TRUST IN AIRBNB TRANSACTIONS:

TRUST THE PLATFORM, TRUST THE PEOPLE?

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ABSTRACT

Over the past few years, the online sharing economy has been subject to plentiful research. Especially in the context of Airbnb, the question of establishing trust among its users picks many a researcher's brain. The bulk of said research however fails to recognise the role of the Airbnb platform itself. Accordingly, present paper includes the role of the Airbnb platform as intermediary. In doing so, it attempts to add to the fundamental understanding and resolving of trust problems in the online sharing economy. In this very same spirit, a seemingly under-explored host's perspective is employed to further give shape to the specific factors influencing trust in Airbnb transactions.

KEYWORDS:

Online sharing economy, Airbnb, trust, experience, host perspective

CONTENTS

INTRODUCTION

With the rise of the sharing economy over the past decade, attitudes towards consumption have changed dramatically. The shift from a traditional market to an online arena has prompted new issues regarding trust. While risk would be limited to monetary loss in traditional platforms (Deng & Ravichandran, 2017), risks in the sharing economy involve safety and security (Ert Fleischer & Magen, 2016). Since the emergence of online sharing economy platforms, questions of consumer protection and legal regulations have surfaced (Malhotra & Van Alstyne, 2014; Yoon & Occeña, 2015). Hamari, Sjöklint & Ukkonen (2016, p. 2047) define the online sharing economy as: "*The peer-to-peer-based activity of obtaining, giving or sharing the access to goods and services, coordinated through community-based online services.*"

With millions of available listings worldwide, Airbnb is considered one of the most successful online sharing economy accommodation platforms (Gutiérrez et al., 2017). Its recent and successful emergence has brought together hosts and guests from all over the world. However, it seems participation in the online sharing economy can come at a price. For instance, Devine (2014) describes situations in which Airbnb hosts' properties were badly damaged or stolen. Trust is considered crucial in order to overcome issues of consumer safety, and establish long-term success of the platform (Ter Huurne et al., 2017). The majority of Airbnb research focuses on dyadic relationships between hosts and guests. Ert et al. (2016) found Airbnb guests' booking choices were affected by assessed trustworthiness, derived from hosts' profile pictures. Yet in this scenario, no further attention was given to the Airbnb platform. Unfortunately, the role of a possible intermediary is mostly neglected. In turn this denies Airbnb any opportunity to possibly contribute to solving trust issues. This is problematic, as Airbnb transactions in fact are a three-way exchange between host, guest and the Airbnb platform itself (Liang, Choi & Hoppe, 2018). As intermediary, Airbnb could directly mitigate the trust relationship between host and guest. Hence, present paper will include the role of the "community-based online service" Airbnb itself. After all, all good things (should) come in threes.

Moreover, the guest perspective seems well-studied in current peer-to-peer Airbnb research. Robust reputation systems have been introduced to ensure user safety and stimulate trust[1]. Furthermore, specific guest characteristics such as race (Edelman, Luca & Svirsky, 2017) and gender (Abrahao et al., 2017) have been found to significantly influence hosts' trust in Airbnb transactions. The eventual three-way exchange of trust however implies a different theoretical model of trust. Specifically the trust relationship between host and the Airbnb platform seems underexplored.

Therefore, present paper will approach trust from a host's perspective: What host characteristics influence trust in the Airbnb platform itself? Rather than using predisposed characteristics of trust, such as race and gender, present paper will conceptualise process-based characteristics of trust: thus rendering them influenceable. In turn, these host characteristics are projected to affect trust independent of mentioned guest characteristics. McKnight & Chervany (2001) already highlighted the importance of an individual's perception of the institutional environment. Should hosts trust the people, or the platform?

In conclusion, the main research question of this paper reads: "*To what extent do host characteristics influence trust in Airbnb transactions?*"

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[1] See Airbnb co-founder Joe Gebbia's TED talk for more information on introduced reputation systems.
Available at: https://www.ted.com/talks/joe_gebbia_how_airbnb_designs_for_trust?language=en

TRUST BACKGROUND

Trust as a concept is studied intensively across various disciplines such as anthropology, psychology and sociology (Ter Huurne et al., 2017). Its implications and definitions are numerous, which necessitates a clear and encompassing definition. One common definition of trust (Mayer et al., 1995, p. 712) is: "*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.*"

Vulnerability originates specifically in the online sharing economy as for example "*transaction partners are unable to inspect and evaluate goods upfront and there is little opportunity for interpersonal interaction*" (Ter Huurne et al., p. 486). In order to overcome problems of uncertainty and risk in online sharing economy transactions, trust is required (McKnight & Chervany, 2001). Only whenever the trustor expects trust to be upheld by the trustee, are they willing to be vulnerable. Consequently, a great quantity of literature focuses on how trust can be established in online sharing economy transactions. McKnight & Chervany additionally provide an elaborate overview that distinguishes between numerous concepts of trust. For instance, trusting-related behaviours, institution-based trust and disposition to trust are mentioned in their typology (Ter Huurne et al., 2017). Disposition to trust (or trust propensity) is a well-mentioned concept throughout literature that, simply put, refers to a person's natural inclination to trust others (Gill et al., 2005). Some individuals are naturally more prone to trust than other individuals. Defining exact mechanisms of establishing trust in this case could become problematic, as trust varies randomly by a person's nature.

Familiarity is considered another important antecedent of trust (Ter Huurne et al., 2017). (Perceived) Familiarity points to "*a mechanism whereby trust is based upon common characteristics between the trustor and trustee*" (Ter Huurne et al, p. 492). These common characteristics in its turn relate to sociodemographic and intrapersonal characteristics such as, for example, gender, race or age (McPherson, Smith-Lovin & Cook, 2001). Sociological research also refers to this phenomenon as *homophily*, or *in-group favouritism*. Even though the authors could not account for a specific driving mechanism, Edelman, Luca & Svirsky (2017) indeed found guest race to be a significant antecedent of trust in Airbnb transactions.

TRUST IN THE PLATFORM

Trust propensity and guest characteristics are significant antecedents of trust in online sharing economy transactions. Yet, as both antecedents refer to the trust relationship between host and guest, they seem insufficient. As mentioned, present paper aims to highlight the presence and importance of a host-platform trust relationship. Whereas institution-based antecedents of trust (referring to "*a buyer's perception that third party guarantees are in place to facilitate online transactions*" (He, 2011, p. 3)) are considered essential, present paper will emphasise the importance of knowledge-based antecedents of trust in Airbnb transactions. According to He (2011, p. 2), "*The more knowledge and experience one has accumulated with a website, the more trust one is likely to form in that website.*" Hence, host characteristics must be identified that influence trust in the Airbnb platform through knowledge- and experience-based processes. In this paper, host experience and year in which the Airbnb host has joined the platform will be discussed. Trust in the platform is expressed through guest acceptance rates, meaning that trust in the Airbnb platform increases the likelihood of accepting guests unconditionally (independent of guest characteristics).

HOST EXPERIENCE

To begin with, meta-analysis of the sources and impacts of trust in e-commerce (He, 2011) provides a sophisticated explanation as to why exactly trust propensity is an insufficient condition for establishing trust in Airbnb transactions. While trust propensity is found to "*exert a notable influence on trust*" (He, p. 5) it remains small in magnitude. Simply trusting people, is an insufficient condition to engage in online transactions. In line with previous statement, He (2011, p. 5) also mentions knowing the internet is "*an insufficient condition to embrace in e-commerce, if the person does not have the special knowledge of conducting transaction with certain e-vendors.*" In fact familiarity with the e-vendor is mentioned as a strong antecedent of trust in online transactions. Familiarity is established through repeated interaction with the e-vendor. Positive transactions reinforce trust between both parties, thus leading them to repeat those transactions in the future. Whereas recent research has focused on trust relationships between hosts and guests, this theoretical approach emphasizes a trust relationship between host and e-vendor, namely Airbnb. Consequently, hosts that have dealt more frequently with Airbnb will have established an improved trust relationship with the platform compared to inexperienced hosts.

Yet, what if hosts experience negative outcomes of Airbnb transactions? Literature (Malazizi, Alipour & Olya, 2018) mentions financial, safety and security risks as having a strong negative influence on host continuation intention. Logically, hosts will not repeat negative interaction. In 2016, three to seven percent of 80 million Airbnb transactions had "*gone awry*" (iPropertyManagement, 2020). Issues ranged from cancellation problems to discrimination. Without undermining the importance of these issues, the majority of Airbnb transactions involve no problems whatsoever. Building on the concept of transaction experience, experienced hosts will have gathered a more detailed insight in the various risks regarding these online transactions. Knowing most of Airbnb transactions are completed successfully, experienced hosts will gain trust in the platform. As a result, experienced hosts will be more likely to accept guests unconditionally in the future. Hence, the first hypothesis reads:

H1 = "*Host experience significantly increases the likelihood of accepting guests unconditionally in Airbnb transactions*"

YEAR OF JOINING THE PLATFORM

As the Airbnb platform has gathered popularity rapidly over the past few years, adoption motivation has become a popular topic for researchers. Especially adoption motivation from a consumer point of view has gathered interest. One recurring question in Airbnb research remains: "Why do consumers prefer booking with Airbnb over traditional accommodation?" (Guttentag et al., 2018). Most existing literature regrettably overlooks adoption motivation from a host's perspective. As "*Airbnb users can be divided into market segments based on their reasons for choosing the service*" (Guttentag et al., p. 343), so can hosts. Relevant to this essay, adoption motivation among Airbnb hosts might help expand our knowledge of trust problems in Airbnb transactions.

In 2019, the Airbnb platform counted over 650,000 hosts, accounting for 7 million listings worldwide (iPropertyManagement, 2020). Undeniably, Airbnb now dominates the online sharing economy accommodation sector. As for most innovations however, its success could not be guaranteed in the beginning. Throughout its year of founding in 2008, the Airbnb platform gathered a total of zero bookings (MuchNeeded, 2020). Consequently, the question rises whether this affects trust in Airbnb transactions: Why should we expect differences in trust among hosts that have joined the platform at a different point in time?

Roger's Diffusion of Innovation theory (2010) explains why we might find different effects of trust in Airbnb transactions for early and late Airbnb hosts. His theory explains the process of adopting innovations over time among "members of a given culture". Innovations are broadly defined, as these constitute ideas, products, opinions or literal innovations. They can occur in multiple forms, yet the shared factor in all forms is "*perceived newness of the idea to the individual*" (Rogers, p. 11). Relevant to this essay, Rogers provides a classification of individuals, complemented by extensive psychological argumentation, that places individual behaviour at the heart of adoption. Additional assumptions of his model are: an innovation is *not* adopted simultaneously by all members of a culture, and information exchange between members of a culture is crucial to distribution of the innovation. In general, Rogers distinguishes five adopter categories, as visualised by figure 1.

Figure 1. *Diffusion of Innovation Adopter Categories*
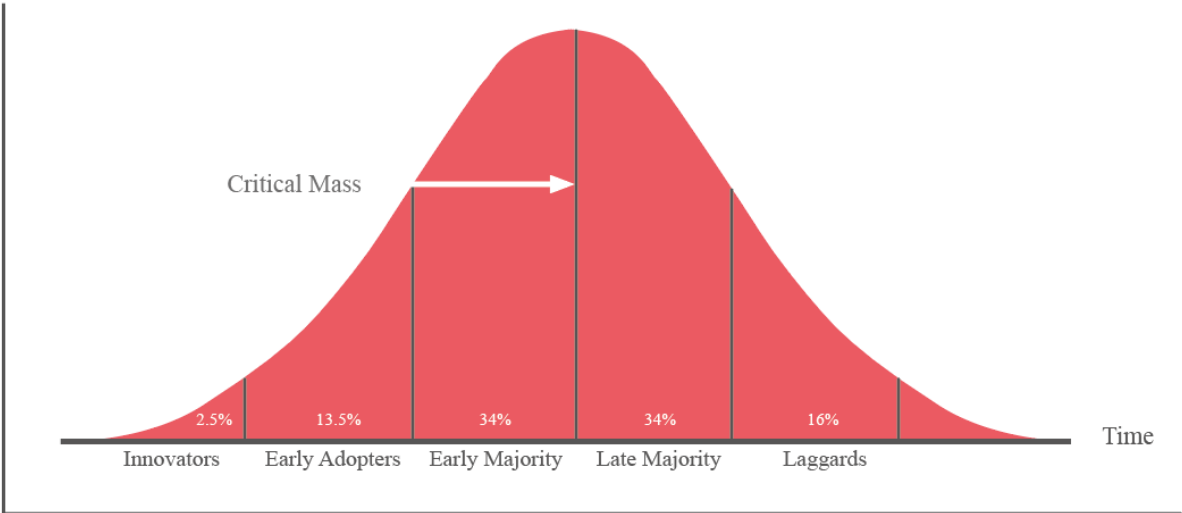
Innovators are the first individuals to adopt an innovation. They are considered venturesome, risk-taking, and like to take on the role of change agent (Rogers, 2010). They are willing to accept the risks that innovations bring, because they have substantial financial resources to back them up. In general, innovators are "*able to cope with higher levels of uncertainty than any other adopter category*" (Rogers, p. 22). Following after, early adopters are considered adventurous trend-setters who are attracted by high-risk/high-reward projects (Kaminski, 2011). Individuals in both adopter categories share an adventurous, risk-taking attitude that leads them to adopt an innovation. Latter adoption categories too explain adoption through individual behaviour, yet do not share the risk-taking mindset of mentioned adopters.

Being venturesome alone however, is an insufficient explanation for adoption in this stage. In his book, Christensen (1997) describes "disruptive innovations" as products that are logically speaking less desirable than their prevailing counterparts. Their appeal is not based on improved performance. In fact, most disruptive innovations underperform in many ways compared to prevailing alternatives. Yet they do hold a small set of alternative benefits, that mostly rely on to them being cheaper and easier to use (Guttentag et al., 2018). Airbnb as a "disruptive innovation" competes with the traditional hotel industry, as they lose approximately $450 million in direct revenues per year to Airbnb (iPropertyManagement, 2020). Its consumer appeal derives from the opportunity it provides to generate substantial income with relative ease, as hosts on average earn up to $10.000 a year (iPropertyManagement, 2020).

On one hand, a risk-taking attitude combined with substantial margin for profit can cause adoption among early Airbnb hosts. Through adopting, in spite of the involved risks, these hosts display trust in the Airbnb platform. Therefore, these hosts might likewise display trust in the guest. On the other hand, Rogers' same model proposes an additional, reversed mechanism.

As mentioned, Airbnb has now reached its threshold for success. Rogers (p. 284) mentions this as a crucial step in the diffusion process, as "*an innovation must definitely have the weight of system norms behind it to convince the late majority*". In other words, the critical mass threshold must be crossed (figure 1). Whenever the innovation is widely adopted, risk and uncertainty problems diminish. The exact implications of the innovation become salient over time, and even the sceptics can become convinced. And, whenever problems of risk and uncertainty are solved, trust is established (McKnight & Chervany, 2001). Popularity of an innovation could in turn be considered convincing in assessing trustworthiness. If a lot of people adopt the innovation, it must be trustworthy. The only requirement for this hypothesised mechanism is an upward popularity trend. Over time, more individuals must choose to utilise the platform. As specific Airbnb user statistics are scarce, no detailed user trend can be obtained. Yet the Airbnb platform rose from gathering zero bookings in 2008, to constituting 5.5% of the total demand for lodging in the United States in 2018 (iPropertyManagement, 2020). Hence in this paper, an upward popularity trend is assumed.

The exact directional effect of year of joining the platform on trust in Airbnb transactions remains unclear. On one hand, Rogers' diffusion of innovation model mentions innovators as prone to risk taking. Early Airbnb hosts indeed faced a lot more uncertainty than late Airbnb hosts. Yet, considering their nature and the potential pay-off, were willing to trust the platform. On the other hand, the same model proposes a reversed mechanism: adoption risk decreases over time. Late Airbnb hosts face a lot less risk and uncertainty as the platform is already deemed trustworthy. Thus hosts that become member of the Airbnb platform at a later point in time, display more trust in the platform itself. Trust in the platform in turn increases the likelihood of accepting guests unconditionally. Current research on the effect of year of joining the platform on trust in Airbnb transactions remains unclear, and warrants further attention. That is why the second hypothesis of this paper reads:

H2 = "*Year of joining the Airbnb platform significantly influences the likelihood of accepting guests unconditionally in Airbnb transactions*"

INTERACTION

Following this literature overview, another possible factor must be considered. Host experience and year of joining the platform are both hypothesised significant antecedents of trust in Airbnb transactions. However, there's a theoretical reason to assume these variables cannot be treated separately. For example, hosts that joined the platform in the beginning will *logically* have had more time to gain experience than hosts that joined the platform at a later point in time. Then again, host experience in this paper is dependent on user intensity, instead of membership duration. Individuals in the late majority adopter category are generally of lower socio-economic status than earlier adopters and motivated by a need to keep up with competitors in their industry. In general, they respond to economic necessity (Rogers, 2011; Kaminski, 2011). In terms of margin for profit, they have a disadvantaged position relative to earlier Airbnb hosts. Thus, in what perhaps could be called a need to compensate, late Airbnb hosts might attempt to bridge that gap in experience. After all, experience equals transactions, and transactions equals income.

Although the directional effect remains unclear, the effect of host experience is expected to differ by year of joining the platform. Therefore, the third hypothesis of this essay reads:

H3 = "*The effect of host experience on trust in Airbnb transactions is influenced by year of joining the platform*"

Figure 2 summarises the theoretical relationships as suggested by literature.

Figure 2: *The proposed effects of host experience and year of joining the platform on trust in Airbnb transactions.*
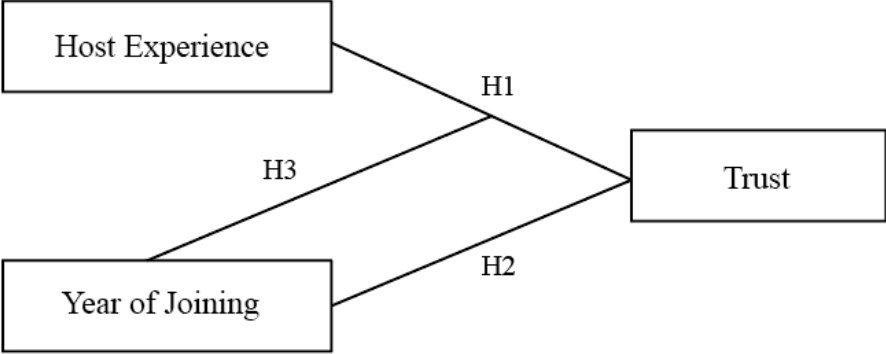
METHODOLOGY

In order to conduct analysis as proposed in this research, data from previous research (Edelman, Luca & Svirsky, 2017) was used. Said data was collected by the authors in July 2015 throughout the cities of Baltimore, Dallas, Los Angeles, St. Louis and Washington DC, USA. Their research focused on the role of racial discrimination in Airbnb exchanges. Twenty fictional Airbnb guest profiles were created, with either distinctively African American or Caucasian sounding names (e.g. Rasheed Jackson versus Greg O'Brien). Within each category, male and female names were used to research gender differences. Gender and race were the *only* notable differences. These fictional profiles were then used for a field experiment in which they applied for roughly 6,400 Airbnb listings across the aforementioned cities. The authors applied for listings from small-time landlords to hosts that own multiple properties. The experiment's primary goal was to research the role of race in Airbnb exchanges. Hosts' responses were measured and categorised. For instance, some hosts accepted or rejected guests immediately, while other hosts required additional information before accepting or rejecting a guest. Hosts' race and gender were defined to control for spurious results (e.g. homophily as driving factor in Airbnb exchanges). Overall, their research found African Americans were 16% less likely to be accepted by hosts than Caucasian guests. While the authors "*cannot identify the mechanism causing worse outcomes for guests with distinctively African American names*" (Edelman et al., p. 17), their research is considered robust. Discrimination occurs among "*landlords of all sizes*" (Edelman et al., p. 1), but is specifically high among hosts that have never previously accommodated an African American guest. Among hosts that have accommodated African American guests in the past, discrimination dropped significantly. Information was partially collected from the Airbnb platform (number of reviews, listings, et cetera) while additional information was collected through experimental design. Mechanical Turk workers were employed in order to establish hosts' gender, race and age based on hosts' profile pictures. The dataset contains a total of $N = 6392$ hosts.

The dependent variable was operationalised through host's response categories. The original variable "host_response" contained 17 response categories and was recoded into a dichotomous variable "yes_by_host". Unconditional "yes" response was given value 1, while all other remaining response categories were given value 0. Other response categories for example indicated declination, required additional guest information, or were otherwise incorrect. Hosts that accept guests unconditionally are considered more trusting than hosts that accept

conditionally, or reject guests. In total, 2092 hosts replied with "yes" unconditionally. There were 0 missing values.
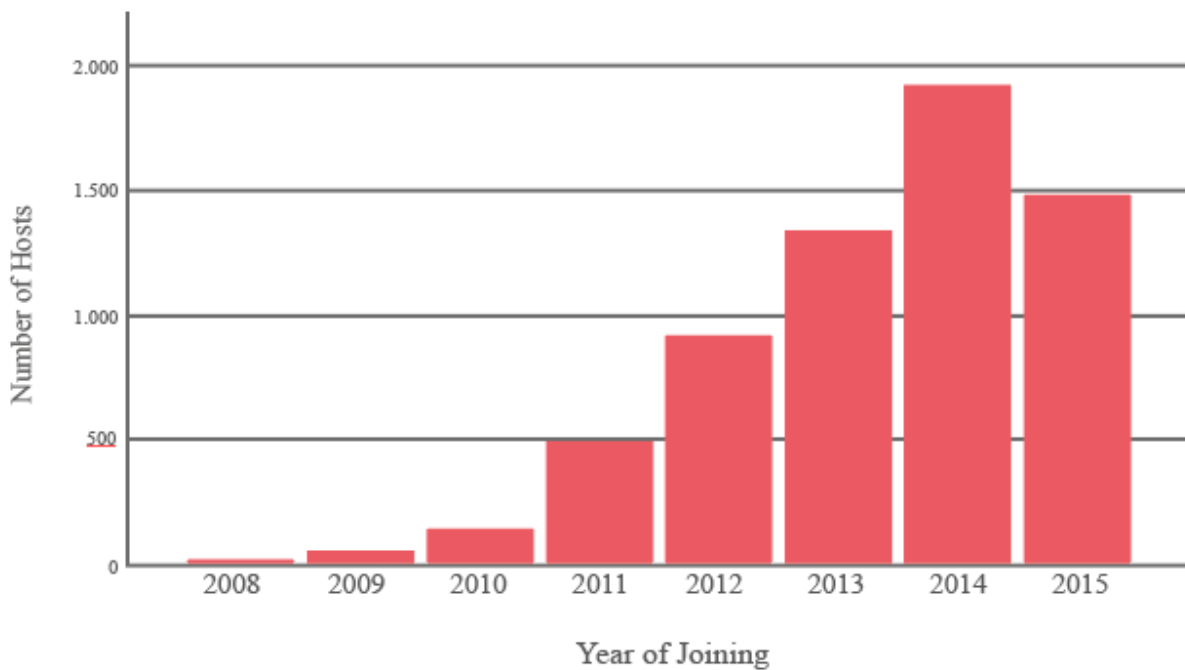
The first independent variable "host_experience" was operationalised through number of reviews. Number of reviews is considered to be the most accurate indicator of host experience[2]. With each transaction completed, a host gains experience. Meaning, a host that has over 40 reviews on his Airbnb account is considered to be more experienced than a host that has ten reviews. Yet, host experience only becomes tangible through the amount of reviews that are actually left. Fewer reviews, does not necessarily indicate less experience. Some guests simply leave more or less reviews than others. Then again, there is no reason to assume any significant differences between hosts, as this phenomenon applies randomly to the entire set of hosts. Research (Fradkin et al., 2018) indicates 67% of Airbnb guests actually leave a review (Fradkin et al., p.14). The nature of reviews (positive versus negative) is deemed irrelevant as it is of no importance relating to the content of host experience, as the variable is based on transaction quantity, not quality. In general, host's profiles (N = 6390) contain an average of M = 30.87 reviews. A total amount of 2 values were missing. These missing values refer to hosts of whom the number of reviews could not be identified.

The second independent variable "year_of_joining" was operationalised through recoding the original variable "member_since". The original variable measured the month in which hosts became a member of the Airbnb platform, from 2008 until 2015. Recoding was necessary as host membership was based on the month of joining (e.g. August 2008, or February 2011), instead of each year. The new variable "year_of_joining" contains eight response categories, measuring the amount of years since the founding of Airbnb in 2008. After recoding, a total of N = 21 hosts joined in 2008, N = 59 hosts joined in 2009, N = 145 joined in 2010, N = 494 joined in 2011, N = 920 joined in 2012, N = 1338 joined in 2013, N = 1921 joined in 2014 and lastly N = 1481 hosts joined in 2015 (figure 3). Evidently membership peaked in 2014. A total of 13 values were missing. These missing values refer to hosts of whom the year of joining the platform could not be clearly identified.

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[2] The exact number of completed transactions is recognised by Airbnb. However, this data is not publicly available, and remains exclusive to Airbnb. Therefore, the number of reviews is considered the most accurate indicator of host experience.

Figure 3: *Number of Airbnb hosts that joined the platform per year*

The third independent variable "experience_year_of_joining" was operationalised through constructing an interaction term for host_experience and year_of_joining. After construction, the interaction term (N = 6380) contained a total of 12 missing values. These missing values again refer to hosts of whom year of joining the platform could not be clearly identified.

Lastly, control variables were operationalised. The first control variable "host_female" was operationalised through recoding the original variable "host_gender". The original variable contained 11 response categories based on Mechanical Turk worker's assessment, derived from hosts' profile pictures. Two Mechanical Turk workers both individually categorised hosts' gender, age and race. For example, hosts were categorised as "female", "male" or "unclear". Only when both Mechanical Turk workers agreed on a host characteristic, was it confirmed. In the event that Mechanical Turk workers were unable to agree on a host's gender, age or race, a third Mechanical Turk worker was hired to settle the discussion. For clarity's sake, profile pictures that unambiguously showed either one or two males were categorised as male, and profile pictures that showed either one or two females were categorised as female. After adjustment, "host_female" (N = 4571) contained 2034 male, and 2537 female hosts. A total amount of 1821 values were missing. These missing values refer to hosts whose gender did not fit in the aforementioned categories.

The last control variables "host_race_white", "guest_female" and "guest_white" did not need recoding as they represent the variables from the original research by Edelman et al. (2017).

This research deviates from conventional research as it contains a binary dependent variable[3]. As proposed by literature (Caudill, 1988), Linear Probability Modelling (LPM) was performed in order to conduct the required statistical analyses. Criticism of LPM must be discussed as for example "*ordinary least squares is inefficient, disturbances are not distributed normally and predicted probabilities from the LPM can lie outside the 0-1 interval*" (Caudill, p. 425). Yet, necessity surmounts optimality as the dependent variable could not be operationalised continuously.

Multiple regression analysis was conducted in order to test the main effect of host experience and year of joining the Airbnb platform on trust. After which a second model was in order that included additional control variables. While theoretically this research emphasises a trust relationship between host and platform, guest characteristics were accounted for as control variables to possibly strengthen the conceptualised main effect. Both guest race and gender are proven to be significant predictors of trust between host and guest (Edelman et al., 2017) and were controlled for. Including guest characteristics therefore either expanded, and/or enriched current scientific findings. A third model analysed the effect of an interaction term of host experience and year of joining on trust without control variables. Lastly, the fourth regression model analysed the effect of the interaction term while controlling for other variables. Interaction terms must be treated carefully, as they can increase artificial multicollinearity. General guidelines consider VIF[4]s of 10 and upwards problematic (Hair et al., 1998). After centring, collinearity diagnostics indicated VIFs of < 2.3 across all models.

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[3] Research containing a binary dependent variable favours logistic regression analysis over linear regression analysis.
[4] Abbreviation for Variance Inflation Factor. For more information on VIF in context of regression analysis see: https://doi.org/10.1081/QEN-120001878

RESULTS

Table 1 summarises descriptive statistics for all included variables. After selection, multiple regression analysis was conducted for a total of N = 4563 valid cases. The dependent variable "yes_by_host" was constructed dichotomously, meaning only hosts that scored the maximum of 1 were considered to be trusting. In general, 33% of Airbnb hosts scored the maximum of 1. The host experience variable was divided by 10 to provide a more accurate and interpretable scale. Year of joining the Airbnb platform ranged from 2008 (Minimum = 0) to 2015 (Maximum = 7). On average, Airbnb hosts in this dataset joined the platform in 2013 (M = 5.34).

Table 1: *Descriptive statistics*

	N	Minimum	Maximum	Mean	SD
Yes by host		0	1	.33	
Host experience		.00	120.8	3.09	7.25
Year of Joining		0	7	5.34	1.41
Host Female		0	1	.56	
Host White		0	1	.63	
Guest Female		0	1	.51	
Guest White		0	1	.50	
Valid N (listwise)	4563				

Table 2 summarises the results of host experience and year of joining on trust in Airbnb transactions, including control variables and interaction term. The first hypothesis *"Host experience significantly increases the likelihood of accepting guests unconditionally in Airbnb transactions"* can be confirmed. Regression model 2 indicates a significant positive relationship between host experience and trust (b = .010, t = 9.555, p = < .001/2) even after controlling for guest characteristics. While effect size b = .010 might seem insignificant, this indicates for every 10 reviews a host gathers, the likelihood of accepting a guest unconditionally increases with .01. With a maximum of 1208 reviews, this can amount to a significant effect size. In general, experienced hosts are more trusting than inexperienced hosts.

The second hypothesis "*Year of joining the Airbnb platform significantly influences the likelihood of accepting guests unconditionally in Airbnb transactions*" can also be confirmed (b = .032, t = 6.382, p = < .001). Regression model 2 indicates that for every year since the founding an Airbnb host joins the platform, the likelihood of accepting a guest unconditionally increases with .032. In general, hosts that became member of the platform at a later point in time are more trusting than early hosts.

Regression model 4 shows the results for the interaction term after adding control variables. The third hypothesis "*The effect of host experience on trust in Airbnb transactions is influenced by year of joining the platform*" cannot be confirmed (b = .001, t = 1.400, p = .162). It seems the effect of host experience is not influenced by year of joining the platform. Null hypothesis cannot be rejected.

As proposed by Edelman et al. (2017), race and gender are considered significant predictors of trust in Airbnb transactions. Regression model 2 indicates this finding was replicated (R^2 change = .007, F change = 15.763, p = < .001). Meaning, female guests were significantly more likely to be accepted unconditionally (b = .033, t = 2.440, p = .015), as were white guests (b = .069, t = 5.099, p = < .001). Guest characteristics account for 0.7% of variation in host responses in Airbnb transactions. Yet, model 1 shows that guest characteristics do not reign supreme, as 2.4% of variation in host responses in Airbnb transactions is accounted for by host characteristics (R^2 = .024, F = 28.325, p = < .001). This finding was confirmed when controlling for host characteristics while analysing the effect of guest characteristics on trust (R^2 change = .024, F change = 28.435, p = < .001). Guest characteristics remain significant predictors. Nevertheless, this analysis highlights the importance of previously neglected host characteristics. Additionally, model 2 indicates a significant influence of host race on trust in Airbnb transactions, as white hosts were significantly less likely to accept guest unconditionally than hosts of other races (b = -.047, t = -3.134 , p = .002). No significant effects were found for host gender.

Figure 4 summarises the effects of host experience and year of joining the platform on trust in Airbnb transactions. While the first two hypotheses were confirmed, no significant evidence was found for an interaction effect. The theoretical model was therefore partly confirmed.

Figure 4: The *effect of host experience and year of joining on trust in Airbnb transactions*
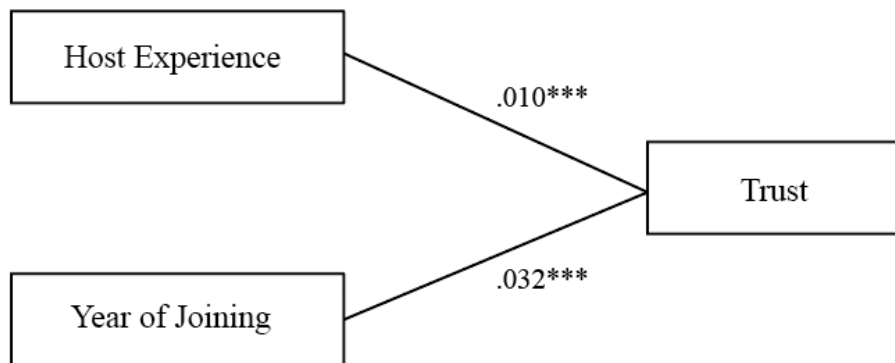
Host Experience — .010*** → Trust

Year of Joining — .032*** → Trust

Table 2: *Summary of the effects of host experience and year of joining on trust (N = 4563)*

Variable	Model 1 B	SE B	Model 2 B	SE B	Model 3 B	SE B	Model 4 B	SE B
Constant	.142***	.032	.093**	.034	.136***	.033	.088**	.034
Host Experience	.010***	.001	.010***	.001	.012***	.002	.012***	.002
Year of Joining	.032***	.005	.032***	.005	.033***	.005	.033***	.005
Host Female	.012	.014	.011	.014	.013	.014	.012	.014
Host White	-.045**	.015	-.047**	.015	-.046**	.015	-.048**	.015
Guest Female			.033**	.014			.033**	.014
Guest White			.069***	.014			.069***	.014
Interaction term					.001	.001	.001	.001
R2	.024***		.031***		.025		.031***	
F Change			15.763		2.180		11.164	

*** significant at p = < 0.01 ** significant at p = < 0.05

CONCLUSION

Present paper focused on the role of host characteristics on trust in Airbnb transactions. In contrast with existing literature, this paper theorised a trust relationship between host and platform. Guest characteristics are dominant in Airbnb literature, yet the role of host characteristics remains understudied. The main research question of this paper was: "*To what extent do host characteristics influence trust in Airbnb transactions?*"

In summary, host characteristics appear to be significant predictors of trust in Airbnb transactions, independent of guest characteristics. The first host characteristic built on the concept of transaction experience: for every ten reviews a host gathers, the chance of accepting a guest unconditionally increases. This finding is in line with the assumptions of He's model of the sources and impacts of trust in e-commerce (2011). Familiarity with the e-vendor increases trust, and repeated interaction with the e-vendor increases familiarity. Transaction experience reinforces a positive trust relationship between host and platform. Therefore, experienced hosts are more trusting than inexperienced hosts. Trust in the sharing economy knows multiple antecedents, each considering different aspects of trust (Ter Huurne et al., 2017). McKnight and Chervany highlight these different aspects of trust in their typology (2001). Trust propensity is considered an important antecedent throughout literature. Yet present paper evokes a different debate, as proposed by He (2011): To what degree is trust propensity a *sufficient* explanation for trust in the online sharing economy? Current findings suggest trust propensity is an insufficient explanation. Perhaps it is time for research to shift its focus to antecedents of trust influenced by experience. Acknowledging their function in turn creates opportunity to exert influence on establishing trust.

The second host characteristic was based on year of joining the platform. Rogers' Diffusion of Innovation model (2010) proposed two possible mechanisms, assigning hosts to two categories: early Airbnb hosts, and late Airbnb hosts. Findings indicate the latter group displays more trust in the Airbnb platform. For every year later a host joined the platform, the likelihood of accepting a guest unconditionally increased. As an innovation is adopted by members of a culture over time, utilising risks decrease. While innovators or early adopters face risk in adoption, late adopters are aware of every involved risk as they have become salient over time. Risks might even diminish altogether. Adoption of an innovation becomes easier as the innovation is deemed trustworthy by the individuals in their surroundings. Even if new risks arise, it effects all involved individuals: at least they are not alone. Year of joining the platform

aligned with Airbnb's user growth assumption which implies additional evidence for the popularity argument.

Present paper could not identify a significant interaction effect for host experience and year of joining the platform. The effect of host experience is not influenced by year of joining the platform. On one hand, this paper assumed early Airbnb hosts were more experienced than late Airbnb hosts, thus more trusting. On the other hand, as derived from Rogers' late majority adopter category, late Airbnb hosts were expected to display more trusting behaviours towards guests out of economic necessity. As they have had less time and opportunity to gain experience, late Airbnb hosts were expected to behave more trustingly. Simply put, late Airbnb hosts were considered more trusting as they can't afford to behave critically. Neither seem to be the case. Although this result deviates from theoretical expectations, it provides clear practical implications for Airbnb, as both findings can be treated separately.

LIMITATIONS

Customary to scientific research, limitations of this paper must be discussed. As mentioned earlier, LPM was performed as the dependent variable was constructed dichotomously. Multiple regression analysis naturally favours a continuous dependent variable, as interpretation of the effects becomes less problematic, and more meaningful. However, this was not realised in present paper. It must also be mentioned that the distribution of host experience is right-skewed (figure 5). Host experience was operationalised through amount of reviews. The majority of Airbnb hosts in this dataset however had zero reviews. Skewed distributions can act as outliers as they do not follow normal distribution, and interpretation of effects can become problematic (Neuman, 2014).

Figure 5. *Distribution of amount of reviews divided by 10.*
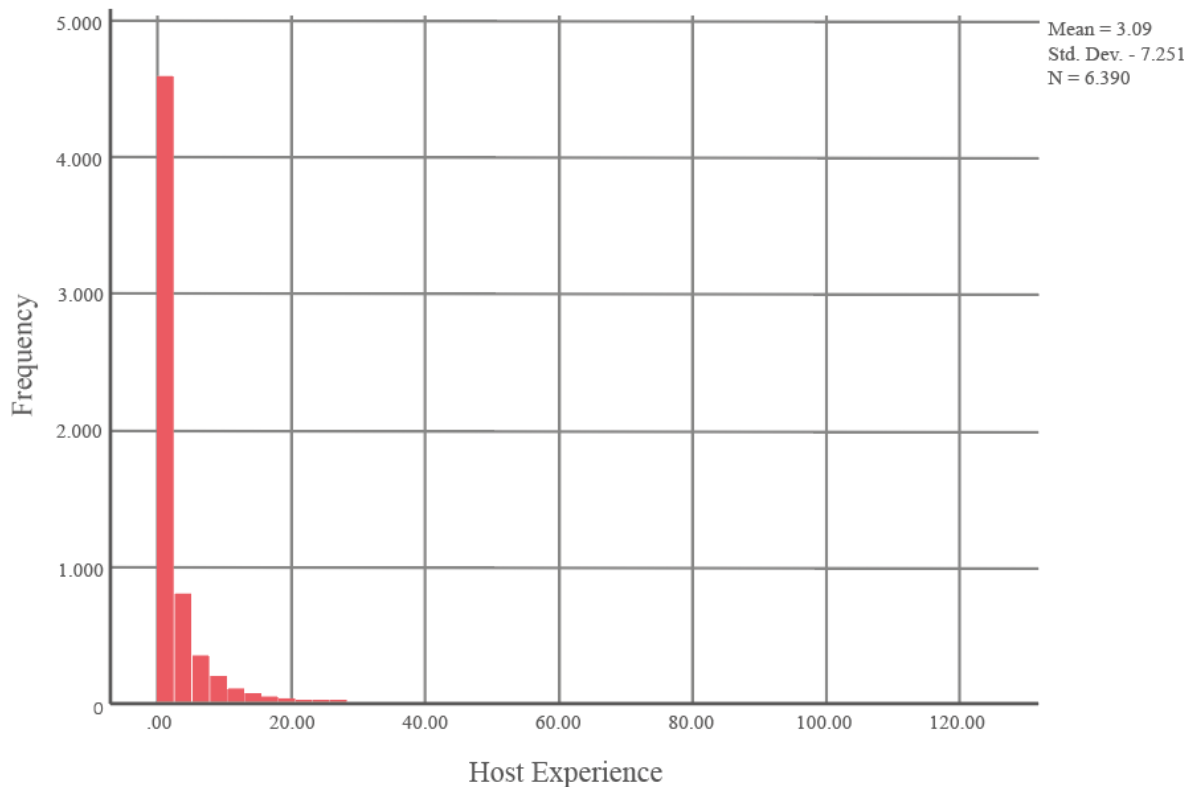
Another limitation worth mentioning relates to the information-gathering process of Edelman, Luca & Svirsky in the original research. They sent out all their applications for listings at one specific moment in time. Likewise, they gathered all tangible information (number of reviews) at one specific moment in time. This demands caution in interpreting the actual effects of host experience and year of joining the platform on trust. Habitually, research captures user trends over time that uncover specific mechanisms. Number of reviews, for instance, is ideally documented over multiple moments in time. The utilised dataset however did not allow for multiple moments of measurement. Thus, as all the information was collected at one moment, discrete interpretation of findings is required.

In line with previous limitation, causality must be discussed. In order to establish causality in scientific research, three principles must be adhered (Neuman, p. 35): The principle of association, temporal order and elimination of plausible alternatives. In this paper, the principle of association has been adhered to as the variables significantly correlate. Adhering to the principle of temporal order encompasses the independent variable preceding the dependent variable in time. While host experience (amount of reviews gathered) precedes trust in Airbnb transactions in time, this in turn might influence host experience. That is: for every review a host gathers, the likelihood of accepting guests unconditionally increases. With every

transaction completed, the host might gather more reviews. A certain degree of interaction hence cannot be excluded. In an attempt to account for most variance, multiple control variables have been introduced in this paper. However, full elimination of plausible alternatives could not be realised. Lastly, it must be mentioned that the principle of causality provides guidelines that must be followed as closely as possible. Yet, full realisation of these principles can be challenging. Choice-making is hence an important tool for researchers to navigate the causality framework, as long as these choices are acknowledged.

IMPLICATIONS FOR FUTURE RESEARCH

To conclude, present paper indicates several implications for future research. For instance, current findings posit significant influence of host experience and year of joining the platform on trust. However, the utilised data ranged from the founding of Airbnb in 2008 until 2015. As a still growing innovation it is crucial to test whether current findings still apply nowadays, especially in a scenario that emphasises user trends over time.

Also, not hypothesised by this paper, a significant influence of host race on trust in Airbnb transactions was found. Additional research might investigate why exactly white hosts were significantly less likely to accept guests unconditionally than hosts from other races.

As host experience and year of joining the platform have been found to significantly influence trust, they have highlighted an additional side of the trust debate: To which extent is trust propensity a sufficient predictor? Future research could however combine both sides of the debate to provide an even more sophisticated explanation: To what degree do the effects of host experience and year of joining the platform differ by hosts of different trust propensity?

Lastly, this paper could not identify a significant interaction effect for host experience and year of joining the platform. Future research could identify why exactly these variables that share theoretical similarities, do not interact practically. As it is crucial to expand our knowledge of host characteristics on trust in the online sharing economy, it is equally important to fully specify its constraints and practical implications.

IMPLICATIONS FOR AIRBNB

Firstly, future research should investigate whether popularity is the *exact* mechanism causing for trust in Airbnb transactions. Present paper hints at this mechanism, yet it cannot be confirmed. In this case however, it poses questions for the Airbnb platform. Logically, popularity of an innovation leads to adoption by new individuals. And it is these exact individuals that display more trust in the platform. Airbnb should consider how and which factors influence its popularity. In order to stimulate trust amongst its users, Airbnb could consider adopting market strategies that boost popularity. Not only in order to attract new users, but to include and boost popularity among early Airbnb users. It also implies caution: whenever Airbnb loses popularity, it might lead to a decrease in trust in the future. Whenever Airbnb loses popularity it should consider its cause and deploy strategies that intend to better the situation, and restore trust. Either way, it should be of concern to Airbnb to further investigate *why* popularity possibly leads to an increase in unconditional trust among its hosts.

Secondly, it might be important for Airbnb to consider how to include inexperienced hosts in order to generate trust. These hosts lack transaction experience, which Airbnb cannot make up for. However, Airbnb could consider special attention for these hosts. Simply asking why these hosts have not completed as many transactions, might increase our knowledge to the cause of trust problems among inexperienced hosts. Airbnb already maintains an elaborate help centre for all hosts to make use of. Perhaps a specialised team might help tackle the trust problem specifically among inexperienced hosts. Airbnb could familiarise inexperienced hosts to the platform in a different manner, nevertheless increasing trust.

Airbnb must take on an active role in emphasising the importance of host characteristics on trust. Guest characteristics remain an important factor for Airbnb to consider, yet it could be in their best interest to partially shift that focus. Increased trust among hosts can reduce the importance of guest characteristics. This is considered a crucial step in order to overcome the problems of discrimination and sexism that Airbnb faces.

All in all it seems a crucial role is put aside especially for the Airbnb platform. While existing literature mostly overlooks the influence of a possible intermediary, this research emphasises the direct influence Airbnb can exert on trust in the online sharing economy. Or, as Hamari and colleagues (2016, p. 2047) put it, Airbnb can *"coordinate the peer-to-peer based activity of obtaining, giving or sharing the access to goods and services"*.

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