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Exploring the Effects of Consumers' Trust: A Predictive Model for Satisfying Buyers' Expectations Based on Sellers' Behavior in the Marketplace

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ABSTRACT In recent years, consumer-to-consumer (C2C) marketplaces have become very popular among Internet users. However, compared to the traditional business-to-consumer (B2C) stores, most modern C2C marketplaces are reported to be associated with stronger negative sentiments among consumers. These negative sentiments arise from the inability of sellers to meet certain buyers' expectations and are linked to the low trust relationship among sellers and buyers in C2C marketplaces. The growth of these negative emotions might jeopardize buyers' decisions to opt for C2C marketplaces in their future purchase intentions. In the present study, we extend the definition of trust as an emotion to cover the digital world and demonstrate the trust model currently used by most online stores. Based on the buyer's behavior in the C2C marketplace, we propose a conceptual framework to predict trust between the buyer and the seller. Given that the C2C marketplaces are rich sources of data for trust mining and sentiment analysis, we perform text mining on Airbnb to predict the trust level in host descriptions of offered facilities. The data are acquired from the US city of Ashville, Alabama, and Manchester in the U.K. The results of the analysis demonstrate that the guest negative feedbacks in reviews are high when the description of the host's property has the emotion of joy only. By contrast, the guest negative sentiments in reviews are at a minimum when the host's sentiment has mixed emotions (e.g., joy and fear).

INDEX TERMS Trust, social media, sentiment analysis, B2C, C2C, tone analyzer.

I. INTRODUCTION

Recent years have witnessed an unparalleled growth of the spectrum of services offered at Customer-to-Customer (C2C) marketplaces [1]. In modern C2C marketplaces, such as Uber and Airbnb, almost any individual can offer a product or a service, such as sharing a ride or renting out a coach in a living room. The broad range of currently available C2C services has also resulted in an increase in the complexity surrounding finalising a deal online [1]. Specifically, in order to complete a transaction in modern C2C marketplaces, buyers and sellers must trust each other. In essence, modern C2C marketplaces are becoming an industry of trust [2].

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The concept of trust, conventionally defined as the expectation of trustors towards trustees to meet certain expectation (e.g. quality of a product/service or payment on time), has been extensively addressed in previous research [1], [3], [4]. Varying in detail, most definitions of trust involve three main parts: trustor, trustee, and expectations. The probability of the trustee meeting the expectations of the trustor is referred to as the level of trust. This study considers trust to be both a mental attitude and an emotion.

In this relation, numerous other studies focused on commercial reputation or rating systems in online communities (e.g., [4]–[7]). For instance, evidence is available showing that negative sentiments on social media towards C2C marketplaces are much stronger as compared to those towards traditional Business-to-Consumer (B2C) marketplaces [7].

In this body of research, trust was quantified based on which members of a social network choose to partner with or avoid. However, the field lacks a quantitative model to estimate trust levels among buyers and sellers at the transaction level, which warrants further research to better meet user expectations and to better control C2C marketplaces. In the context of the current study, we focus on trust among individuals engaging in the C2C hospitality services industry.

As stated before, this study considers trust to be both a mental attitude and an emotion. Plutchik [8] states that, a human experiences 8 basic emotions that are the foundation for all other emotions. As per Plutchik's list, trust is deemed to be one of the eight basic emotions along with joy, fear, surprise, sadness, disgust, anger, and anticipation. On the other hand, Ekman [9] stated that there are only 6 basic emotions that can be inferred from human facial expressions. As per Ekman's list, Trust is not deemed to be one of the six basic emotions [10]. However, both agree that non-basic emotions are combinations of the basic ones, which may be called blended or mixed emotions. Regardless of whether trust is considered as a basic or non-basic emotion, later in this study, we will combine multiple emotions in order to calculate trust.

Sentiment analysis has been widely used to detect basic emotions in various types of texts, such as joy, anger, fear, disgust, and sadness. In essence, sentiment analysis focuses on word choice and frequency of occurrence of a given phrase near a set of positive or negative words [11]. In the present study, we rely on Plutchik's Wheel of Emotions, as illustrated in Figure 1, where trust is deemed to be one of the eight basic emotions, positioned between joy and fear [8]. Accordingly, the two key research questions addressed in the present study are as follows:

- Research Question 1: Can trust, one of the eight basic emotions, be detected in C2C texts, such as Airbnb accommodation descriptions?
- Research Question 2: If joy and fear are detected in text, can we infer trust?

The remainder of this study is structured as follows. In Section II, we provide the theoretical background of the present study, including working definitions of major concepts, such as trust, and a review of currently available models of quantifying trust. Furthermore, in Section III, we outline the proposed conceptual framework to measure trust. Sections IV, V present the results of two case studies: one based on the data collected in Ashville, the US, and the other on the data collected in Manchester, the UK. Finally, conclusions are drawn, and directions of further research are outlined in Section VI.

II. BACKGROUND

In this section, we introduce the definitions of trust as a mental attitude (Section II.A) and as an emotion (Section II.B). Furthermore, we introduce and discuss several models of trust (Sections II.D Opinion Mining) and highlight the weakness/shortcomings in each model in relation to calculating

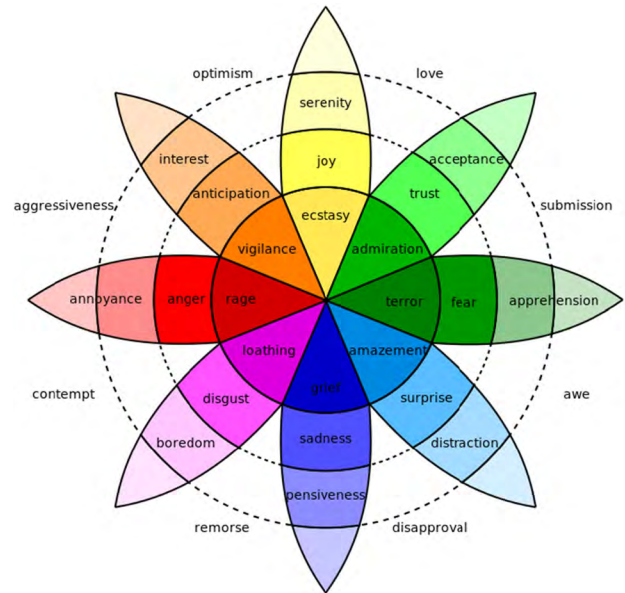


FIGURE 1. Plutchik's wheels of Emotions [8]. Layers show forms of emotions as basic, weaker, and stronger.

trust in e-Commerce. Those models are considered the most relevant and innovative computational models to calculate trust in distributed networks (e.g. C2C, P2P).

A. DEFINITION OF TRUST

In the literature, numerous studies have focused on the concept of trust within e-commerce. However, in most of these studies, the concept of trust was conflated with other concepts, such as risk, privacy, and security [3], [4]. In e-commerce interactions, some of these concepts overlap at various points in time, thereby contributing to the success or failure of online transactions. Each concept has a different impact on the decisions of either buyers or sellers. The concept of trust can be better explained in a situation characterised by the following aspects:

“One party (the trustor) is willing to rely on the actions of another party (the trustee) in some situation in the future. Additionally, the trustor (voluntarily or otherwise) abandons control over the actions performed by the trustee. Therefore, the trustor is uncertain of the outcome of the trustee's actions. This uncertainty involves the risk of failure or harm to the trustor if the trustee does not behave as expected [12].”

While there is no consensual definition of trust in the literature, the many and varied definitions of trust rely on the following three aspects pertinent to trust: trustor, trustee, and expectations [13]. The trustor abandons control and builds expectations based on results from the trustee. In the digital domain, trust has been defined as:

“Trust is the confidence placed in an organisation (trustee) to collect, store, and use the digital

TABLE 1. Strong and weaker forms of the 8 basic emotions [8].

Weaker	Normal (Basic)	Stronger
Serenity	Joy	Ecstasy
Acceptance	← Trust →	Admiration
Apprehension	Fear	Terror
Distraction	Surprise	Amazement
Pensiveness	Sadness	Grief
Boredom	Disgust	Loathing
Annoyance	Anger	Rage
Interest	Anticipation	Vigilance

information of others (trustors) in a manner that benefits and protects (expectations) those to whom the information pertains [14].”

B. TRUST AS AN EMOTION

According to major emotion theories, emotions are elicited by certain acts or events, also called emotion antecedents. Richard Lazarus, a pioneer in cognitive emotion, states that “Thinking must occur first before experiencing emotion” [15]. According to Lazarus theory, the series of activities first need a stimulus, followed by thought which then ends in the immediate experience of a physiological reaction and the emotion. For example, reading a story can provoke reader’s emotion based on writer’s phrases and selection of words. The frequency of occurrence for a set of positive or negative words is a provoke readers brain which then turn into a thought followed by immediate experience of an emotion. Another example to elicit an emotion can be a threatening sight of a tiger.

In Plutchik’s classification [8], each basic emotion has a stronger and a weaker form. In the case of trust, its weaker form is acceptance, while its stronger form is admiration. A complete list of the 8 basic emotions and their strong and weaker forms is given in Table 1.

The present study focuses on analysing the emotions found in the text used by hosts and guests engaged in a transaction in the C2C hospitality services industry. Just like reading a story, the writer selection of words and phrases triggers readers brain to build a thought then experience an emotion. Overall, there is a tendency for hosts to fall into the trap of over-promoting their facilities, which leads to higher expectations from their guests. The higher the guest expectation, the higher the trust level built. Only the host knows whether and, if so, to what extent the description of a property differs from the reality. Many hosts work hard to meet the high expectations of their guests, but not all of them succeed, which leads to disappointments on both sides. Anticipating this type of transactions ahead of time and help the hosts to write realistic description can prevent hosts and guests from having disappointing transactions and increase the number of trusted transactions.

C. BEHAVIOUR OF BUYERS AND SELLERS IN E-COMMERCE DEALS

In both offline and e-commerce, buyers and sellers are essential to any deal. Both parties have their own wants and needs that must be satisfied to finalise a deal. The process of finalising a deal is also known as the process of trade-offs between buyers and sellers to reach a state that satisfies both sides [16].

When a buyer or a seller is represented by an organisation, behaviours and trade-offs may be structured and documented by the organisation. For example, an organisation may have a rule to engage in potential deals only if the profit margin is greater than or equal to 10%. In contrast, if the buyer or seller is an individual or simple group of individuals, wants and needs may vary, and trade-offs may not be defined in a structured form. This variance adds ambiguity to the deal [16]. In the present study, we focus on the deals between individuals.

The following aspects highlight the main characteristics that influence individual consumers’ behaviour in approaching deals [16], [17]:

- **Personal/demographic characteristics:** e.g., gender, age, weight, occupation, income status, education, and lifestyle. For instance, a buyer might make or break a deal if the seller is from the opposite gender, income status, education or lifestyle.
- **Psychological characteristics:** i.e. consumers’ psychological state(s) at the time of finalising the deal. An individual emotion (e.g. joy, anger, trust, or fear) can be a deal maker or breaker.
- **Social characteristics:** i.e. aspects that include, but are not limited to, previous feedback to a similar transaction. Specifically, other buyers’ reviews and comments can exert pressure on the consumer or bias decision as to whether or not to finalise a deal [18].
- **Cultural characteristics:** i.e. collective mental programming of the mind for an individual or group. This distinguishes members of one group of people from another. For example, individual’s nationality, religion, political party or favourite football team can be a deal maker or breaker.

In the present paper, trust between buyers and sellers is considered to be one of the *psychological* characteristics that influence the decision-making processes.

D. OPINION MINING

Due to the uncertainty about quality of the offerings provided by users, it is important for marketplaces to calculate the trust level of its users before initiating any transaction. In general, users in C2C market places have to know how much trust to give to others with whom they might have had no earlier transaction. This kind of models are also known as reputation models.

In the hospitality services industry, hosts often fall into the trap of over-promoting their facilities, which leads to building higher expectations from their guests. Only the host knows to what extent the description of a facility differs from

the reality. Many hosts work hard to meet the high expectations of their guests, but not all of them succeed, which leads to disappointments on both sides. Anticipating this type of transactions ahead of time can prevent hosts and guests from having disappointing transactions and increase the number of trusted transactions.

Moreover, the existing user's reviews are mostly positive which introduces the "all good reputation problem" [18]–[21]. This is due to the fact that guests in C2C market places fear the fact the hosts might write similar feedback on them, which might damage their own reputation and risk deals in the future with other hosts. The same users who wrote a positive feedback about a particular host, might go to other social media platform to share a very negative experience and post a more truthful opinion. But this time it will be a generic negative post about the C2C marketplace in general. Negative posts toward C2C marketplaces in general are growing [7] and made it harder to identify a specific host who is responsible. You can see that, a host setting a high expectation by over-promoting their facilities can cause not only a disappointment to multiple guests but also lots of negative posts published randomly about the C2C market place in general. There are multiple attempts to quantify trust, this paper list the following selected methods:

"Aspect Based Opinion Mining" which aims to automatically discover whether a guest free text review expresses positive or negative opinion towards the host [22]. Section II.D.1 lists more details about the model

"The AuctionRules Algorithm" suggests following a classification set of rules tailored for capturing signs of negativity in the text review comments provided by C2C users [23]. Section II.D.2 lists more details about the model

"PowerTrust and reputation model" after studying 10,000 eBay users' feedback [24]. The model shows that users with a very high number of feedback comments were extremely rare (power users). Those users can be used as bases to calculate reputation for others who belong to the same network. Section II.D.3 lists more details about the model.

EigenTrust and reputation model [25] is another trust and reputation model built to be used in Peer-to-Peer (P2P) networks. The aim of this model is to reduce malicious and fraud contributors in the network. It can be used to reduce fraud and malicious reviews and feedbacks given automatically to a specific product in order to increase its reputation in the system. Section II.D.4 discusses in more details how this model works and what are the limitations of using it in the C2C market places.

There are other reputational models in the literature that calculate trust using different parameters other than customer feedback. For example, Parallel network of acquaintance and Real network of acquaintance both calculate the trust between two individuals (a)(b) using the reputation between the chains of individuals who hypothetical link (a)(b). Section II.D.5 discuss an ideal scenario while Section II.D.6 discuss a more realistic scenario and its

limitation in our day to day market places. Another example is Chernoff Bound-based trust model [4] which depends on the number of encounters between buyer and seller during a transaction. This model assumes that the guest and the host will interact with each other before finalizing a deal (e.g. chat). Section II.D.7 discusses this model in more details, and it shows the limitation of using it in the C2C market places. Some researchers build a Bio-inspired Trust and Reputation Model for Wireless Sensor Network [26] to be used as a distributed trust and reputation model. The model is inspired by how ants find their way searching for food and how they navigate back to their colony. Section II.D.8 discusses in more details how we can learn from the ant's trust algorithm and how similar it can be to human purchase behaviour. The section also lists the limitations of generalizing this algorithm in order to calculate trust.

1) ASPECT BASED OPINION MINING

Aspect Based Opinion Mining aims to solving the problem mentioned above, the algorithm is also known as, Sentiment Analysis [22]. It aims to automatically discover whether a given piece of text expresses positive or negative opinion towards a subject. Sentiment analysis can be looked at as a general text categorization problem. It combines the techniques of natural language processing, data retrieval, text analytics and computational linguistics. Opinion mining is basically a supervised method in which one needs to train a classifier on the training set before it is to be carried out on a test set. It can analyse people's feedback, reviews, and appraisals to find out emotions towards specific subjects which includes but not limited to products, offerings, sellers, or buyers.

Aspect Based Opinion mining is also known as, phrase-level opinion mining and works on three levels, namely document-level, sentence-level, and phrase-level. But Document-level and sentence-level usually return a generalised opinion about a subject. However, phrase-level opinion mining can return a more granular opinion towards a specific aspect in the product or service. This algorithm is mainly used to discover sentiments on aspects of items. Aspects that are explicitly mentioned as nouns or noun phrases in a sentence are called explicit aspects. For example, cleanness aspect in a review sentence such as "The house was very clean" is considered as an explicit aspect. On the other hand, Implicit Aspects are not explicitly mentioned in a sentence but are implied, e.g. "The room rate was overpriced" implies the price aspect of the room.

Applying this algorithm on reviews captured in C2C hospitality industry, enables the marketplace to identify the exact explicit and implicit aspects that makes or breaks a future deal. The negative aspect can then be highlighted to the host as a feedback to improve.

This approach doesn't work effectively unless there are multiple reviews on the facility already. Fraud review comments can mislead this algorithm in order to hide a negative aspect. Moreover, genuine guests should take leap of faith to

try their luck when the host doesn't have any review recorded in the system. In other words, in order for this algorithm to work effectively, some of the guests have to go through the experience of not meeting their expectation that was built by the host facility description.

2) AUCTIONRULES ALGORITHM

O'Donovan [23] proposed the AuctionRules algorithm to deal with the problem, of un-naturally high trust ratings on C2C market places. The algorithm suggests following a classification set of rules tailored for capturing signs of negativity in the text review comments provided by C2C users. In those feedbacks, a positive score might have been made, however the commenter still voices some complaint inside the free text feedback field.

The aim of the algorithm is to correctly classify users' comments into positive or negative according to a predefined threshold. AuctionRules is built on the fact that the online markets are restricted in nature and the actions are limited to the workflow defined by the marketplace. Having said that, there are few silent factors the (buyer or seller) care about which are reflected in their comments. The output of the algorithm is a summarized sentence from the market place with a set of core features in order to set the expectation correctly for any future deal (trust level)

For example, in a C2C marketplace such as eBay, the following seven core features are taken in consideration in order to calculate the trust in the user feedback text: The terms in brackets are the contents of each feature set.

- Item - The quality/condition of the product being bought or sold. (item, product)
- Person - The person the user makes the transaction with. (buyer, seller, dealer)
- Cost - Cost of item, cost of shipping, hidden costs and other similar keywords (expense, cost)
- Shipping - Delivery of the item, security, time and other similar keywords (delivery, shipping)
- Response - Communication with the other party. (response, comment, email, communication)
- Packaging - The packaging quality/condition of the item (packaging)
- Payment - how the payment will be made to the seller, or back to buyer for return (payment)
- Transaction - the overall transaction quality (service, transaction, business)

For example, after analysing all the comments provided on an individual user in eBay, the algorithm will produce the following sentence: "User X is trusted when it comes to payment, but shipping has been unsatisfactory in the past".

Similar to the previous approach, the limitation of this algorithm lies on the fact that it requires multiple reviews in the system in order to calculate the trust level. Unlike the previous approach, AuctionRules pre-defined a set of aspects that can fit a specific industry or marketplace. The algorithm search user text review searching for those 7 core features (aspects) only and discard others.

3) POWERTRUST AND REPUTATION MODEL

PowerTrust is another P2P trust and reputation model based on distributed peer feedback [24]. Zhou and Hwang, 2007, studied the feedback provided by 10,000 eBay users. Users with few feedback comments were quite common; however, users with a very high number of feedback comments were extremely rare (power users).

The model starts with the analysis of the feedback comments of power users. After aggregating all the feedback of power users, the model calculates the global reputation score $v_i \in [0, 1]$ of every peer i . To this end, it first collects all the reputation scores for v_j and the normalized local trust score $r_{ij} \in [0, 1]$; where j are peers who have interacted with i in the past. r_{ij} is defined as follows (see Eq. (1)):

$$r_{ij} = \frac{S_{ij}}{\sum_j S_{ij}} \quad (1)$$

where S_{ij} represents the satisfaction level between peer i & j based on a previous transaction. Said differently, if the feedback from peer i is positive, following a previous transaction with peer j , the global reputation score v_i can be calculated using Eq. (2).

$$v_i = (1 - \alpha) \cdot \sum_j (v_j X r_{ji}) \quad (2)$$

where α is the greedy factor calculated based on the status of the power user.

In a PowerTrust network, each peer has a global reputation score v_i calculated based on the degree of satisfaction associated with historical transactions with other peers in the network. This model takes the feedback between peers into consideration. This model has reported to be effective in identifying fraudulent peers in the P2P network [24]. It is also highly scalable to networks with a large number of peers.

The limitation of this model is that it assumes that all members have some interaction with others before. New joiners will need to build their interactions one transaction at a time. Moreover, this model keeps the highly trusted peers trusted regardless of their future transactions. It will take many bad transactions for a highly trusted peer to lose its score.

4) EIGENTRUST AND REPUTATION MODEL

EigenTrust [25] is another trust and reputation model built to be used in Peer-to-Peer (P2P) networks. In this model, what determines the trust value for each peer is successful historical transactions. The aim of this model is to prune down malicious and fraud contributors in the network.

Each peer i in an EigenTrust network of peers holds a vector of trust values at every point in time for all the peers in the network. The trust value is calculated based on Eq. (3).

$$t_i^{(k+1)} = (1 - a) \cdot C^T \cdot t^k + a \cdot p \rightarrow \quad (3)$$

where $t_i^{(k+1)}$ is the trust value for a peer i in a specific time $(k + 1)$; $a \in [0, 1]$ is a constant to calculate the global trust value; C^T is the transposed matrix of $[C_{ij}]$, and

C_{ij} represents the trust from peer i towards peer j based on the historical successful transactions between them. However, if peer i does not know anyone or has not had any previous successful transactions, s/he will choose to trust pre-trusted peers. Furthermore, p_i^{\rightarrow} is the distribution over pre-trusted peers ($p_i^{\rightarrow} = 1/P$ if $i \in P$ and $p_i^{\rightarrow} = 0$ Otherwise, P is the pre-trusted peers).

This model is built on the assumption that each EigenTrust network has several known trusted peers with high trust values. Presumably, this helps other peers in the network to rapidly build their trust values. Eq. (3) repeats for every peer in the network until all trust values are calculated. After calculating all the trust values, each peer can select who to transact with. A simple way is to select the peer with the highest trust value in the vector of trust; this is the deterministic selection process. On the other hand, is the probabilistic process where selection is based on a probability of 10% random peer with a low trust in the network.

The limitation of this model is that it is not computationally efficient while solving real-world problems. Calculating trust in big EigenTrust networks can grow exponentially. In order to calculate the trust for a single node, the trust for all other nodes in the network has to be calculated first. Moreover, if an EigenTrust network had no high trusted nodes, all the other members will not have high trust values. On the other hand, calculating trust in micro EigenTrust networks can be insignificant.

5) PARALLEL NETWORK OF ACQUAINTANCES

Parallel network of acquaintances [4] is another model to calculate trust—specifically, within a network of acquaintances. This approach is based on the assumption that the social network between the trustor and the trustee can indicate the probability of the trustee to meet the expectation of the trustor based on the trustee’s reputation in social network.

Figure 2 shows K chains between the trustor (a) and the trustee (b). Each chain consists of at least one link between two people in the network. The reputation between two people can be considered as a function of the number of cooperative events in the chain divided by the number of encounters. If we assign the reputation to be the weight of the link, then, in theory, we can calculate the reputation between the trustor (a) and the trustee (b). The estimate of the trustee’s (b) reputation across the entire parallel network can be calculated as a weighted sum across all the chains.

This is a theatrical more than a realistic model, it is usually used to explain the following section (Real network of acquaintances). The limitation of parallel network of acquaintances assumes that the nodes between (a) and (b) don’t intersect, in other word the people from one of the chains between (a) and (b) don’t know anyone from the next chain. In real life this is not usually the case. Moreover, in order for this model to be computed all the nodes between (a) and (b) should be known and all the interactions between all node are captured.

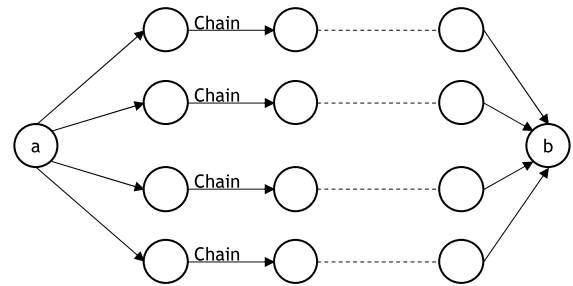


FIGURE 2. Parallel network between a trustor (a) and a trustee (b) [4].

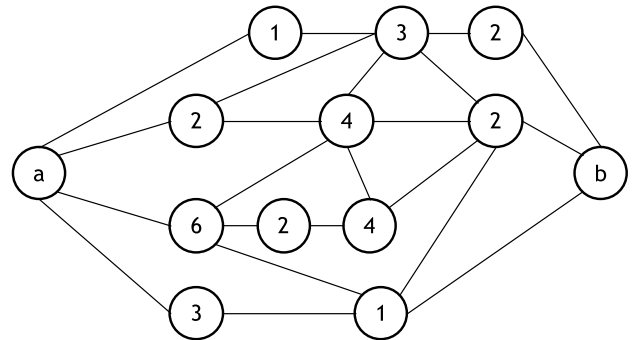


FIGURE 3. Generalized social network of acquaintances [4].

6) REAL NETWORK OF ACQUAINTANCES

This model is built on top of the previous model (Parallel network of acquaintances). Real network of acquaintances forms an arbitrary chain that overlaps between the trustor and the trustee. Figure 3 shows a generalised representation of a social network of acquaintances in real life.

The entirety of these links can be considered to constitute a Bayesian Network which grows exponentially with an increase of the number of nodes. However, in solving real-world problems, this approach is not computationally efficient. To estimate the reputation of the trustee (b) in a real social network, all possible paths should be taken into consideration. Any new node introduced between (a) and (b) will increase the complexity to calculate the trust level. However, several assumptions and techniques to simplify and reduce the complexity of this problem to an acceptable computational level are available [4].

The social network of acquaintances assumes that every trustor (a) has a chain of links to the trustee (b). However, the limitation of this model of trust is that, while its key assumption might be true, capturing the network and all the events among people is rather challenging. Another limitation of this approach is that it does not account for people who are heavily surrounded with people who are not trustworthy:

“Would Mahatma Ghandi get a lower reputation because of his social network and how they used to interact with him?”

This question raises a concern that according to this model, Mahatma Ghandi will not be considered as a trusted person. His network of acquaintances was full of people with

conflicts and their interactions didn't lead to low trusted relationships.

In order to use this trust model in e-commerce to calculate the trust between buyers and sellers, all relationships that connects buyers and sellers should be identified. Moreover, each relationship that connects a buyer with seller and their network of acquaintances should be identified and ranked. Collecting all this data makes this model challenging to use specially that buyers and sellers can be from different content. Even if this data was identified in a way or another, the network will be considered as Bayesian Network, the complexity of calculating the trust level between buyers and sellers grows exponentially with an increase of the number of nodes in the network which makes the model computationally un-friendly.

7) CHERNOFF BOUND-BASED TRUST AND REPUTATION MODEL

Chernoff bound-based trust model is based on the reputation of the trustee to the trustor [4]. The reputation of the trustee is considered as a function of cooperative events towards the trustor divided by the number of encounters. Each cooperative event adds to the overall probability of trustee meeting the expectation of the trustor. Let $X_{ab}(1), X_{ab}(2), \dots, X_{ab}(m)$ be a sequence of m independent encounters, each one being the probability of success. The minimum number of encounters necessary to achieve the desired level of confidence and error is represented by (m) .

The result of Eq. (4) will be a random variable representing the portion of success of the trust relationship between Trustor (a) and Trustee (b).

$$\alpha = (x_{ab}(1) + x_{ab}(2) + \dots + x_{ab}(m)) / m \quad (4)$$

With regard to most C2C marketplaces, this approach has a limitation—specifically, under this approach, it is assumed that the trustor and the trustee have interacted before the transaction. However, in most C2C marketplaces, this is not always the case (e.g. the first time you interact with an Uber driver is when you ride the car towards your destination).

Another weakness of this approach is the impact of the negative events that are equal to the positive ones. However, in everyday life, this assumption is unrealistic. Moreover, each trustee has to perform negative events in the first place towards the trustor to decumulate the portion of success.

8) BIO-INSPIRED TRUST AND REPUTATION MODEL FOR WIRELESS SENSOR NETWORK

The Bio-inspired Trust and Reputation Model for Wireless Sensor Network (BTRM-WSN) proposed by Mármol and Pérez [26] is a trust and reputation model inspired by the behaviour of ants. Based on their research on how ants find a trusted path, searching for food, and navigate back to their colony, the authors developed a trust and reputation model that can be used in the distributed sensor networks. The trusted path is not necessarily the shortest or the fastest, but it is the path that ants trust to take them to their destination.

While ants are sent to discover a new route, they leave trails of pheromone for other ants to follow. Since not all paths are worth being followed, ants build a trust matrix for all the paths that they go through. When multiple paths cross, the path with the strongest pheromone level gets higher points than those with less pheromone. Moreover, when an ant reaches the desired destination, the ant will consider this path as the most trusted path. In future journeys it will always use it to reach the desired destinations. Other ants also produce pheromone in the process of selecting their trusted paths. This makes the trusted path even more trustworthy for other ants. On the other hand, other paths lose their pheromones over time. As a result, all ants can easily decide which path to select, since less optimal paths lose significant parts of their pheromone, while a single path (the one with the strongest pheromone level) has been consistently by other ants.

Extrapolating this model to e-commerce, a similar pattern observed in human buyers/sellers is the so-called bandwagon effect. Buyers/Sellers prefer to use a marketplace that many other buyers/sellers have previously used, despite the fact that there might be other marketplaces with better processes or workflows. Similarly, buyers tend to buy from sellers who have recorded more successful deals or who have higher stars ranking in the system.

In order to calculate trust using BTRM-WSN in e-commerce, both buyers and sellers need to have multiple previous transactions. This can be considered as a limitation since calculating trust using BTRM-WSN will work against new sellers or buyers. It will only help those who are well established with previous history. In other words, trusted sellers will become more trusted, regardless of their future conduct behaviour. New sellers or buyers will be forced to fake a historical track of transactions just to be looked at as trusted resource.

E. SUMMARY

Modern C2C marketplaces are becoming an industry of trust [2]. Due to the uncertainty about quality of the offerings provided by users, it is important for marketplaces to calculate the trust level of its users before initiating any transaction. For example, in the hospitality services industry, hosts tend to build higher expectations from their guests by over-promoting their facilities. When guests don't find what they expected, they go through a disappointing experience. Disappointed guests tend to write a very positive feedback to the hosts hiding their disappointment due to the fact that the guests want hosts to write similar feedback on them. This will hide the problem and create another problem called "all good reputation problem" [18]–[21]. Some of disappointed guests tend to share their disappointing experience in other social media which makes it general to the market place rather than a specific host. Others might give a 5 stars feedback to the host but express their disappointment implicitly in the free text feedback form, a careful reader might be able to detect this.

Rangari [22], O'Donovan [23], Zhou and Hwang [24] studied guests feedback in an attempt to correct the "all good feedback" and calculate hosts real trust level based on the guests free text feedback. Their approaches used sentiment analysis (a.k.a opinion mining) in order to identify the hidden message in the guests feedback. Despite the fact that this approach can enrich the existing feedback system, it is built on the assumption that there are multiple feedbacks given to an offering. Many people have to go through many disappointing experiences and write about it in the marketplace feedback form. If you consider all the offering in any market place that will add up to a lot of disappointing experiences before the marketplace can identify who is good or bad offering. Moreover, hosts can always create new offerings for the same facility and start all over again.

Parallel and Real network of acquaintance, Chernoff Bound-based trust model [4] and EigenTrust and reputation model [25] are other forms of computable trust and reputation models. Unlike the other models, those are built to calculate trust and reputation before a transaction is finalized. They are built on different assumptions, some of which might be hard to achieve. For example, for the network of acquaintance reputation mode to work, it might be hard to identify the full network of people that link hosts and guests with each other. Not only that but also, it is very hard to calculate the reputation between each pair in the network in order to estimate the trust level between host and guest before they finalize a transaction. Another example, in order for the Chernoff Bound-based trust model to work, all the interactions between hosts and guests before they finalize a transaction has to be captured and analysed. Given that most of the transactions can be finalized in one click, and the interaction between hosts and guests can happen outside the marketplace.

This study focusses on managing guests' expectations rather than analysing their negative feedbacks'. It proposes a model that can help C2C hospitality marketplaces to automatically identify the trust level in the hosts description for any offering. This will help in identifying when hosts set the expectation so high which leads into a guest disappointing experience. By managing trust level in text, marketplace can avoid many disappointing experiences by just calculating the trust level in the hosts text. They can also help their hosts to edit their offering in order to set the right expectations that can lead into a positive experience. This model was trained on Airbnb data acquired from the US city of Ashville, Alabama. The model was tested on Airbnb data acquired from Manchester in the UK.

III. RESEARCH METHOD

In this section, we develop and present a conceptual framework to detect and measure trust as an emotion in the text written by C2C users. While section III.A discuss data sources selected for this project, section III.B presents the data model of the selected data.

A. DATA SELECTION

In the present study, we used Airbnb's published data that were available to us under a licence agreement. Specifically, we focused on the following cities:

1. Asheville, North Carolina, United States. Data published on the 18th of April 18, 2017
2. Manchester, England, United Kingdom. Data published on the 10th April 10, 2017

Those two cities were selected because of their similarity in size and the number of rooms/homes/apartments listed on Airbnb (at the time of data collection). Asheville will be used to train the model while Manchester will be used for its evaluation.

The data for analysis were collected from the Inside Airbnb website¹. Table 2 lists several representative cities datasets published by Inside Airbnb. Specifically, in Table 2, the first column is the city name, while the second column ("Listings") shows the number of rooms/homes/apartments offered in that city. The column "Occupied Nights/Year" is the average number of nights each listing is occupied per year, thus providing information on how active the city is. The column "Reviews" shows the total number of reviews received from all guests who booked accommodation in that city. The last column ("Review/Listing") shows the average number of reviews received per listing in that city given that writing a review is not mandatory on Airbnb, the "Review/Listing" varies across cities depending on how active/keen guests are in writing reviews of hosts/accommodation on Airbnb. The cities compared in the present study are highlighted and appear in bold.

As it can be seen from Table 2, while Asheville has a low number of listings on the Airbnb site compared to other cities (at the time of data collection), its average number of reviews per listing is one of the highest (32 reviews). For instance, Austin has 10 times more listings on Airbnb than Asheville (8,808 vs. 742, respectively). However, the average number of reviews per listing in Austin is half that of Asheville (16 vs. 32, respectively). Manchester is similar to Asheville in terms of the number of listings (865 vs. 742, respectively), but has a two times lower average number of reviews per listing (32 vs. 17 reviews, respectively).

Figures 4-5 show the densities and distributions of Airbnb listings in each of the two cities. Red dots represent all homes/apartments offered on Airbnb, while green dots represent private rooms offered on Airbnb. As can be seen in Figures 4-5, the densities and distribution of homes/apartments in Ashville and Manchester are similar.

B. DATA MODEL

The Airbnb data model published for those cities (Asheville and Manchester) consists of the following five data components (and given in Figure 6):

- *Listings* include summarised versions of the listed properties.

¹See <http://insideairbnb.com/get-the-data.html>

TABLE 2. A selection of cities data from the Inside Airbnb website.

City	Listings	Occupied Nights/Year	Reviews	Review /Listing
Amsterdam	18547	84	337,118	18
Antwerp	1227	99	26,547	22
Asheville	742	130	27,721	32
Athens	5,127	96	124,227	24
Austin	8,808	70	140,479	16
Barcelona	17,369	99	388,184	22
Berlin	20,576	95	265,631	13
Boston	4,870	107	120,737	25
Brussels	6,192	81	111,676	18
Chicago	5,207	118	132,147	25
Dublin	6,729	98	141,065	21
Edinburgh	9,638	126	259,251	27
Geneva	2,408	71	25,479	11
Hong Kong	6,474	67	82,393	13
London	49,348	89	564,297	11
Vancouver	4,838	151	160,138	33
Los Angeles	31,253	93	651,392	21
Madrid	12,775	99	290,810	23
Málaga	4,853	88	97,811	20
Mallorca	14,858	37	109,522	7
Manchester	865	103	14,880	17
Melbourne	12,174	85	182,120	15
Montréal	10,619	55	97,204	9

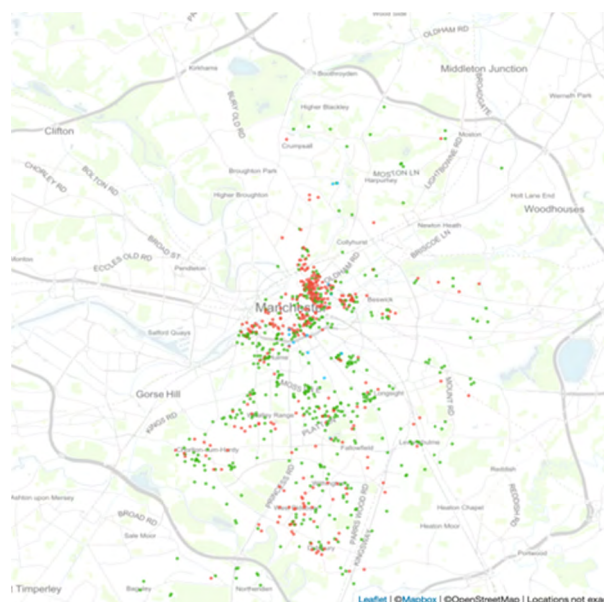


FIGURE 5. Accommodation available in Manchester, UK (Red: Entire house, Green: Private room).

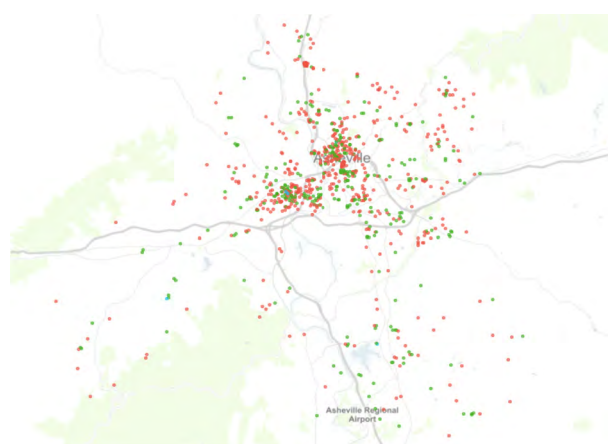


FIGURE 4. Accommodation available in Asheville, USA (Red: Entire house, Green: Private room).

- *Listings_details* include full details regarding listed properties, including a description from the host and directions to the nearest subway station. This is one of the main files used in the present study

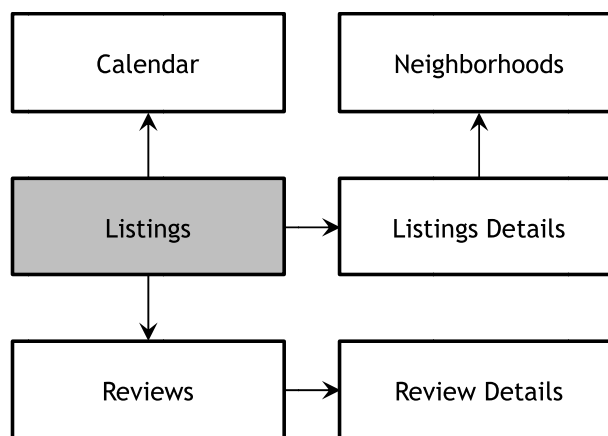


FIGURE 6. Airbnb data model.

- *Review_details* include all guests' reviews of the properties they used. Review details are linked to listings and listings details through a foreign key (*listing_id*). This is another main type of files used in the present study
- *Neighbourhoods* include segmentations of the city and link the properties to the segments they belong to.

IV. TEXT MINING AND CONCEPTUAL FRAMEWORK

This study proposes a model that can help C2C hospitality marketplaces to advise hosts when they set the expectation so high while writing the description for their facility. In order to train the model, we perform opinion mining on Airbnb to predict the trust level in host descriptions of offered facilities. In order to test the model, we ran the same algorithm on a different city in order to predict which host description will be trusted by guests more than others.

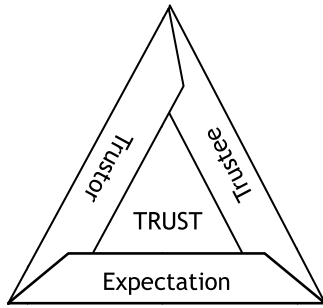


FIGURE 7. Trust Triangle.

A. TRUST DEFINITION

Trust is a basic emotion that has a psychological impact on the decision-making processes in e-commerce. Specifically, trust can influence individual behaviour and decisions when finalising deals and performing actions.

In the present paper, we adopt the definition of trust where trust is assumed to consist of the following three main parts: trustor, trustee, and expectations (Figure 7). The more dependent the trustor is on the trustee to meet expectations, the higher is the impact of trust. The probability of the trustee meeting the expectations is the level of trust. Most of the literature studied the trust and reputation of the trustor or the trustee in e-commerce. However, this study targets the third part of trust definition which is setting the ‘‘Expectation’’ right. The aim of this study is to build a framework that will help the trustee to set the right expectation for the trustor in a C2C marketplace.

B. TEXT MINING

This section describes the text mining and conceptual framework proposed to measure trust in Airbnb host listings. As mentioned in Section II.B, basic emotions of joy, anger, fear, disgust, and sadness can be detected in texts using sentiment analysis tools. Trust is also one of the eight basic emotions. The conceptual framework is designed to identify trust, using the texts about the listings written by the hosts (i.e. listing descriptions). Figure 8 shows a flowchart showing the stages of the text mining steps used in the present study.

Figure 9 shows the steps of the conceptual framework we used to train the analyser and generate trust rules. The first two steps, B1 and B2, were the text mining steps performed on the Airbnb data, as discussed previously in Figure 8. After analysing the sentiment used in the text for host listings, each listing would have five emotional sentiments (anger, disgust, fear, joy, and sadness). We selected several strongest sentiments found in the text and then performed Principal Component analysis for the dimension reduction. This reduced the output to a two-dimensional representation. Finally, hosts’ emotional sentiments were classified using a K-means classifier.

The IBM Watson™ Tone Analyzer service, conventionally used to perform linguistic analysis to detect emotional and language tones in written text [27], was used.

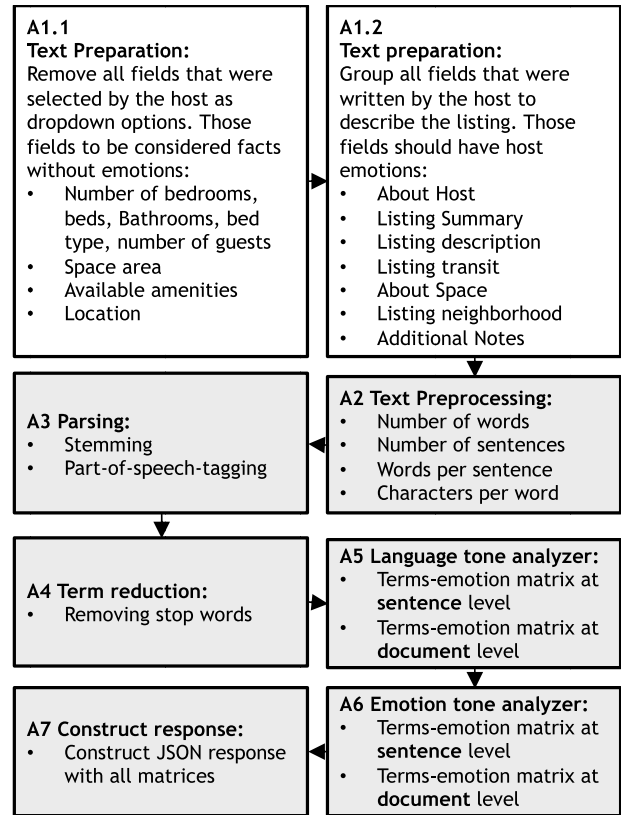


FIGURE 8. Text mining steps used in the present study.

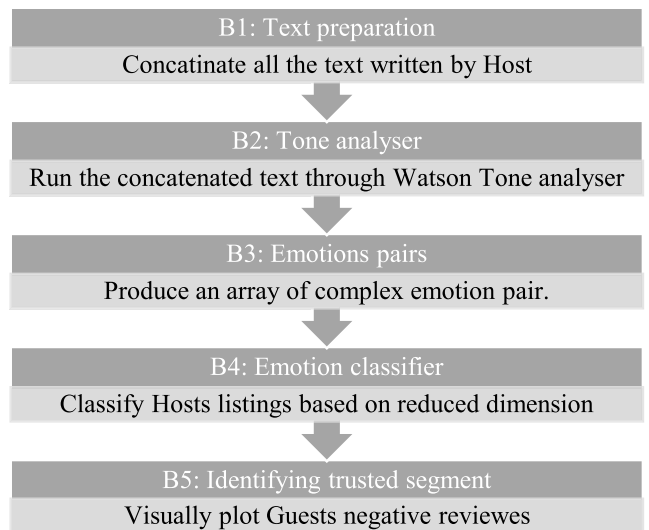


FIGURE 9. Conceptual framework to train and generate trust rules.

The service can analyse tone at both document and sentence levels. It is trained to analyse large corpora to predict the tone of new texts. For each of the tones, Watson trains its model independently using One-Vs-Rest paradigm. During prediction, the tones predicted with at least 0.5 probability are taken as the final tones. In the present study, Watson Tone Analyzer was used to perform steps A5-A6 shown in Figure 8.

Our proposed framework classified guest reviews of Airbnb hosts into the following two groups: (1) negative; (2) positive. If the review gave 1, 2, 3 or 4 stars to the host/accommodation, it was classified as a negative review; by contrast, a 5-star review was considered a good review. Previous studies demonstrated that guest reviews on Airbnb tend to be biased and are mostly positive [18], [20], [21]. This trend is due to the fact that Airbnb guests want the host to write a similarly positive review of them. This, in turn, guarantees that the guest will be accepted by other hosts and will get better deals in the future.

V. CASE STUDIES: RESULTS

In this section, the proposed conceptual framework is evaluated against the results obtained in two case studies (Ashville and Manchester). To this end, on identifying hosts' sentiments in Airbnb listings in the two cities (Sections V.A and V.D), we classify those sentiments (Sections V.B and V.E). This is followed by identification of guests' sentiments while writing reviews of Airbnb listings in the two cities (Sections V.C and V.F).

A. IDENTIFYING HOSTS' SENTIMENTS IN AIRBNB LISTING (ASHVILLE)

The first step in calculating the sentiment of the host was to concatenate all texts written for each listing into one single document. This included the texts written under the following columns from the data model: Summary, Description, Space, Notes, Neighbourhood Overview, and Transit. The next step was to parse the document into fundamental Parts of Speech (POS tagging). POS tagging, tags words in the document sentences into structural elements like verbs, nouns, adjectives, adverbs, and so forth. Each sentence was then analysed both in isolation and in conjunction with the remaining sentences. The selections of the words and the frequency of occurrence of a given phrase occurs near a set of positive or negative words was used to establish whether the phrase was positive or negative in general. The IBM Watson™ Tone Analyzer was used to analyse the emotional sentiments in the documents.

B. CLASSIFYING HOST SENTIMENTS IN AIRBNB LISTINGS (ASHVILLE)

K-means classifier was used to classify the host emotional sentiments found in the texts of the listings. The classification process embraced the following three steps.

Step 1: We combined the emotional sentiments into pairs, for example (joy and sadness), (joy and disgust), (joy and anger), and (joy and fear). The combinations resulted in 25 pairs of emotions. After plotting all those pairs together, we obtained the diagrams for all the host listings' emotions as illustrated in Figure 10.

As it can be seen in Figure 10, in Ashville, most hosts had dual emotions in the description of their Airbnb listings. Most of the emotion pairs can be classified into two clusters. We can assume that each cluster has a central point called

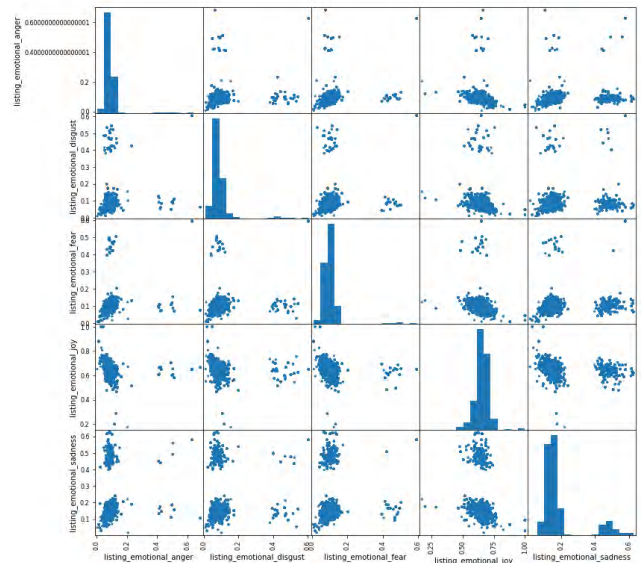


FIGURE 10. Host emotions in Airbnb listings (Ashville).

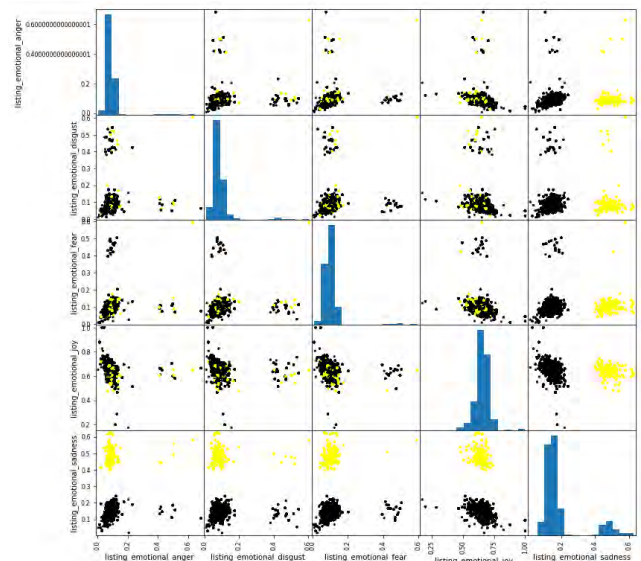


FIGURE 11. K-means cluster for hosting listing emotion pair (joy and sadness) applied on all other emotional pairs (Ashville).

centroid. Let us assume these are c_1, c_2 with random values (see Eq. (5)):

$$C = c_1, c_2 \tag{5}$$

where C is the set of all centroids.

The diagonal histogram graphs represent the matching emotional pairs—for example, (joy and joy) or (sadness and sadness). The histogram shows the frequency of that emotion and its intensity. In Figure 11, joy is the most frequent emotion with a high intensity across all host listings, followed by sadness, fear, disgust, and finally anger.

Step 2: To classify each host listing, the emotional pair (joy and sadness) was selected to be the base of the classification.

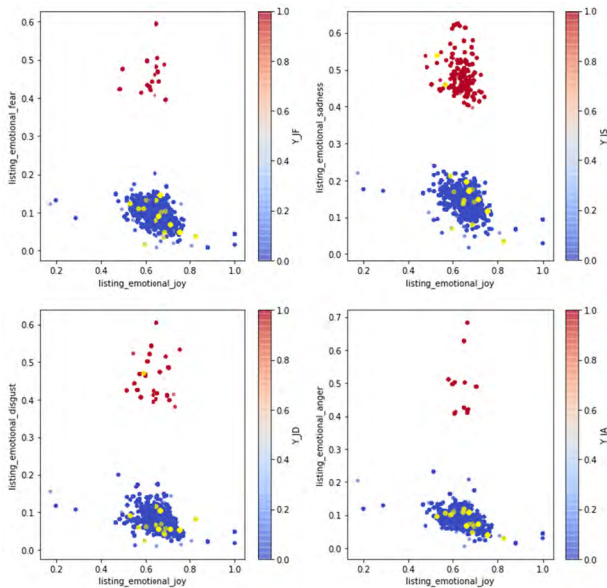


FIGURE 12. Emotional pairs combinations with joy (Ashville).

We calculated the Euclidean distance between each emotional pair to the centroid that was nearest to it using Eq. (6).

$$\min \text{dist}(c_i, X)^2 \tag{6}$$

where $\text{dist}(c_i, X)^2$ is the Euclidean distance, and X is the emotional pair point.

Step 3: After calculating the distance between all emotional pair points with the nearest centroid, we updated the centroid location to best match the centre of all points that belong to it (see Eq. (7)).

$$c_i = \frac{1}{|P_i|} \sum_{X_i \in P_i} X_i \tag{7}$$

where P_i is the set of all points assigned to the c_i cluster.

The algorithm was repeated until the clusters assigned to each emotional pair did not change.

C. IDENTIFYING GUEST SENTIMENTS WHILE WRITING AIRBNB REVIEWS (ASHVILLE)

Joy was the most prominent emotion in all hosts' Airbnb listings in Ashville. Figure 12 visualises the relationship between all four possible emotional pairs, on the one hand, and joy, on the other hand. The K-means classifier was used on each diagram separately. The classifier classified each diagram in isolation from other pairs. Each diagram consists of 27,721 points with transparency equal to half. Each guest review was mapped to its host. Host sentiment was duplicated according to the number of reviews it received. The darker the point shown in the diagram, the more reviews it received.

The yellow points in Figure 12 represent the guest reviews with listing of four stars or less. As discussed in the literature, Airbnb guests tend to give five stars to hosts more frequently than lower ratings [18], [19]. This tendency is linked to the fact that guests want the host to give them a high rating in

TABLE 3. Joy and fear segment reviews analysis (Ashville).

Class	Total Listings	Total Reviews	Reviews / Listing	Negative Reviews	% Negative Reviews
High joy & high fear	19	748	39.3	0	0%
High joy & low fear	723	26,973	37.3	86	100%
Total	742	27,721	37.3	86	100%

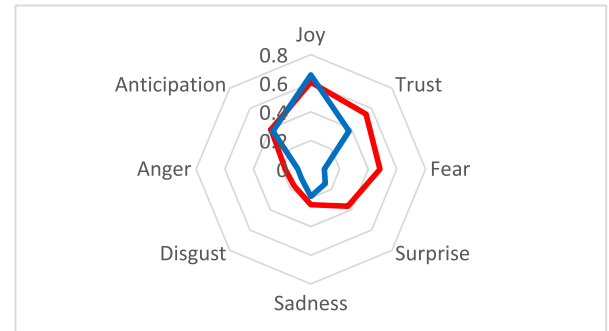


FIGURE 13. Joy and Fear radar chart (Ashville).

return. High ratings on Airbnb help guests to be more readily accepted by future hosts and, therefore, to get better deals. Accordingly, it was assumed that ratings of four stars or below will be considered as bad reviews.

From Figure 12, we can see that the first emotional pair (joy and fear) are clearly segmented. The percentage of the yellow points on the red segment is lower than that on the blue segment. Tables 3 report the values of reviews and listings in each segment.

The percentage of negative reviews is calculated based on the number of Negative reviews for a particular segment over all negative reviews given to all segments. In this use case, 0/86 results in zero.

As per Plutchik's Wheel of Emotions, the following radar charts show eight basic emotions. As stated earlier Ekman didn't consider trust as a basic emotion however, he agreed with Plutchik that a combination of two emotions leads to other emotions [8], [10]. Until the date of this study, the IBM Watson™ Tone Analyzer service is capable of measuring the values of only five emotions from the text (joy, fear, sadness, disgust, and anger). For this study, the values of the remaining three emotions (trust, surprise, and anticipation) will be considered to be a function derived from the neighbour basic emotions. For now, the value of the remaining three emotions will be obtained by averaging the value of the nearest two emotions (nearest as per Plutchik's Wheel of Emotions in Figure 3). For example, trust was the average of joy and fear, while anticipation was the average of joy and anger.

As shown in Figures 13-16, the highest value for trust comes in the red cluster in Figure 13. This finding is con-

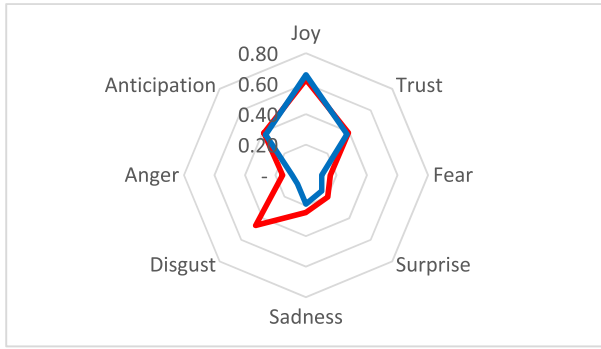


FIGURE 14. Joy and disgust radar chart (Ashville).

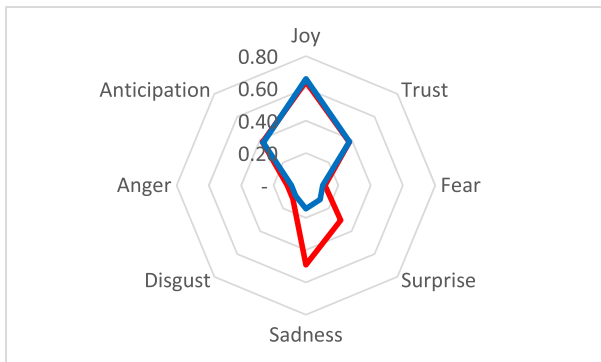


FIGURE 15. Joy and sadness radar chart (Ashville).

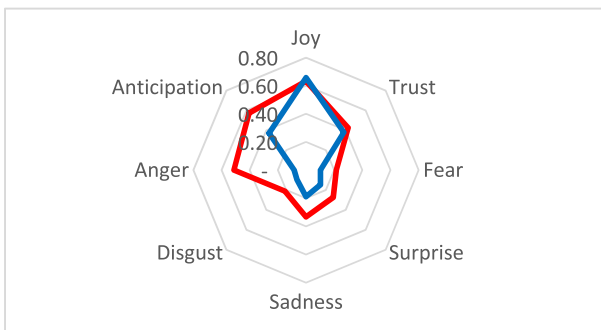


FIGURE 16. Joy and anger radar chart for all basic emotions (Ashville).

sistent with the results shown Figure 12. We can also see that the blue cluster in all emotional pairs is dominated by joy. All other emotions appear to be of a low intensity. The shape of the radar chart for the blue cluster does not change much in any of the combinations.

As shown in Figure 18, the emotional pair (joy and fear) was clearly segmented, and the percentage of the yellow points on the red segment was very low. Tables 4 provide the values for each emotional pair.

D. IDENTIFYING HOSTS SENTIMENTS IN AN AIRBNB LISTING (MANCHESTER)

Sentiments expressed in the listing descriptions from Manchester were analysed using the same approach as the one

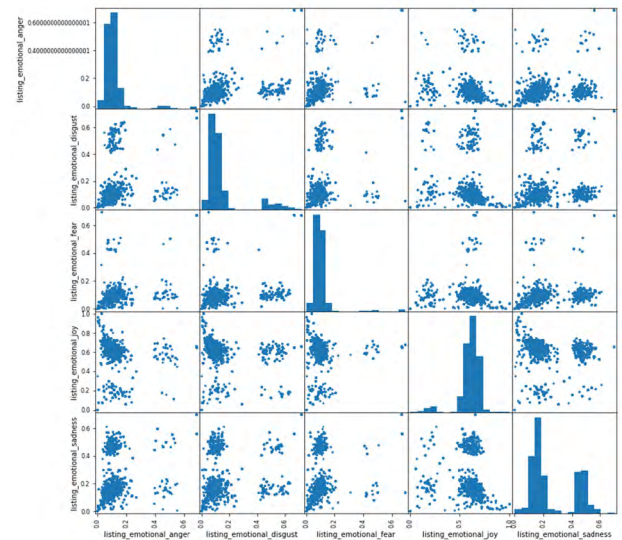


FIGURE 17. Host emotion listings (Manchester).

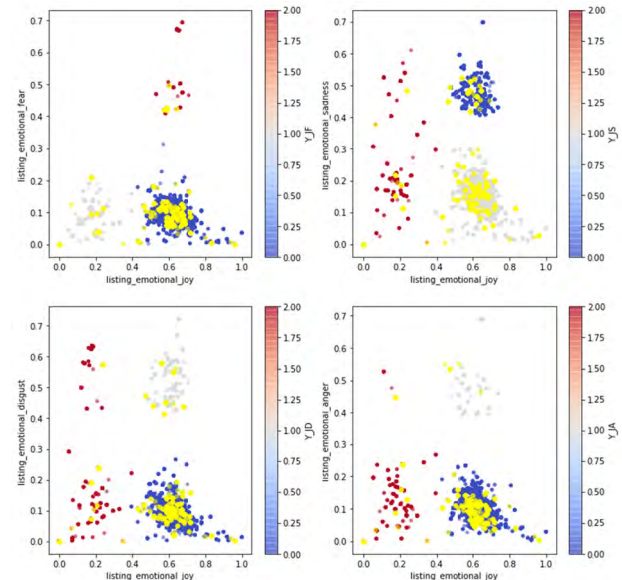


FIGURE 18. All possible emotional pair combinations with joy (Manchester).

outlined in Sections V.B, V.C for the Ashville data. The five basic emotions found in the text were used to categorise the listings. As specified in Section II.B, each emotional pair reveals a more complex emotion. Figure 17 shows all combinations of emotional pairs extracted from the Manchester dataset. The diagonal in the figure shows the histogram of the frequency of a single emotion.

E. CLASSIFYING HOST SENTIMENTS IN AIRBNB LISTINGS (MANCHESTER)

As it can be seen in Figure 17, joy was the most prominent emotion in the Manchester Airbnb listings as well. However, unlike in the Ashville data, sadness level in Manchester was

TABLE 4. Joy and fear segment reviews analysis (Manchester).

Class	Total Listings	Total Reviews	Reviews / Listing	Negative Reviews	% Negative Reviews
High joy & high fear	20	278	13.9	36	3.1%
Low joy & low fear	60	748	12.4	77	6.7%
High joy & low fear	596	13854	23.2	1038	90.2%
Total	676	14880	22.0	1151	100%

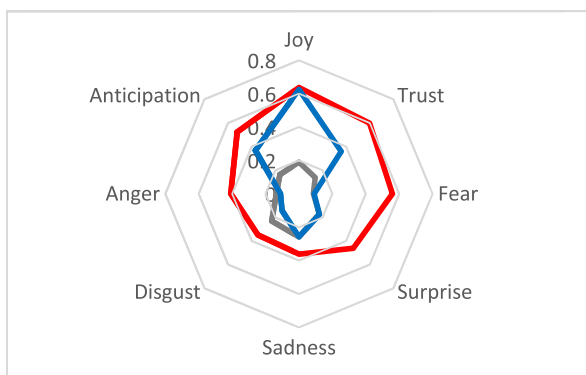


FIGURE 19. Joy and fear radar chart (Manchester).

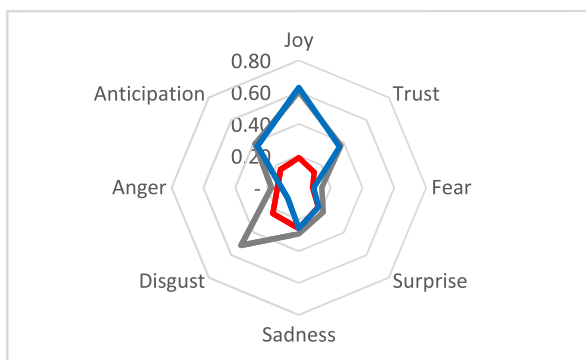


FIGURE 20. Joy and disgust radar chart (Manchester).

also high. In Figure 17, it can also be seen that most emotion pairs could be classified into three clusters. Figure 18 provides further details on all emotional pairs with respect to joy in the Manchester dataset.

F. IDENTIFYING GUEST SENTIMENTS IN AIRBNB REVIEWS (MANCHESTER)

Since, as was demonstrated in Section V.E, joy was the dominant emotion in all host sentiments in Manchester Airbnb listings, Figure 18 visualises the relationship between all four possible emotional pairs with joy. The K-means classifier was used on each emotional pair separately. The classifier

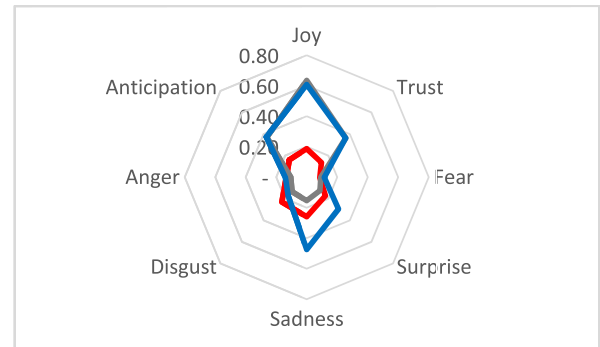


FIGURE 21. Joy and sadness radar chart (Manchester).

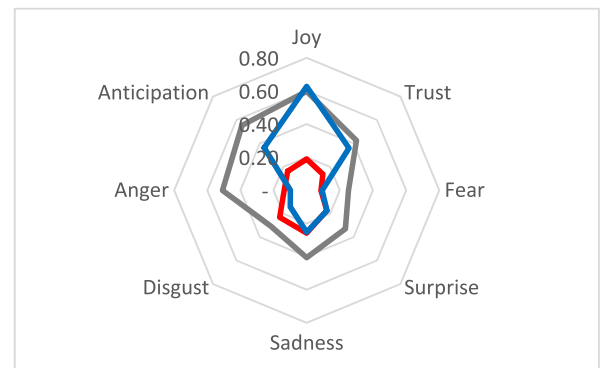


FIGURE 22. Joy and anger radar chart (Manchester).

classified each emotional pair in isolation from other pairs. Each emotional pair diagram comprises 27,721 points with transparency equal to half. Each review was mapped to its host. Host sentiment was duplicated according to the number of reviews it received. The darker the point shown in the diagram, the more reviews it received.

The yellow points represent the Guest reviews that marked listing accuracy equal to four stars or below. We considered four stars or below to be a bad review.

As it can be seen in Table 5, the red cluster in the joy and fear emotional pair had high Joy and high Fear. To investigate what other emotions in the red cluster in this emotional pair, radar charts (Figures 19-22) were created to show the average of all emotions found per cluster per emotional pair.

The highest value for trust appeared in the red cluster in Figure 19. This finding is consistent with the results shown in Figure 18. It can also be observed that the blue cluster in all emotional pairs was dominated by joy only. All other emotions had a low intensity. The shape of the radar chart for the blue cluster did not change much in any combination.

VI. SUMMARY AND CONCLUSIONS

The study findings answered the research questions raised earlier:

Research Question 1: Can trust, one of eight basic emotions, be detected in C2C texts, such as Airbnb accommodation descriptions? The answer is yes, Trust can be detected in text written by hosts describing their facilities.

Research Question 2: If joy and fear are detected in text, can we infer trust? The answer is also yes, as per the algorithm shown in this study, detecting Joy and Fear in hosts text was foundation to infer trust.

At present, almost any individual can make use of C2C marketplaces to offer a product or provide a service, such as sharing a ride or renting out a coach in a living room. With the rapid development of modern C2C marketplaces in the last decade, the spectrum of trust has become broader and increasingly complex. In any online transaction in C2C marketplaces, such as Uber and Airbnb, buyers and sellers must trust each other [1]. Therefore, modern C2C marketplaces heavily depend on trust among their users [2].

In response to this need, in the present study, we performed text mining and subsequent sentiment analysis of the Airbnb host descriptions of listing and guests reviews to predict the trust level based on the hosts' descriptions of their listed facilities. The data acquired from the Inside Airbnb website on the city of Ashville in Alabama, the US, and Manchester, the UK, were used for the analysis. The results from both cities were highly comparable. After detecting 5 of the basic emotions in host text using existing tools (i.e. joy, anger, fear, disgust, and sadness) we were able to calculate the trust level which is the 6th basic emotion from text.

The five emotions were combined into pairs to produce 25 pairs. Joy was found to be the dominant emotion in all hosts' sentiments in both cities, followed by sadness and fear. A K-means classifier was used to classify the host emotional sentiments found in the text. Each pair was interesting to study; however, after plotting negative guest reviews on top of all pairs, the emotional pair of joy and fear was decided to be the most interesting classification to measure trust. The results showed that negative guest reviews were higher when the host sentiment while writing descriptions was a singularly joyful emotion. By contrast, negative guest sentiments were at their minimum when the host sentiment hinted at a mixture of joy and fear.

Due to the uncertainty about quality of C2C offerings provided by hosts (Trustors), it is important for marketplaces (e.g. Airbnb) to maintain the trust triangle (Figure 7) balanced and detect a disappointing transaction a head of time. This paper suggests that market places should analyse hosts (Trustors) sentiments while writing the listing descriptions (Expectation) before releasing it to the public (Trustors). This study proposes a model that can help C2C hospitality marketplaces to advise hosts to set the expectation correctly while describing their facilities. This aims to reduce a guest (Trustor) disappointing transaction and hopefully reduce negative posts published about C2C marketplace in general.

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