; 64.57 vs. 71.44; 65.80) in line with theory. Based on WPS and in line with the theory, utilitarian categories appear to be more complexly structured than hedonic categories. Table 1 reports the correlative results of the data. Table 1 contains not just essential variables as in Table 1 in Appendix S2 but expands its scope by incorporating sub-dimensions of the language. For instance, it might be interesting not just to study the presence of emotional language but also which emotions (e.g., negative emotions such as “anger” or “sad”) are encountered and can be seen as linguistic control variables. In Appendix S2, you can find an example of four actual gig descriptions used for the study. In Appendix S2, you can find examples of the LIWC words.

RESULTS

Correlative results suggest that the number of stars a gig receives is only slightly positively related to the number of reviews ($r = 0.036$, $p = 0.144$) and only slightly related to the price ($r = 0.004$, $p = 0.895$). However, the number of stars of a gig is significantly related to the number of stars of sellers ($r = 0.765$, $p = 0.00$) and the number of reviews ($r = 0.057$, $p = 0.031$). This indicates a strong path-dependency of successful sellers. G7 sellers are given fewer stars ($r = -0.081$, $p = 0.001$). Gigs with more reviews have more orders in the queue ($r = 0.308$, $p = 0.00$) and are also associated with the number of reviews of the seller ($r = 0.394$, $p = 0.000$). Gigs with a higher WC show more reviews ($r = 0.109$, $p = 0.000$) and obtain a higher status with the platform ($r = 0.267$, $p = 0.000$). Gigs from the United States receive the highest number of reviews ($r = 0.072$, $p = 0.003$). Sellers with higher ratings can enforce slightly higher prices ($r = 0.061$, $p = 0.024$). Higher prices are linked significantly to higher analytical linguistic styles ($r = 0.107$, $p = 0.000$) and clout tone ($r = 0.056$, $p = 0.019$). In addition, higher prices are related to linguistic proxies of complexity, namely, WPS ($r = 0.110$, $p = 0.000$) and six letters ($r = 0.132$, $p = 0.000$) and information transmission (WC, $r = 0.110$, $p = 0.000$). In addition, higher prices are associated with a higher status of the seller ($r = 0.113$, $p = 0.034$). Sellers with more stars employ a language style that is significantly more analytical ($r = 0.065$, $p = 0.004$) and less authentic ($r = -0.048$, $p = 0.034$) and emotional ($r = -0.62$, $p = 0.006$). Sellers with just one offering receive, on average, more star ratings ($r = -0.116$, $p = .000$). Similarly to price, sellers with more stars employ more complex language as proxied by six letters ($r = 0.107$, $p = 0.000$) and more textual disclosure (WC, $r = 0.118$, $p = 0.000$).

The one-way analysis of variance (ANOVA) revealed a statistically significant difference between language

styles as measured by the LIWC master variables and the four service categories. Analytical style ($F(3, 2659) = 25.334$, $p = 0.000$), clout ($F(3, 2659) = 16.189$, $p = 0.000$), authentic ($F(3, 2659) = 22.447$, $p = 0.000$), and emotional tone ($F(3, 2659) = 5.122$, $p = 0.002$) show highly significant differences. Therefore, I reject the null hypothesis (Hypothesis 1), which means linguistic master styles do not differ. A Tukey post hoc test reveals that the differences are not significant between groups 1 and 2 (analytic, $p = 0.398$) and not significant between groups 4 and 2 (emotional tone, $p = 0.999$) and groups 2 and 3 (emotional tone, $p = 0.956$). Category 1 has the highest emotional tone, whereas category 3 has the highest authentic language but the lowest emotional tone. Figure 1 in Appendix S2 graphically indicates that the analytical language across both hedonic categories (“Arts & Crafts” and “Creative Writing”) is, on average, lower than in utilitarian categories. Similarly, emotional tone is, on average, the highest in the two hedonic categories (“Creative writing” and “Arts and Crafts”), as shown in Table 1 or Figure 1 in Appendix S2. Thus, I find evidence for Hypotheses 2a and 2b.

As I find significant bivariate correlations between the price and the linguistic style “analytical” but do not find significant results in the first ordinary least squares (OLS) model, I suspect interaction terms. I follow recommendations by Brambor et al. (2006) and create four additional dummy variables to account for interaction effects.

In Hypothesis 3, I proposed that more analytical service offerings are related to higher prices. To test this, I use the two master variables as predictors only in the first step and enter the two main categories, “authentic” and “clout.” Again, LIWC summary variables are percentiles based on standardized categories, rather than raw frequencies. I neglect other structural elements such as Six Letter Words (analytical language: $b = 0.708$, $p = 0.00$) and content elements such as Positive Emotions as they are sufficiently covered by the master variables. Table 2 shows the results of the multiple regression models with inserted variables. Model 1 uses only the hypothesized variables analytic and emotional tone. The results indicate that a unit increase of analytical language increases the price by 0.209 (unstandardized) and 0.098 (standardized) ($p = 0.092$), whereas emotional tone does not significantly affect the emotional tone ($p = 0.306$). The variance inflation factors (VIFs) remain under control throughout the models and remain under 8, thereby reducing concerns regarding multicollinearity. Model 2 inputs the moderator variables that have been created before via the dummy variables: creative writing (hedonic), digital marketing (utilitarian), financial consulting (utilitarian), and arts and crafts (hedonic). Model 3 inputs the master variables “Clout” and “Authentic” as well as WC as control variables for the language. Model 4 adds the seller’s status (whether the gig’s seller has several gigs) and the origin of the seller (dummy variables

TABLE 2 OLS results with dependent variable price and variance inflation factors (VIFs)

Variables	Model 1			Model 2			Model 3			Model 4			Model 5		
	<i>b</i> (un.)	<i>b</i>	<i>p</i> value	<i>b</i> (un.)	<i>b</i>	<i>p</i> value	<i>b</i> (un.)	<i>b</i>	<i>p</i> value	<i>b</i> (un.)	<i>b</i>	<i>p</i> value	<i>b</i> (un.)	<i>b</i>	VIF
(Constant)	6.476		0.573	5.960		0.607	-5.313		0.772	-4.494		0.807	-63.048		0.264
Analytic	0.209	0.066	0.092	0.145	0.045	0.351	0.136	0.043	0.387	0.188	0.059	0.234	0.156	0.049	0.301
Emotion Tone	0.098	0.040	0.306	0.042	0.017	0.736	-0.055	-0.022	0.670	-0.034	-0.014	0.793	-0.110	-0.045	0.382
Emotion × Financial Consulting				0.229	0.145	0.131	0.290	0.184	0.059	0.272	0.172	0.079	0.371	0.235	0.013
Analytic × Creative Writing				0.074	0.042	0.678	0.052	0.030	0.770	-0.026	-0.015	0.884	0.025	0.014	0.887
WC							0.127	0.115	0.007	0.112	0.102	0.017	0.113	0.102	0.012
Clout							0.096	0.028	0.509	0.058	0.017	0.688	0.088	0.025	0.530
Authentic							-0.184	-0.069	0.098	-0.199	-0.075	0.072	-0.270	-0.101	0.011
Dummy Same seller (1 if the same seller)										-9.029	-0.069	0.080	-10.569	-0.080	0.033
G7 US										18.465	0.132	0.001	12.426	0.089	0.022
G7 France										-14.393	-0.009	0.815	-23.754	-0.015	0.686
G7 Italy										3.407	0.006	0.868	5.706	0.011	0.771
G7 Canada										-0.902	-0.002	0.957	-13.424	-0.031	0.405
G7 Germany										-28.451	-0.031	0.419	-34.022	-0.037	0.311
G7 United Kingdom										22.793	0.085	0.030	17.169	0.064	0.088
Number of stars of the Gig													-2.510	-0.011	0.807
Number of reviews of gig													-0.039	-0.064	0.127
Number of stars of seller													12.387	0.045	0.305
Number of reviews of seller													0.006	0.018	0.678
Orders in Queue													-0.144	-0.064	0.095
Delivery in days													6.137	0.300	0.000
R^2	0.006			0.018			0.036			0.063			0.157		
Adj. R^2	0.003			0.012			0.025			0.042			0.131		

Abbreviation: OLS, ordinary least squares.

for G7 countries). The final Model 5 adds the seller's success elements and reputation aspects. This includes the number of stars of the gig and the number of stars of the sellers or orders in queue. In the final model, R^2 and adjusted R^2 increase to 15.7% and 13.1% of explained variance. In the final Model 5, analytical ($p = 0.301$) and emotional tone ($p = 0.382$) become insignificant. The moderator's emotional tone \times the category financial consulting becomes significantly positive ($p = 0.013$). In addition, WC becomes significantly positive with unstandardized beta values of 0.113. In addition, authentic languages become negatively related to price with beta values of -0.270 ($p = 0.11$). The G7 dummies "The United Kingdom" ($p = 0.88$) and "US" ($p = 0.22$) become positively significant, indicating that sellers from those countries can enforce higher prices. To further inspect the relationship between the language categories, dependent variable, and service, I report correlational statistics in Table 4 in Appendix S2. There appears to be a negative yet insignificant relationship between emotional tone and price ($p = 0.684$) and a direct positive, significant relationship between analytical language and price ($p = 0.000$). The results indicate that there is a direct positive, significant relationship between analytical language and price (Hypothesis 3a). Hypothesis 3b states that there is a negative relationship between emotional style and price, which can be partially confirmed although this relationship is not significant. The analytical style \times digital service category (utilitarian) and the price are significantly related ($r = 0.188$, $p = 0.00$), as well as the moderator analytic style \times financial consulting and price ($r = 0.066$, $p = 0.006$). In contrast, analytical style \times arts and crafts and price are negatively related ($r = -0.137$, $p = 0.000$), as well as emotion \times arts and crafts ($r = -0.150$, $p = 0.000$). In contrast, emotion \times digital marketing strategy and price are positively related ($r = 0.112$, $p = 0.000$). Emotion \times financial consulting and price are significantly positively related ($r = 0.077$, $p = 0.001$). These results suggest that employing rhetoric congruent to its category (Hypothesis 3) is a beneficial strategy for sellers. The positive relationship between price and analytical language is being reinforced in both service categories (digital marketing/strategy and financial consulting). However, the effect is more pronounced in the digital marketing strategy service category. The paper finds evidence that in at least one of two service categories (arts and crafts), incongruence between rhetoric and service category (i.e., employing analytical language in a hedonic category) significantly negatively affects the price. Interestingly, the emotional language employed in the congruent service category (emotion \times arts and crafts) decreases the negative relationship between emotional language and price. I find that deliberate deviation from the congruency hypothesis can be beneficial (e.g., emotional language \times digital strategy; emotional \times financial consulting), but this effect is in no case larger than the

congruence assumption. For instance, employing emotional language in a digital marketing category (incongruence) positively affects the price ($r = 0.112$, $p = 0.000$), but employing analytical language congruent to the digital marketing strategy service category affects the price more strongly ($r = 0.118$, $p = 0.000$), indicating an increase by 67.86%.

FURTHER DISCUSSION AND CONTRIBUTION

The purpose of the current study was to derive empirical linguistic taxonomies using online gig descriptions across two hedonic and utilitarian service categories. The empirical and practical contributions of the paper are multi-fold. First, the paper studies a new context, online work services, shifting the focus from demand towards supply-side approaches via language. This is important because language might seem an obvious choice for research due to its ubiquity, but the language has been neglected in the past because signals of quality such as warranties and easily observable high/low-cost signals were at the center of attention (Boulding & Kirmani, 1993; Mavlanova et al., 2012). Therefore, the article extends the scope of previous literature to analyze language as an additional focal signal that might affect the buyer/seller interaction. Language lies under the seller's discretion, and language is a cost-efficient strategy for freelancers, in line with research portraying language use as a strategic choice (e.g., McKenny et al., 2018; Parhankangas & Renko, 2017). Second, the paper introduces boundary conditions (i.e., service categories) that can be found similarly in other contexts (e.g., crowdfunding and online marketplaces). Therefore, the papers offer a better understanding of freelancing platforms by examining specific linguistic determinates of gig workers and their boundary conditions. Apart from textual variables, the article commences by considering negative/positive seller and service signals as a form of collective reputation. According to the studies, the number of sellers and stars of a gig is highly correlated, forming a strong collective reputation signal. Although significantly positively correlated, the number of reviews of a seller and a gig appears to send a less strong reputation signal. Gigs with more words appear to be linked with more reviews and obtain a higher status with the platform, whereby the status of a seller appears to be linked to higher prices. Although one may argue that status signals should be precisely distinguished and Fiverr may opt to change the composition of its status function at any time, the results indicate that the Fiverr status function acts as a strong collective signal as it groups several financial and nonfinancial aspects of a seller.

Third, the paper introduces standardized psycholinguistic categories that can be used by other researchers in other contexts and by users in online work services to

improve their linguistic style by having external benchmarks in the form of standardized psycholinguistic categories. Exploiting the numerous benefits of CATA, such as large sample sizes or the avoidance of interviewer biases (e.g., Bligh et al., 2004; Cho et al., 2014; Pfarrer et al., 2010), is an important first step toward a better understanding of large amounts of linguistic data in online contexts.

Fourth, the results suggest that linguistic descriptions are distinct strategic decisions employed depending on the service category. Therefore, linguistic descriptions in gig contexts *cannot* be seen as arbitrary effects but show distinct linguistic profiles. The theory suggests that sellers should focus on the congruence of the linguistic style and its service category. For this purpose, the paper introduces the concepts of hedonic versus utilitarian service categories as well as introduces analytical versus emotional language as two contrasting ways to frame content. According to the data, gig descriptions contain more emotional language on average across categories, confirming entrepreneurial research that entrepreneurs use more emotional language than non-entrepreneurs (Tata et al., 2017).

Furthermore, the data suggest that an analytical style is more beneficial (i.e., linked to higher prices) than an emotional style across all categories. This is similar to Parhankangas and Ehrlich (2014), who argue that Entrepreneurs need to “seduce” their audience. Sellers with more stars employ a language style that is significantly more analytic and less authentic and emotional. In conjunction with the effect that increased information disclosure (i.e., textual length) of the description matters for the enforcement of higher prices, the article indicates that the amount of disclosure and its style matter for gig workers. Therefore, the article complements signaling and platform research in contexts such as eBay to show which specific structural indicators (e.g., textual length) of online efforts matter and that more self-disclosure signals higher quality gigs (e.g., Akerlof, 1970; Lewis, 2011). Higher prices appear to be related to linguistic proxies of complexity, namely, WPS, six-letter words, and the overall WC. This directly complements research on language concreteness (Pan et al., 2017; Parhankangas & Ehrlich, 2014) and language complexity (Tausczik & Pennebaker, 2010) to show that it may affect key outcome variables such as price in gig contexts. Surprisingly, I find limited evidence that cultural dimensions (Hofstede, 1980) matter for both language style and outcomes, indicating that a linguistic strategy appears to be independent of cultural perception.

Fifth, the results also complement research on crowdfunding (e.g., *Kickstarter*) and platform (e.g., *eBay*) business models whereby linguistic aspects are signals of quality that help to sell services online (e.g., Anglin, Short, et al., 2018a; Backus et al., 2019; Lewis, 2011). In addition, the results indicate that Fiverr itself is a rich source for conducting large-scale empirical

analyses with individuals, complementing previously employed platform research focused on a firm level such as Amazon (e.g., Kronrod & Danziger, 2013), eBay (e.g., Gregg & Walczak, 2008), or Kickstarter (e.g., Parhankangas & Renko, 2017).

Sixth, whereas these previous studies tend to emphasize that language *is* important in these contexts (e.g., Lewis, 2011), it remained unclear *what* specific linguistic strategies are important under which boundary conditions. Due to the usage of standardized psycholinguistic strategies, the approach provided here is replicable and transferable, improving the accuracy of CATA as requested in the literature (e.g., via eliminating algorithm errors stemming from different software packages, McKenny et al., 2018).

Seventh, given the level of the newness of these business models and the level of asymmetric information between buyer and seller, it might indicate that these results can be generalized to these contexts. The provided framework of signaling theory does not make assumptions about the quality of signals. It is therefore neutral under incomplete information, but psychological research in the form of linguistic analysis can test whether sellers' signals are consistent with consumers' perceptions. Although the study does not incorporate direct assessment by consumers, the study lays the foundation that signaling theory can be linked via language to consumer processing, similar to previous calls (e.g., Boulding & Kirmani, 1993).

MANAGERIAL IMPLICATIONS

Based on these insights, at least three practical suggestions for freelancers (supply side) can be derived. First, freelancers should be aware that tweaking language is a cost-efficient strategy to differentiate offerings from competitors that do not require changing other dimensions of the offering (e.g., quality). Therefore, freelancers should devote sufficient resources to their linguistic strategies. In particular, the analysis suggests that a standard description in freelancing services is relatively less focused on language and text (less than half a page on average) compared with text-intensive crowdfunding contexts that require detailed descriptions of the project or technology. Simply increasing the informational content (e.g., via the number of words) makes the offering more distinguishable and decreases uncertainty around it. Freelancers should be aware that emotional language style is the most prevalent within and across service categories. Second, freelancers are advised to incorporate external software programs to tweak their linguistic strategies in addition to informational content. Apart from general and commercially distributed software such as DICTION or LIWC, particularly useful if freelancers have long descriptions and several offerings, research offers more customized dictionaries for different contexts that enable

ex post verification of the writing. Third, freelancers should consider that services such as hedonistic and utilitarian are two distinct domains with different agreed norms within the domain and different expectations of the audience. Freelancers should only compare their offerings with sellers within their own domain. Therefore, for instance, employing emotional language aligns with the logic of the hedonic domain, but employing a relatively less emotional language (i.e., more analytic) to what is dominant *within* the (hedonic) domain is recommendable. Hence, decreasing the emotional language style in favor of a more analytic style may provide opportunities for individuals to differentiate their service offerings. Freelancers should be aware that emotional language is the most prevalent style within and across service categories, thereby providing strategic linguistic opportunities.

LIMITATIONS AND FUTURE RESEARCH

As with any approach, the article is not without limitations. These limitations can be addressed in future research. First, the approach is cross-sectional, and its variables stem from a single platform (possibility of a common-method bias). However, the article chose one of the largest and most representative platforms, Fiverr, and the chosen method (quantitative content analysis) enables to gather of larger data sets that are closer to the average of the whole population (law of large numbers) compared with competing methods. In addition, the approach and method systemically minimize biases compared with competing qualitative methods (e.g., interviewer bias and interviewee bias; McKenny et al., 2013). However, future studies may further complement the results using other sources (platforms) and settings such as a questionnaire or experimental data. This would also enable researchers to study more systemically the actual assessment of language content and language style on individuals (e.g., Filieri, 2016) instead of neglecting the reception of linguistic cues in the signaling theory. This may also show more systemically how situational cues affect the diffusion of linguistic strategies across time that are unlikely to be addressed in a cross-sectional setting. Experimental settings would also be beneficial to clearly distinguish between the credibility of a seller and the signal itself, similar to previous research (e.g., Boulding & Kirmani, 1993).

Second, relatively low R^2 values may indicate that there is sufficient variance to be explained via other variables that were not part of the study. For instance, it would be interesting for future research to study how other “cheap” cues such as pictures (Van Der Heide et al., 2013) and language jointly affect the signaling possibilities for individuals on freelancing platforms. Other research avenues include more inherent signals specific to a particular platform, such as the timing of listing

(e.g., Filieri et al., 2022). Future studies may also study in greater detail how “expensive” cues of sellers work in conjunction with “cheap” signals such as language. Educational attainments are possible avenues to model expensive cues for future research. However, researchers should be aware that disclosing personal information such as education is voluntary, possibly leading to decreasing sample sizes.

Third, the paper only studied a limited number of boundary conditions in the form of two different service categories. A strength of this approach is that (a) hedonic and utilitarian categories provide theoretical underpinnings (e.g., Overby & Lee, 2006) and (b) that two service categories for each hedonic and utilitarian services were examined, making the results more robust and unlikely to occur through random selection. However, future studies should explore more boundary conditions relevant to linguistic strategies and more linguistic strategies in general (e.g., assertive and figurative language; Kronrod et al., 2012, Kronrod & Danziger, 2013). Because research in the field of e-commerce finds that certain groups of signals are likely to be used together (high-cost/easy-to-verify signals forming the first cluster and low-cost and difficult-to-verify signals in the second cluster; Mavlanova et al., 2012), future research should analyze how language interacts with these signals. As previously mentioned, this hinges on the ability of research to distinguish high/low credibility sellers.

Fourth, although the focus is on the seller side to shape the impression of buyers (i.e., requesters) of services, the current article neglects the actual perceptions of buyers. Future research may capture this via a shift in the method or possible amendments in the platform’s structure. For instance, in line with current research (e.g., Filieri et al., 2021), this may entail the number of helpful votes received from textual gig descriptions or via similar implementations.

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DATA AVAILABILITY STATEMENT

The data that support the findings of this study are available on request from the corresponding author. The data are not publicly available due to privacy or ethical restrictions.

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