Promoting trust through linguistic features of provider profiles in the sharing economy

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Abstract: Trust between providers and consumers in the sharing economy are crucial to complete transactions successfully. From a consumer’s perspective, a provider’s profile is an important source of information for judging trustworthiness, because it contains multiple trust cues. However, the effect of a provider’s self-description on perceived trustworthiness is still poorly understood. We examine how the linguistic features of a provider’s self-description predict perceived trustworthiness. To determine the perceived trustworthiness of 259 profiles, real consumers on a Dutch sharing platform rated these profiles for trustworthiness. The results show that profiles were perceived as more trustworthy if they contained more words, more words related to cooking, and more words related to positive emotions. Also, a profile’s perceived trustworthiness score correlated positively with the provider’s actual sales performance. These findings indicate that a provider’s self-description is a relevant signal to consumers, even though it seems easy to fake.

Keywords: sharing economy; trust; perceived trustworthiness; linguistic inquiry and word count; LIWC; linguistic features; C2C.

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Biographical notes: Maarten ter Huurne is a researcher at the University of Applied Sciences Utrecht. His research interests revolve around the question how trust in the sharing economy is influenced and created. His preferred research method is quantitative methodology.

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Vincent Buskens is a Professor of Theoretical Sociology at the Faculty of Social and Behavioural Sciences of Utrecht University. His most prominent research focuses on the various forms of cooperation within our society. More specific, he researches the impact of social networks on cooperation. Some networks facilitate cooperation better than others.

1 Introduction

The sharing economy is viewed as one of the most important economic developments of the last decade, and is associated with environmental, economic and social gains (Frenken, 2017; Frenken and Schor, 2017). It is characterised by a mode of consumption where consumers share underutilised resources with one another via online platforms. Its popularity can be derived from the spectacular rise of companies such as Airbnb and Blablacar [with an estimated value of $31 billion and $1.6 billion, respectively (CNBC, 2017; Fortune, 2015)]. However, consuming in the sharing economy is not without risks. Guests on Airbnb, for example, can be confronted with disappointing accommodation or unreliable hosts. Solving these issues with the intervention of Airbnb seems to be rather difficult 1; this is characteristic of the regulatory uncertainty and consumer protection issues of the sharing economy as a whole (Katz, 2015; Ranchordás, 2015). These institutional uncertainties can seriously hamper trust, possibly leading to a decrease in willingness to participate in the sharing economy (Hawlitschek et al., 2016a). Thus, trust of consumers in providers, as well as trustworthy behaviour of providers, are considered to be key challenges in transactions (Horton and Zeckhauser, 2016; Kim and Peterson, 2017; Wu et al., 2016). In this paper, we focus on the trust of consumers in providers; in other words, the perceived trustworthiness of providers for consumers.

From a consumer’s perspective, one of the main sources for estimating a provider’s trustworthiness is a provider’s online profile page. It contains multiple important trust cues, such as reputation scores, a profile picture and a textual self-description. Self-descriptions are important, because they provide information in a situation where it is scarce, and they form a gateway for future face-to-face interaction (Ellison et al., 2012). Also, they offer a stage for self-presentation, and for the promotion of the product or services being sold. Moreover, self-disclosed personal profile information is
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considered to be cues of source credibility by travellers (Park et al., 2014). However, providers can behave opportunistically, leading to inaccurate and selective self-descriptions, making their trustworthiness questionable. Nonetheless, we know that self-descriptions convey a particular, intended or unintended, impression of the provider (Evans et al., 2008), and that self-descriptions are used by perceivers in online contexts to assess someone’s trustworthiness (Larrimore et al., 2011; Toma and Hancock, 2012).

Linguistic features have been shown to influence perceptions of trustworthiness when people write about themselves (Larrimore et al., 2011; Toma and D’Angelo, 2014). Language use can say something about a person’s psychological needs (Toma and D’Angelo, 2014), and is therefore used by readers to infer trustworthiness (Larrimore et al., 2011; Rodriguez et al., 2010). For instance, the number of words in an online dating profile influences users’ judgement of a dater’s trustworthiness; specifically, profiles with shorter descriptions are perceived as more deceptive than longer profiles (Toma and Hancock, 2012). This can be explained by the fact that these profiles contain fewer details. Also, an experiment by Choi and Horvát (2019) showed that signals of safety expressed through linguistic features in reviews are important to generate trust by female Airbnb travellers. As a consequence, they used more safety-related words in their reviews.

Most studies related to reducing consumer uncertainty in the sharing economy investigated uncertainty reduction mechanisms, such as reputation, the use of profile pictures and reviews (e.g., Bente et al., 2012; Ert et al., 2016; Fagerstrøm et al., 2017), leaving the effect of linguistic features underexposed. For a rare exception, see Ma et al. (2017), who found that linguistic features affect perceived trustworthiness in the context of a lodging platform. Therefore, it remains unclear whether linguistic features are effective in promoting trust; and more specifically, which particular mechanisms are used by consumers to reduce their uncertainty about the trustworthiness of providers. Additionally, researching the effect of linguistic features could provide insights into the uncertainty reduction process, which may be extended to other online markets.

The aim of this study is to investigate specific mechanisms that consumers use to infer perceived trustworthiness of providers in the sharing economy. The central research question is: what linguistic features of providers’ profile text predict perceived trustworthiness in the sharing economy? Besides this central aim, we explore whether trustworthiness perceptions extend to actual behaviour by investigating the effect of these perceptions on sales performance.

We tested the effects of providers’ profile descriptions in the context of one of the largest sharing platforms of the Netherlands, Shareyourmeal (SYM). SYM is a platform on which people can share meals with people in their neighbourhood. It has attracted 14,971 providers and 94,110 consumers since its inception in 2012. We asked actual consumers on the platform to judge provider profile descriptions on trustworthiness. Text analysis software (linguistic inquiry and word count – LIWC) was used to analyse specific linguistic features of the profile descriptions. To determine the influence of the linguistic features on the perceived trustworthiness scores of the providers’ profiles, we used cross-classified mixed effects modelling.

First, we provide a background of the relevant theoretical concepts (Section 2), after which hypotheses are formulated (Section 3). This is followed by a description of the empirical context of the study and the study design (Section 4). We then present the results (Section 5), and subsequently, conclusions and implications for both theory and practice are presented in Section 6.
2 Background

The term sharing economy is used as an umbrella term for many platforms that enable online peer-to-peer exchanges of underutilised resources. The sharing economy covers a vast domain that, according to Botsman and Rogers (2010), incorporates different consumption systems, i.e., product service systems (e.g., Airbnb), redistribution markets (e.g., The Freecycle Network), and collaborative lifestyles (e.g., Taskrabbit). Although there is no agreement on how to exactly define the sharing economy (Botsman, 2013), we define the sharing economy as “an economic model based on sharing underutilized assets between peers without the transfer of ownership, ranging from spaces, to skills, to stuff, for monetary or non-monetary benefits via an online mediated platform” [ter Huurne et al., (2017), p.2]. This definition stresses the fact that underutilised resources are shared online; this sets it apart from the broader field of e-commerce, where resources do not have to be underutilised per se, and ownership transfers from providers to consumers.

Trust is generally recognized as a key ingredient for participating in, and successfully completing transactions in, the sharing economy (Hawlitschek et al., 2016a; Tussyadiah, 2016). According to Möhlmann (2016), trust in the sharing economy needs to be differentiated from trust in other economic exchanges for four reasons. First, transactions are performed in a triad of relationships, namely, between peers, platforms, and underutilised products, resulting in three targets of trust. Trust in peers is influenced by the belief that the supplying individual has the competencies to fulfil his/her part of the transaction, as well as being a benevolent and honest person. Also, trust in peers is shaped by the expectation that the consuming peer will handle shared products with care and act with the provider’s interest in mind. Trust in the product is understood as the product being reliable in the consumer’s view, and initially has to be evaluated on virtual cues. Both the consumer and the provider need to have favourable trusting beliefs towards the platform. This implies that the platform is well-qualified to play a facilitating role in the transaction and is a reliable partner that, for example, deals honestly with privacy and security issues (Hawlitschek et al., 2016b).

Second, transactions do not only occur online, but also have an offline component, making social aspects more relevant compared with transactions that exclusively take place online. Third, the use of products and services in the sharing economy is based on access to ownership (Hamari et al., 2015); this requires higher trust levels compared with peer-to-peer transactions with a transfer of ownership [e.g., eBay (see Hawlitschek et al., 2016b)]. Lastly, it is often proposed that the sharing economy includes service-exchange activities [e.g., cleaning, offering taxi rides and running errands (Botsman, 2013; Smolka and Hienerth, 2014)]; these are more complex activities than product-exchange, as they include many additional components [e.g., cleanliness, hospitality and accuracy (see Möhlmann, 2016)].

2.1 The concept of trust

Trust is a widely researched concept across various academic fields, such as psychology, sociology and economics (Rousseau et al., 1998). Across disciplines, trust is considered to act on multiple levels (individual, interpersonal and institutional), and risk and interdependence are suggested as necessary conditions for trust problems to arise (ibid.). Risk is the perceived probability of loss, which creates the need for trust to alleviate uncertainty. Interdependence refers to the situations in which the interests of one party
cannot be served without reliance upon the other party (Rousseau et al., 1998). Trust is therefore considered to be a crucial instrument serving as a control and cooperation mechanism (Borgen, 2001).

In this study, we view trust from an interpersonal perspective, meaning that trust implies that a trustor has favourable beliefs about the characteristics of the trustee, and that the trustee will act according to the expectations of the trustor. Mayer et al. (1995, p.715) define trust as “the willingness of a party to be vulnerable to the actions of another party based on the expectation that the other will perform a particular action important to the trustor, irrespective of the ability to monitor or control that other party.” In their review of trust, Mayer et al. (1995) present trust as a trait that leads to a generalised expectation of others, i.e., perceived trustworthiness. According to these authors, perceived trustworthiness is a multidimensional concept consisting of the dimensions ability, benevolence and integrity. To trust in another’s ability is to hold the belief that another party possesses the skills, competencies, and characteristics to deliver certain outcomes. The concept of benevolence refers to the question of whether the trustee is believed to do good, and whether he/she acts in the best interest of the trustor; and integrity refers to the belief that the trustee adheres to a set of moral principles perceived as acceptable by the trustor (Mayer et al., 1995). For all three dimensions, consumers may experience uncertainty; different aspects of the provider’s profile might reduce uncertainty on each of these dimensions.

The development of trust is considered to progress in stages, such as initial trust and continuous trust (Lewicki and Bunker, 1996; Wu et al., 2014). These stages vary in the level of familiarity between the parties involved, and consequently, the amount of information that is available about each other (McKnight et al., 2004). Parties who are familiar with each other possess reliable information about each other, whereas unfamiliar parties do not. In the latter case, trust (or initial trust) is based on whatever information is available, and inferences are based on that (Meyerson et al., 1996). Most first-time transactions in the sharing economy take place in the initial trust stage, because a consumer has limited information about the trustworthiness of a provider, and is thus faced with a situation of information asymmetry (a situation where one party possesses more information than the other).

To reduce this situation of information asymmetry, a consumer can resort to information sources available on a provider’s online profile, such as reputation scores, a profile picture, feedback from other users, or a self-description. A provider’s self-description is a valuable trust source, because it can be used to promote the provider’s uniqueness to an assumed audience by displaying the provider’s ability, benevolence and integrity (Pera et al., 2016). Nonetheless, online self-presentation is “more selective, malleable, and subject to self-censorship in computer-mediated communication than it is in face-to-face interaction” [Walther, (1996), p.20], which makes it unsure whether consumers will use a provider’s self-description to determine his or her trustworthiness.

2.2 Uncertainty reduction theory

Uncertainty can be understood through uncertainty reduction theory (URT) (Berger and Calabrese, 1975). URT focuses on the initial encounter between people prior to the actual communication process, and states that people actively seek to reduce feelings of uncertainty by acquiring as much information as possible about the other person. In doing
so, people are able to predict each other’s future attitudes and behaviour. URT formulates, among others, several non-verbal strategies to reduce uncertainty in interpersonal communication, such as eye contact, head nods and physical distance between people. However, these strategies are not available in online settings, forcing individuals to resort to other information seeking strategies. Research into online dating, for example, has shown that participants use strategies such as asking questions via e-mail, viewing photos and profile descriptions and googling prospective dates (Gibbs et al., 2011).

To examine uncertainty reduction in the sharing economy, we investigated four mechanisms that are related to major sources of uncertainty in the online buying process, i.e., seller and product uncertainty (Dimoka et al., 2012). Mechanisms that reduce seller uncertainty are seeking information about the:

1. provider
2. focusing on perceptions of a provider’s ability
3. benevolence
4. integrity (Doney and Cannon, 1997; Jiang et al., 2010; Standifird, 2001).

Also, product uncertainty can be reduced through the information mechanism by having enough product information at one’s disposal as well as detailed information which could help consumers to infer how products would perform in the future (Dimoka et al., 2012). Based on these mechanisms, we formulate and test hypotheses that predict the reduction of uncertainty in the online buying process through the use of linguistics.

3 Hypotheses

Language is called “the currency of most human social processes” because it conveys emotions, stories and thoughts [Chung and Pennebaker, (2007), p.343]. In the process of developing trustworthiness, linguistics features have shown to be a useful marker in creating trusting beliefs (Ellison et al., 2012; Larrimore et al., 2011), because they can say something about the mental state of a person, as psychological processes are reflected in language use (Toma and D’Angelo, 2014). Toma and D’Angelo (2014) reason that perceivers experience psychological needs relating to the context (i.e., buying a quality meal) and the goals (i.e., assessing a provider’s trustworthiness) of the task at hand and that they use linguistic cues to satisfy these needs.

3.1 General information richness

A frequently used strategy to reduce uncertainty between people in the online environment, is to increase the amount of information available (Dimoka et al., 2012; Toma and Hancock, 2012). For instance, Larrimore et al. (2011) found that in the context of an online peer-to-peer lending platform, the number of words in a lending request is a significant predictor of funding success. A longer lending request generally contains more information, and this could lead to reducing the uncertainty of a potential borrower. Since longer descriptions appear to be effective in increasing trust in online environments, we believe that this also applies to SYM. One of the primary concerns of a
consumer on SYM, is whether a provider is able to prepare a tasty meal. More information provided by the provider could help reduce a consumer’s uncertainty, if this information elaborated on the provider’s cooking abilities.

Furthermore, experts might use lengthier descriptions than novices, as was shown in the case of wine tasting, when describing smells and flavours (Croijmans and Majid, 2016). Wine experts tend to possess a greater lexicon for describing wines and engage more often in talking about wine; this allows them to express themselves in many different ways (ibid.). This might also be the case for SYM, in the sense that an expert provider could be identified by the number of words used to describe his/her offerings. Finally, a lengthier description might also provide additional cues on the benevolence and integrity of the provider assuming that providers will not explicitly provide suggestions for the opposite. Consequently, we propose the following hypothesis:

**H1** The more words a provider’s profile contains, the more the provider is perceived as trustworthy.

### 3.2 Belief in creating ability

An essential component of perceived trustworthiness is the perception that a person possesses skills, competencies, and characteristics in a certain domain (Mayer et al., 1995). Mayer et al. (1995) view perceived expertise as an integral part of ability. On SYM, providers can show their expertise by providing very concrete descriptions of their products, cooking skills, techniques and use of ingredients.

We reason that more concrete and specific information provided by a provider reduces a consumer’s uncertainty, and enhances the consumer’s trust in acquiring a quality meal. One might even claim that while more words are rather easily added to a profile, really concrete text showing cooking skills are less easily produced if you are not an expert. Thus, more concrete information in a provider’s profile is likely to increase a consumer’s trust in the quality of a meal. This will improve the perceived trustworthiness of the provider.

We use two linguistic dimensions as indicators of concreteness, i.e., articles (e.g. ‘a’ and ‘the’) and prepositions (e.g., ‘in’, ‘at’) (Larrimore et al., 2011; Toma and D’Angelo, 2014). According to Tausczik and Pennebaker (2010) articles and prepositions often indicate concrete information about a topic, because these dimensions signal the presence of a concrete noun. For example: the keys are in the box by the lamp under the painting. Based on the above reasoning, we assume that concreteness predicts perceived trustworthiness and hypothesise that:

**H2a** The more words related to concreteness an online profile contains, the more the provider is perceived as trustworthy.

In addition, we predict that consumers appreciate the expertise of providers specifically when they use cooking-related words, such as ‘baking’, ‘homemade’ and ‘healthy’. Therefore, we hypothesise that the use of cooking-related words predicts the perceived trustworthiness of a provider.

**H2b** The more words related to cooking an online profile contains, the more the provider is perceived as trustworthy.
3.3 Belief in creating benevolence and integrity

A benevolent provider would take the interests of the consumer into account and would not be perceived as opportunistic (McKnight and Chervany, 2001). Unfamiliarity between consumers and providers in online marketplaces, provides for an anonymous environment, which makes trading an impersonal activity (Diekmann et al., 2014). This hampers relationship building between transaction partners, and consequently, the development of a consumer’s trusting beliefs about a provider’s benevolence.

One way to strengthen the relationship between the agents involved in a transaction, is through social connection. From a linguistic point of view, second-person pronouns are relevant to social connections and create consumer involvement (Cruz et al., 2017). Chung and Pennebaker (2007) propose that the use of second-person pronouns (e.g., ‘you’, ‘your’, ‘yourself’) suggests that the person cares for other people. Moreover, second-person pronouns invite readers to join and engage in the conversation, thus reducing the impersonality of communication (Pollach, 2005). Or as Hyland (2005, p.359) states: “you is the most interactive device in the writer’s repertoire as it explicitly acknowledges the reader’s presence” (e.g., your preferences are important to me).

Therefore, we consider the second-person pronouns (singular and plural; e.g., ‘you’, ‘your’, ‘yours’) as an indicator for building social connections and as a predictor for perceived trustworthiness. Consequently, providers who use many second-person pronouns in their profile are expected to convey higher levels of benevolence towards the consumer. They are expected to be perceived as more trustworthy than providers who use few second-person pronouns. We thus hypothesise that:

H3a The more words expressing social connections an online profile contains, the more the provider is perceived as trustworthy.

In the early stages of creating trust, conveying enthusiasm is important because it contributes to a good first impression (Jarvenpaa and Leidner, 2006). In the case of a salesperson, enthusiasm can be displayed by performing sales duties with eagerness, a positive attitude and/or a high level of energy (Weilbaker, 1990). It is considered one of multiple relationship traits that are predictive of salespeople’s performance (Anselmi and Zemanek, 1997). Enthusiasm can influence one’s likeability (Oksenberg et al., 1986), and likeable salespeople are more likely to be approached by a consumer (Wood et al., 2008). Also, likeability was found to be positively related to the degree someone is trusted by others (Rotter, 1980). These perceptions of trust could be evoked by the intentionality process: consumers attribute integrity to those they like (Doney and Cannon, 1997). The provider appears motivated to deliver a good product, and thus seems less likely to optimise short-term monetary gains at the expense of product quality.

Moreover, a provider’s enthusiasm is relevant for consumers, because it increases their satisfaction with the transaction. Consumers perceive enthusiasm as desirable and praiseworthy, leading them to experience positive emotions as well (Lee and Dubinsky, 2003). In the SYM case, we think that consumers will appreciate enthusiasm displayed by a provider, and that this will be translated into favourable trusting beliefs about the provider. We reason that providers who express a high level of enthusiasm in their self-description are perceived as more trustworthy. Consequently, we hypothesise the following:
Promoting trust through linguistic features of provider profiles

H3b The more words related to enthusiasm an online profile contains, the more the provider is perceived as trustworthy.

3.4 Perceived trustworthiness effect on sales performance

A crucial question is whether a provider’s perceived trustworthiness translates into sales. Should a provider care about his/her perceived trustworthiness (as derived from his/her profile text) or is it a factor that can be ignored? The answer to this question could be of importance to a provider’s success and might have implications for his/her self-promotion strategy. The relation between perceived trustworthiness and trusting behaviour was also found in a choice experiment by Ma et al. (2017), which showed that perceived trustworthiness indeed predicted a rater’s choice of an Airbnb listing. On SYM, a consumer would proceed to buy a meal if he perceived the provider as trustworthy. Therefore, we hypothesise the following:

H4 The perceived trustworthiness score of a provider’s profile text is positively associated with his/her sales performance.

Figure 1 displays the determinants of perceived trustworthiness through the lens of URT, and the underlying hypothesised relations.

Figure 1 The research model

4 Study design

The design of our study consists of several parts: the empirical context, the development of the measurement instrument, the procedure of administering the survey, the characteristics of the final survey, the text analysis procedure and the statistical approach used. All these elements will be described respectively.

4.1 Empirical context

We test these hypotheses in the context of the SYM platform in the Netherlands. SYM was founded in 2012 and is a social enterprise with the mission to bring people together through sharing meals in their own neighbourhood. Between 2012 and 2016,
14,971 providers and 94,110 consumers joined the platform, and 96,797 meals were offered. SYM provides a strong and real-life case suitable for the aim of our research for a number of reasons. First, the purchase situation of SYM consumers resembles that of sharing economy consumers in general. SYM consumers are confronted with provider and product uncertainty, which can be reduced by reading a provider’s self-description. Second, the risks encountered by SYM consumers, stem from several sources that also appear in the sharing economy in general. Providers on SYM are amateur cooks; consequently, it is uncertain what the quality of the meal will be, and whether food safety is guaranteed. Also, amateur cooks are non-professionals in describing and presenting themselves and their offerings, thereby increasing provider and product uncertainty (see Figure 2 for an example of a provider’s profile page). Lastly, meals are picked up at the provider’s house; this can pose a possible safety risk for the consumer. These trust issues between providers and consumers make SYM a good case for the purpose of this study.

4.2 Instrument development

Before the data collection for the main study, a pre-test was done to select appropriate questionnaire items. Items to measure perceived trustworthiness were developed on the basis of Mayer and Davis’ (1999) commonly used trustworthiness items, translated into Dutch, and adapted to the current context. The scale consists of three dimensions: ability (four items), benevolence (five items), and integrity (four items), on a five-point Likert scale ranging from 1 (‘disagree strongly’) to 5 (‘agree strongly’). Using these items, 12 participants (university colleagues) rated a random selection of 20 real SYM provider profiles via an online survey.

Although, we have theoretical arguments that some linguistic variables have predominantly effects of specific subdimensions of trust, the restriction on the size of the questionnaire were such that we could not include enough items to measure each subdimension reliably. By using a six-item measure, we aimed to prevent questionnaire fatigue and thus optimising the sample size. This is also in line with Ma et al. (2017) who also used a six-item measure for perceived trustworthiness in their study of Airbnb profiles. To select the items that were most apt, Cronbach’s alpha (α) per construct and the average intraclass correlation (ICC) per item were calculated. We selected per construct two items (6 in total) that together had the highest α. Additionally, we checked whether the ICC score per item was ≥ 0.60 to ensure a sufficient level of agreement between raters (Cicchetti, 1994). The Cronbach’s α for ability was 0.97, for benevolence 0.98, and for integrity 0.93. The Cronbach’s α for the complete perceived trustworthiness scale was 0.97. All these values were above the suggested threshold of 0.80 (Hair et al., 1998). The selected perceived trustworthiness items are presented in Table 1.

<table>
<thead>
<tr>
<th>Dimension</th>
<th>Item</th>
</tr>
</thead>
<tbody>
<tr>
<td>Ability</td>
<td>I feel very confident about the cook’s skills.</td>
</tr>
<tr>
<td>Ability</td>
<td>The cook has a lot of knowledge about cooking.</td>
</tr>
<tr>
<td>Benevolence</td>
<td>My needs and desires are very important to the cook.</td>
</tr>
<tr>
<td>Benevolence</td>
<td>The cook will go out of his/her way to help me.</td>
</tr>
<tr>
<td>Integrity</td>
<td>I can assume that this cook acts honestly.</td>
</tr>
<tr>
<td>Integrity</td>
<td>I never have to wonder whether the cook will stick to his/her word.</td>
</tr>
</tbody>
</table>
4.3 Procedure

Actual SYM providers’ self-descriptions were shown via online survey software in isolation and rated by actual SYM consumers. Each self-description was rated with the developed perceived trustworthiness scale. SYM provided us with a dataset containing all transactions between providers and consumers from the start of SYM in March 2012 to December 2016. The dataset also contained the profile information of 10,619 providers. Only profiles that had self-descriptions containing 20 words or more were included in the sampling pool (to ensure a minimum amount of text to be analysed), leaving a total of 5,582 profiles.

In total, 400 profiles were randomly selected to be rated. Of those, 200 profiles were of providers who had never sold a meal, and 200 profiles were of providers who had sold one meal or more. We did this in order to investigate a possible relation between perceived trustworthiness and sales performance.
E-mail invitations to participate in the online survey were sent out to 7,965 actual SYM consumers and ten small gifts were offered via a random lottery to increase participation. The profiles were presented in a pseudo-random order to the raters. The response during the study was lower than expected; this necessitated a step in which we excluded those profiles from further analysis that were not yet frequently rated. In total, 203 raters completed the survey.

To take into account the possibility of careless response, we excluded those raters who selected the same response category for 52 or more items (out of 60). This cut-off was chosen post-hoc because it showed a clear separation into two clusters of raters. This procedure resulted in a final total of 259 profiles with a minimum of five ratings or more (M = 7.3, SD = 2.5), rated by 188 raters. We performed an interrater reliability analysis using the percentage of agreement and Gwet’s AC1 statistic to determine consistency among raters. The raters agreed 90.42% of the time, and the interrater reliability was found to be Gwet’s AC1 = 0.71 (p = 0.001), 95% CI (0.681, 0.736), which may be considered ‘substantial agreement’ [Landis and Koch, (1977), p.165]. This also implies that a number of five raters are sufficient to have reliable measurements of the different profiles.

To verify whether our sample resembles the SYM user population, we compared it with the earlier Stipo (2015) study on SYM users, because SYM does not keep a record of its users’ demographics. This study reported a distribution of 25% male consumers, which corresponds to the percentage that we found (27.66%). Also, the raters’ age distribution of our study matches that of earlier research carried out by SYM (Shareyourmeal, 2015). Comparison of the sample characteristics with SYM population data reveals large similarities. So although our main aim was to have sufficiently reliable ratings for a large enough number of profiles to do the subsequent analyses, it is also reassuring that our selection of raters does not seem to be particularly biased.

4.4 Characteristics of the survey

Perceived trustworthiness was examined using the items from the pre-test on a seven-point Likert-type scale, to allow for sufficient scale sensitivity. To control for demographic variables, raters were asked to state their sex, age and education. We also asked whether raters recognised one or more profiles, to account for possible familiarity of the rater with a profile. Additionally, we controlled for misspellings. Misspellings have been shown to influence perceptions in online profiles (Gibbs et al., 2006; Scott et al., 2014) and should therefore be taken into account. To determine the number of misspellings per profile, we used the Dutch dictionary OpenTaal (version 2.00 G). In the analysis, we included the proportion of misspellings relative to the number of words in a profile. Lastly, raters’ disposition to trust was measured, because research has shown it to be a significant determinant of trusting beliefs in the online environment (Gefen, 2002; McKnight et al., 2002). Disposition to trust was measured using three items adapted from Yamagishi and Yamagishi (1994) well-established scale. Table 2 shows the descriptive statistics of the demographic and control variables included in the study.
Table 2  Respondents descriptive statistics

<table>
<thead>
<tr>
<th>Dimension</th>
<th>Number</th>
<th>%</th>
<th>Mean</th>
<th>SD</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sex</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Male</td>
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<td></td>
<td></td>
</tr>
<tr>
<td>Female</td>
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<td>72.34</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Age</td>
<td></td>
<td>55.04</td>
<td>13.86</td>
<td></td>
</tr>
<tr>
<td>Educational level</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>No diploma</td>
<td>2</td>
<td>1.06</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Elementary school</td>
<td>1</td>
<td>0.53</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Lower vocational education</td>
<td>8</td>
<td>4.26</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Higher general continued education</td>
<td>24</td>
<td>12.77</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Preparatory middle-level applied education</td>
<td>9</td>
<td>4.79</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Middle-level applied education</td>
<td>20</td>
<td>10.64</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Higher-level applied education</td>
<td>71</td>
<td>37.77</td>
<td></td>
<td></td>
</tr>
<tr>
<td>University</td>
<td>53</td>
<td>28.19</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Disposition to trust (7-point Likert-type scale)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Most people are reliable</td>
<td></td>
<td>5.23</td>
<td>1.13</td>
<td></td>
</tr>
<tr>
<td>Most people are honest</td>
<td></td>
<td>5.07</td>
<td>1.12</td>
<td></td>
</tr>
<tr>
<td>Most people are of good faith</td>
<td></td>
<td>5.12</td>
<td>1.26</td>
<td></td>
</tr>
<tr>
<td>Number of profiles recognised</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>0</td>
<td></td>
<td>82.54%</td>
<td></td>
<td></td>
</tr>
<tr>
<td>1</td>
<td></td>
<td>2.65%</td>
<td></td>
<td></td>
</tr>
<tr>
<td>2</td>
<td></td>
<td>3.70%</td>
<td></td>
<td></td>
</tr>
<tr>
<td>3+</td>
<td></td>
<td>11.11%</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

4.5 Text analysis procedure

To determine the specific linguistic features of the provider’s profile that influence perceived trustworthiness, we used the text analysis program LIWC (Pennebaker et al., 2007). LIWC is a validated tool to measure psychological dimensions in texts. It counts the number and percentage of words in texts and classifies them into various syntactical and semantic categories. LIWC analyses linguistic content against an internal dictionary containing 90 output variables, grouped by categories and subcategories (e.g., standard linguistic dimensions, summary language variables and word categories tapping psychological constructs).

The Dutch LIWC Dictionary 2007 (developed by Zijlstra et al., 2004) was used to analyse the providers’ self-descriptions. To analyse the linguistic features related to cooking, we developed a customised cooking dictionary. It was developed by two researchers who, independently of each other, selected words related to cooking based on all profiles used in this study. The results of both researchers were compared;
words on which agreement was reached were included in the dictionary. Agreement was reached in 95% of all cases. In the event of disagreement, a third researcher decided whether to include a specific word or not. Table 3 shows the LIWC categories used in relation to the formulated hypotheses, Table 4 provides descriptive statistics of the linguistic features, and Table 5 demonstrates the correlations between the linguistic features included in the study.

### Table 3 Hypotheses and examples of words in each LIWC category

<table>
<thead>
<tr>
<th>Hypothesis</th>
<th>LIWC category</th>
<th>Examples</th>
</tr>
</thead>
<tbody>
<tr>
<td>H1 More words</td>
<td>Word count</td>
<td>N/A</td>
</tr>
<tr>
<td>H2a Words relating to concreteness</td>
<td>Articles</td>
<td>‘The’, ‘a’, ‘an’</td>
</tr>
<tr>
<td></td>
<td>Prepositions</td>
<td>‘On’, ‘under’, ‘in’</td>
</tr>
<tr>
<td>H2b Words relating to expertise</td>
<td>Cooking-related words</td>
<td>‘Baking’, ‘organic’, ‘homemade’</td>
</tr>
<tr>
<td>H3a Words expressing social connections</td>
<td>You</td>
<td>‘You’, ‘your’, ‘yours’</td>
</tr>
<tr>
<td>H3b Words relating to enthusiasm</td>
<td>Positive emotions</td>
<td>‘Humour’, ‘impressive’, ‘interesting’</td>
</tr>
</tbody>
</table>

### Table 4 Descriptive statistics of linguistic features

<table>
<thead>
<tr>
<th>Dimension</th>
<th>Linguistic feature</th>
<th>Example</th>
<th># LIWC words</th>
<th>Mean (%)</th>
<th>SD (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Words captured by LIWC dictionary</td>
<td>Dictionary</td>
<td></td>
<td>6,551</td>
<td>67.11</td>
<td>10.37</td>
</tr>
<tr>
<td></td>
<td>Cooking dictionary*</td>
<td></td>
<td>567</td>
<td>15.70</td>
<td>9.08</td>
</tr>
<tr>
<td>General information richness</td>
<td>Word count</td>
<td></td>
<td>58.17</td>
<td>49.9</td>
<td></td>
</tr>
<tr>
<td>Ability</td>
<td>Articles</td>
<td>‘A’, ‘an’, ‘the’</td>
<td>3</td>
<td>5.41</td>
<td>3.46</td>
</tr>
<tr>
<td></td>
<td>Prepositions</td>
<td>‘On’, ‘under’, ‘in’</td>
<td>48</td>
<td>12.96</td>
<td>4.49</td>
</tr>
<tr>
<td></td>
<td>Cooking words</td>
<td>‘Baking’, ‘frying’, ‘durable’</td>
<td>560</td>
<td>15.55</td>
<td>9.11</td>
</tr>
<tr>
<td>Benevolence and integrity</td>
<td>You</td>
<td>‘You’, ‘yours’,</td>
<td>7</td>
<td>1.10</td>
<td>1.67</td>
</tr>
<tr>
<td></td>
<td>Positive emotions</td>
<td>‘Happy’, ‘pretty’, ‘good’</td>
<td>690</td>
<td>3.04</td>
<td>2.87</td>
</tr>
</tbody>
</table>

Note: *This linguistic category is not part of the standard LIWC Dictionary.

### 4.6 Analysis of perceived trustworthiness effects on sales performance

To determine a provider’s sales performance, we used SYM transaction data containing the number of meals sold per provider. Because of the skewness of these data, we applied a $\log$ transformation to this variable.

Because the dataset did not show whether a provider edited his/her profile, we assumed that a profile was constant over time. Subsequently, we used the perceived trustworthiness score of a profile to predict sales performance.
Table 5  Correlation matrix for linguistic features

<table>
<thead>
<tr>
<th></th>
<th>Trustworthiness</th>
<th>Word count</th>
<th>Articles</th>
<th>Prepositions</th>
<th>Cooking-related words</th>
<th>You</th>
<th>Positive emotions</th>
</tr>
</thead>
<tbody>
<tr>
<td>Trustworthiness</td>
<td>1.00</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Word count</td>
<td>0.26</td>
<td>1.00</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Articles</td>
<td>-0.02</td>
<td>0.23</td>
<td>1.00</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Prepositions</td>
<td>0.02</td>
<td>0.17</td>
<td>0.10</td>
<td>1.00</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Cooking-related words</td>
<td>0.04</td>
<td>-0.18</td>
<td>-0.26</td>
<td>-0.19</td>
<td>1.00</td>
<td></td>
<td></td>
</tr>
<tr>
<td>You</td>
<td>0.08</td>
<td>0.17</td>
<td>0.04</td>
<td>-0.06</td>
<td>-0.22</td>
<td>1.00</td>
<td></td>
</tr>
<tr>
<td>Positive emotions</td>
<td>0.03</td>
<td>-0.09</td>
<td>0.10</td>
<td>0.11</td>
<td>-0.12</td>
<td>-0.08</td>
<td>1.00</td>
</tr>
</tbody>
</table>
Table 6  Cross-classified analyses for perceived trustworthiness with linguistic features and respondent characteristics

<table>
<thead>
<tr>
<th>LIWC categories</th>
<th>Empty model</th>
<th>Control variables only</th>
<th>Linguistic features only</th>
<th>Full model</th>
</tr>
</thead>
<tbody>
<tr>
<td>Word count (log2)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>0.367***</td>
<td>0.363***</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.032)</td>
<td>(0.032)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Articles</td>
<td>–0.023**</td>
<td>–0.019*</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.009)</td>
<td>(0.009)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Prepositions</td>
<td>0.017**</td>
<td>0.018**</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.006)</td>
<td>(0.006)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Cooking</td>
<td>0.011***</td>
<td>0.010***</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.003)</td>
<td>(0.003)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>You</td>
<td>0.026</td>
<td>0.029</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.016)</td>
<td>(0.016)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Positive emotions</td>
<td>0.019*</td>
<td>0.022*</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.009)</td>
<td>(0.009)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Sex</td>
<td>–0.073 (0.137)</td>
<td>–0.093 (0.138)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Age</td>
<td>–0.005 (0.005)</td>
<td>–0.005 (0.005)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Education</td>
<td>–0.152***</td>
<td>–0.159***</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.044)</td>
<td>(0.044)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Number of recognised profiles</td>
<td>0.019 (0.041)</td>
<td>0.015 (0.042)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Disposition to trust</td>
<td>0.245***</td>
<td>0.240***</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.063)</td>
<td>(0.064)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Misspellings</td>
<td>1.89* (0.868)</td>
<td>1.778* (0.726)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Intercept</td>
<td>4.663***</td>
<td>4.522***</td>
<td>2.281***</td>
<td>2.206***</td>
</tr>
<tr>
<td></td>
<td>(0.071)</td>
<td>(0.497)</td>
<td>(0.219)</td>
<td>(0.538)</td>
</tr>
</tbody>
</table>

Random effects

<table>
<thead>
<tr>
<th></th>
<th>Empty model</th>
<th>Control variables only</th>
<th>Linguistic features only</th>
<th>Full model</th>
</tr>
</thead>
<tbody>
<tr>
<td>Respondent level</td>
<td>0.746**</td>
<td>0.614***</td>
<td>0.753</td>
<td>0.623***</td>
</tr>
<tr>
<td></td>
<td>(0.083)</td>
<td>(0.070)</td>
<td>(0.084)</td>
<td>(0.070)</td>
</tr>
<tr>
<td>Profile level</td>
<td>0.198***</td>
<td>0.197***</td>
<td>0.091</td>
<td>0.091***</td>
</tr>
<tr>
<td></td>
<td>(0.025)</td>
<td>(0.025)</td>
<td>(0.016)</td>
<td>(0.016)</td>
</tr>
<tr>
<td>Residual</td>
<td>0.506***</td>
<td>0.506***</td>
<td>0.506</td>
<td>0.506***</td>
</tr>
<tr>
<td></td>
<td>(0.020)</td>
<td>(0.020)</td>
<td>(0.020)</td>
<td>(0.020)</td>
</tr>
<tr>
<td>N (respondents)</td>
<td>188</td>
<td>188</td>
<td>188</td>
<td>188</td>
</tr>
<tr>
<td>N (profiles)</td>
<td>259</td>
<td>259</td>
<td>259</td>
<td>259</td>
</tr>
</tbody>
</table>

Notes: Standard errors in parentheses. ***p < 0.001, **p < 0.01 and *p < 0.05.

4.7 Statistical procedure

Because of the cross-classified nature of the data (raters rated multiple profiles and a profile is rated by multiple raters), we applied cross-classified mixed effects modelling
Promoting trust through linguistic features of provider profiles

(Snijders and Bosker, 2012). The dependent variable in our model was the mean of the six perceived trustworthiness items per profile, because factor analysis of these items yielded only one factor; following Büttner and Göritz (2008), we chose a unidimensional approach to measure this construct. The perceived trustworthiness score can be denoted as \( Y_{ijk} \), referring to rater \( i \) rating profile \( j \), together forming the \( k \)th observation. The explanatory variables are the various LIWC categories and control variables \( (X_{ijk}\beta) \), modelled by the rater \( (e_i) \) and profile level \( (e_j) \), leaving a residual variance component \( (u_k) \). The random effects were assumed to be normally distributed. Consequently, the model can be denoted as:

\[
Y_{ijk} = X_{ijk}\beta + e_i + e_j + u_k
\]

The effects of linguistic features on perceived trustworthiness were assessed in different stages (see Table 6). First, a baseline model was evaluated to partition the variance components of the profile and the rater. In preliminary cross-classified analyses, separate models were tested for LIWC categories and control variables. The results showed that these models did not explain additional variance compared with the baseline and the full model. Finally, the full model was run containing all LIWC categories and control variables. The analysis was conducted using Stata Statistical Software: Release 13.1 (StataCorp LP, 2013).

To analyse whether the perceived trustworthiness score of a profile predicted a provider’s sales performance, we used linear regression on the log-transformed number of meals sold (Table 7). The predictor variable in this analysis was the profile’s trustworthiness score, corrected for rater bias. The control variables were omitted because they were measured at rater level and the analysis was performed at profile level.

<table>
<thead>
<tr>
<th>Variables</th>
<th>Perceived trustworthiness</th>
<th>Constant</th>
<th>Observations</th>
<th>R-squared</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>0.688*** (0.175)</td>
<td>-2.071* (0.822)</td>
<td>251</td>
<td>0.059</td>
</tr>
</tbody>
</table>

Notes: Standard errors in parentheses. *** \( p < 0.001 \) and * \( p < 0.05 \).

5 Results

Table 6 shows the regression estimates for the influence of linguistic features on perceived trustworthiness.

The empty model explains how the total variance is divided between the variance components associated with the rater and the profile level. The results show significant variance at the rater level (\( \sigma_i^2 = 0.75 \), standard error SE = 0.083) and at the profile level (\( \sigma_j^2 = 0.20 \), SE = 0.025). These results justify the use of cross-classified models. The addition of the LIWC and control variables led to a small decrease in both variance
components, i.e., for the rater level (\( \sigma_1^2 = 0.62, \ SE = 0.070 \)) and for the profile level (\( \sigma_2^2 = 0.091, \ SE = 0.016 \)).

Our first hypothesis predicted that the more words a profile contains, the more the provider is perceived as trustworthy. For ease of interpretation, the category word count was transformed to a \( \log_2 \) variable (so that the regression coefficient can be interpreted as the effect of doubling the number of words). The number of words indeed seemed to be a positive and significant predictor of perceived trustworthiness (\( b = 0.363, \ p = 0.001 \)); H1 is thus supported.

Hypothesis 2a predicted that words relating to a concrete description of an object would positively influence perceived trustworthiness. The results showed that the use of articles had a negative effect (\( b = -0.019, \ p = 0.024 \)), whereas the prepositions showed a positive effect on perceived trustworthiness (\( b = 0.018, \ p = 0.003 \)). We found no consistent support for H2a.

Our Hypothesis 2b claimed that a provider’s display of expertise in his/her profile through cooking-related words would increase his/her perceived trustworthiness. Indeed, using cooking-related words had a positive significant effect on perceived trustworthiness (\( b = 0.010, \ p = 0.001 \)). Hence, H2b is also supported.

H3a stated that online profiles that use more words aimed at building social connections would increase perceived trustworthiness. Words related to this concept (e.g., 'you', 'yours') did not have a significant effect on perceived trustworthiness (\( b = 0.029, \ p = 0.077 \)). H3a was therefore not supported.

Hypothesis 3b predicted that the use of positive emotions, as an indicator for enthusiasm, would lead to higher perceived trustworthiness. The use of positive emotions indeed had a positive significant effect (\( b = 0.022, \ p = 0.015 \)). H3b is thus supported.

While the results above show linguistic features are important drivers of perceived trustworthiness of a profile, we are also interested in whether such trustworthy profiles lead to higher sales. The related fourth hypothesis stated that the perceived trustworthiness score of a provider’s profile positively predicts his/her sales performance. We found that a profile’s perceived trustworthiness score does indeed have a positive effect on whether a provider sells a meal or not (\( b = 0.688, \ p = 0.001 \)) (Table 7). Thus, the results support H4.

6 Discussion

This study set out to determine whether consumers use linguistic features of providers’ profile texts to reduce their uncertainty within the context of the sharing economy (specifically, on a meal-sharing platform). We found that linguistic features do matter when one is trying to form perceptions of trustworthiness in the sharing economy. Extending Ma et al.’s (2017) findings, our study illustrates that linguistic features contribute to perceived trustworthiness across different contexts, including the sharing economy. In addition, perceived trustworthiness appears to drive buying behaviour. Also, in our study, actual platform users participated to rate the profiles which increases the ecological validity, compared to studies that use, for example, workers from Mechanical Turk (e.g., Ma et al., 2017; Tussyadiah and Park, 2018).

More specifically, we found that, in line with URT, offering more information by using more words has a positive effect on perceived trustworthiness. The effects of
reducing uncertainty by using more concrete words (i.e., the use of articles and prepositions) are less straightforward, contrary to what other studies found (e.g., Toma and Hancock, 2012). The use of articles had a significant and negative effect on perceived trustworthiness, whereas the use of prepositions was found to have a positive effect. Perhaps focusing on the presence of nouns, by counting articles and prepositions (Tausczik and Pennebaker, 2010) is not a very valid way of measuring the concreteness of text. Nouns per se are not concrete; they can have different degrees of concreteness (Pander Maat and Dekker, 2016). For example, words like ‘stove’, ‘pan’, and ‘meat’ are considered to be concrete words, whereas words such as ‘additives’ and ‘cereal products’ are seen as more abstract – yet, all are nouns. Our suggestion to improve the measurement of concreteness would be to build a dictionary in LIWC, containing a list of words denoted by experts as concrete (an example of such a dictionary is used by T-scan).

Although SYM is a platform that aims to support social connections between people, socially oriented words (i.e., second-person pronouns) did not seem to influence a provider’s perceived trustworthiness. Literature (e.g., Stirman and Pennebaker, 2001) indicates that first-person pronouns (‘I’) denote a focus on the self, while second-person pronouns (you) have a focus on the other person (Chung and Pennebaker, 2007). We expected this focus on the other to translate into higher levels of perceived trustworthiness, which did not happen. However, note that the use of second-person pronouns was relatively rare and highly variable (see Table 4). This makes it more difficult to find any effect on perceived trustworthiness.

Furthermore, expressing enthusiasm by means of words related to positive emotions (e.g., ‘humour’, ‘to adore’, ‘to thank’) did have a positive effect on perceived trustworthiness. Also, the use of cooking-related words (e.g., ‘homemade’, ‘ingredients’, ‘baking’) had a positive significant effect, meaning that displaying expertise in one’s profile is effective in raising perceived trustworthiness.

Next, we found a significantly positive effect of perceived trustworthiness on the actual sales performance of a provider. This indicates that perceived trustworthiness derived from a provider’s profile text is an important factor that drives consumers’ decisions; this concurs with earlier findings by Ert et al. (2016) and Ma et al. (2017) in the sharing economy.

This study has several theoretical and practical implications. On a theoretical level, our study adds to the comprehension of language use in online peer-to-peer transactions, and more specifically in the sharing economy. It shows that self-presentation in a profile text is important in the sharing economy, similar to other contexts, such as online dating, peer-to-peer lending, social media and online medical advice. Given that most studies focused on lodging platforms (e.g., Airbnb) to study the effects of linguistic features on trust in the sharing economy (e.g., Ma et al., 2017; Tussyadiah and Park, 2018), we show that also in the context of meal sharing, and more broadly spoken in the context of sharing skills, self-presentation through linguistic features matter. We have evidence that several uncertainty reduction mechanisms are at play when judging a provider’s trustworthiness; namely, information richness, and perceptions about ability, benevolence and integrity. Furthermore, our study underlines the assumption that the number of words is a relevant indicator for information richness. Also, words related to positive emotions are positively related to trustworthiness. Concerning the measurement of expertise, we would recommend developing a customised dictionary because expertise is very context-specific.
From a practical point of view, providers in the sharing economy would be advised to pay close attention to their profile text and develop a description of sufficient length, including elements of enthusiasm and expertise in order to increase their trustworthiness. However, it must be noted that features that are easy to fake (e.g., lengthy descriptions), can become less important in their contribution to perceived trustworthiness. Second, owners of sharing platforms could design their website in such a way that users are encouraged to curate their profile, to stimulate trust; this could result in more transactions. For example, users could be obliged to provide a minimum number of words about themselves. In the SYM case, 48% of providers have a profile containing fewer than 20 words. Providing enough information may seem to be an obvious task when attracting customers, it is one that is often neglected. A platform could actively give pointers about what to write in a profile, so that users are stimulated to write about relevant topics to enhance their trustworthiness.

6.1 Limitations

We believe that our research helps to elucidate how trust is built via online profiles in the sharing economy. By using actual SYM consumers in our research, we ensured that the results had ecological validity. However, our study encountered some challenges that should be addressed. First, the response to the survey was lower than expected, which could make it difficult to generalise the results to the SYM population. However, a comparison between our sample data with SYM population data showed large similarities, indicating that the results may be generalisable.

We included profiles in the analysis if they had five ratings or more, to ensure that the main analysis contained a satisfactory number of profiles. While more ratings on more profiles would have increased the accuracy in determining the trustworthiness score for profiles and the power of our analysis, we did find significant results for most of our explanatory variables, suggesting that a lack of power was not a large issue. In addition, the interrater reliability of the raters over the profiles was high suggesting that with five raters we could be confident that we had sufficiently reliable rating of the profiles. Next, profiles with 20 words or less were excluded for analysis to make sure that enough information was gathered regarding the linguistic features of interest. This means that the results tell us something about the trustworthiness of longer profile texts. Although it might be the case that shorter profile texts contain signals of trustworthiness as well, it is likely that for such profiles other elements as a photo or reputation become more important for trust development. Investigating how different elements jointly contribute to the trustworthiness of a complete profile and what the role of the length of the text then is, is an interesting aspect for further research.

Lastly, the setting in which raters read the profiles deviated from the natural online setting. It is highly likely that the raters paid more attention reading the content of the profile in the research condition than they would do in practice, because online reading behaviour is characterised by browsing, scanning, and selective reading, and less time is spent on in-depth reading (Liu, 2005). In line with the elaboration likelihood model of persuasion, recipients of information probably follow the central route (looking for additional information and scrutinising the arguments) when they view the source as untrustworthy (Petty and Cacioppo, 1986). Given that our raters likely followed a more central route when rating the profiles, this could have caused a tendency towards a different rating score as a result of paying more attention to the profiles.
6.2 Future research

Research into developing trust between peers in the sharing economy has focused on several antecedents, such as reputation, profile pictures and characteristics of the peer (Bente et al., 2012; Ert et al., 2016; Karlsson et al., 2017). It would be interesting to study how linguistic features would relate to other trust antecedents (e.g., a user’s reputation score, reviews and a profile picture) and their relative importance. Also, it would be of interest to examine possible boundary conditions of linguistic features: when do they and when do they not affect trust and/or sales. For instance, features such as word count might be used more often when uncertainty is higher, for instance, when ordering from a novice provider. Additionally, the fact that linguistic features are easy to fake opens interesting pathways for future research. For instance, one could pose the question to what extent linguistic features are effective in influencing trusting beliefs when opportunists purposely misuse them. Next, providers could gain valuable experience regarding drawing up their profile when they are members of the platform for a longer time. To exclude this potential ‘experience-effect’ in the analysis, future research should control for this aspect.

Furthermore, we assumed that perceived trustworthiness is an underlying mechanism for a successful transaction. To test whether this is the case, future research could be conducted with the aim to find a mediation effect of perceived trustworthiness on the relation between linguistic features and sales performance. In doing so, it is important to include an adequate sample size of profiles, because of the small effect sizes of linguistic features on perceived trustworthiness, and perceived trustworthiness on sales performance.

Finally, we found indications that linguistic features are relevant in creating a trustworthy image in the context of one sharing platform. It would also be of interest to know whether these results can be extrapolated to other peer-to-peer commerce contexts (e.g., car sharing, exchange of goods).

6.3 Conclusions

To conclude, language use in providers’ profiles can affect their perceived trustworthiness and therefore is of importance in creating trust, which as we have shown also affects sales performance. To create a more trustworthy image, providers could address consumers’ specific psychological needs and deploy persuasive strategies. If this is done, trust can be effectively enhanced and transactions in the sharing economy might be boosted.

References


Notes

1 For examples of stories of dissatisfied Airbnb users (see http://www.airnbnhell.com).
2 The Dutch name is Thuisafgehaald (http://www.thuisafgehaald.nl).
3 We used Gwet’s AC1 statistic, because ratings were unevenly distributed and agreement was high leading to low values of Cohen’s kappa and Fleiss’ kappa, known as the paradox of kappa (Cicchetti and Feinstein, 1990). Gwet’s (2016) AC1 is a paradox-resistant alternative agreement coefficient to remediate this issue.
4 Note that compared to the study by Ma et al. (2017), the profiles in our study received more ratings on average than theirs (i.e., five ratings).
Additionally, we explored whether the relation between linguistic features and trustworthiness is bounded. We chose word count, because it proved to have the largest significant regression coefficient. Unfortunately, 94.21% of our data has a word count smaller than 27 which make it difficult to make statistical inferences. However, the outliers in our data suggest that the effect of word count on trustworthiness is limited, indicating that it is not effective to use an extremely large amount of words.

T-scan is software for complexity analysis of Dutch texts (Pander Maat et al., 2014).