

Consumers' trust in the sharing economy

Avikaar Ramphal

19405864

19405864@mygibs.co.za

A research project submitted to the Gordon Institute of Business Science, University of Pretoria, in partial fulfilment of the requirements for the degree of Master of Philosophy (Corporate Strategy).

01 February 2021

Declaration

I declare that this research project is my own work. It is submitted in partial fulfilment of the requirements for the degree of Master of Philosophy in Corporate Strategy at the Gordon Institute of Business Science, University of Pretoria. It has not been submitted before for any degree or examination in any other University. I further declare that I have obtained the necessary authorisation and consent to carry out this research.

Avikaar Ramphal

Name & Surname

Signature

Abstract

The sharing economy (SE) challenges consumers to participate in services characterised by information asymmetry, heterogeneous quality and risks of interacting with strangers who are consumers themselves, rather than traditional firms. Hence, the functioning of the SE requires consumers to trust the individual service provider and the platform facilitating the service.

Reputation systems help signal quality and reduce information asymmetries. Platforms employ systems for consumers to rate service providers on a scale from 1 to 5 stars. Correspondingly, independent regulatory bodies rate the quality of a service provider's establishment on a similar numeric scale—something unique to the short-term accommodation sector. In addition, the platform brand also conveys certain characteristics of the structural assurance of the SE platform.

Through an online survey, 635 respondents were exposed to a between-subjects experimental vignette that altered the level of platform reputation and independent reputation systems. The resultant covariance-based structural equation modelling analysis revealed that: (i) consumers' trust in service providers was heavily influenced by platform reputation systems, rather than independent reputation systems, (ii) platform reputation systems were more effective in building trust at higher levels, underscoring the prevalence of a higher rating floor, (iii) independent reputation systems were not statistically significant in influencing trust in the service providers, (iv) trust in the platform was significantly influenced by the platform brand, (v) trust in the service provider played a bigger role in influencing consumers' propensity to participate in the SE, relative to trust in the platform, and (vi) trust in the service provider and trust in the platform partially mediated consumers' propensity to participate in the SE.

Keywords

sharing economy, trust, reputation, SEM

Contents

Declaration	ii
Abstract.....	iii
Keywords	iii
List of tables	viii
List of figures.....	x
List of abbreviations and acronyms	xi
Chapter 1: Introduction to the research problem.....	1
1.1 Background to the research problem	1
1.2 The research problem.....	3
1.3 Research questions	4
1.4 Research aims.....	6
1.5 Research contribution	6
1.6 Research scope.....	6
1.7 Conclusion.....	7
Chapter 2: Literature review and hypotheses	8
2.1 Introduction.....	8
2.2 The sharing economy	9
2.2.1 Terminology	9
2.2.2 Traditional economy comparison.....	11
2.2.3 Information asymmetry	13
2.2.4 Risk and regulation.....	14
2.3 Trust in the sharing economy.....	16
2.3.1 Terminology	17
2.3.2 Linguistic syntax of trust	18
2.3.3 Interpersonal trust	21
2.3.3.1 Platform reputation systems.....	22
2.3.4 Institutional trust	24
2.3.4.1 Independent reputation systems	25
2.3.4.2 Platform brand	27
2.4 Propensity to participate in the sharing economy	28
2.5 Conclusion.....	29
Chapter 3: Research methodology and design.....	32
3.1 Introduction.....	32
3.2 Research paradigm.....	33
3.3 Research design.....	34
3.4 Research setting.....	36

3.5	Population.....	38
3.6	Sample	41
3.7	Measurement instrument	43
3.7.1	Pilot survey.....	43
3.7.2	Survey sections	43
3.7.2.1	Introduction and qualification.....	45
3.7.2.2	Vignette	45
3.7.2.3	Measures	47
3.7.2.4	Demographics.....	50
3.8	Data gathering process.....	52
3.8.1.	Confidentiality and anonymity of participants.....	53
3.9	Analysis approach.....	53
3.9.1.	Preliminary analysis	54
3.9.1.1.	Data preparation and coding.....	54
3.9.1.2.	Sample determination	54
3.9.1.3.	Data screening.....	55
3.9.2.	Descriptive statistics.....	55
3.9.3.	Data validation	56
3.9.3.1.	Exploratory factor analysis (EFA).....	56
3.9.3.2.	Confirmatory factor analysis.....	58
3.9.4.	Structural equation modelling.....	62
3.9.4.1.	Notation and terminology	63
3.9.4.2.	Types of structural equation models used in this research	65
3.10	Research limitations.....	71
3.11	Conclusion.....	72
Chapter 4: Results.....		73
4.1	Introduction.....	73
4.2	Preliminary data analysis	74
4.2.1.	Data preparation and coding	74
4.2.2.	Sample determination	75
4.2.3.	Data screening.....	77
4.3	Descriptive statistics	78
4.3.1.	Demographics.....	79
4.3.2.	Likert scale data summary statistics.....	82
4.4	Data validation.....	84
4.4.1.	Exploratory factor analysis	84
4.4.2.	Confirmatory factor analysis	88

4.5 Structural equation modelling.....	94
4.5.1 Structural equation model (MSEM)	94
4.5.2 Structural equation model with CVs (MALL CV).....	96
4.5.3 Structural model with significant CVs (MCV).....	98
4.5.4 Structural model with significant CVs and mediation (MMED)	100
4.5.5 Structural models with significant CVs and mediation per treatment condition	102
4.6 Conceptual model.....	105
4.7 Conclusion.....	107
Chapter 5: Discussion	108
5.1 Introduction.....	108
5.2 Model fit and explanatory power	108
5.3 Hypotheses.....	109
5.3.1 Hypothesis 1	110
5.3.2 Hypothesis 2	111
5.3.3 Hypothesis 3	112
5.3.3.1 H3a.....	112
5.3.3.2 H3b.....	113
5.3.4 Hypothesis 4	114
5.3.5 Hypothesis 5	114
5.3.6 Hypothesis 6	115
5.3.7 Hypothesis 7	117
5.3.8 Hypothesis 8	118
5.3.9 Hypothesis 9	119
5.4 Conclusion.....	119
Chapter 6: Conclusion.....	121
6.1 Introduction.....	121
6.2 Theoretical implications	121
6.3 Contribution	122
6.4 Implications for practice	123
6.5 Limitations	126
6.6 Suggestions for future research	127
6.7 Conclusion.....	127
References.....	129
Appendices	149
Appendix A: Questionnaire	149
Appendix B: Pilot survey feedback and improvements.....	156

Appendix C: Treatment conditions operationalised in Qualtrics..... 158
Appendix D: Code book..... 159
Appendix E: Demographic data per treatment condition 162
Appendix F: Box and whisker plots 164
Appendix G: Operationalisation of categorical independent variables in AMOS..... 165

List of tables

Table 1: Research opportunity	4
Table 2: Sharing economy definitions.....	10
Table 3: Comparison of traditional and sharing economy for accommodation	11
Table 4: Selected trust definitions.....	17
Table 5: Trust predicates and trustees	19
Table 6: Research questions and hypotheses	31
Table 7: Calculation for population estimation	40
Table 8: Nine-cell 3 x 2 design (3 ²) matrix	45
Table 9: Analysis of Cape Town Airbnb data to construct vignette details	46
Table 10: Comparison of reflective and formative measurement	48
Table 11: Indicators selected for survey from prior research	49
Table 12: Demographic questions	51
Table 13: Data analysis phases.....	54
Table 14: Model fit indices.....	59
Table 15: SEM notation and concepts.....	64
Table 16: Dummy variables for exogenous predictors	67
Table 17: Responses flagged with constant responses	75
Table 18: Demographic questions updated	77
Table 19: Collinearity statistics	78
Table 20: Descriptive statistics for Likert scale measurement indicators.....	83
Table 21: Correlation matrix of measures.....	83
Table 22: Total variance explained from EFA.....	85
Table 23: Rotated solutions (pattern matrices)	87
Table 24: Initial measurement model with standardised estimate	90
Table 25: CFA model fit results	90
Table 26: Internal consistency of measures	91
Table 27: Harman's single factor test	91
Table 28: Measurement invariance results	93
Table 29: Model fit and explained variance for full structural model.....	95
Table 30: Results for full structural model.....	95
Table 31: Model fit for full structural model with CVs	96
Table 32: Results for full structural model with CVs.....	97
Table 33: Model fit for full structural model with significant CVs.....	99
Table 34: Results for full structural model with significant CVs	99
Table 35: Model fit for full structural model with significant CVs and mediation	100
Table 36: Results for full structural model with significant CVs and mediation	101
Table 37: Mediation test using bootstrap analysis with a 95% confidence interval.....	101
Table 38: Model fit per treatment condition.....	102
Table 39: Results per treatment condition	103
Table 40: Mediation results per treatment condition	104
Table 41: Status on hypotheses	105
Table 42: Model fit and squared multiple correlation.....	108
Table 43: Summary of results per hypothesis.....	109
Table 44: Excerpt of results for H1	110
Table 45: Excerpt of results for H2	111
Table 46: Excerpt of results for H3a and H3b per treatment condition	112
Table 47: Excerpt of results for H4	114
Table 48: Excerpt of results for H5	114
Table 49: Excerpt of results for H6	115

Table 50: Excerpt of results for H6 per treatment condition	116
Table 51: Excerpt of results for H7	117
Table 52: Excerpt of results for H7 per treatment condition	117
Table 53: Excerpt of results for H8	118
Table 54: Excerpt of results for H9	119
Table 55: Contribution	123
Table 56: Demographic data per treatment condition	162

List of figures

Figure 1: Literature and research question synthesis	5
Figure 2: Literature review roadmap.....	8
Figure 3: Peer-to-peer sharing taxonomy	11
Figure 4: Conceptual model	30
Figure 5: Research methodology roadmap.....	33
Figure 6: Population boundaries.....	39
Figure 7: Sample size calculation	42
Figure 8: Survey decision logic.....	44
Figure 9: Vignette and treatment conditions	46
Figure 10: Responses over time.....	53
Figure 11: Conceptual structural equation model	64
Figure 12: Mediation relationships.....	69
Figure 13: Multiple Indicators Multiple Causes Model.....	70
Figure 14: Flow from Chapter 3 to Chapter 4.....	74
Figure 15: Conditions applied for eligibility of sample respondents.....	76
Figure 16: Number of responses per treatment condition	76
Figure 17: Cook's distance assessment	78
Figure 18: Summary of demographic information	80
Figure 19: Representation of respondents by country	81
Figure 20: Scree plot.....	86
Figure 21: CFA measurement model with standardised estimates	89
Figure 22: Full structural model	94
Figure 23: Full structural model with control variables	96
Figure 24: Full structural model with significant control variables.....	98
Figure 25: Full structural model with significant control variables and mediation	100
Figure 26: Revision of conceptual model.....	106

List of abbreviations and acronyms

AMOS	Analysis of Moment Structure
BR	Brand reputation
CFA	Confirmatory factor analysis
CV	Control variable
EFA	Exploratory factor analysis
IR	Independent reputation systems
PP	Propensity to participate in the sharing economy
PR	Platform reputation systems
SE	Sharing economy
SEM	Structural equation modelling
SPSS	Statistical Package for the Social Sciences
TGCSA	Tourism Grading Council of South Africa
TH	Trust in service provider / host
TP	Trust in sharing economy platform

Chapter 1: Introduction to the research problem

1.1 Background to the research problem

The sharing economy (SE)—sharing of underutilised assets, enabled through technology (Görör, 2016)—is presenting opportunities and challenges to businesses, consumers and societies. The SE has the potential to alter future consumption behaviour because of technological advances, shifts in consumer values, environmental sustainability and financial reasons (Kathan, Matzler, & Veider, 2016). Amid various SE definitions, this study adopted the, pseudo-sharing interpretation, characterised by profit motives and peer reciprocity (Sainaghi, Köseoglu, & Mehraliyev, 2020). A popular example of underutilised assets are people's houses, which when not occupied fully by its owners, allow for owners to share this idle capacity with others.

The SE's newfound opportunities and challenges relate to its disintermediation of traditional sectors (Guttentag, 2015), extension of value to consumers in engaging and beneficial ways (Shaughnessy, 2016), and the lowering of barriers to entry for new service providers, posing various regulatory and consumer safety considerations. This scaled sharing phenomenon has been spurred on by technological advances. Mobile and digital technologies have fostered the emergence of digital platform businesses, which provide infrastructure and rules that mediate such sharing between service providers and consumers (Van Alstyne, Parker, & Choudary, 2016). Following this, Airbnb is a SE platform archetype, which monetises peoples' properties for short-term accommodation.

While the International Organization for Standardization is working on establishing international standards for the SE to address its newfound challenges (Gasiorowski-Denis, 2017; Naden, 2019), locally, incumbents have lobbied the South African government to level the playing field for the short-term accommodation sector, as Airbnb service providers are not subject to the same regulatory standards—health, safety, tourism quality grading—enforced on traditional establishments (Cape Business News, 2016). Consequently, in 2019, the South African government gazetted the Tourism Amendment Bill, which proposes a mandatory grading system determined by criteria of an independent body (Department of Tourism, 2019).

Currently, traditional establishments can be graded by the Tourism Grading Council of South Africa (TGCSA), where they are awarded a star rating (out of 5) in recognition of meeting certain quality criteria, which provides a signal to consumers in terms of what

can be expected for a particular accommodation (du Plessis & Saayman, 2011; TGCSA, 2019). Should the Tourism Amendment Bill be enforced, Airbnb service providers would incur additional costs in grading their establishments. For self-catering accommodation, this includes a joining fee (R295) and an annual membership fee (between R2268 and R4365), based on published fees for 2020 (TGCSA, 2020). While some opine that this regulatory oversight protects consumers (du Plessis & Saayman, 2011), others argue that regulation designed for incumbents cannot be applied equally to the SE, as protecting incumbents then removes the very innovation upon which platforms were built (Dalberg, 2015). For instance, Airbnb already has a self-regulating reputation system of star ratings (Ert & Fleischer, 2019), which lets consumers make informed choices, based on the aggregation of ratings from other consumers (Tadelis, 2016). As the SE continues to grow, the market will have to eventually balance the tension between two different systems—one formal and regulated (TGCSA) and the other informal and social (Airbnb rating)—as they both compete for legitimacy.

Nevertheless, participating in the SE involves asymmetrical information for consumers as they may not be privy to all information about the service provider and the service offering (Akerlof, 1978; Sundararajan, 2016). In addition, engaging in the SE entails physical risk due to the intimacy of assets shared, such as a home in accommodation sharing, which are conventionally purchased for private use (Santana & Parigi, 2015). Internationally, Airbnb guests have been victims of scams, unsafe conditions, fake listings and discrimination (Fergusson, Ahlqvist, & Smith, 2017). Considering that safety is a major SE concern (Kamal & Chen, 2016; Yaraghi & Ravi, 2017), trust alleviates uncertainty in such complex digital settings and mitigates stranger-danger risk (Möhlmann, 2019), that is, the probable physical harm by strangers or unacquainted environments (Hong, Kim, & Park, 2019).

Trust is multi-disciplinary; however, it is important in circumstances characterised by risk, uncertainty and interdependence (McKnight & Chervany, 2001), which are characteristics that play out in the SE when interacting with strangers. Specifically, a consumer's trust in the service provider and trust in the SE platform are key targets of trust in the SE (Hawlitschek, Teubner, & Weinhardt, 2016; Möhlmann & Geissinger, 2018). Hence, trust-generating mechanisms are important in building trust in these two targets. In this regard, platform reputation systems, such as the star-rating of a service provider's accommodation, serves as a way of inferring a consumer's interpersonal trust in a service provider since it is derived from the ratings of previous consumers. By extension, independent reputation systems, such as the TCGSA star-rating, acts as a mechanism of inferring a consumer's institutional trust (Crane, 2020) in a service

provider since the rating is determined by an independent institution—the TGCSA—rather the consumers.

Mazzella, Sundararajan, Butt d’Espous, and Möhlmann (2016) recommended that while platforms facilitate trust amongst consumers and service providers, they must also engender trust in their own capabilities to be viewed as a proxy of trust. Chasin, von Hoffen, Hoffmeister, and Becker (2018) indicated that SE platforms’ lack of control on service quality results in trust and safety concerns, which eventually results in the inability to scale and the demise of newly forming SE platforms. Consequently, the platform brand becomes paramount. In a short space of time, SE platforms have become ubiquitous brands that consumers have come to trust in reducing the frictions of interacting with strangers in the SE (Steenkamp, 2020). However, the restrictions from the coronavirus (COVID-19) pandemic has resulted in wide-ranging cancellations of reservations with Airbnb, which has brought trust in this particular SE platform brand into the spotlight from consumers and SE providers alike (Boros, Dudás, & Kovalcsik, 2020). As a result, increasing trust and differentiating a platform brand that fosters consumer confidence will be vital for SE platforms (Sundararajan, 2019).

1.2 The research problem

This research problem was derived from recommendations spanning marketing, information systems and sociology domains, as per Table 1. As recommend by the below-mentioned scholars, trust in the SE is a current focus of academic inquiry. According to Ter Huurne, Ronteltap, and Buskens (2017), “the current body of literature on antecedents of trust in the sharing economy is meagre” (p. 495). In response, the literature points towards the use of trust-generating mechanisms, such as reputation systems (Frenken & Schor, 2017; Mittendorf, Berente, & Holten, 2019), which seek to help establish trust in the SE and therefore mitigate risk. By examining trust-generating mechanisms, key insights into consumers’ trusting behaviours come to the fore.

Table 1: Research opportunity

Research opportunity	Reference	Journal and quality*
“What is the nature of trust in the sharing economy, and to what degree can it regulate sharing economy transactions? From a consumer perspective, is the trust engendered by reputation systems as strong as consumers’ trust in formal regulators?” (p. 11)	Eckhardt et al. (2019)	Journal of Marketing ABS: 4* ABCD: A* Scopus: 98.38%
“Eckhardt et al. (2019, p. 17) discuss the importance of understanding whether digital trust systems can be an effective substitute for other regulatory mechanisms. More salient, however, for the marketing research community is understanding the relative importance of these digital trust systems and platform brand in creating consumer trust.” (p. 34)	Sundararajan (2019)	Journal of Marketing ABS: 4* ABCD: A* Scopus: 98.38%
“What is the relative importance of trust-generating mechanisms on sharing economy platforms, including past ratings,...?” (p. 7)	Frenken and Schor (2017)	Environmental Innovation and Societal Transitions ABS: Not rated ABCD: B Scopus: 98.81%
“Information types, such as profile photos, reviews, ratings, and historical information, might be highly influential towards the perception and necessity of trust in sharing encounters we recommend ... providing or withholding certain information in order to influence information transparency, as well as doing research on the specific information types on trust in the respective sharing partner(s).” (p. 1106-1107)	Mittendorf et al. (2019)	Information Systems Journal ABS: 3 ABCD: A* Scopus: 92.94%

Note. ABS: Chartered Association of Business Schools. ABCD: Australian Business Deans Council. References for excerpts provided in table.

1.3 Research questions

Given the practitioner and academic needs for further research of consumers’ trust in the SE, the overarching research question (RQ1) and sub-questions are as follows:

RQ1: What is the role of trust in influencing consumers’ participation in the SE?

RQ1.1: What is the role of platform reputation systems in consumers’ trust in the SE?

RQ1.2: What is the role of independent reputation systems in consumers’ trust in the SE?

RQ1.3: What is the role of platform brand reputation in consumers’ trust in the SE?

Firstly, RQ1 is informed by Eckhardt et al.’s (2019) call for understanding “what is the nature of trust in the sharing economy” (p. 11), and the consumer perspective thereof originates from Sundararajan’s (2019) invitation for understanding the “creati[on] of consumer trust” (p. 34) in the SE. Secondly, the aspects of platform reputation systems (RQ1.1) and independent reputation systems (RQ1.2) is derived from the recommendations by Eckhardt et al. (2019) to determine if “trust engendered by reputation systems [is] as strong as consumers’ trust in formal regulators?” (p. 11) and Frenken and Schor (2017) to determine “relative importance of trust-generating

mechanisms on sharing economy platforms, including past ratings” (p. 7). In this regard, RQ1.1 and RQ1.2 relies on Mittendorf et al.'s (2019) call for providing or withholding certain information types, which this research operationalised through an experiment, as per section (§) 3. Lastly, the brand element in RQ1.3 originates from Sundararajan's (2019) suggestion to determine the “importance of...platform brand in creating consumer trust.” (p. 34). The derivation of the research questions is illustrated in Figure 1.

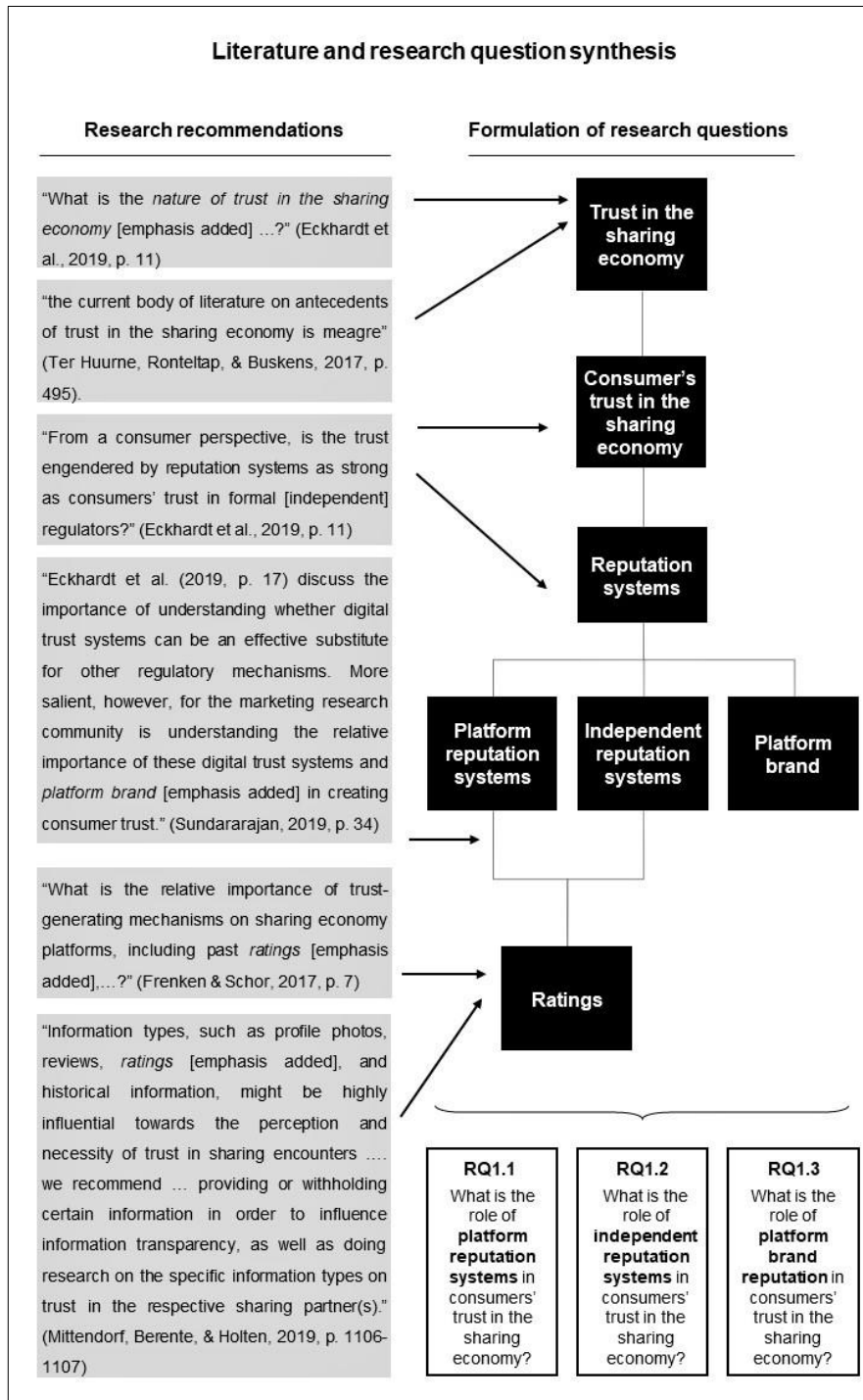


Figure 1: Literature and research question synthesis
Source: Author

1.4 Research aims

The research sought to explain how consumers' trust in the SE influenced their propensity to participate in the services offered in the SE. In particular, the research aimed to determine to what extent platform reputation systems and independent reputation systems influenced consumers' trust in the SE service provider, and the extent to which platform brand influenced consumers' trust in the SE platform.

In this regard, the research aimed to assess consumers' trust in the SE service provider through the lenses of interpersonal trust and institutional trust. From an interpersonal trust perspective, the platform reputation system of star ratings was used to predict consumers' trust in the SE service provider, due to the social aspect of this rating mechanism being derived from other consumers' experiences. From an institutional trust perspective, the independent reputation system of the TGCSA's star rating system was used to predict consumers' trust in the SE service provider. In addition, the research aimed to assess consumers' trust in the SE platform, specifically through platform brand, as a form of institutional trust.

1.5 Research contribution

The research contributed to the SE and marketing literature by using trust literature, to compare consumers' trust in the SE across SE platform reputation systems (existing self-regulation), independent reputation systems (accreditation by an external formal regulatory body) and platform brand reputation. While, there is a plethora of research that has studied trust in e-commerce and SE platform settings, previous literature has not incorporated the distinction between platform reputation systems and independent reputation systems from reputation scores / ratings alone. This gap therefore created the need for further academic enquiry.

1.6 Research scope

The research scope was centred on the commercial interpretation of the SE in an emerging market context of South Africa, from a consumer perspective, with the SE platform of Airbnb. Airbnb's five-star rating system was operationalised as the platform reputation system, while independent oversight of the broader tourism sector through the TGCSA's five-star rating system was operationalised as the independent reputation system. The rationale for the specific scope selected is outlined in Chapter 3, [§3.4](#).

1.7 Conclusion

The research sought to explain how consumers' trust in SE platform reputation systems, independent reputation systems and SE platform brand reputation influences their participation in the SE. The interplay between these three forms of reputation has relevance for a broad range of stakeholders—for consumers in deciding on participating in SE services and choosing the appropriate SE service provider; for SE service providers in conveying their quality to potential consumers and extracting value from the SE platform; for SE platforms in creating enabling environments for both demand (consumers) and supply (SE service provider) sides that use the platforms; and for regulatory bodies in providing the institutional mechanisms to reduce moral hazards and foster a conducive environment for both businesses and consumers to participate.

Scholars are evidently seeing the SE as an emerging phenomenon requiring further academic inquiry (Ter Huurne et al., 2017), specifically with regards to the interplay among platform reputation systems (Mittendorf et al., 2019), independent reputation systems (Eckhardt et al., 2019) and the platform brand (Sundararajan, 2019) in fostering consumer trust and participation. The academic contribution in this regard was to combine the platform and independent reputation systems in assessing trust in the SE service provider. This research was conducted in a South African setting and operationalised through the SE platform of Airbnb, the platform reputation system of Airbnb's rating system, the independent reputation system of the TGCSA's rating system, and the platform brand of the Airbnb platform.

The subsequent chapters are divided into the literature review and hypotheses (Chapter 2), research methodology (Chapter 3), results (Chapter 4), discussion of the results (Chapter 5) and conclusion (Chapter 6). The appendices contain information related to Chapter 3 and Chapter 4.

Chapter 2: Literature review and hypotheses

2.1 Introduction

This chapter is organised along three main sections that form the literature review, which culminate in the deduction of a conceptual model with hypothesised relationships. Figure 2 depicts a sequential roadmap of the topics in the literature review, with sections and sub-sections numbered accordingly.

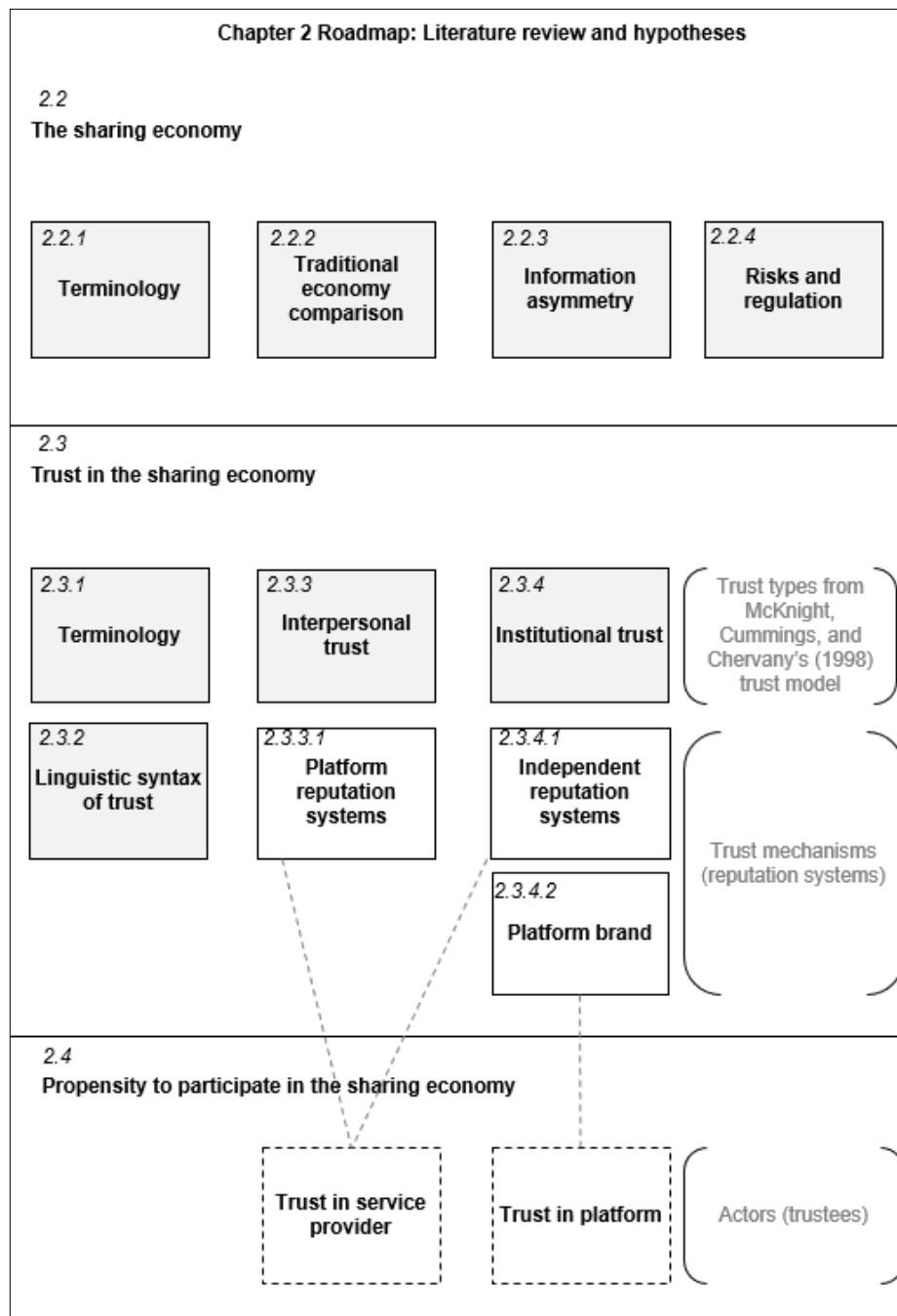


Figure 2: Literature review roadmap
Source: Author

Section 2.2 of this chapter contextualises the commercial SE definitional interpretation that was adopted for this research ([§2.2.1](#)). In addition, the commercial SE interpretation is then positioned against traditional economic exchange forms that dominated economies before the emergence of commercial SE platforms ([§2.2.2](#)). The differences between these two forms of economic exchange—traditional sectors and the SE—then sets the scene for the specific challenges consumers face in the SE ([§2.2.3](#), [2.2.4](#)). It is these challenges that then forms the pre-conditions for trust to be built.

The second section ([§2.3](#)) clarifies trust terminology ([§2.3.1](#)) in framing the relationship of a trustor and trustee ([§2.3.2](#)), which establishes the basis for the interpersonal ([§2.3.3](#)) and institutional ([§2.3.4](#)) trust types that were selected for inquiry. Next, trust-generating mechanisms are reviewed in terms of their functions in building consumers' trust in two trustees (service providers and platforms).

The three lenses of the actors (consumer, service provider and platform), trust types (interpersonal trust and institutional trust) and trust-generating mechanisms (platform reputation systems, independent reputation systems and platform brand reputation) are then organised to form a conceptual model in answering the aforementioned research question.

2.2 The sharing economy

The following sections position the SE literature among competing terminology to clarify the interpretation used in this research. Then, the SE is compared to the traditional economy. Lastly, the SE is juxtaposed against the challenges inherent of this emerging phenomenon.

2.2.1 Terminology

The concept of sharing among people has always been part of consumer behaviour and has been part of scholarship from the 1980s (Rudmin, 2016). Belk (2007) defined sharing as “the act and process of distributing what is ours to others for their use as well as the act and process of receiving something from others for our use” (p. 127). Yet, while sharing is as longstanding as humankind, the SE's novelty is unique to the internet age (Belk, 2014). Schor (2014) ascribed this newness to stranger sharing, as SE platforms facilitate sharing among strangers and involve greater risk of intimate experiences, such as sharing one's house or vehicle. Specifically, accommodation sharing, Airbnb, and car sharing, Uber, are used as exemplars in the recent SE literature (Rudmin, 2016).

The SE is a broad concept and includes various terms (Hawlitschek, Teubner, & Gimpel, 2018). Discussions on SE, collaborative consumption and peer-to-peer economy have increased recently due to the advent of digital platforms and mediating technologies playing a central role in consumer lives (Sutherland & Jarrahi, 2018). These definitions are presented in Table 2 and subsequently discussed.

Table 2: Sharing economy definitions

Terminology	Definitions	Reference
Sharing economy	“consumers granting each other temporary access to under-utilized physical assets (“idle capacity”), possibly for money” (p. 2–3).	(Frenken & Schor, 2017)
	“people coordinating the acquisition and distribution of a resource for a fee or other compensation” (p. 1597).	(Belk, 2014)
Collaborative consumption	“resource circulation schemes that enable consumers to both receive and provide, temporarily or <i>permanently</i> [emphasis added], and valuable resources or services through direct interaction with other consumers or through an intermediary” (p. 32).	(Ertz, Durif, & Arcand, 2019)
Peer-to-peer economy	“based on economic transaction between individuals that are enabled by IT, do not involve ownership transfer, can <i>vary on the scale between sharing and commerce</i> [emphasis added], and require a physical object, that one of the individuals possesses, to be shared or collaboratively consumed.” (p. 297).	(Chasin, von Hoffen, Cramer, & Matzner, 2018)
Sharing economy (peer taxonomy)	Transactions being (i) non-corporate (between private individuals), (ii) commercial (involving exchange of money), (iii) temporal (temporary and short-term resource transfer), and (iv) tangible (based on physical products or product-services).	(Hawlitschek et al., 2018)

Source: Author

The first definition of the SE by Frenken and Schor (2017) does not align to the scope of the research, which is on the commercial SE, as alluded to in Chapter 1. Ertz et al. (2019) built on by Belk’s (2014) definition in terms of the temporal nature of the resource or service. However, the permanent part of the definition also does not align to the commercial SE. Chasin et al. (2018) built on peer-to-peer sharing and collaborative consumption in terms of the fluidity of monetary exchange. Similarly, this definition does not fit the commercial SE notion.

Acknowledging the various definitions, Hawlitschek et al. (2018) used a taxonomy (Figure 3) to consider the dimensions of the degree of commerciality (from private to corporate) on the vertical axis and resource type (from product to service) on the horizontal axis. Consistent with the four characteristics in the last definition in Table 2, the authors denoted their definition within the four boundaries of the shaded region in Figure 3.

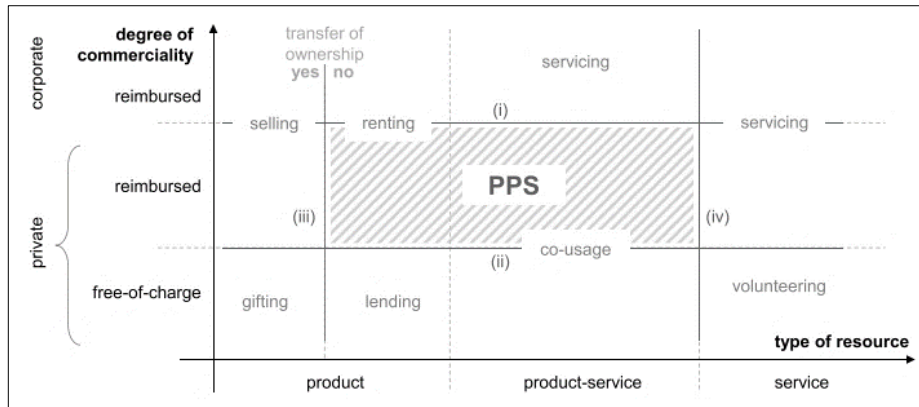


Figure 3: Peer-to-peer sharing taxonomy

Reprinted from “Consumer motives for peer-to-peer sharing,” by F. Hawlitschek, T. Teubner and H. Gimpel, 2018, *Journal of Cleaner Production*, 204, p. 145. Copyright 2018 by Elsevier Limited.

Regarding the tangible aspect of the definition, this research scoped the definition to focus on product-services through underutilised assets. In summary, the SE definition used henceforth has been adapted from Hawlitschek et al.'s (2018) definition: Transactions between private individuals, involving exchange of money, temporary resource transfer, and based on product-services through underutilised assets.

2.2.2 Traditional economy comparison

Having defined the SE for this research, this section focusses on the comparison of this commercial SE definition to that of the traditional economy. Table 3 compares traditional firms (namely hotels) in the short-term accommodation sector to SE platforms.

Table 3: Comparison of traditional and sharing economy for accommodation

	Traditional economy	Sharing economy
Asset	Owned by firms Fairly homogenous	Owned by individuals Fairly heterogenous
Service provision	Firm's employees	Individuals
Consumers' safety perceptions	Higher	Lower
Regulation	Firms subject to sector-specific regulation	Individuals not subject to sector-specific regulation
Brand	Firm has a corporate brand	Individual does not have a corporate brand

Note. Created by the author. Concepts incorporated from Mody, Suess, and Lehto (2017); Yang, Lee, Lee, and Koo (2019); Martin-Fuentes, Fernandez, Mateu, and Marine-Roig (2018) and Delgado-Ballester, Munuera-Aleman, and Yague-Guillen (2003).

From an asset perspective, the traditional economy firms have invested in assets (commercial real estate) to make a return. In the SE, consumers can simply lease out their own unutilised asset space (residential real estate), for example, a spare room in one's home. Dellaert (2019) conceptualised how this renders consumers as co-producers (service providers) in the SE, whereby they can create value for other consumers. As a result, this creates a different consumer experience. On one hand, consumers have a fairly standardised experience with a traditional firm in terms of similar room types. On the other hand individuals' accommodation varies; however, it is this very heterogeneity that has been an attraction for those consumers seeking local and authentic experiences (Mody, Suess, & Lehto, 2017).

In terms of the actual provision of the service, traditional firms own the assets and the service is provided through its employees, for example, receptionists and service staff. Contrastingly, in the SE, individuals own the assets, provide the service simultaneously and are typically present in the same property if they are letting out a room, rather than letting out an entire accommodation (Yang, Lee, Lee, & Koo, 2019). Intuitively, such shifts in service provision creates differences in expectations on the part of the consumer. In particular, some consumers will be deterred from participating in the SE due to security concerns, as naturally guests will be cautious about staying in a stranger's home (Guttentag, 2015). For instance, Xu, Pennington-Gray, and Kim (2019) demonstrated that high crime rates are present in shared accommodation properties that are characterised by Airbnb's shared room type listing. Also, safety incidents are not within the control of the platform company (Richard & Cleveland, 2016) as they are with traditional hotels who already have implemented various measures, from emergency plans to 24-hour uniformed security guards (Chan & Lam, 2013).

In terms of regulation, traditional firms are subjected to regulations and standards that are unique to their sector. For example, in short-term accommodation, firms are classified along a 5-star rating scale by an independent body as a means of signalling their quality to consumers (Martin-Fuentes, Fernandez, Mateu, & Marine-Roig, 2018). Yet, individuals letting out their underutilised asset space are not governed by such independent rating and classification schemes. Rather, they rely on other reputation aspects provided by the SE platform, such as textual descriptions of their accommodation (Mauri, Minazzi, Nieto-García, & Viglia, 2018) and ratings from other consumers that have used their service (Abrahamo, Parigi, Gupta, & Cook, 2017) as a way of communicating their quality and thus imbuing trust in potential consumers.

Brand also plays a key role in signalling quality to consumers (Delgado-Ballester, Munuera-Aleman, & Yague-Guillen, 2003; Shankar, Urban, & Sultan, 2002). Traditional hotel chains have established brands that provide customers with a sense of comfort in knowing what can be expected from a given brand (Kang, Manthiou, Sumarjan, & Tang, 2017). In contrast, service providers in the SE do not have this backing of an established brand for their properties. Instead they depend on the brand of the platform upon which they market their services. For example, these hosts rely upon their familiarity of using the particular platform interface (Mittendorf, 2016), the service quality offered by the platform brand to assist in issues (Wang, Asaad, & Filieri, 2020) and the security, payment and insurance structures within the platform to facilitate their interactions with guests seamlessly in the SE (Li & Wang, 2020).

In summary, consumers are exposed to consumer-to-consumer interactions (rather than with firms) that lack the regulatory and branding elements that has been used traditionally to infer quality. Given these distinguishing features between the traditional economy and the SE, consumers are placed in a position of navigating how they trust the service provider as well as the platform simultaneously, which presents a form of information asymmetry—this is discussed next.

2.2.3 Information asymmetry

Both the traditional economy and SE are prone to be negatively impacted by quality uncertainty from the supply of poor quality goods or services, that is, 'lemons', which George Akerlof posited in his seminal paper on the market for 'lemons' (Akerlof, 1978). The premise of Akerlof's model was that sellers have more information on a product or service's quality (quality certainty) compared to buyers (quality uncertainty), therefore resulting in information asymmetry. Because the provider has control over the product / service characteristics, consumers are typically not privy to the same information as the provider (Akerlof, 1978). This is prevalent in the SE, as the asset that underpins the service generally cannot be conveniently inspected *a priori* by the consumer, and rather the consumer has to rely on what is provided on the platform about the service, such as photos (Bente, Baptist, & Leuschner, 2012), reviews (Tsao, Hsieh, Shih, & Lin, 2015) and other descriptions (Tussyadiah & Park, 2018) common to e-commerce. For example, in e-commerce, information asymmetry results in less trust of the buyer in the seller (Pavlou, Liang, & Xue, 2007).

Further, SE consumers must feel comfortable relinquishing control and interacting with service provider strangers, which are consumers themselves in a consumer-to-

consumer setting. This relinquishing of control to prosumers—being both producers and consumers (Ritzer & Jurgenson, 2010)—means that consumers consuming such services must trust other consumers that are providing the service, rather than trusting providers affiliated with traditional firms. This has implications for responding to a new form of information asymmetry beyond just buy / sell interactions of products or services experienced in traditional and e-commerce transactions.

Perceived differently, consumers have to deal with information overload in certain contexts (Martin-Fuentes et al., 2018). For example, certain popular destinations on accommodation SE platforms may have a very large amount of user-reviews, which makes it difficult for the average consumer to interpret and decide on a particular accommodation (Marine-Roig, 2017). This is also exacerbated by fake reviews (Banerjee, Chua, & Kim, 2015).

Given that consumers interact with other consumers in the SE, and not with other established firms; the inability of examining the asset beforehand; information asymmetry, as well as the generally higher amount of user-generated information on SE services and service providers, there are inherent risks that consumers face in their engagements in the SE. Such risks need to be addressed.

2.2.4 Risk and regulation

This last sub-section of the SE literature review outlines the salient risks that consumers face in the SE. This account of risks is then juxtaposed against the role of regulation in the SE.

Taylor (1974) explained that consumers are obliged to handle uncertainty or risk, because outcomes of choices are known *ex post*. While consumers face various risks types in their purchase decisions that are contingent on the product or service setting (Jacoby & Kaplan, 1972; Mitchell, 1992), the risks from consumer participation in the SE is different to that of the traditional economy. The risks specific to the SE can be summarised along the themes of performance risk, physical risk and privacy (Hong et al., 2019; Nadeem, Juntunen, Shirazi, & Hajli, 2020).

First of all, SE platforms can supply services with little investment and may thus not have a professional or standardised offering, for example, misrepresentation in advertisements by the service providers (Hong et al., 2019). Therefore, consumers face the risk of the service provider and / or SE platform not fulfilling the service per the consumer's expectations, resulting in this form of performance risk (Mitchell, 1992). Secondly, security / physical risk emanates from the meaning of the SE itself. The

interaction typically involves strangers and the sharing of assets that are rather personal in nature, for example, one's home in accommodation-sharing, which creates safety concerns for consumers (Santana & Parigi, 2015; Schor, 2016). By contrast, with the traditional hotel sector, consumers would have the confidence of the establishment's brand that offers more safeguards than another consumer's home.

Another concern that is common with internet-enabled services and the SE relates to the use (misuse) of consumers' data. The SE shares similar operating functionalities with its internet-enabled counterparts, such as e-commerce and social networks. Therefore, online data privacy issues that affect consumers of such internet-enabled companies, also affect consumers of SE platforms. Here, the issue of data privacy relates to the disclosure of personal information by consumers that could be misused, for example, in social networks (Krasnova, Spiekermann, Koroleva, & Hildebrand, 2010) as well as in general online purchasing / e-commerce contexts.

While consumers may have concerns about data they knowingly divulge, they are also at risk of having undisclosed data being used without their knowledge. According to Basukie, Wang, and Li (2020), SE platforms exploit consumers' data in the operation of their algorithms, which raises ethical concerns in terms of monitoring of user behaviour and using consumer data without their consent. The authors cited an example of how Uber bypassed law enforcement by detecting if users of their app were affiliated with a police union, based on their credit card data.

Such new and emergent risks create the need for requisite risk mitigation for consumers to feel comfortable and restore trust. Likely substitutes for trust are institutional safety measures, which can assist in implementing required behaviours (Ferrari, 2016). Equally, Sundararajan (2019) considered government and regulation as key sources of trust in the SE, in that regulatory institutions would provide recourse during negative eventualities. Yet in practice, this is difficult. Exemplar SE platforms—Airbnb and Uber—have operated on the fringes of regulatory boundaries when they were newly established and then legitimised through high user volumes, which then obliged regulators to yield in an often reactive manner to accommodate such platforms in existing policies (Chalmers & Matthews, 2019). While the need for regulatory institutions is important, the challenge lies in the nuances of regulatory regimes across sectors and countries.

From a sectoral perspective, regulatory responses have been observed in the short-term accommodation and meter-taxi sectors for the more popular and wide-spread SE platforms, Airbnb and Uber respectively. For example, in a cross-country comparison,

Airbnb was subjected to more stringent regulation in Singapore than in Australia, while Uber enjoyed more access in Singapore than in Australia (Tham, 2016). From a country perspective, a key distinction with regulation is apparent when distinguishing regulatory regimes between developing and developed countries (Basukie et al., 2020). According to the authors, the SE in developing countries exploits institutional voids by setting *de facto* practices that become *de jure* standards, which contrasts with developed countries, whereby *de jure* standards are circumvented to create *de facto* activities.

Brescia (2018) made the case for a new regulatory regime, that provides guidance on standards, codes of conduct and self-regulation. However, such guidance is interpreted differently across stakeholders due to their vested interests. For example, in an experiment that assessed consumers' desires for a fictional accommodation-sharing platform to be regulated, the overall finding was that consumers actually wanted the platform to be less regulated (Newlands & Lutz, 2020). Therefore, regulating the SE is challenging due to its evolving nature (Ferrari, 2016), slow pace of enacting regulation (Brescia, 2018) and divergent stakeholder viewpoints. Given that the cornerstone of the SE is the interaction with strangers, this presents a unique set of uncertainty and risks among the peers, which does not necessarily have the regulatory enforcement of external institutions by design. This gap in the institutional regulatory regime requires trust.

2.3 Trust in the sharing economy

“A theory of trust presupposes a theory of time, and so leads us into a territory so difficult and obscure”

(Luhmann, 1979, p. 10)

The above excerpt from one of the leading sociologists, Niklas Luhmann, underscores the extent of the task in attempting to define, interpret and situate the notion of trust in this research. Nonetheless, the remainder of the literature review attempts to contextualise the aspects of trust used in the research study through the following sequence. First, a brief overview of the conceptualisation of trust is provided, which results in the selection of two trust types (interpersonal trust and institutional trust). Second, the trust in a SE context is posited in terms of consumers' trust in the main actors (service provider and platform), which is operationalised through trust-generating mechanisms (platform reputation systems, independent reputation systems and platform brand reputation).

2.3.1 Terminology

Trust has been defined in a variety of ways, based on the discipline in which it has been studied. Rather than offering a multitude of definitions, selected definitions from management- and business-related disciplines are outlined in Table 4, and then discussed.

Table 4: Selected trust definitions

Definition	Reference	Context
“The willingness of a party to be vulnerable to the actions of another party based on the expectation that the other party will perform a particular action important to the trustor, irrespective of the ability to monitor or control that other party”	(Mayer, Davis, & Schoorman, 1995, p. 712)	Organisational setting
“a psychological state comprising the intention to accept vulnerability based upon positive expectations of the intentions or behavior of another”	(Rousseau, Sitkin, Burt, & Camerer, 1998, p. 395)	Organisational setting
“Trust is an expectancy of positive (or nonnegative) outcomes that one can receive based on the expected action of another party in an interaction characterized by uncertainty”	(Bhattacharya, Devinney, & Pillutla, 1998, p. 462)	Management
“Feeling of security held by the consumer in his/her interaction with the brand, that it is based on the perceptions that the brand is reliable and responsible for the interests and welfare of the consumer”	(Delgado-Ballester & Luis Munuera-Alemán, 2001, p. 1242)	Branding
“confident expectations about the brand’s reliability and intentions in situations entailing risk to the customer”	(Delgado-Ballester et al., 2003, p. 47)	Branding

Note. References for excerpts provided in table.

While, Mayer et al.’s (1995) definition was created in the context of trust in organisational settings, the last part, “irrespective of the ability to monitor or control that other party” (p. 721), can be questionable in a SE context. As will be outlined in subsequent sections, there are mechanisms available in SE transactions that allows for such monitoring to occur, for example, consumer reviews and ratings. After reviewing trust literature across disciplines, Rousseau, Sitkin, Burt, and Camerer (1998) defined trust in a manner that is more widely applicable, although their intention was to define trust in an organisational setting, for within and between firms. Based on a mathematical interpretation, Bhattacharya, Devinney, and Pillutla (1998) defined trust similar to the two previous definitions, but they included the condition of uncertainty explicitly and allowed for their definition to be applicable in individual, firm and institutional settings.

Extending the concept of trust to brands, and by extension, companies managing such brands, results in a definition of brand trust—a consumer’s trust in a brand. Here, the brand’s reliability is important in meeting the consumer’s (trustor’s) expectations, as well

as the brand's intentions of protecting the consumer's welfare during unexpected problems (Delgado-Ballester et al., 2003).

Consistent with all definitions is the two-actor notion of trust. Simply put, trust is always described as a concept between two parties, a trustor and a trustee (Mayer et al., 1995). However, in the SE, interactions require three parties, namely, the consumer, the SE platform and the service provider (who provides services to the consumer through the SE platform's technologies and processes). So, when applying the definitions to the SE from the consumer's perspective, it is necessary to distinguish trust in the SE service provider and the SE platform to fulfil transactions.

The need for trust also emerges under conditions of risk (the perception of probable loss) and interdependence (where one's interests is reliant upon another) (Rousseau et al., 1998). Again, in the SE context, consumers are faced with risks, such as performance and physical risks (discussed in [§2.2.4](#)) and are reliant on service providers (typically other consumers, rather than traditional firms) for the provision of services, and the platform to facilitate the service provision.

2.3.2 Linguistic syntax of trust

The following discussion adopts a uni-directional trust relationship, that is, trust is being examined from the consumer's point of view in other objects / actors. The consumer takes on the trustor role and other objects / actors are the trustees. In this regard, trust can be understood by examining its linguistic syntax from two perspectives. The first perspective relates to predicates, that is, how the verb of 'trust' functions in articulating a relationship of a trustor. The second perspective is understanding the object that is being trusted, that is, the trustee. These two perspectives (predicate and trustee) are drawn from Faulkner (2015) and McKnight and Chervany (2001) respectively, and are compared in Table 5, along with the application in the SE context.

From a predicate perspective, Faulkner (2015) outlined three trust predicates, that is, (i) one-place trust predicate (trustworthiness in general), (ii) two-place trust predicate (trust as an attitude), and (iii) three-place trust predicate (trust in an actor to do something). These can be distinguished by the way of some elementary examples. First, trustworthiness often refers to one's disposition, for example, one may be more inclined to trust people than others, based on a whole range of reasons. Instead of viewing this as a trust type, Tallant and Donati (2020) saw this as a quality of an individual. Second, one typically trusts their family and close friends; but trust for what end or expectation is implicit. Defined as attitudinal trust (Faulkner, 2015), this is described as the

psychological attitude of the trustor towards the trustee (Castelfranchi & Falcone, 2010). Third, trust in an actor to do something, goes beyond one's attitude and has an element of expectation. For example, citizens trust their banks to safely store their money. Here, trust is a decision and the act of the trustor relying / depending on the trustee (Castelfranchi & Falcone, 2010). Faulkner (2015) termed this type of trust as contractual.

By focussing on what was being trusted, that is, the trustee, McKnight and Chervany (2001) distinguished among three types of trust in an e-commerce setting: interpersonal trust (in specific trustees), institutional trust (in a situation or structures) and dispositional trust (in general others). With interpersonal trust, the direct object being trusted is a specific other individual (trustee), and the consumer (trustor) willingly becomes vulnerable to the trustee, having considered the trustee's characteristics (McKnight & Chervany, 2001). The authors distinguished between institution-based trust as being determined by the setting one finds oneself in, rather than factors within the individual as with interpersonal trust. Lastly, disposition to trust is one's "faith in humanity and trusting stance" (p. 43) to others (trustees) generally (McKnight & Chervany, 2001).

Table 5: Trust predicates and trustees

Trust predicate perspective	Trustee type perspective	Application in SE
One-place trust <ul style="list-style-type: none"> • X is trusting • Number of subjects: One (X) • Individual's quality of trustworthiness 	Dispositional	The e-commerce consumer trusts others generally
Two-place trust	Interpersonal	The e-commerce consumer trusts the e-vendor
	Institutional	The e-commerce consumer trusts the web itself
Three-place trust	Interpersonal	The SE consumer trusts the SE service provider to provide the service
	Institutional	The SE consumer trusts the SE platform to fulfil the service

Note. X = Trustor, Y = Trustee, A = Action. Adapted from Castelfranchi and Falcone (2010); Faulkner (2015); McKnight and Chervany (2001); Tallant and Donati (2020)

Given the discussion of the three trust types in e-commerce, the application thereof is useful in the SE due to the similarities between e-commerce and the SE. Table 5 therefore applies the e-commerce vocabulary from McKnight and Chervany (2001) to that of the SE. The above sentence structure clearly distinguishes between the trustor and trustee from the perspectives of the consumer, and approaches the trustee to not

only represent a person, but also an object in which the consumer imbues trust in. A notable difference is that with e-commerce, the e-vendor can represent an individual person or the company supplying the products or services, whereas with the SE, the SE service provider is always an individual.

Similarly, understanding the trust predicates becomes intuitive when applied to the subject of this research, that is, the SE context from the consumer's point of view. Following on from Table 5, one-place trust and dispositional trust relates to the consumer's general trust in others and these can be other consumers using the service as well the other service providers supplying the service in the SE. With two-place trust, rather than only trusting the service provider (interpersonal trust), the consumer also must have some level of trust in the platform (institutional trust) that enables the service provider to operate. In terms of three-place trust, the consumer again has two subjects to trust, and has an expectation for each to perform their requisite functions.

From a philosophical standpoint, Faulkner (2015) argued that one-place and two-place trust predicates are more fundamental forms of trust and does not require the complexity inherent in three-place trust, which requires an understanding of trust from the trustee's perspective. By contrast, Castelfranchi and Falcone (2010) described trust dyadically, as a psychological attitude (two-place trust predicate), and secondly, as a decision and action (three-place trust predicate). Furthermore, they see that psychological attitude as a pre-condition to the three-place trust predicate.

In conceptualising trust for a research study, Tallant and Donati (2020) outlined the lack of conceptual clarity employed by management scholars researching trust in their respective studies due to the conflation of terminology. Therefore, this research did not focus on trustworthiness (one-place trust, dispositional trust) for two reasons. First, assessing one's trustworthiness is very much grounded on the sociology and psychology disciplines. The inclusion of trustworthiness would have extended the scope beyond the focus of management literature. Second, dispositional trust applies more readily to SE services that have more collaborative non-commercial sharing (as per the first four SE definitions in [§2.2.1](#)), where there may be a higher tendency for interaction with other participants than just the SE service provider. As a reminder, this research focussed on the commercial SE.

Rather, the stance adopted in this research was to conceptualise how this complex construct of trust played out between consumers and their trust in service providers and the SE platform to do something. This 'something' formed the basis of the transactional

relationship to be honoured, for example, getting from point A to B with an Uber or staying in an accommodation with Airbnb.

Since trust is key in influencing consumers' participation in the SE, the next sub-sections clarify the two objects that consumers trust in the SE. Möhlmann and Geissinger (2018) explained the requirement for interpersonal trust (relationships among peers of consumers and service providers) and institutional trust (facilitating mechanisms on the SE platform) in the SE. The consumer and service provider are roles assumed by private individuals, whereas the platform serves as a mediator between both supply and demand sides (Hawlitschek et al., 2016). Thus, the following sections delve into these two objects of trust from a consumer perspective, namely, trust in the SE service provider and trust in the SE platform. Lastly, by drawing on different scholars focussing on trust, the mechanisms to generate trust are then discussed in the SE.

2.3.3 Interpersonal trust

Interpersonal trust is based on the trust between individuals; therefore, a starting point on evaluating a consumer's trust in a SE service provider (another individual) would begin with interpersonal trust. Drawing mainly from social psychology, McKnight and Chervany (2001) included the concepts of trusting beliefs and trusting intentions as part of interpersonal trust. According to the authors, trusting beliefs have affective and cognitive aspects and means that the consumer wants the service provider "to be willing and able to act in the consumer's interest, honest in transactions, and both capable of, and predictable at, delivering as promised" (p. 46). Similarly, with trusting intentions, the consumer "is willing to depend on, or intends to depend on, the [service provider] even though [the consumer] cannot control that party" (McKnight & Chervany, 2001, p. 46).

In this regard, scholars have examined interpersonal trust of a consumer in a service provider through certain personal characteristics of the service provider, in terms of their ability, integrity and benevolence consistent with McKnight and Chervany's (2001) typology. These include e-commerce (Kim, Ferrin, & Rao, 2008; McKnight, Choudhury, & Kacmar, 2002; Pavlou & Fygenson, 2006), online business-to-business marketplaces (Pavlou, 2002) and sharing economy settings (Hawlitschek et al., 2016; Tussyadiah & Park, 2018; Yang et al., 2019).

2.3.3.1 Platform reputation systems

Reputation serves as a measure of one's trustworthiness based on past behaviour and can be used to predict future behaviour (Vavilis, Petković, & Zannone, 2014). In this regard, platforms provide certain mechanisms to signal the trusting personal characteristics of its service providers on the platform. So, rather than assessing perceived service provider personal characteristics explicitly, scholars have evaluated interpersonal trust by inferring ability, integrity and benevolence from the types of trust-generating mechanisms available on such platforms. These platforms encourage their users to share information, rate peers and develop a digital reputation (Zloteanu, Harvey, Tuckett, & Livan, 2018) through trust-generating mechanisms. Examples of these trust-generating mechanisms that engenders interpersonal trust from the consumer to the service provider, include the service provider's photographs (Ert, Fleischer, & Magen, 2016), online reviews (Mao, Jones, Li, Wei, & Lyu, 2020; Penz, Hartl, Schüßler, & Hofmann, 2020), sales history disclosure (Xie, Mao, & Wu, 2019) and ratings (Abraham et al., 2017).

Such trust-generating mechanisms are provided as tools on platforms and can be termed platform reputation systems. Rather than personal service provider characteristics, reputation has been prominent in creating trust—this has been used as the main point of enquiry as per RQ1.1. It is commonplace now to be asked to relay one's feedback after a product or service encounter. This type of system of feedback and reputation was first launched by the e-commerce company, eBay, in 1995 and has since been copied by every other online market place and platform (Tadelis, 2016). SE platforms also prompt consumers to rate their SE experiences on their platforms.

Reputation systems provide an assessment of a service provider's reputation by aggregating the ratings that other consumers have rated that service provider (Vavilis et al., 2014). According to Querbés (2018), this consolidation of consumer reviews allows for information about the service provider's particular products / services to be created and disseminated in the market, upon which platforms then rely on to engender trust and build reputation among consumers.

Aligning to RQ1.1, the concept of platform reputation systems was bound to refer to the online reviews and resultant ratings performed by consumers of their experience with a service provider. While, reviews are also textual in nature, the focus of the research was on the numeric rating of the consumer's review of the provider on a predetermined scale,

made available by the SE platform. For example, service providers on the Airbnb platform can have a rating from one star (worst) to 5 stars (best).

Specific to the SE, Yang et al. (2019) and Mao et al. (2020) examined interpersonal trust through such platform reputation systems. Consistent with McKnight et al.'s (2002) trust building model, Yang et al.'s (2019) study posited reputation as one of the antecedents of affective-based trust (associated with emotional characteristics) in SE service providers. Here, the SE service provider's reputation was determined by other SE consumers' assessments of the provider, which was captured through online reviews of the SE service provider (Yang et al., 2019). In line with McKnight and Chervany's (2001) e-commerce trust formation model, Mao et al.'s (2020) study examined personal trust, consisting of cognition-based trust, among others. From a consumer's perspective of trust in the provider, cognition-based trust arose from the cues of the provider's reliability and dependability for service provision, which was captured through online reviews (Mao et al., 2020).

Another side of platform reputation systems is the unintended consequences. For example, a study in Norway of SE platforms showed that there was a bias towards positive ratings, where consumers were less inclined to complain (in terms of a low rating), which reduced the credibility of trust in the SE (Berg, Sletteameås, Kjørstad, & Rosenberg, 2020). This could be due to the bilateral nature of most SE platforms, whereby service providers also rate consumers after they have used the service. In this regard, Newlands, Lutz, and Fieseler (2019) found that such bilateral rating systems also condition consumers to perform more socially desirable behaviours during SE transactions. While some customers perceived the bilateral rating mechanism as passive compliance and a cognitive burden to be more polite in their interactions, other consumers welcomed it as a tool to generate trust (Newlands et al., 2019)

The aforementioned scholars associated the platform reputation systems as a way of building interpersonal trust, that is, a way of consumers to trust SE service providers. For example, a SE service provider's positive reputation fosters trust based on the experiences by other consumers (Yang et al., 2019). Even though the mechanism to provide the rating is created by the SE platform, it is the peer community that rates their experiences of the SE providers, which builds interpersonal trust. It is these trust-generating mechanisms, that is, reputation systems, and ratings in particular, that is hypothesised to cause consumers to trust service providers. In other words, service providers can use such ratings to signal their ability, integrity and benevolence so that

consumers' beliefs and intentions towards them are underpinned by trust. Accordingly, the following hypotheses were established,

Hypothesis 1: Platform reputation systems (ratings) affect consumers' trust in the SE service provider.

Hypothesis 1a: Low platform reputation ratings have a weaker effect on consumers' trust in the SE service provider.

Hypothesis 1b High platform reputation ratings have a stronger effect on consumers' trust in the SE service provider.

2.3.4 Institutional trust

According to Zucker (1986), institutional structures—bureaucracy within firms; intermediaries, such as banks, to facilitate transactions; and regulation and legislation—emerged to restore economic order (and trust) in the USA between the mid-1800s to early 1900s. Zucker (1986) described two mechanisms for producing institutional trust, the first dealing with group similarity, 'membership in a subculture' (p. 63), such as certification and professional memberships, and the second dealing with the facilitation of transactions in creating certainty, such as insurance and escrows. Specifically, the certification and professional membership will be focussed on in the form of independent reputation systems which creates trust for the consumer in the service provider, in alignment with RQ1.2.

The second form of institutional trust is posited as the platform brand, thus influencing the consumer to trust the platform. With the evolution of trust, contracts and regulations served as a trust-generating mechanism for customers; however, the advent of corporations' brands has substituted this need for formality (Möhlmann & Geissinger, 2018). This means that consumers are willing to trust a brand that they recognise for product or service provision. Though, with the advent of the SE, the brands of SE platforms are dependent on the service providers to fulfil the requirements of the platform's brand. Therefore, the following sub-sections outline independent reputation systems and platform brand as forms of institutional trust in service providers and platforms respectively.

2.3.4.1 Independent reputation systems

In accordance with RQ1.2, the concept of independent reputation systems was bound to refer to reviews of the SE service provider performed by an independent and formal body, that is external to the SE parties of the consumer, service provider and platform. Such independent reviews are also referred to as accreditation in the literature. Bartlett, Pallas, and Frostenson (2013) conceptualised accreditation “to concepts of legitimacy in which firms may acquire credibility by meeting formalized standards of certification.” (p. 531). By clarifying the approver of such standards, van Damme (2004) defined accreditation as “the formal approval of an institution [service provider] ... that has been found by a legitimate body to meet predetermined and agreed upon standards, eventually resulting in an accredited status granted to that provider ... by responsible authorities” (p. 129). In addition, accreditation takes the form of process and output accreditation, where the former relates to certain standards being adhered to, which ultimately results in the latter, that is, determination of product / service quality (Grepperud, Mathisen, & Pedersen, 2019; Grepperud & Pedersen, 2020).

Naturally, the extent of accreditation varies across sectors and contexts. For example, in an academic setting potential students often check the accreditation status of an institution before registering with that institution—a common example is the pursuit of an MBA. The healthcare sector is another example of a service that has very stringent accreditation requirements due to the life-and-death implications of dealing with people’s lives. While MBAs and medical procedures are serious, often costly and time-intensive undertakings, the same cannot be said for partaking in a service in the SE. The temporal and monetary costs are simply not comparable. This could be why accreditation in such SE markets are not as mature, as in academia and healthcare.

Pavlou (2002) examined the development of institution-based trust through perceived accreditation in online B2B environments in order to facilitate buyers’ trust in sellers. The author defined perceived accreditation as “the extent to which buyer organizations believe that the accreditation mechanism is able to provide reliable information about the capacity of seller organizations to perform as expected” (p. 222). Although his study is not explicitly in the SE setting, the B2B aspects of accreditation can be readily applied to a SE setting, whereby consumers’ trust in the SE service provider is determined by perceived accreditation. According to Pavlou (2002), when accreditation is conducted independently, it serves as a reliable measure to assess competence and can also be

seen as a substitute for reputation. Similarly, star classification systems developed by independent institutions alleviate information asymmetry (Martin-Fuentes et al., 2018).

While independent reputation is seen as an effective mechanism in ensuring certain standards are adhered to, they can also unintentionally result in moral hazards. For example, in a nursing-home context, nursing-homes misrepresented results of certain processes in fear of being downgraded to a lower star rating (Ody-Brasier & Sharkey, 2019). Thus, according to the authors, higher star-rated nursing homes were not associated with better quality (better patient outcomes).

Based on the above discussion, the following hypotheses were established.

Hypothesis 2: Independent reputation systems (ratings) affect consumers' trust in the SE service provider.

Hypothesis 2a: Low independent reputation ratings have a weaker effect on consumers' trust in the SE service provider.

Hypothesis 2b: High independent reputation ratings have a stronger effect on consumers' trust in the SE service provider.

Having discussed both platform reputation systems and independent reputation systems, using the example of accommodation sharing adds clarity on how both reputation systems in a non-SE and SE context can operate. In the case of the short-term accommodation sector, Airbnb (SE platform) connects hosts (service providers) of accommodation space (underutilised assets) to guests (consumers) seeking short-term accommodation. An obvious group of firms that are being disintermediated in this regard is the traditional short-term accommodation establishments, such as hotels and guesthouses. These traditional establishments subscribe to a star-rating classification that is common to the short-term accommodation sector. An official institution assesses the overall quality of the hotel according to a specific standard, by assigning a star-rated score to the establishment (Fang, Ye, Kucukusta, & Law, 2016). For example, in South Africa, the Tourism Grading Council of South Africa assigns stars to member establishments that subscribe to its services. In this regard, du Plessis and Saayman (2011) found that South African accommodation that were star-rated provided a good indication of their quality.

As mentioned in the previous chapter, Eckhardt et al. (2019) asked “[f]rom a consumer perspective, is the trust engendered by reputation systems as strong as consumers' trust in formal [independent] regulators?” (p. 11). As such, this mechanism of independent

reputation system (star rating) employed by the Tourism Grading Council of South Africa serves as a useful comparison to the platform reputation system (star rating) that Airbnb employs. Juxtaposing both reputation systems to consumers provides a combined view of consumers' perceptions of trust emanating from interpersonal (platform reputation from other consumers' ratings) and institutional (independent reputation from an official body) sources. Following this derivation, the following hypothesis is established:

Hypothesis 3: The combination of platform reputation systems (ratings) and independent reputation systems (ratings) affect consumers' trust in the service provider at differing levels

2.3.4.2 Platform brand

Consumers' trust formation in corporations includes an assortment of antecedents in the marketing literature. Sundararajan (2019) asserted that platform brand is one of the significant sources of trust in the SE and he defined platform brand as "confidence gained because the platform's brand effectively communicates the promises of safe and high-quality service" (p. 34). Due to the inherent risks in the SE, Gielens and Steenkamp (2019) described that without a branded digital SE platform, interactions between service providers and consumers would necessitate significant costs in vetting each person before contractually committing to a transaction. Through a recommendation for further research, Steenkamp (2020) even suggested that branded SE platforms could potentially serve as safeguards in countries with high transaction costs, immature legal systems or high corruption.

Brands play an important role in signalling quality and assurance in engendering trust among consumers (Shankar et al., 2002). Sundararajan (2019) articulated how consumer trust is produced by the interaction "between decentralized digital cues and centralized corporate brands" (p. 32). Therefore, consumers have to trust the service provider through such digital cues (that is, platform and independent reputation systems) as well as the actual platform (that is, the corporate brand of the platform) through which they engage in the SE service. Such branded SE platforms offer standard contracts and payment systems that reduce frictions in building trust between the platform's consumers and service providers (Gielens & Steenkamp, 2019).

It is these safety and quality promises promulgated by the platform brand that is key in facilitating trust. This type of trust is considered as a structural assurance factor, which is part of institutional trust and creates the consolation of protection on the part of the consumer (McKnight & Chervany, 2001). For instance, Pavlou and Gefen (2004) examined how consumers entrusted the market intermediary (as a form of institutional trust) in their transactions with sellers in online marketplaces. This can also be applied in assessing consumers' trust in SE platforms, where market intermediaries are substitutable with SE platforms and the sellers can be viewed as the SE service providers. In online market place / e-commerce settings, manifestations of institutional trust include guarantees, contracts, promises, procedures (McKnight & Chervany, 2001), escrow mechanisms and credit card protection (Pavlou & Gefen, 2004). In an accommodation-sharing context, institutional trust is created through standards for service providers and policies outlining non-discrimination, privacy and refunds (Wu & Shen, 2018). Against this background, the following hypothesis was set,

Hypothesis 4: Platform brand reputation positively affects consumer's trust in the SE platform

2.4 Propensity to participate in the sharing economy

A key source of consumer dynamics, that is, "temporal changes in consumer attitudes and behaviors" (p. 2), is the evolving macro-environment's cultural, institutional and technological norms (Zhang & Chang, 2020), which has entered consumers' lives through the SE. Thus, consumers' intentions are subject to influences and changes as the SE evolves. Given this evolving environment, the consumer's propensity to participate in the SE can be defined as their likelihood to request or use a sharing service (Mittendorf et al., 2019).

Based on economics literature relating to seller reputation, Tadelis (2016) summarised that sellers with better reputations are expected to attract more potential customers. Thus, the corollary holds that sellers with worse reputations may attract fewer potential customers. From an empirical perspective, Fang et al. (2014) studied how trust in an e-commerce vendor influenced consumers' repurchasing intention. Also, Zloteanu et al. (2018) demonstrated how a service provider's digital identity (with ratings as a component) positively influenced consumers' intentions to book a room in a hypothetical accommodation sharing platform. Hence, it is posited that trust in the service provider (which is created from the previously discussed reputation systems) positively influences

a consumer's propensity to participate in the SE service. The following hypotheses were set:

Hypothesis 5: Trust in the SE service provider influences consumers' propensity to participate in the sharing economy

Hypothesis 6: The relationship between platform reputation systems (ratings) and consumers' propensity to participate in the SE is mediated by trust in the service provider

Hypothesis 7: The relationship between independent reputation systems (ratings) and consumers' propensity to participate in the SE is mediated by trust in the service provider

From a platform perspective, according to Akhmedova, Marimon, and Mas-Machuca (2020), consumers' behavioural intentions to participate in the SE occurs when they trust the platform, which mitigates consumer uncertainty originating from the risks and unstandardised and unprofessional nature of the SE. For instance, Ter Huurne et al.'s (2017) analysis concluded on five dimensions of trust in a SE platform, namely, "safety measures, guarantees, website quality, service quality, and reputation of the platform" (p. 494). In addition, Lee, Chan, Balaji, and Chong's (2018) investigation of Uber showed a causal relationship between trust in the Uber platform and consumers' intention to participate in the SE. Therefore, platform companies can influence consumers to participate in their SE service by signalling that their platform can be trusted (Akhmedova et al., 2020). Therefore,

Hypothesis 8: Trust in the SE platform influences consumers' propensity to participate in the sharing economy

Hypothesis 9: The relationship between platform brand reputation and consumers' propensity to participate in the SE is mediated by trust in the SE platform

2.5 Conclusion

Based on the review of SE and trust literature, this chapter sought to establish how scholars have addressed the overarching research question of, what is the role of trust in influencing consumers' participation in the SE? First, the case was made that differences between the traditional and sharing economies have beset consumers with newfound challenges, which have in turn created the necessary preconditions for trust (interpersonal, institutional) as a solution in responding to these challenges. Second, it was then outlined how the two key actors in the SE (service providers, platforms) make use of interpersonal and institutional trust-generating mechanisms (platform reputation,

independent reputation, platform brand) in signalling their trustworthy qualities to consumers in order for them to engage in SE services.

Nine hypotheses were established based on prior literature in order to develop a conceptual model (Figure 4) between different constructs to answer the stated research question. As such Figure 4 has different variable types and interactions through hypotheses. While independent variables influence dependent variables (Creswell & Creswell, 2018), a dependent variable can also be indirectly influenced by mediating variables, that is, variation in the independent variable produces variation in the mediator, which then produces variation in the dependent variable (Hayes, 2018). This is illustrated in Figure 4.

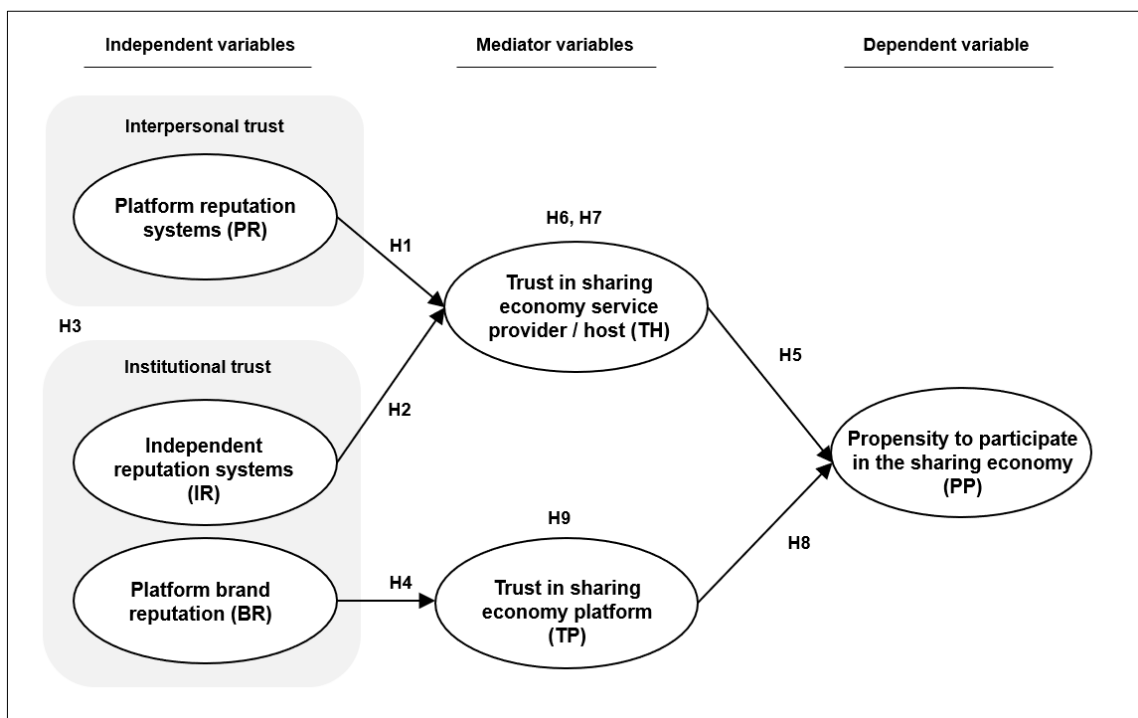


Figure 4: Conceptual model
Source: Author

In summary, the research questions and the corresponding hypothesised relationships discussed in Chapter 1 and Chapter 2 respectively are outlined in Table 6.

Table 6: Research questions and hypotheses

RQ	Hypotheses		
1.1	H1	Platform reputation systems (ratings) affect consumers' trust in the SE service provider	PR → TH
	H1a	Low platform reputation ratings have a weaker effect on consumers' trust in the SE service provider	
	H1b	High platform reputation ratings have a stronger effect on consumers' trust in the SE service provider	
1.2	H2	Independent reputation systems (ratings) affect consumers' trust in the SE service provider	IR → TH
	H2a	Low independent reputation ratings have a weaker effect on consumers' trust in the SE service provider	
	H2b	High independent reputation ratings have a stronger effect on consumers' trust in the SE service provider	
1.1, 1.2	H3	The combination of platform reputation systems (ratings) and independent reputation systems (ratings) affect consumers' trust in the service provider at differing levels	PR + IR → TH
	H3a	Main effect: There is a significant difference on trust in the SE service provider based on platform reputation systems (ratings)	
	H3b	Main effect: There is a significant difference on trust in the SE service provider based on independent reputation systems (ratings)	
	H3c	Interaction effect: There is a significant interaction effect between platform reputation systems (ratings) and independent reputation systems (ratings) in terms of trust in the SE service provider	
1.3	H4	Platform brand reputation positively affects consumer's trust in the SE platform	BR → TP
1.1	H5	Trust in the SE service provider influences consumers' propensity to participate in the sharing economy	TH → PP
	H6	The relationship between platform reputation systems (ratings) and consumers' propensity to participate in the SE is mediated by trust in the service provider	PR → TH → PP
1.2	H7	The relationship between independent reputation systems (ratings) and consumers' propensity to participate in the SE is mediated by trust in the service provider	IR → TH → PP
1.3	H8	Trust in the SE platform influences consumers' propensity to participate in the sharing economy	TP → PP
	H9	The relationship between platform brand reputation and consumers' propensity to participate in the SE is mediated by trust in the SE platform	BR → TP → PP

Notes:

- 1.1: What is the role of platform reputation systems in consumers' trust in the sharing economy?
 1.2: What is the role of independent reputation systems in consumers' trust in the sharing economy?
 1.3: What is the role of platform brand reputation in consumers' trust in the sharing economy?

PR: Platform reputation system
 IR: Independent reputation system
 BR: Platform brand
 TH: Trust in sharing economy service provider / host
 TP: Trust in sharing economy platform
 PP: Propensity to participate in the sharing economy

Chapter 3: Research methodology and design

3.1 Introduction

The purpose of this chapter is to describe the specific components of the research methodology and design that were utilised to achieve the research aims stated in [§1.4](#), namely, how consumers' trust in SE platform reputation systems, independent reputation systems and SE platform brand reputation influences their participation in the SE. For ease of reference, these components are group along four pillars as shown in Figure 5.

First, from a method perspective, this chapter commences with a discussion on the research paradigm that was appropriate for the study ([§3.2](#)). Thereafter, details of the research design ([§3.3](#)) is introduced. This is followed by the specific setting ([§3.4](#)) chosen for the research, that is, the country, SE platform, platform reputation system and independent reputation system upon which the research was based. The subsequent two sections specify details of the population of relevance for the research ([§3.5](#)) and the sample used ([§3.6](#)) to draw conclusions from the population.

The second pillar specifies the measurement instrument ([§3.7](#)) that was used to administer the research. This section outlines the details of the pilot ([§3.7.1](#)) that was conducted to improve the instrument, the four main sections of the instrument ([§3.7.2](#)), and how data was collected from the sample ([§3.8](#)).

The third pillar provides an exposition of the multi-faceted data analysis approach utilised ([§3.9](#)). Details on how the data was prepared, coded and screened forms part of the preliminary data analysis ([§3.9.1](#)), which is followed by an account of statistics used to describe the data ([§3.9.2](#)). The data validation ([§3.9.3](#)) sub-section outlines the two approaches used to validate the data from the survey instrument: exploratory factor analysis (EFA) and confirmatory factor analysis (CFA). The last analysis sub-section stipulates that structural equation modelling (SEM) ([§3.9.4](#)) approach used to infer conclusions from the data. Lastly, in the fourth pillar, limitations ([§3.10](#)) of the method, instrumentation and analysis are acknowledged.

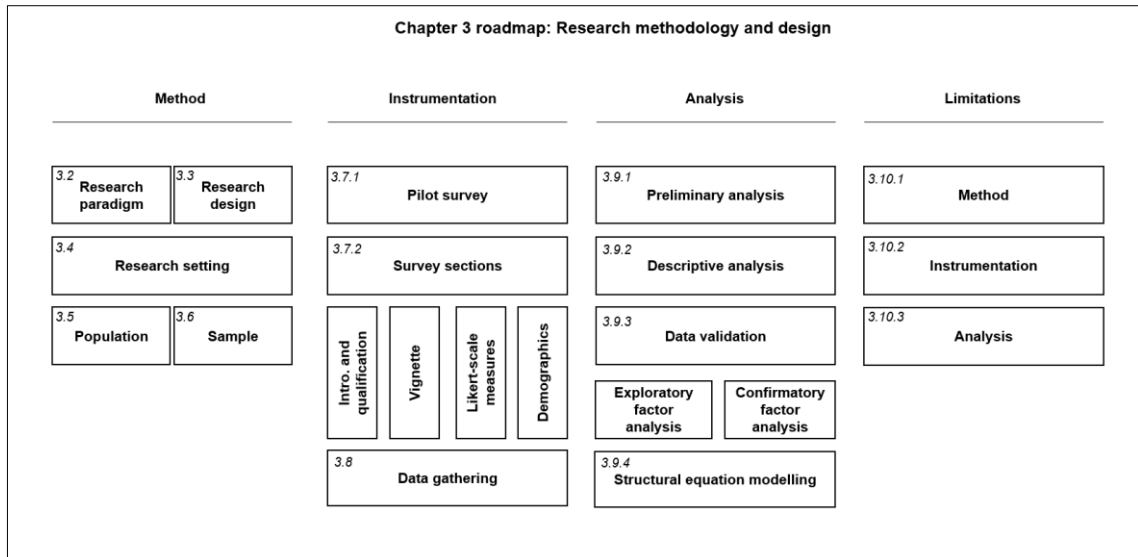


Figure 5: Research methodology roadmap
Source: Author

3.2 Research paradigm

Four key aspects that informed the choice of the research paradigm in the study, included decisions relating to the essence of reality (ontology), the formation of knowledge (epistemology), the process of obtaining such knowledge (methodology) and the causation of events in forming reality (etiology) (Sousa, 2010). In this regard, a positivist philosophical worldview (Creswell & Creswell, 2018) was adopted for the research, characterised by an ontology where the world comprises quantifiable phenomena, an epistemology where observation or experimentation develops knowledge, a methodology employing quantitative research methods, and an etiology concerned with cause-effect relationships (Sousa, 2010). This is in contrast to postmodernism, characterised by an open, inductive, and socially discursive world, and to critical realism, where the world is mainly independent of knowledge necessitating the critique in tentatively explaining phenomena (Sousa, 2010). In the ensuing paragraphs, the positivist worldview is unpacked along ontological, epistemological, methodological and etiological perspectives.

Firstly, from an ontological perspective, a realist stance was adopted, that is, the existence of a tangible social reality was assumed irrespective of those creating such a reality and their knowledge thereof (Pickard, 2017). In other words, reality constitutes phenomena that can be empirically observed, and what cannot be observed or experienced cannot be scientifically researched (Sousa, 2010). Given this, the research

included latent constructs that could be empirically observed through observable measurement indicators.

Secondly, in terms of epistemology, an objectivist / dualist stance was taken. This meant that the researcher and the subjects researched existed within the research process independently of each other, which allows for the research (and knowledge created) to be replicated, thus establishing objectivity of the research results (Pickard, 2017). Additionally, the approach to theory development was deductive, that is, it started with widely accepted premises (Leedy & Ormrod, 2005), whose truth or falsity was known *a priori* (Hart, 2018) as demonstrated through the hypothesised relationships in Chapter 2. This verification (or falsification) was achieved by evaluating the proposed hypotheses through statistical tests, which is detailed in later sections ([§3.9](#)).

Thirdly, from a methodological standpoint, a quantitative research method was employed. Here, the phenomena under study was condensed to variables signifying the unobservable latent constructs; hypotheses were posited on the relationships thereof, which were empirically tested through experimentation; and then the results analysed through statistics to create generalisations of what was studied (Pickard, 2017). In terms of the statistical stance, a frequentist approach (based on significance levels of hypothesis tests) was adopted, rather than a Bayesian approach (based on subjective beliefs) (Gelman, 2018; Howell, 2014).

Lastly, with regards to etiology, the hypothesised relationships proposed in Chapter 2 were evaluated to determine the extent of predictability and explanation of certain exogenous variables causing endogenous variables in a theorised model of relationships among such variables. The culmination of the research project resulted in a conceptual model of cause-and-effect relationships among latent constructs.

3.3 Research design

Since a quantitative methodology was adopted, two broad research designs to be considered were experimental designs and survey designs. With experiments, one or more variables are manipulated to assess its impact on an outcome, whereas surveys quantitatively test for relationships among variables of a population through a sample (Creswell & Creswell, 2018). Cross-sectional surveys collect data at a specific point in time, whereas longitudinal surveys collect data over a longer time period (Bryman & Bell, 2011).

Experimental designs are considered essential in consumer behaviour research as knowledge on consumer behaviour is deemed to be primarily based on the results from experiments (Peterson & Umesh, 2018). Yet, the majority of research conducted is of a passive observational nature (rather than experimental) and there is a scarcity of experimental designs used by scholars in management- and business-related fields (Aguinis & Bradley, 2014). Therefore, a combined research design was established for this study. An experimental design in the form of an experimental vignette methodology (EVM), also known as a factorial design experiment, was administered online through a cross-sectional survey. Therefore, elements of the experiment design and survey design were utilised, which forms the remaining discussion of this section.

In an EVM, dependent variables, such as intentions, attitudes and behaviours, are evaluated through the manipulation of independent variables, through the presentation of different vignettes to participants (Aguinis & Bradley, 2014), where a vignette is “a carefully constructed description of a [...] situation, representing a systematic combination of characteristics” (Atzmüller & Steiner, 2010, p. 128). When applied to this research, the dependent variables of trust in service provider (TSP), trust in platform (TP), and propensity to participate (PP), were evaluated by manipulating the combination of characteristics (levels) of the independent variables of platform reputation systems (PR) and independent reputation systems (IR). This was applied specifically to RQ1.1 and RQ1.2, while the effect of platform brand reputation (BR) on TP (RQ1.3) was assessed through the survey component of the design in the form of Likert-scale questions. The vignettes that were used are discussed in [§3.7.2.2](#) as part of the measurement instrument.

As introduced in [§1.2](#), Mittendorf et al. (2019) recommended providing or withholding certain information from reputation systems. Thus, the intent of this design was to empirically explain what effect platform reputation systems (RQ1.1) and independent reputation systems (RQ1.2) had on the consumer’s trust in the SE service provider, and ultimately their propensity to participate in the SE. Further reasons for the choice of an EVM was its usefulness when independent variables (PR, IR) need to be controlled to obtain evidence of causation and also where they can potentially correlate (Aguinis & Bradley, 2014).

There are two types of EVM studies, namely, paper people studies and policy capturing, with the former focussing on participants’ explicit answers to hypothetical situations and the latter on implicit processes and outcomes (Aguinis & Bradley, 2014). According to

the authors, participants are usually subjected to textual vignettes and choose among options in a paper people study; whereas, with policy capturing, participants are subjected to scenarios containing systematically manipulated variables and decide between scenarios. Policy capturing is applicable when the factors influencing one's decision-making processes are known *a priori* (Aguinis & Bradley, 2014). For the proposed research, such factors influencing consumers' decision-making process are not known *a priori*, which makes paper people studies the preferred option.

In experimental research, there are mainly two types of designs, within-subject and between-subject designs. These designs differentiate in how treatment conditions are applied to subjects / participants (Tabachnick & Fidell, 2007). The treatment condition refers to the combination of the levels of the independent variables that are applied in the experiment. In EVM, a within-subject design exposes each participant to the same vignettes, so each participant goes through a number of different (Aguinis & Bradley, 2014). Here, differences due to treatment conditions are measured within the same set of participants (Tabachnick & Fidell, 2007). By contrast, a between-subjects design exposes each participant to just one vignette, rather than all vignettes (Aguinis & Bradley, 2014). This means that differences due to the treatment conditions are tested between different groups of participants (Tabachnick & Fidell, 2007).

Within-subject designs have three advantages as discussed by Charness, Gneezy, and Kuhn (2012), namely (a) internal validity does not require randomisation, (b) have statistical power, and are (c) aligned to most situations, such as one reacting to a price change, rather than examining two individuals reacting to two different price changes. A disadvantage of within-subject designs is that participants may alter their behaviour to follow a pattern after the first vignette, thereby creating confounds (Charness et al., 2012). Two between-subject design advantages include (a) the ease of statistically conducting such designs and (b) minimal participant effort (Charness et al., 2012). The authors list two drawbacks, namely, (a) potentially missing real-world decision-making patterns characteristic of within-subject designs, and (b) difficulty in achieving statistical power. Given the relative drawbacks and merits of the above-mentioned designs, a between-subjects design was used to minimise participant fatigue and pattern-seeking behaviour, which tends to create spurious effects.

3.4 Research setting

This section outlines the context under which the research was conducted. The milieu of a particular research study is important when contextualising the subsequent results, as this can have implications for replication and generalisability under different contexts.

Specifically, the choices relating to the country, SE platform, platform reputation system and independent reputation system are stipulated next.

First of all, Chen and Wang (2019) argued that the SE in emerging economies lack the specialised foundations of market institutions, such as legal systems protecting property rights, upon which developed markets are built, thus rendering trust as the key barrier and institutional role in emerging markets. Therefore, the authors concluded that this distinctive market feature compels SE platforms in emerging markets to first build consumer trust. Additionally, Cheng (2016) has suggested more attention be focussed on emerging markets that have enjoyed rapid growth of the SE. Considering the recommendation to focus on SE emerging market perspectives, this research focussed on the emerging market of South Africa as the situational setting.

From a SE platform perspective, the research scope was centred on the commercial SE platform definition, as positioned in Chapter 1 and outlined against other definitions in [§ 2.2.1](#). Two well-known SE platforms in South Africa aligning to this commercial interpretation are Uber and Airbnb (Mara, 2020). During the conceptualisation of the research project, research on both SE platforms, Uber and Airbnb, were considered. However, due to the lack of a comparable independent reputation mechanism in the South African meter-taxi industry, Uber was removed from the scope. Also, the most common independent reputation mechanisms for metered taxis are their operating licenses and their company-specific branding on the car itself. These would be difficult to operationalise in an experimental vignette in terms of a comparable reputation mechanism for Uber.

Given the operationalisation difficulties of researching the Uber SE platform, Airbnb was selected as the SE platform for the research. Furthermore, Guttentag (2019) advised that studies on Airbnb in Africa “have received minimal attention” (p. 253) and “that because Airbnb and its regulatory environment are evolving so rapidly, older findings could quickly become outdated and need to be re-examined.” (p. 254). Also, “additional understanding of this growing sector and its new consumers is necessary through future research so as to continuously refine both product offerings and management practices.” (So, Oh, & Min, 2018, p. 234). Therefore, Airbnb was used as the SE platform archetype through which the research was conducted.

While platform reputation systems are operationalised into various facets, such as “profile photos, reviews, *ratings* [emphasis added], and historical information” (Mittendorf et al., 2019, p. 1106), the specific platform reputation system of ratings—Airbnb’s star

rating system—was chosen as the independent variable (platform reputation system) to be manipulated in the EVM. This was also consistent with Frenken and Schor's (2017) recommendation to determine the “relative importance of trust-generating mechanisms on sharing economy platforms, including past *ratings* [emphasis added]” (p. 7).

From an independent reputation system perspective, the SA government gazetted the Tourism Amendment Bill in April 2019, which proposed a mandatory grading system (Department of Tourism, 2019). This is currently being administered by the Tourism Grading Council of South Africa (TGCSA) and will then apply to Airbnb, which involves the rating of the short-term accommodation sector by means of number of stars from one to five if the establishment meets its respective requirements. The TGCSA star rating system shares the same numerical structure with that of Airbnb's star rating system, that is, both reputation systems have a one to five-star scale. This comparison between the platform reputation system and the independent reputation system tied back to Eckhardt et al's. (2019) recommendation to determine if “trust engendered by reputation systems [is] as strong as consumers' trust in formal regulators?” (p. 11). Furthermore, Sainaghi, Köseoglu, d'Angella, and Mehraliyev's (2020) analysis of research conducted on SE accommodation platforms showed a paucity on theoretical topics at the regulatory level, and the authors stated that “there are few papers analyzing, comparing and discussing different regulatory mechanisms” (p. 933). Hence, the TGCSA's five-star rating system was selected as the independent variable (independent reputation system) to be manipulated in the EVM.

Given the above rationale, the research setting can then be delimited to encapsulate the SE in an emerging market location of South Africa, with the SE platform of Airbnb, Airbnb's five star rating system and independent oversight of the broader tourism sector through the TGCSA's five star rating system.

3.5 Population

In the previous section, the country of South Africa, and the SE platform, Airbnb, were selected as the setting upon which the research was conducted. This section now outlines details of the population aligned to the above-mentioned situational setting. The population can be stipulated in terms of the population units, population boundaries and population size. These three elements are discussed in turn.

Firstly, the population of interest is the set of units upon which conclusions from the research are drawn (Blair & Blair, 2015). The unit of analysis in this instance was at the micro level and included individual persons. Secondly, population boundaries are

conditions that delineate individuals of interest in the research versus those who are not eligible (Blair & Blair, 2015). As per Figure 6, the population boundaries were specified as individuals that matched A, B and C, such that the intersection condition of $A \cap B \cap C$ was satisfied. In other words, the target population included individuals that: were familiar with Airbnb (boundary A); and stayed in short-term accommodation or were considering doing so in the future (boundary B); and were familiar with South Africa (boundary C).

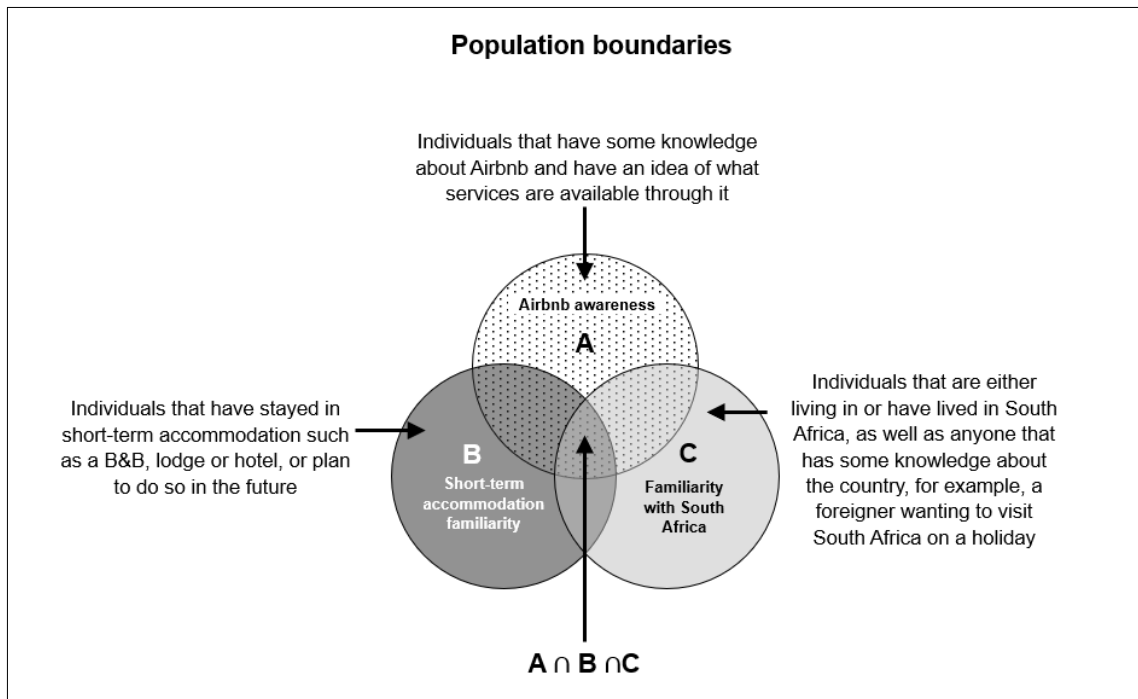


Figure 6: Population boundaries

Considering that Airbnb primarily attracts tourists, the population was not restricted to just South African consumers, but also included foreigners that met the above-mentioned population boundaries. Fulfilment to the boundaries was coded in the survey instrument as filter questions, such that if responses to boundaries A, B and C were not satisfied, then the respondent was not allowed to continue with the survey.

Lastly, the calculation of the population size required an estimation of the population units that took into account the aforementioned population boundaries. Population boundaries A, B and C independently yielded considerably large population sets, so the intersection thereof yielded a more practical number to work with, albeit still substantially large. This intersection condition, and thus the population size, was estimated by understanding the demand for short-term accommodation in South Africa. This was estimated in Table 7 based on publicly available data from Statistics South Africa (Stats SA) and Airbnb, and the researcher’s assumptions, in order to provide a basic approximation of the targeted population size.

Table 7: Calculation for population estimation

Short-term accommodation demand	2017 *	2018 *	2019 *	2020 *
(1) Yearly unit nights sold of non-Airbnb establishments	23 257 300 ^a	22 637 100 ^a	22 400 200 ^a	12 948 100 ^b
(2) YOY % Δ of yearly unit nights sold of non-Airbnb establishments ^c		-2.67%	-1.05%	-42.20%
(3) Yearly stay unit nights sold of Airbnb establishments ^d	651 000 ^e	1 074 150 ^f	1 062 909 ^g	614 399 ^h
(4) Total demand ⁱ	23 908 300	23 711 250	23 463 109	13 562 499

Note. Details on calculations, assumptions and sources:

* Periods are from the 1st September of the prior year to the 1st September of the current year, due to how Airbnb reported data, for example, 2017 is from 1 September 2016 to 1 September 2017.

a. Given sum of "Stay units nights sold - Total industry" for specified periods (Stats SA, 2020).

b. Values available up until May 2020. For the remainder of 2020, assumed constant May 2020 value from June to September 2020.

c. $\% \Delta = (\text{current year value} - \text{prior year value}) / \text{prior year value}$.

d. Airbnb inbound guests used as a proxy for stay unit nights sold with one person per stay unit per night.

e. Given yearly inbound guests of 651 000 between 1 Sep. 2016 - 1 Sep. 2017 (Airbnb, 2017, p. 14)

f. Given "YOY growth in guest arrivals = 65%" (Airbnb, 2018, p.6). Applying 65% to 651 000 yielded a value of just over one million for 2018. This is validated by the following statement: "Since Airbnb's founding in 2008, of the 2 million guests who have arrived at listings in South Africa, roughly half of these arrivals have occurred just in the past year" (Airbnb, 2018, p.6).

g. $1\,074\,150 * (1 + (-1.05\%))$

h. $1\,062\,909 * (1 + (-42.20\%))$

i. (1) + (3)

The first two rows in Table 7 examined the demand for non-Airbnb establishments in terms of number of units and percentage change respectively. Short-term accommodation demand was inferred from the unit nights sold, which is defined as "the total number of stay units occupied on each night" (p. 12), where a stay unit is the "the unit of accommodation available to be charged out to guests" (Statistics South Africa, 2020, p. 12). Stats SA records these values for establishments that are listed on the business register for value added tax (VAT). It was assumed that such establishments were not Airbnb establishments, since service providers hosting their properties on Airbnb are typically consumers, rather than traditional firms, hence assumed to have not registered for VAT.

Next, the third row in Table 7 examined the demand for Airbnb establishments. According to Airbnb (2017), its listings in South Africa experienced 651 000 inbound guests in 2017,

where inbound guests were defined as “all guests visiting a particular location....includ[ing] guests who live in the same location they may have stayed in.” (p. 20). This served as an approximation of unit nights sold with one person per stay unit per night for Airbnb establishments. It is acknowledged that this was not realistic as a particular individual can stay more than one night and stay in more than one establishment during the period under consideration; however, it served as a basic lower bound of the Airbnb demand population estimation.

Considering that the research targeted both Airbnb and non-Airbnb users, demand for non-Airbnb establishments and Airbnb establishments was aggregated. Therefore, the sum of non-Airbnb and Airbnb unit nights sold (rows 1 and 3 respectively in Table 7) yielded a total demand of 13 562 499 unit nights sold, which served as an estimate of the target population in 2020.

In summary, the population for the research study that was conducted in 2020, was estimated at 13.5 million (population size) individuals (unit of analysis) that were familiar with Airbnb (population boundary A); and stayed in short-term accommodation or were considering doing so in the future (population boundary B); and were familiar with South Africa (population boundary C).

3.6 Sample

Having stipulated the population characteristics in the previous section, this section outlines details of the sample that was used to draw conclusions from the population. The sampling method and sample size calculation are discussed next.

Probability sampling entails that an individual in the population has an equal chance of random selection either from a specific database (single stage sample design) or different clusters / groups (multistage sample design), which is different from non-probability sampling, where individuals are chosen based on ease of accessibility (Creswell & Creswell, 2018). While probability sampling is preferred, accessing a database of individuals or lists of clusters of individuals that met the population boundaries was not achievable. For example, obtaining access to Airbnb’s customer database as well as other short-term accommodation establishments was not permitted due to their respective privacy policies.

Given the inability to use probability sampling, a nonprobability sampling method was used, which comprised of convenience, snowball and self-selection sampling. From a convenience sampling stance, the researcher’s professional network was contacted to

participate in the research if they met the population boundaries. In terms of snowball sampling, those individuals that were initially contacted were then asked to distribute the survey to others that also met the criteria of the population boundaries, thus creating a 'snowball' effect. Lastly, from a self-selection / volunteering sampling perspective, there are websites that have respondents that participate in research, for example, SurveyCircle (www.surveycircle.com) allows academic researchers to post their studies online and other researchers participate reciprocally.

The sample should reflect the population as accurately as possible; however, nonprobability sampling is affected by selection bias, where certain individuals would have been afforded an unequal chance of selection (Blair & Blair, 2015). As a result, the conclusions drawn from the sample about the population in subsequent chapters were tempered due to the concern of sample homogeneity.

The sample size and number of participants per condition were calculated with the G*Power software as shown in Figure 7 (Creswell & Creswell, 2018). Firstly, the numerator degrees of freedom (df) was determined by the interaction effect between the two independent variables, that is: Numerator df = (number of levels for 1st variable – 1) x (number of levels for 2nd variable – 1) = (3 – 1) x (3 – 1) = (2) x (2) = 4. Secondly, the number of groups were nine due to the number of combinations in the factorial table (cf. §3.7.2.2). This yielded a sample size of 302. So, for each of the 9 conditions, 34 participants were required at a minimum per cell, that is $302/9 \approx 34$.

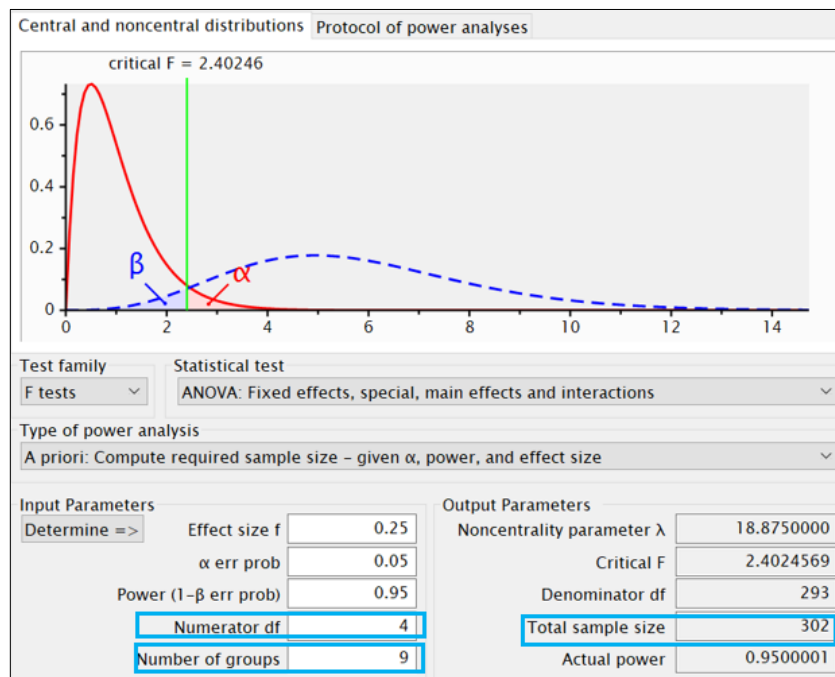


Figure 7: Sample size calculation
Source: G*Power software

3.7 Measurement instrument

An online survey was used as the measurement instrument. A key requirement for the experimental component of the survey was the randomisation feature, such that respondents were randomly exposed to the pre-determined vignettes. Due to this randomisation feature, Qualtrics (used through the University of Pretoria's licence) was selected as the preferred survey tool, over Google Forms and Survey Monkey.

The following sub-sections outline details on the pilot survey and the three survey sections (introduction and qualification; vignette; demographics). The full survey is outlined in [Appendix A](#).

3.7.1 Pilot survey

Before activating the survey, a pilot was run amongst eight students, whereby they were requested to suggest how the survey could be improved. The eight students had a background in survey methods as they were from the 'Principles of quantitative research' elective at GIBS. They were also within the population boundaries.

[Appendix B](#) includes their actual feedback, along with actions taken to improve the survey. In summary, the feedback centred on updating the vignette to indicate the number of customer reviews upon which the platform rating was based; clarifying the questions to be specific to the vignette, rather than one's general Airbnb experience; formatting; page structure; and rationalising the demographic values.

3.7.2 Survey sections

Before delving into each section of the survey, it is necessary to understand the decision logic used in the survey as illustrated in Figure 8, as this filtered out respondents that were not part of the target population.

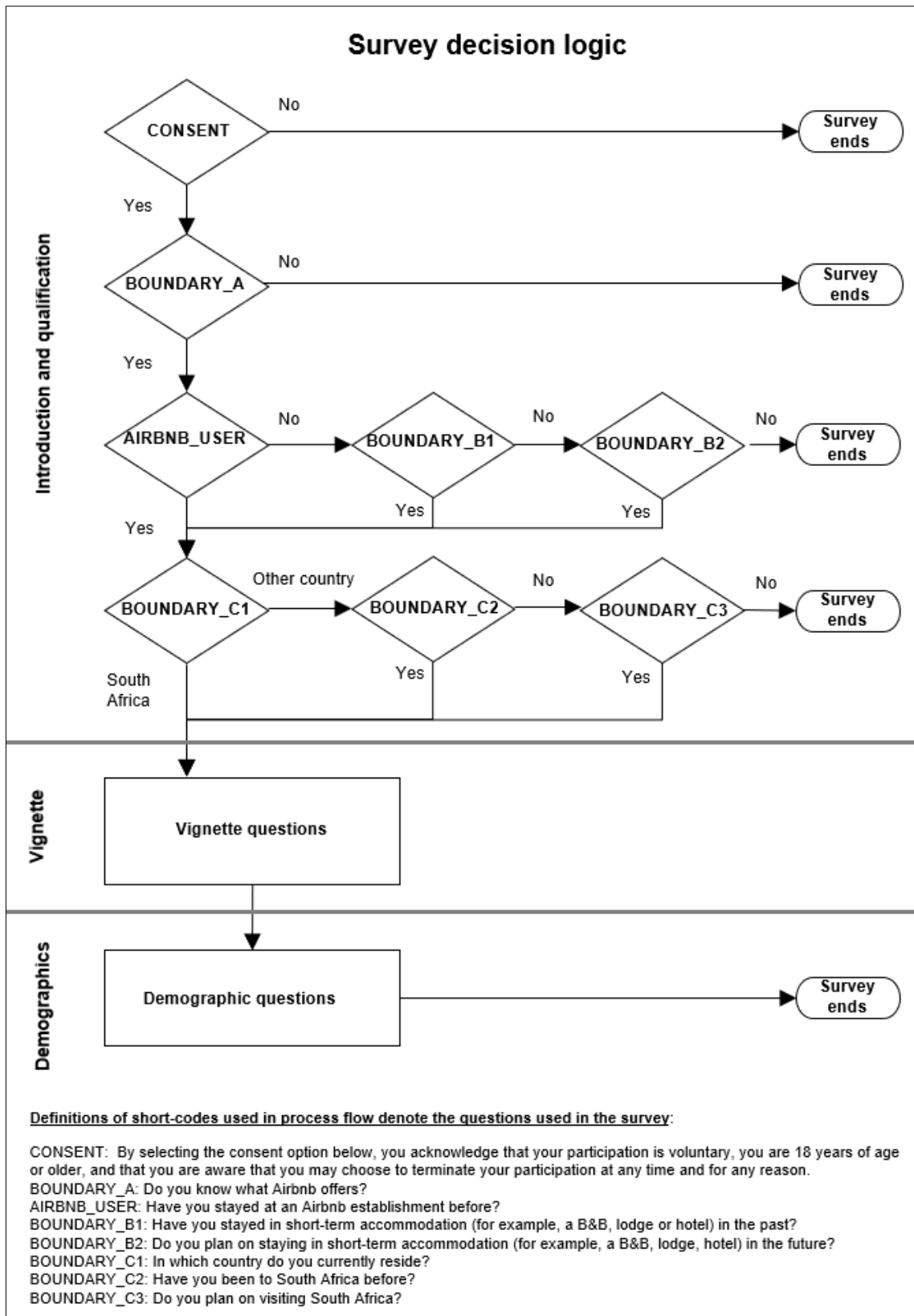


Figure 8: Survey decision logic

3.7.2.1 Introduction and qualification

The introductory section of the survey outlined the intent of the research and asked for participants' consent to continue with the survey. Thereafter, the first round of questions (BOUNDARY_A, BOUNDARY_B2 and BOUNDARY_C3 in Figure 8) aligned to the population parameters in §3.5, and filtered out unsuitable respondents. The survey ended if the above-mentioned population boundaries were not met.

3.7.2.2 Vignette

The second section of the survey dealt with the vignette. The variables that were manipulated in the vignette included the two independent variables of platform reputation (PR) and independent reputation (IR) as discussed in §3.4. PR was represented by the Airbnb star ratings, while IR was represented by the TGCSA star ratings. PR and IR were operationalised as having three levels of low (1-star), medium (3-star) and high (5-star) ratings. The combination of two independent variables with three levels each, resulted in a 3 x 2 design matrix of nine (3²) different treatment conditions represented in Table 8.

Table 8: Nine-cell 3 x 2 design (3²) matrix

		PR		
		1	3	5
IR	1	Treatment 1	Treatment 2	Treatment 3
	3	Treatment 4	Treatment 5	Treatment 6
	5	Treatment 7	Treatment 8	Treatment 9

Each participant was exposed to one of the nine hypothetical vignettes as shown in Figure 9 and operationalised in Qualtrics (Appendix C), such that treatment conditions were evenly presented and randomised automatically. The vignette content remained constant for all participants, except for the two variables (PR, IR) that were randomised.

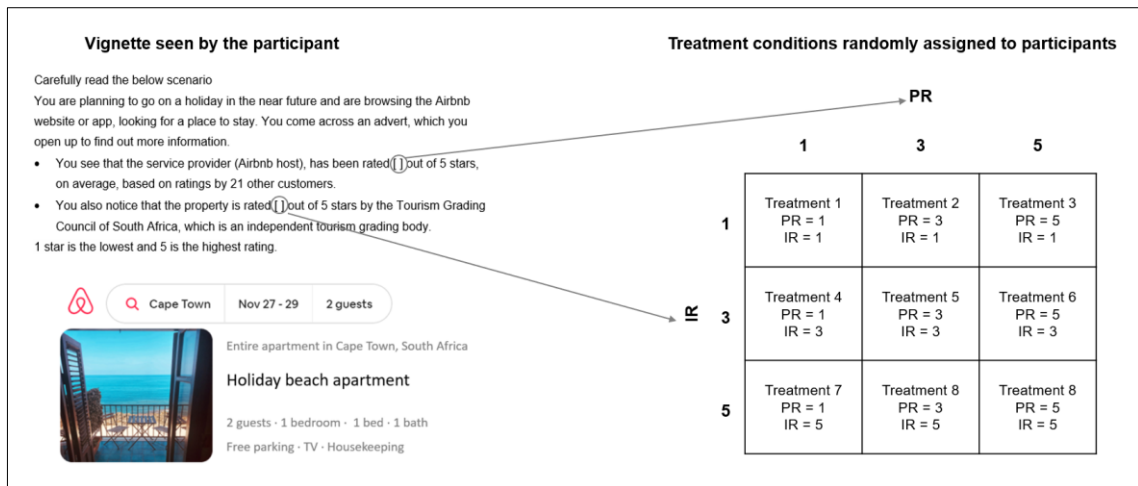


Figure 9: Vignette and treatment conditions

The advertisement in the vignette was created to closely resemble that of the Airbnb interface. The rationale for the choice of elements used therein was informed by an analysis of South African Airbnb data. Cape Town was chosen as the hypothetical destination as Airbnb listings are most predominant in Cape Town, compared to any other province in South Africa (Airbnb, 2018). Since the research was expected to be conducted between September and October, a weekend in November was chosen to simulate planning from the participant's perspective. For five of the characteristics in the vignette, publicly available Airbnb data from Cox and Morris (2020) were analysed to determine which were the most common characteristics across all Cape Town Airbnb listings. This then informed the description of an 'entire apartment', '2 guests', '1 bedroom', with '1 bed' and '1 bathroom' in the vignette (Figure 9). As shown in Table 9, this is because the majority of Cape Town Airbnb listings are entire homes or apartments (76%), accommodate for two guests (41%), have one bedroom (43%) with one bed (39%) and one bathroom (53%) (Cox & Morris, 2020).

Table 9: Analysis of Cape Town Airbnb data to construct vignette details

Airbnb characteristics	Details for vignette	Number of listings	Percentage of listings
Room type	Entire home / apartment	18294	76%
Number of guests per listing	2	9756	41%
Number of bedrooms	1	10317	43%
Number of beds	1	9278	39%
Number of bathrooms	1	12667	53%

Note. Researcher's analysis of data raw data retrieved from Cox and Morris (2020)

Considering that the vignette details (picture and description) remained the same for all nine treatment conditions, the picture and amenity details had to be general enough to not skew the respondent's perception of the accommodation being either low-budget or

high-end. Thus, a royalty-free, generic picture from Buccola (2019) of a view from a room was offered, rather than a picture of an actual room. Also, very generic amenities were listed (free parking, TV, housekeeping), which are expected in most short-term accommodation establishments, whether traditional or Airbnb.

3.7.2.3 Measures

Brand reputation, trust in the Airbnb service provider, trust in the Airbnb platform and propensity to participate in the SE introduced in Chapter 2, are all theoretical constructs (also known as latent variables) that cannot be directly measured and are unobservable. As such, a measurement model outlines relationships between a construct and its measures (Diamantopoulos, Riefler, & Roth, 2008), whereby the construct is at a higher level of unobservable abstraction that needs to be operationalised at an observational level for empirical research (Schwab, 2011). Such constructs are usually measured through respondents' scores on a series of statements (indicators or manifest / observed variables) in a survey (Davvetas, Diamantopoulos, Zaefarian, & Sichtmann, 2020).

The way in which such constructs can be measured can take on a reflective measurement approach or a formative measurement approach. Causality originates from the construct to the measures in reflective measurement, whereas with formative measurement, it flows from the measures to the construct (MacKenzie, Podsakoff, & Jarvis, 2005). Stated differently, scale items reflect the construct in reflective measurement, while in formative measurement, indicators form or determine the construct (Bollen & Lennox, 1991). Thus, constructs exist independent of measures in reflective measurement, whereas it is formed by the measures in formative measurement (Coltman, Devinney, Midgley, & Venaik, 2008). Further distinctions between the two measurement approaches are outlined in Table 10, which are used in the ensuing discussion of the selected scale items that were used in the survey.

Table 10: Comparison of reflective and formative measurement

Reflective measurement	Formative measurement
Causality	
<ul style="list-style-type: none"> • Construct \Rightarrow measure (Jarvis, MacKenzie, & Podsakoff, 2003) • Δ construct \Rightarrow Δ measures (Coltman et al., 2008) • Δ measures \nRightarrow Δ construct (Coltman et al., 2008) 	<ul style="list-style-type: none"> • Measure \Rightarrow construct (Jarvis et al., 2003) • Δ construct \nRightarrow Δ measure (Coltman et al., 2008) • Δ measures \Rightarrow Δ construct (Coltman et al., 2008)
Interchangeability	
<ul style="list-style-type: none"> • Removing an indicator does not change construct meaning (Jarvis et al., 2003) • Measures are thematically similar and are interchangeable (Coltman et al., 2008) 	<ul style="list-style-type: none"> • Removing an indicator may change construct meaning (Jarvis et al., 2003) • Measures do not need to be thematically similar and are not interchangeable (Coltman et al., 2008)
Correlations	
<ul style="list-style-type: none"> • Correlation among measures is expected (measures should have internal consistency reliability) (Jarvis et al., 2003) • Test for internal consistency and reliability: Cronbach alpha, AVE, factor loadings (Coltman et al., 2008) 	<ul style="list-style-type: none"> • Correlation among measures is not expected (internal consistency not implied) (Jarvis et al., 2003) • Test for internal consistency and reliability: No unanimously accepted criteria exist (Coltman et al., 2008)
Relationships with other constructs	
<ul style="list-style-type: none"> • Measures have similar sign and significance of relationship with the construct's antecedents and consequences (Coltman et al., 2008) • Test for convergent validity and discriminant validity 	<ul style="list-style-type: none"> • Measures may not have similar sign and significance of relationship with the construct's antecedents and consequences (Coltman et al., 2008) • Test for external validity: Multiple-indicator-and multiple-causes (MIMIC) model (Diamantopoulos & Winklhofer, 2001)

Note. References for excerpts provided in table.

To ensure that the posited constructs were accurately represented (through indicators) in the survey, indicators from previous research studies were leveraged specifically from Delgado-Ballester, Munuera-Aleman and Yague-Guillen (2003), and Mittendorf et al. (2019). The scale item used by these authors (Table 11) was aligned with a reflective measurement approach, as items for each construct were interchangeable due to the similarity of themes therein, so removing items did not significantly change the construct's domain (Coltman et al., 2008). Also, each variable was underpinned by items with a consistent theme, therefore aligning to a reflective approach.

Reflective measurement entails items to be highly correlated to each other and internal consistency and reliability can be evaluated through coefficient alpha (α) (commonly referred to as Cronbach's alpha) and standardised factor loadings (λ) (Coltman et al., 2008). Therefore, the reliability and convergent validity of these indicators were assessed using the α and λ measures that were reported by Delgado-Ballester et al. (2003) and

Mittendorf et al. (2019). Reliability is about reproducibility—it holds when there are similar results if measurement is repeated under identical circumstances (Blunch, 2013), and is also a sign of convergent validity, that is, indicators really measure the theoretical construct that they were designed to measure (Hair, Black, Babin, & Anderson, 2010). The coefficient alpha, as a measure of reliability, ranges from 0 to 1, with 0.70 deemed as the lower acceptable limit as an indication of reliability (Hair et al., 2010). The standardised loadings represent the association between the indicator and the construct (Davvetas et al., 2020), ranging from -1.0 to +1.0 and should ideally be 0.5 or higher as an indication of strong convergent validity (Hair et al., 2010).

Given the above discussion of how indicators were selected, the indicators from the above-mentioned prior studies were selected and adapted accordingly as shown in Table 11, together with their respective α and λ measures. However, due to the lack of scales relating to the specificity of including the PR and IR impacts on the trust in service provider / host, and propensity to participate constructs, TH1, TH2, PP1 and PP2 were created by the researcher.

Table 11: Indicators selected for survey from prior research

Code	Indicator	Measures	Key references
<i>Trust in service provider (host)</i>			
TH1	Because of the star rating from other customers, I trust the service provider (Airbnb host)	*	*
TH2	Because of the star rating from the independent tourism grading body, I trust the service provider (Airbnb host)	*	*
<i>Trust in platform</i>			
TP1	I trust Airbnb to continue to meet my expectations in the future	α : not provided $\lambda = 0.899$	(Mittendorf et al., 2019, p. 1116)
TP2	I feel confident in Airbnb's brand name	$\lambda = 0.890$	(Delgado-Ballester et al., 2003, p. 41)
TP3	Airbnb's brand name guarantees satisfaction	$\alpha > 0.700$ $\lambda = 0.750$	(Delgado-Ballester et al., 2003, p. 41)
<i>Brand reputation</i>			
BR1	Even if not monitored by an independent body, I would trust Airbnb to do the job right	α : not provided $\lambda = 0.917$	(Mittendorf et al., 2019, p. 1116)
BR2	I could rely on Airbnb's brand name to solve any problem experienced with this accommodation	$\alpha > 0.70$ $\lambda = 0.82$	(Delgado-Ballester et al., 2003, p. 41)
BR3	Airbnb's brand name would compensate me in some way for any problem with the product or service experienced with this accommodation	$\alpha > 0.70$ $\lambda = 0.88$	(Delgado-Ballester et al., 2003, p. 41)
<i>Propensity to participate</i>			
PP1	Because of the star rating from other customers, I will book this Airbnb accommodation	*	*

Code	Indicator	Measures	Key references
PP2	Because of the star rating from the independent tourism grading body, I will book this Airbnb accommodation	*	*
PP3	I am very likely to request a booking for this accommodation on Airbnb in the future	α : not provided $\lambda = 0.757$	(Mittendorf et al., 2019, pp. 1116–1117)
PP4	I would not hesitate to request a booking for this accommodation on Airbnb	α : not provided $\lambda = 0.847$	(Mittendorf et al., 2019, p. 1116)
PP5	I would feel comfortable requesting a booking on Airbnb for this accommodation	α : not provided $\lambda = 0.870$	(Mittendorf et al., 2019, p. 1116)
PP6	I would use Airbnb to request a booking for this specific accommodation	α : not provided $\lambda = 0.887$	(Mittendorf et al., 2019, pp. 1116–1117)

Note. * TH1, TH2, PP1 and PP2 were created by the researcher and were subsequently tested in the exploratory factor analysis.

After reading the vignette, respondents indicated their extent of agreement with statements regarding their trust in the service provider (host of the property), trust in the platform brand of Airbnb and their propensity to participate in booking the indicated accommodation with Airbnb. These took the form of the above-mentioned 14 statements (Table 11) that used a five-point Likert scale, ranging from 1 (strongly disagree) to 5 (strongly agree).

3.7.2.4 Demographics

Gender, age, race, education and location are the most common demographic questions (Hughes, Camden, & Yangchen, 2016). Such questions provide insight into the types of respondents and indicates if there are certain demographic information that may impact the studied variables (Dobosh, 2017). For example, the propensity to use Airbnb could be more skewed towards millennials (part of the age group between born 1981–1999) as Amaro, Andreu, and Huang (2019) and Mittendorf et al. (2019) have shown that millennials are a key target group for SE platforms. Ultimately, the demographic information collected from the sample indicates the extent to which the research is generalisable to a broader population.

However, participants may hesitate to complete such sensitive questions at the beginning of a survey, but will be inclined to answer after rapport has been built up front (Malhotra, 2006). Also, participants may find these questions about themselves easier to answer after having invested effort in the survey (Dobosh, 2017). Furthermore, socio-economic status questions asked first may influence the participant to think that the ensuing questions will evaluate insights on the basis of the socio-economic questions

(Salkind, 2010). Thus, the survey for this study concluded with demographic questions outlined in Table 12. The only exception was the question relating to the country (cf. BOUNDARY_A in Figure 8, §3.7.2), listed in the first section of the survey, as this was used as a qualifying question to assess participants' familiarity with or intention to visit South Africa.

Table 12: Demographic questions

Short form	Measures	Answer choices
GENDER	How do you currently describe your gender identity?	<input type="checkbox"/> Male <input type="checkbox"/> Female <input type="checkbox"/> Please specify: <input type="checkbox"/> I prefer not to answer
AGE	Indicate your age	<input type="checkbox"/> Under 23 years old <input type="checkbox"/> 24 - 39 years old <input type="checkbox"/> 40 - 55 years old <input type="checkbox"/> Over 55 years old <input type="checkbox"/> I prefer not to answer
RACE	Which category best describes you?	<input type="checkbox"/> Black African <input type="checkbox"/> Coloured <input type="checkbox"/> Indian or Asian <input type="checkbox"/> White <input type="checkbox"/> Other, please specify: <input type="checkbox"/> I prefer not to answer
EDU	Which category best describes your level of education?	<input type="checkbox"/> High school <input type="checkbox"/> Vocational training <input type="checkbox"/> Bachelor's degree <input type="checkbox"/> Post graduate degree <input type="checkbox"/> Other, please specify: <input type="checkbox"/> I prefer not to answer
MARITAL	What is your marital status?	<input type="checkbox"/> Single (never married) <input type="checkbox"/> Married, or in a domestic partnership <input type="checkbox"/> Widowed <input type="checkbox"/> Divorced / separated <input type="checkbox"/> Other, please specify: <input type="checkbox"/> I prefer not to answer
EMPLOY	Are you currently...?	<input type="checkbox"/> Employed part-time <input type="checkbox"/> Employed full-time <input type="checkbox"/> Self-employed <input type="checkbox"/> Not employed <input type="checkbox"/> A student <input type="checkbox"/> Retired <input type="checkbox"/> Other, please specify: <input type="checkbox"/> I prefer not to answer
SHOP	How often to do purchase online per month?	<input type="checkbox"/> 0 times <input type="checkbox"/> 1 - 3 times <input type="checkbox"/> 4 - 6 times <input type="checkbox"/> 7 or more times <input type="checkbox"/> I prefer not to answer

In articulating the demographic questions, firstly, the question (and choices) related to gender was adapted from Hughes et al. (2016, p. 140) to consider other gender forms,

such as transgender, beyond just binary male and female options. Secondly, rather than having respondents enter in a value for their age, age groups were set based on generational groups, that is, “baby boomers/traditionalists (born before 1965), Gen Xers (born 1965–1980), and millennials/Gen Zers (born 1981–1999).” (Salesforce Research, 2018, p. 3). Thirdly, for the race question, the words ‘race’ and ‘ethnicity’ were not used in the question. Such terms are confusing and misused, thus the question was phrased as ‘which category best describes you?’, adapted from Hughes et al. (2016, p. 141). The last demographic question sought to determine the respondents’ usage of online shopping as a potential control variable and was copied from Mittendorf et al. (2019, p. 1098).

3.8 Data gathering process

Organisations in the accommodation, tourism and hospitality sectors were approached to gain access to potential respondents from their client bases. However, they did not want to reveal their customers’ contact details without their prior consent. Numerous attempts to contact Airbnb were made; however, no feedback was received. Contact was also made with representatives from the TGCSA and they chose to not participate as they felt that their participation may compromise the objectivity of the results.

Therefore, as per [§3.6](#) on sampling, self-selection and snowball sampling was used, where the researcher made use of his personal network and asked those that completed the survey to pass it on to others that met the qualifying criteria. Participants were solicited to participate in the survey through LinkedIn, emails, WhatsApp and also www.surveycircle.com; however, only 12 respondents emerged from the latter channel (details on the total sample and eligible sample are provided in Chapter 4, [§4.1](#)).

To ensure that only one response was received per participant, the ‘Prevent Ballot Box Stuffing’ functionality was enabled on the survey. In other words, if someone had already completed the survey, they would have not been able to re-take it.

A total of 760 responses were received over 21 days (3 weeks) from the 24th September to the 14th October 2020. From Figure 10, approximately 400 responses were already received within the first week (24th to 30th September), which was above the minimum sample size of 360 responses as calculated in [§3.6](#).

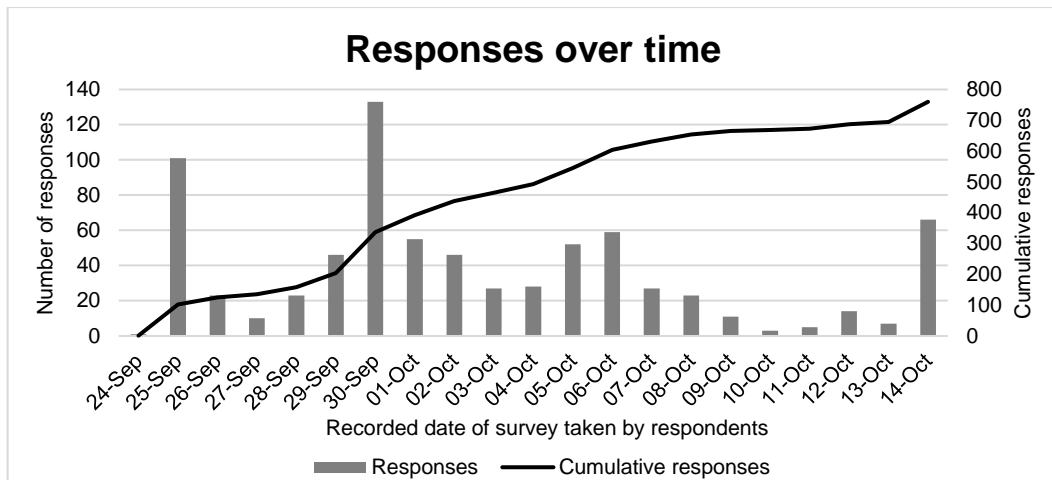


Figure 10: Responses over time

3.8.1. Confidentiality and anonymity of participants

Confidentiality is concerned with how participants’ data is protected after being collected (Kennedy, 2008). In this regard, the data was securely stored on an encrypted file storage system after being downloaded from Qualtrics without any identifiers. This data will be kept for at least ten years. Furthermore, the personal details of the participants were not known.

Anonymity refers to when the data of a participant cannot be traced (Coffelt, 2017). This was adhered to as no personally identifiable information was collected. Although there were demographic questions, these were used in aggregate reporting. Additionally, the ‘Anonymize Response’ option was enabled in Qualtrics so that internet protocol addresses and location data were not collected.

3.9 Analysis approach

The data gathered was analysed in four main phases, namely (1) preliminary analysis, (2) descriptive statistics, (3) data validation and (5) structural equation modelling (SEM). These high-level phases, along with the selected tools and key steps, are tabulated in Table 13 and are subsequently discussed.

Table 13: Data analysis phases

Phase	Tools	Key steps
Preliminary analysis	Qualtrics, Excel, IBM SPSS	<ul style="list-style-type: none"> • Data preparation and coding • Sample determination • Data cleansing
Descriptive statistics	Microsoft Excel, IBM SPSS	<ul style="list-style-type: none"> • Central tendency • Variability • Skewness • Kurtosis • Correlation
Data validation	IBM SPSS, AMOS	<ul style="list-style-type: none"> • Exploratory factor analysis • Confirmatory factor analysis
Structural equation modelling	AMOS	<ul style="list-style-type: none"> • Structural model • Structural model with controls • Structural model with significant controls • Structural model with significant controls and mediation • Structural model with significant controls and mediation per treatment condition

3.9.1. Preliminary analysis

3.9.1.1. Data preparation and coding

Once the survey was closed, the data was exported from Qualtrics and imported into the selected statistics software, that is, IBM Statistical Package for the Social Sciences (SPSS) version 26. The export-import functionality from Qualtrics to SPSS allowed for the Qualtrics data to be numerically coded in a format compatible for analysis in SPSS. This data was simultaneously analysed in Microsoft Excel and in SPSS for preparation of subsequent analyses.

Additional variables were specifically created in SPSS to aid in the analyses and is detailed in the applicable sections of Chapter 4. To ensure that the data was in a suitable format for analysis, a code book for each variable was maintained.

3.9.1.2. Sample determination

Several conditions were applied to the dataset of responses to verify that only valid responses were maintained for analysis. These conditions were consistent with the decision logic process flow (Figure 8), and included whether the respondents provided

consent, met the qualifying criteria (per population boundaries defined in §3.5) and completed the last question of the survey.

A final condition was applied to remove responses that had constant values, indicative of unengaged respondents. To this effect, a data screening Excel macro developed by Gaskin (2016) was used to detect such patterns for the Likert scale data. This was supplemented with the time taken to complete the survey, which was compared to the median completion time to check if respondents actually spent a suitable amount of time to go through the survey.

3.9.1.3. Data screening

Questions related to the population boundaries did not offer a free text option, so data cleansing was not needed for those questions. Secondly, all Likert scale questions were mandatory, which meant that respondents were unable to skip questions, therefore resulting in minimal missing values. Lastly, while the demographic questions included pre-defined categories, an 'other, please specify' option was available. These categories of data were analysed for any free text abnormalities in Excel. Only the last category of demographic questions required some editing for the 'other, please specify' option.

In addition, a check for outliers was conducted using the Cook's distance test on the Likert scale data; however, no outliers were detected. Lastly, multicollinearity was assessed by checking if the variance from other constructs did not overlap too much in predicting the dependent variable by examining the collinearity statistics run through a linear regression.

3.9.2. Descriptive statistics

Descriptive statistics aided in describing the characteristics of the sample, as well as checking if the variables violated assumptions required for subsequent statistical techniques (Pallant, 2001). For all of the categorical questions relating to demographics, frequency statistics and percentages were used. For the Likert-scale questions, the analysis focussed on measures of central tendency, dispersion, kurtosis and skewness.

3.9.3. Data validation

Validity holds when the instrument measures what it is designed to measure (Blunch, 2013). Internal validity is concerned with accurate conclusions about relationships in the data, such as a cause-and-effect relationship (Leedy & Ormrod, 2005). In contrast, external validity refers to extent the results can be generalised other ('external') settings.

Internal validity is a primary concern for experiments as the specific aim is to identify a causal relationship (Leedy & Ormrod, 2005). External validity is a concern for EVM too, as certain outcomes can occur, but not necessarily outside the experiment (Aguinis & Bradley, 2014). However, the authors advised that this can be enhanced by improving the realism by ensuring that the experiment is similar to the natural setting and also suggest more immersive methods such as video. To limit the research cost, a written vignette with a picture was used, which also had characteristics that closely resembled a real-life scenario as detailed in [§3.7.2.2](#). Furthermore, the combination of aspects of experimental and survey design in EVM through administering EVM through online surveys, is a way to offset the weakness of low external validity of experiments and the low internal validity of surveys (Atzmüller & Steiner, 2010).

In ensuring that the data from the survey was measuring what it was designed to measure, an EFA and CFA were conducted.

3.9.3.1. Exploratory factor analysis (EFA)

The goal of an exploratory factor analysis is to define the underlying structure of variables (Hair et al., 2010) through examining their common unobserved sources of influence, which are correlated into groupings, also known as factors (Cudeck, 2000). In a subsequent phase, another form of factor analysis was performed, that is, a confirmatory factor analysis (CFA). In an EFA indicators across all factors are allowed to freely load together, whereas these relationships from indicator to factor are explicitly made in a CFA (Collier, 2020), where relationships between measures and constructs are determined *a priori*. While a CFA is philosophically different from an EFA, Cudeck (2000) suggested that these "are complementary rather than competitive" (p. 294).

Given that an EFA is complementary to a CFA, an EFA is useful to determine if measures are measuring more than one construct and is usually the first step to check if a measure actually measures a latent construct before a CFA is conducted (Collier, 2020). As a

reminder, the questionnaire was compiled based on existing scales as well as the newly formed questions that the author created. Thus, an EFA was conducted to determine how those observable items grouped together, especially for those questions that were created by the author (TH1, TH2, PP1, PP2) and not tested in prior studies. The EFA was conducted on the fourteen variables following Pallant's (2001) three steps of data suitability, factor extraction, and factor rotation and interpretation.

(i) Data suitability for an EFA

Two main requirements for an EFA are a sufficiently large sample size (more than 150) and the strength of the intercorrelations among the questionnaire items, which are assessed through Bartlett's test of sphericity and the Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy (Pallant, 2001). If Bartlett's test of sphericity is significant ($p < 0.05$), then the data is suitable to be factored as part of an EFA (Pallant, 2001). Kaiser suggested the following thresholds when assessing the size of KMO values to determine suitability for an EFA, such that KMO values above 0.90 are "marvellous", in the 0.80s are "meritorious", in the 0.70s are just "middling", and less than 0.60 is "mediocre, miserable or unacceptable" (Pett, Lackey, & Sullivan, 2003, p. 111)

(ii) Factor extraction

During factor extraction, factor loadings are estimated, which link the measures / indicators to the latent constructs / factors (Finch, 2020). While there are many extraction methods, maximum likelihood extraction was used in the EFA as this method is also used in the AMOS software as part of the measurement and structural models during the second-generation statistics analysis. The maximum likelihood extraction calculates parameter estimates that maximise the probability of the observed data (Finch, 2020) and maximises differences between factors (Gaskin, 2016b). An adjustment to Kaiser's criterion ('eigenvalue-greater-than-one rule') as recommended by Jolliffe (Field, 2009, p. 641) and Cartell's scree test were two methods that assisted in determining the number of factors to be extracted (Pallant, 2001). In the scree test, descending eigenvalues were visually examined to locate a break in the eigenvalue size, as an indicator of the number of factors to be extracted (Worthington & Whittaker, 2006).

(iii) Factor rotation and interpretation

Factor rotation is concerned with transforming the set of extracted factor loadings and relating each measure to a latent construct / factor (Finch, 2020). Of the two main rotation

methods, oblique rotation was conducted, whereby factors are allowed to be correlated, rather than orthogonal rotation (uncorrelated factors), as it was difficult to assume independence among the factors (Pallant, 2001). Furthermore, Worthington and Whittaker (2006) recommended that it is good practice to start off with an oblique rotation. The promax option was selected as it was computationally faster than other oblique rotations and also handled large datasets well (Gaskin, 2016b). The oblique promax rotation produced a pattern matrix that provided unique relationships between each measure and each construct after accounting for other constructs, which helped in interpreting the underlying structure (Finch, 2020).

In finalising the number of factors to be retained, item loadings and cross-loadings were assessed by assessing the following thresholds. Items were marked for deletion if their factor loadings were less than 0.3 as recommended by Hair et al. (2010), and if the difference in cross-loadings between factors were less than 0.154 as recommended by Worthington and Whittaker (2006).

(iv) Common method bias

Common method bias is the systematic method error that is common in cross-sectional research due to something unrelated to the question that may have influenced a response from a respondent (Rindfleisch, Malter, Ganesan, & Moorman, 2008). The extent of common method bias was assessed with Harman's single factor test in an EFA, by constraining the number of factors extracted to one, and with no rotation. If the factor accounts for more than 50% of the variance, then common method bias exists.

3.9.3.2. Confirmatory factor analysis

The analysis of the CFA included the following parts: (i) diagrammatic construction of the CFA model to examine factor loadings and significance, (ii) assessment of model fit, (iii) evaluation of reliability and validity, (iv) detection and common method bias and (v) determination of measurement invariance across the nine treatment conditions.

(i) Diagrammatic construction of the CFA model

A measurement model describes the linkages between the latent variables and manifest indicators, with λ as a factor loading coefficient (Collier, 2020). According to Worthington and Whittaker (2006), a CFA is usually conducted after a measurement instrument has

been evaluated by an EFA. Therefore, the resultant EFA pattern matrix from the previous analysis phase was used to construct the measurement model (CFA) in AMOS. The factor loadings were then assessed to determine if they were statistically significant.

(ii) Assessment of model fit

Model fit is concerned with whether the specified model, that is, the proposed theory (estimated covariance matrix) closely represents the empirical data, that is, reality (observed covariance matrix) (Collier, 2020). Proof of confirming the theory is determined by how close the two matrices fit together (Svensson, 2015). Model fit can be measured through absolute fit and comparative / incremental fit indices (Hooper, Coughlan, & Mullen, 2008). Absolute fit indices determine the extent to which the specified model fits the empirical data gathered (Hooper et al., 2008). By contrast, incremental indices compare competing models against a test model (Collier, 2020), that is, a null hypothesis that all variables are uncorrelated (Hooper et al., 2008).

The various model fit indices are summarised in Table 14, followed by a brief discussion on the respective absolute and incremental fit indices that were used to assess model fit in the research. Model fit for all subsequent models (not only the CFA) were assessed against this table.

Table 14: Model fit indices

Measure	Threshold
Absolute fit indices	
χ^2/df	< 3 good; < 5 adequate
Root mean square error of approximation (RMSEA)	< 0.05 good; 0.05 – 0.10 adequate; > 0.10 poor
Standardised root mean square residual (SRMR)	< 0.05 good; 0.05 – 0.09 adequate
Goodness-of-fit statistic (GFI)	> 0.90
Comparative / incremental fit indices	
Comparative fit index (CFI)	> 0.90
Incremental fit index (IFI)	> 0.90
Normed fit index (NFI)	> 0.90
Tucker Lewis index (TLI)	> 0.90
Relative fit index (RFI)	> 0.90

Note. Adapted from “*Applied structural equation modeling using AMOS: Basic to advanced techniques*”, by Collier, J. E., 2020, p. 66-67, New York, NY: Routledge

Three 'badness of fit' measures include the chi-square (χ^2) test, root mean square error of approximation (RMSEA) and standardised root mean square residual (SRMR). A significant p-value ($p < 0.05$) for the χ^2 represents poor fit; however, the χ^2 test is sensitive to large samples, so, dividing the χ^2 by the degrees of freedom (χ^2/df) provides an alternative measure (Hooper et al., 2008). Similarly, the null hypothesis of poor fit with the RMSEA can also be assessed with its confidence interval, where a narrower interval is indicative of better fit (Collier, 2020). SRMR is the average difference between the sample covariance matrix residuals and that of the hypothesised model (Collier, 2020).

The goodness-of-fit statistic (GFI) and the adjusted goodness-of-fit statistic (AGFI) were created as alternatives to the χ^2 test to understand the variance from the estimated covariance matrix; however, it has been recommended to be avoided due to their sensitivities with sample size (Collier, 2020).

Comparative / incremental fit indices include comparative fit (CFI), incremental fit (IFI), normed fit (NFI), Tucker Lewis (TLI) and relative fit (RFI) indices. The CFI compares the model's predicted covariance matrix to the null model's observed covariance matrix, while the other indices are variants of the χ^2 calculation (Collier, 2020).

(iii) Reliability and validity

Construct validity was tested, that is, the degree to which the measurement indicators reflected the latent construct (Hair et al., 2010). Therefore, the CFA involved the determination of how well a set of indicators converged on a specific construct (convergent validity) and if the constructs differed from each other (discriminant validity) (Collier, 2020). Convergent validity was assessed by reviewing the factor loadings, average variance extracted (AVE) and the composite reliability (CR) per construct, while discriminant validity was assessed by examining if the AVE was higher than the shared variance between constructs.

Firstly, for convergent validity, factor loadings should be statistically significant and be 0.5 or higher (Hair et al., 2010). Therefore, the factor loadings were visually assessed from the CFA diagram and the resultant estimates output from AMOS.

Secondly, the AVE, developed by Fornell and Larcker (1981), is the mean variance extracted for the indicator loadings per construct, that is, the sum of standardised λ^2 (i.e.

the R^2) for each indicator (i) per construct divided by the number of indicators (n), represented by the following summary measure (Collier, 2020; Hair et al., 2010).

$$AVE = \frac{\sum_{i=1}^n \lambda_i^2}{n}$$

If the $AVE < 0.5$, then the variance due to measurement error is greater than variance from the construct, thus bringing the validity of the indicators and construct into question (Fornell & Larcker, 1981). Therefore, as part of the CFA the AVE was calculated and examined if it was greater than 0.5 to ensure convergent validity.

Thirdly, the CR per construct was used as the second measure to determine convergent validity. While coefficient alpha (Cronbach's alpha) is widely used as a measure of reliability, CR is seen as an appropriate alternative for SEM as the coefficient alpha may understate reliability estimates, and is denoted by the following measure (Collier, 2020; Hair et al., 2010), where the last term of the denominator represents the sum of indicator measurement errors, either for endogenous constructs (ε) or exogenous constructs (δ). If the $CR \geq 0.7$, then good reliability is present (Hair et al., 2010).

$$CR = \frac{(\sum_{i=1}^n \lambda_i)^2}{(\sum_{i=1}^n \lambda_i)^2 + (\sum_{i=1}^n \varepsilon_i, \delta_i)}$$

However, the above formula assumes that all variables are standardised before being input into a CFA and is thus sensitive to the size of the measurement scale (Gaskin, 2016c). Therefore, Gaskin recommended an alternative CR formula, which is not scale size dependent, and accounts for estimated proportional error instead of exact error variances. CR was calculated using the alternative CR formula, shown below, and examined if it was greater than 0.7 per construct. For completeness, the coefficient alpha (Cronbach's alpha) was also computed.

$$CR = \frac{(\sum_{i=1}^i \lambda_i)^2}{(\sum_{i=1}^i \lambda_i)^2 + (\sum_{i=1}^i 1 - \lambda_i^2)}$$

Lastly, from a discriminant validity perspective, Fornell and Larcker (1981) recommended that the shared variance between constructs (squared correlation) must be less than the AVE per construct (Collier, 2020) This means that the construct should account for more variance in its indicators that it shares with another construct (Hair et al., 2010). As such, all constructs were examined to ensure that the AVE per construct was greater than the shared variance between constructs.

(v) Measurement invariance

Measurement invariance detects if indicators are measuring the same thing across groups, and a lack of measurement invariance signals that the meaning of the unobservable construct is changing across groups (Collier, 2020). Breitsohl stipulated the following tests required for the comparison across groups:

- Configural invariance: equal factor structure as part of multi-group CFA for all treatment conditions, that is, for all combinations of the IV levels (Breitsohl, 2019).
- Metric invariance: indicator loadings (λ) constrained to equality between groups
- Scalar invariance: indicator intercepts constrained to equality between groups

3.9.4. Structural equation modelling

The general linear model (GLM) serves as the statistical theory that underpins many parametric methods, which broadly determines the relationship between independent and dependent variables (Foster, Barkus, & Yavorsky, 2006). GLM-related, first-generation statistical techniques—two-way analysis of variance (ANOVA) and multivariate analysis of variance (MANOVA)—were potential methods of analysis for the study. In a two-way ANOVA, the impacts of the nine combinations of the two independent variables (PR, IR) could have been analysed on a single dependent variable (trust in service provider / host). In a MANOVA this would have applied to more than one dependent variable (trust in service provider / host, trust in platform, propensity to participate).

While the above techniques are powerful statistical tools, they examine only one relationship at a time (Hair et al., 2010). The application of the above first-generation statistics would have necessitated a piecemeal combination of such tests to test the hypothesised model, resulting in questionable methodological rigour and generalisations of the results. Enter the realm of second-generation statistics, structural equation modelling (SEM). Actually, SEM is a form of the GLM as it incorporates many of the GLM techniques. But, SEM tests the overall fit of the model by measuring the suitability of the collected survey measurement indicator data (confirmatory factor analysis), and by estimating the hypothesised relationships among the set of variables (multiple regression) (Davvetas et al., 2020; Pallant, 2001). In other words, SEM assesses the measurement of latent constructs and the relationships between these constructs (Hair, Sarstedt, Hopkins, & Kuppelwieser, 2014).

As alluded to, the primary justification for using SEM over first-generation techniques, is that SEM examines a sequence of dependence relationships simultaneously (Hair et al., 2010), while first-generation techniques examine each relationship individually. Considering that the overall hypothesised model included a series of dependence relationships (through trust in service provider / host and trust in platform), it was clear that SEM was the preferred choice to analyse such relationships. Secondly, first-generation techniques—ANOVA and MANOVA—necessitate assumptions to be held that do not apply when analysing latent constructs, which are not directly measurable. For example, in ANOVA and MANOVA, zero measurement error is assumed on all variables (Breitsohl, 2019), but with SEM measurement error is explicitly modelled (Bagozzi & Yi, 2012). Lastly, the use of SEM in experimental studies have been lacking (Breitsohl, 2019), even though SEM more rigorously tests hypothesised effects of experimental manipulations (Mackenzie, 2001).

There are two main types of SEM, covariance-based SEM (CB-SEM) and partial least squares SEM (PLS-SEM). CB-SEM tests theory as a confirmatory approach through leveraging theory, experience and research objectives to determine which independent variables predict dependent variables, whereas PLS-SEM develops theory as an exploratory approach in explaining variance in dependent variables (Svensson, 2015). In a review of PLS-SEM studies, Hair et al. (2014) found that the use of PLS-SEM, rather than CB-SEM was ascribed to research contexts characterised by non-normal data, small sample sizes and formatively measured constructs. Since the research study had mostly normal data, a relatively large sample size and reflective measured constructs, CB-SEM was chosen. The Analysis of Moment Structure (AMOS) software was used for the SEM component of the research design.

Ultimately, SEM is about testing proposed theory against reality (Svensson, 2015). Support for the hypotheses required the passing of two global tests (model fit and then variance explained or R-squared) first, and then local tests (p-value) (Gaskin, 2020).

3.9.4.1. Notation and terminology

The hypothesised relationships among the theoretical constructs outlined in Chapter 2, along with the measurement indicators (Table 11), is depicted in a preliminary statistical diagram (panel A, Figure 11) in the conventional SEM format, of which the notation and terminology is outlined in

Table 15. Figure 11 and

Table 15 are to be read in conjunction as they form the foundation of interpreting the subsequent structural equation models.

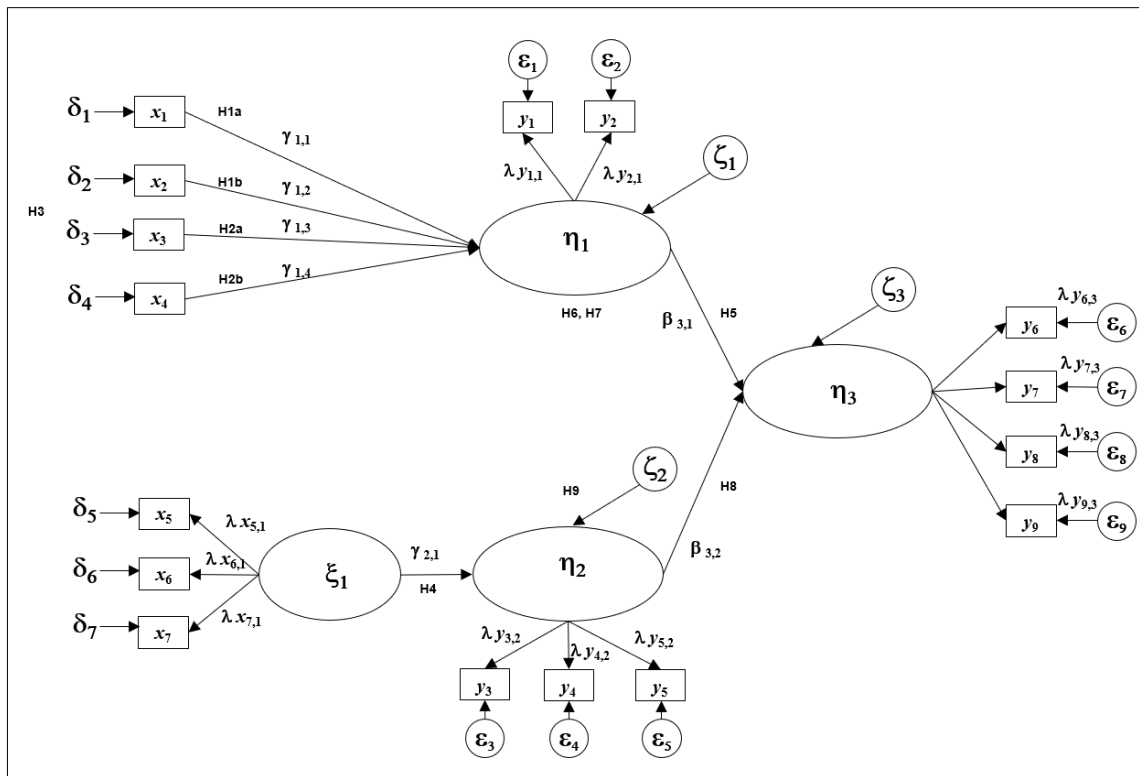


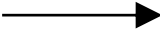



Figure 11: Conceptual structural equation model
Source: Author

Table 15: SEM notation and concepts

Symbol	Term	Description
	Ellipse	Non-measurable latent variable / construct
ξ	Ksi	Exogenous (independent) latent variable / construct
η	Eta	Endogenous (dependent) latent variable / construct
γ	Gamma	Regression relationship from exogenous to endogenous construct
β	Beta	Regression relationship between endogenous constructs
ζ	Zeta	Error term for a latent endogenous construct
ϕ	Phi	Covariance between latent constructs
	Rectangle	Measurable manifest indicators (per survey instrument)
ε	Epsilon	Measurement error term for an indicator measure of an endogenous construct

δ	Delta	Measurement error term for an indicator measure of an exogenous construct
λ	Lambda	Relationship from a latent construct to an indicator; factor loading in measurement model
	One-headed arrow	Hypothesised relationship between two variables
	Two-headed arrow	Covariance unexplained by other variables

Note. Adapted from Blunch (2013), Collier (2020) and Davvetas et al. (2020)

In summary, concepts introduced here will be carried forward into the remainder of the research report. The unobservable, latent constructs are represented as ellipses. Such constructs that are not predicted by the model are referred to as exogenous (ξ), and these predict the endogenous constructs (η) through gamma parameters (γ). Endogenous constructs that predict other endogenous constructs are connected through beta parameters (β). Each construct reflects its observable indicators (survey questions, x for exogenous constructs and y for endogenous constructs) and are connected through lambda parameters / factor loadings (λ) that form part of the measurement model. Regarding the numbering of the parameters (γ , β , λ), the first subscript refers to the variable that the arrow is pointing to and the second subscript denotes where the arrow is originating from. Lastly, all constructs have error explicitly modelled, denoted by delta (δ) for exogenous measures, zeta (ζ) for endogenous constructs and epsilon (ϵ) for endogenous measures.

3.9.4.2. Types of structural equation models used in this research

The analysis necessitated the categorisation of various models (M) to fully respond to the research questions and hypotheses. First of all, the measurement model was specified in the previous section, which is a CFA. Thereafter, a full structural equation model, M_{SEM} , was designed. After analysing M_{SEM} , key control variables (CV) of interest were added to determine its effects, thereby creating the third model, $M_{ALL CV}$. Only significant CVs (three) paths were maintained to create a parsimonious model structure, resulting in M_{CV} . After confirming the effects of the CVs, the mediation analysis was run by specifying the direct and indirect paths, thereby yielding M_{MED} . This last model was then carried through in the factorial design component of the analysis, whereby a model was created for each of the nine treatment conditions, with the first of the subscript denoting the treatment condition and the factor values applied for PR and IR in

parenthesis: M_1 (PR 1*,IR 1*), M_2 (PR 3*,IR 1*), M_3 (PR 5*,IR 1*), M_4 (PR 1*,IR 3*), M_5 (PR 3*,IR 3*), M_6 (PR 5*,IR 3*), M_7 (PR 1*,IR 5*), M_8 (PR 3*,IR 5*), M_9 (PR 5*,IR 5*). The methodological steps taken for the above-mentioned models are discussed next.

3.9.4.2.1 Structural model (M_{SEM})

In path models, composites (factor scores) of a construct's many measurement items are imputed and structural relationships are analysed among these constructs without taking into account the measurement items (Collier, 2020). As a result, such path models do not account for measurement error. Therefore, a path model was not used in the analysis. Rather, a full structural model was used, which included both measurement model aspects and the structural model relationships of the latent constructs.

While setting up the structural models, PR and IR needed to be set up in a specific way due to their polychotomous nature as each had three levels of 1-star, 3-star and 5-star. Indicator coding was used to create dummy variables in a Boolean format (Hayes, 2018). Therefore, $n - 1$ categories were used as dummy variables ($n =$ number of levels or attributes for the categorical variable), whereby the excluded category was omitted as a reference category (Gaskin, 2017; Kremelberg, 2011), because "Boolean variables of a categorical construct's Boolean block always sum to unity, and therefore, introduce singularities into the analysis." (Hair et al., 2019, p. 123). Collier (2020) recommended that it is preferable to use a reference category that is similar to a control group. For this reason, the 3-star rating dummy variables (PR_3STAR and IR_3STAR) were excluded as dummy variables in AMOS (coded as zero), and served as the standard against which the other two categories (1-star, 5-star) were compared. In other words, a 3-star rating for PR was coded as zero in PR_1STAR and PR_5STAR. Similarly, a 3-star rating for IR was coded as zero in IR_1STAR and IR_5STAR. The operationalisation of the predictors is illustrated in Table 16.

- PR_1STAR included respondents who were exposed to a 1-star PR rating compared to those exposed to a 3-star PR rating.
- PR_5STAR included respondents who were exposed to a 5-star PR rating compared to those exposed to a 3-star PR rating.
- IR_1STAR included respondents who were exposed to a 1-star IR rating compared to those exposed to a 3-star IR rating.

- IR_5STAR included respondents who were exposed to a 5-star IR rating compared to those exposed to a 3-star IR rating.

Table 16: Dummy variables for exogenous predictors

Dummy variables for platform reputation systems (PR)

Category (n)	PR_1STAR	PR_5STAR
1-star	1	0
3-star	0	0
5-star	0	1

Dummy variables for independent reputation systems (IR)

Category (n)	IR_1STAR	IR_5STAR
1-star	1	0
3-star	0	0
5-star	0	1

However, for the factorial design discussed later, dummy variables were also created for the 3-star categories for comparisons to be made for all groups, that is, not only have the 3-star rating as a reference group.

3.9.4.2.2 Structural model with CVs ($M_{ALL CV}$)

A key aim of theory-based data analysis is to determine if an empirical connection can be rationally inferred as a causal relationship, and this is achieved by including CVs to exclude spurious causal relationships (Aneshensel, 2013). While CVs are not focal variables in a particular research study, they are included in structural equation models to ensure better estimates of the relationships between exogenous and endogenous variables, that is, the γ parameters will better represent the actual connection between ξ and η (Williams, Vandenberg, & Edwards, 2009). In order to ensure unbiased estimates of M_{SEM} , CVs were tested to account for their potential influence (Collier, 2020). Therefore, AIRBNB_USER, SHOP and AGE as categorical variables were recoded as dummy variables in SPSS for use in AMOS. Statistically controlling for such variables required for these controls to be treated as exogenous variables and thus covaried with other exogenous variables, as well as having direct paths to all endogenous variables in the SEM model (Williams et al., 2009).

3.9.4.2.3 Structural model with significant CVs (M_{CV})

While the inclusion of CVs is important, many researchers do not explain why they have included specific controls in their studies (Becker, 2005). Therefore, this research used three of the socio-demographic items as potential controls, based on prior literature.

Firstly, past experience has been shown to predict future behaviour and intentions in online contexts (Pavlou & Fygenson, 2006). This necessitated the use of AIRBNB_USER as a CV. Secondly, habits representing the frequency of repeated behaviours has been shown to be a factor in online purchasing behaviours (Abramova, Fuhrer, Krasnova, & Buxmann, 2015; Pavlou & Fygenson, 2006). Therefore, SHOP was used as the second CV. Thirdly, age (AGE) was also included, consistent with similar studies in online and platform settings (Mittendorf et al., 2019; Pavlou & Fygenson, 2006). However, only the significant categories of the above controls were maintained in the final model (later reported in Chapter 4).

3.9.4.2.4 Structural model with significant CVs and mediation (M_{MED})

While an independent variable can affect a dependent variable directly, a dependent variable can also be indirectly influenced by an intervening or mediating variable, that is, variation in the independent variable produces variation in the mediator, which then produces variation in the dependent variable (Hayes, 2018). Mediation analysis involves the examination of direct and indirect effects (Collier, 2020). These concepts are best interpreted by applying it to the hypothesised model. As per Figure 12, the model included two mediators (TH, TP) that were part of three hypothesised mediation relationships, namely, $PR \rightarrow TH \rightarrow PP$ (panel A), $IR \rightarrow TH \rightarrow PP$ (panel B) and $BR \rightarrow TP \rightarrow PP$ (panel C).

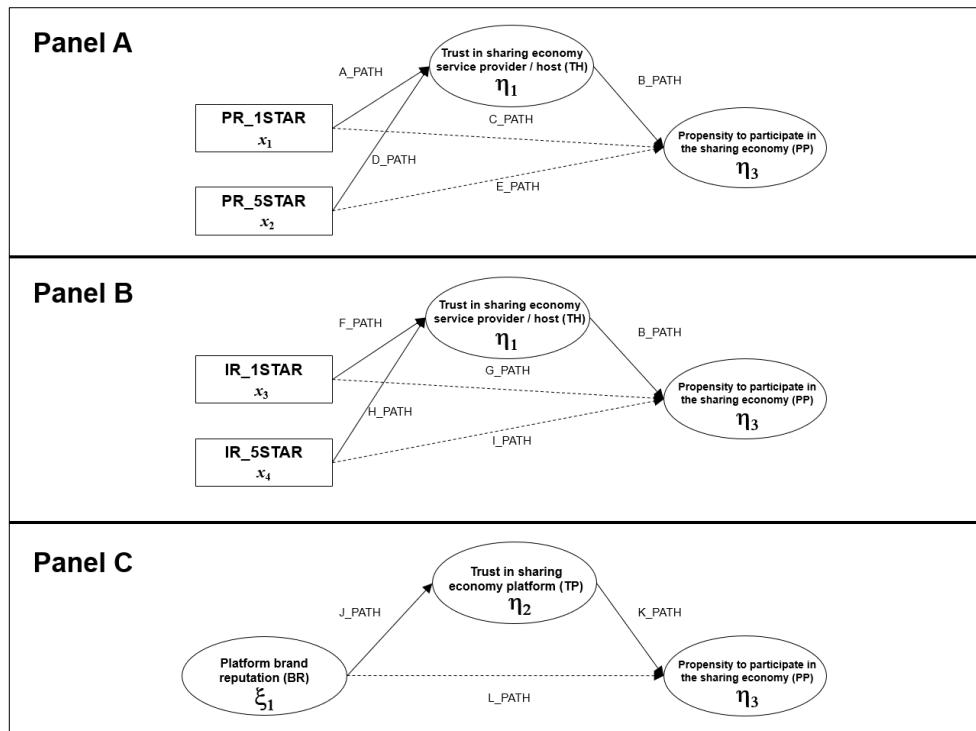


Figure 12: Mediation relationships

A direct effect is a relationship from an independent variable to a dependent variable without a mediator (Collier, 2020). While direct effects were not hypothesised, these had to be estimated to determine whether the mediators were truly impacting the relationships between the given independent and dependent variables. The direct effects are represented as dotted arrows in Figure 12, namely, C_PATH, E_PATH, G_PATH, I_PATH and L_PATH. An indirect effect is a relationship from an independent variable to a mediator and then to a dependent variable (Collier, 2020). Since the model had more than one mediator (TH, TP), the estimands function in AMOS was used to calculate the indirect paths per the below code, where each indirect path is the product of the paths that flow to and from the mediators (Collier, 2020)

- $INDIRECT_PR_1STAR = A_PATH * B_PATH$
- $INDIRECT_PR_5STAR = D_PATH * B_PATH$
- $INDIRECT_IR_1STAR = F_PATH * B_PATH$
- $INDIRECT_IR_5STAR = H_PATH * B_PATH$
- $INDIRECT_BRAND_REPUTATION = J_PATH * K_PATH$

Collier (2020) outlined that the above paths can also take on the forms of full, partial, complementary or competitive mediation. Full mediation occurs when the mediator effect is significant, but the direct path is non-significant between an independent and

dependent variable, whereas partial mediation includes both significant direct and indirect effects (Collier, 2020). The indirect and direct effects have a similar directional relationship in complementary mediation, and the opposite under competitive mediation (Collier, 2020).

Reuben Barron and David Kenny developed a mediation analysis method, also known as a causal steps approach; however, the popularity of the 'Baron and Kenny' method has since waned from its seminal publication in 1986 (Hayes, 2018). Rather, bootstrapping has been endorsed as a superior technique among researchers (Zhao, Lynch, & Chen, 2010), whereby the data is treated like a quasi-population and is randomly sampled with replacement, to determine if the indirect effect is within a confidence interval (Collier, 2020). Therefore, a bootstrapping procedure was conducted for the mediation tests.

3.9.4.2.5 Structural models with significant CVs and mediation per treatment condition

Breitsohl (2019) suggested that researchers employing experimental designs should consider moving past GLM approaches, such as ANOVA, and consider SEM approaches, such as multiple-indicator-multiple-cause (MIMIC). Therefore, this research study used a MIMIC CB-SEM analysis in the construction of the structural model, while representing the categorical variables (PR, IR) consistent with Figure 13.

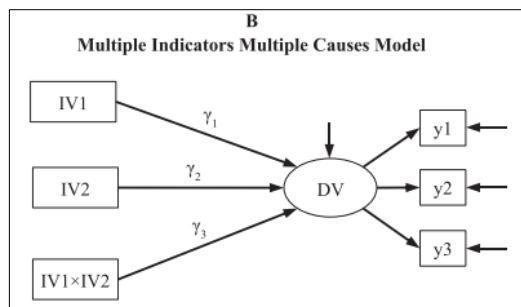


Figure 13: Multiple Indicators Multiple Causes Model.
 Reprinted from "Beyond ANOVA: An introduction to structural equation models for experimental designs,"
 by H. Breitsohl, 2019, *Organizational Research Methods*, 22(3), p. 649–677. Copyright 2019 by
 Sage

The difference with this paper's model and the one proposed by Breitsohl (2019), is that multiplied dummy independent variables (IV1xIV2 in Figure 13) are not sensible when interpreted. This was also confirmed upon engagement with Professor Joel E. Collier, the author of the specialist textbook, 'Applied structural equation modeling using AMOS:

Basic to advanced techniques' as per the conversation transcript from his YouTube channel, which is provided in [Appendix G](#).

The challenge with interpreting the effects of this model based on dummy variables in SEM, is that it is difficult to understand the extent of difference among the nine treatment conditions as initially put forward in the 3 x 2 factorial design. Therefore, the multigroup analysis feature was used in AMOS to determine if there were differences in the model across the nine treatment conditions. This method of treating the factorial design cells as groups in SEM is consistent with the factorial SEM (FAC-SEM) procedure by Iacobucci, Grisaffe, Duhachek, & Marcatti (2003). However, this method was unsuccessful in AMOS, resulting in a 'not positive definite matrix' error message in AMOS. Collier (2020) advised that the error was due to the high collinearity amongst the rating variables, which is expected due to the dummy coded values, resulting in the linear correlation among the predictors being almost perfect, thus resulting in the covariance matrix not being positive definite. Due to the inability of pursuing the above method, nine models were then created for the nine treatment conditions and assessed individually to supplement the analysis.

3.10 Research limitations

In the quest for explaining the nature of causality in the hypothesised relationships, the limitations of the research methodology employed are acknowledged. These are outlined along the perspectives of the method, instrumentation and analysis.

Method

From a research paradigm perspective, a frequentist approach was used; however, trust as a socially constructed concept may require methodologies that adopt a different statistical paradigm, that is, Bayesian statistics. The Bayesian approach uses an *a priori* distribution based on subjective beliefs and could offer different results from a frequentist paradigm (de la Sablonnière, Lina, & Cárdenas, 2019).

Since a cross-sectional study collects data at a point in time (Bryman & Bell, 2011), the ability of analysing the change in a construct over time was not possible with this research. Alternatively, a longitudinal study could have been employed if the time period of the research undertaking was longer so that trust perceptions could have been analysed over a period of time.

Due to the use of non-probability sampling, generalisation to the broader population should be cautioned. Certain individuals were afforded an unequal chance of selection because of the snowball selection process employed (Blair & Blair, 2015).

Instrumentation

The self-completion questionnaire does not allow for many questions to be asked because of respondent fatigue, has the risk of respondents not fully completing the survey, and generally has lower response rates (Bryman & Bell, 2011). Given these limitations, the survey for the study was kept relatively short, questions were programmed as mandatory, and snowball sampling was used to solicit responses.

Common method variance is a concern in cross-sectional surveys and is the methodical error arising from the research instrument (Rindfleisch et al., 2008) and represents the spurious relationships of constructs due to the use of the same survey method to measure the constructs (Tehseen, Ramayah, & Sajilan, 2017). In order to address this Harman's single factor test was conducted.

It is acknowledged that four of the indicators (TH1, TH2, PP1, PP2) were created by the researcher and did not follow a rigorous scale development process. However, in the subsequent EFA it was revealed that two of the indicators had to be removed.

Analysis

Svensson (2015) challenged the business research community to rethink how CB-SEM is used, specifically that pieces from different studies are arbitrarily combined into a hypothesised model that is to be tested. He argued that CB-SEM lacks in its rigour in theoretical contributions due to the absence of empirical replication and validation studies over time and across contexts. While this view is acknowledged, such concerns can be allayed through future tests. Also, SEM was chosen as the preferred tool in the toolbox of statistical techniques due to its integrative function of combining methods holistically, such as mediation (Bagozzi & Yi, 2012).

3.11 Conclusion

This chapter outlined the components of the research methodology and design used to achieve the stated research aims ([§1.4](#)), along four pillars: method, instrumentation, analysis and limitations. First, in terms of the method pillar, a positivist philosophical worldview was adopted, which was characterised by an etiology of cause-effect relationships that made a between-subjects experimental vignette appropriate. The

research setting was delimited to the location of South Africa, with the SE platform of Airbnb, Airbnb's star rating system and independent oversight of the broader tourism sector through the TGCSA's star rating system. The population was estimated at 13.5 million individuals that were familiar with Airbnb; and stayed in short-term accommodation or were considering doing so in the future; and were familiar with South Africa. An indicative sample size of 302 individuals was computed.

Second, from an instrumentation perspective, a pilot group suggested improvements to four substantive sections of the survey (introduction and qualification, vignette, measures, demographics). Thereafter, the survey was edited and activated. Through self-selection and snowball sampling, 760 responses were received over three weeks. Third, a series of analyses were conducted after the data was gathered. In particular, methodical decisions were taken as part of the data validation (EFA, CFA) and SEM, resulting in specific models to be run to answer the research questions. Lastly, in the inference of conclusions from the data, limitations along the method, instrumentation and analyses were acknowledged.

Chapter 4: Results

4.1 Introduction

Having outlined the details of how the quantitative methodology was employed in Chapter 3, this chapter provides the statistical results that was obtained from the aforementioned methods. As such, it is centred on the analysis pillar introduced in Chapter 3. Figure 14 demonstrates this sequence from methods to results through a roadmap of the ensuing sections for Chapter 4.

The ensuing sections provide the results of the research study organised along the phases of preliminary analysis ([§4.2](#)), descriptive statistics ([§4.3](#)), data validation ([§4.4](#)), and SEM ([§4.5](#)). The preliminary analysis, descriptive statistics and data validation (EFA, CFA) are all analyses that did not have a stated hypothesis; hence, these are interpreted and discussed in Chapter 4 (Results). However, the interpretation of the hypothesised relationships, as part of the SEM analysis, is discussed in Chapter 5 (Discussion). Lastly, based on the statistical conclusions from the results, a revised conceptual model ([§4.6](#)) is presented, which outlines the relationships that have been empirically supported by this research.

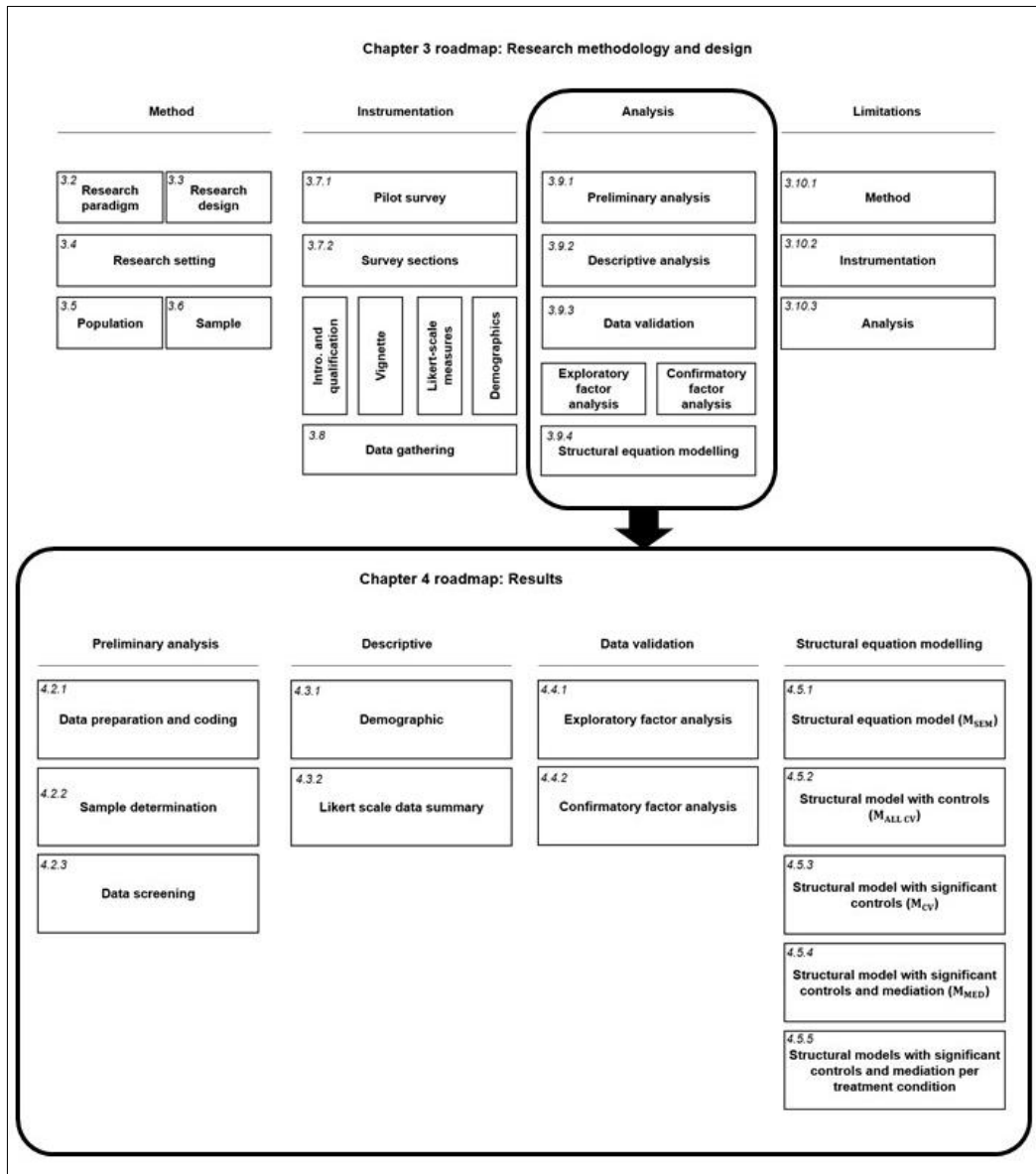


Figure 14: Flow from Chapter 3 to Chapter 4

4.2 Preliminary data analysis

4.2.1. Data preparation and coding

A code book ([Appendix D](#)) was maintained for a comprehensive view of the various categories of variables and their respective descriptions and values. Variables that were part of the survey originated from Qualtrics and some were created in SPSS to aid in the analysis, while others were created in AMOS as part of subsequent analyses. In terms

of the categories of variables in the code book, 'Administrative' was reserved for variables that served an organising function. 'Population boundary' categorised questions that were used to filter out non-eligible respondents. 'Manipulation' represented variables that were manipulated as part of the EVM in. 'Likert' contained the 14 measurement indicators that were used in the subsequent statistical tests. The 'Demographic' category listed all the demographic-related questions, while 'Dummy control' was created for statistical control, that is, dummy variables were created per category of the 'AGE' and 'SHOP' questions. Lastly, 'Outliers' was used for tests to detect for potential outliers.

4.2.2. Sample determination

Several conditions were applied to verify that only valid responses were maintained for analysis, in line with the decision logic process flow (Figure 8), population boundaries (§3.5) and completed surveys. Also, nineteen responses were flagged as having constant values for all Likert questions (Table 17), suggestive of unengaged respondents. For these nineteen responses, the survey duration per response was compared to the median duration (290 seconds / 5 minutes) of the entire valid sample. The mean duration was not used due to the extremely large outliers caused by respondents completing parts of the survey at different times, and not in one session. This resulted in 12 responses being removed (Table 17) from the data set.

Table 17: Responses flagged with constant responses

Answer choice for all Likert questions	SPSS Response ID	Duration to complete survey		Action taken
		Seconds	Minutes	
3	6	231	4	Duration < median. Removed.
3	19	280	5	Duration > median. Maintained.
1	24	712	12	Duration > median. Maintained.
4	33	400	7	Duration > median. Maintained.
4	183	404	7	Duration > median. Maintained.
5	226	212	4	Duration < median. Removed.
1	235	166	3	Duration < median. Removed.
3	238	253	4	Duration < median. Removed.
5	306	165	3	Duration < median. Removed.
4	326	225	4	Duration < median. Removed.
3	382	760	13	Duration > median. Maintained.
1	384	809	13	Duration > median. Maintained.
2	394	197	3	Duration < median. Removed.
3	463	287	5	Duration > median. Maintained.
4	503	66	1	Duration < median. Removed.
5	537	138	2	Duration < median. Removed.
4	609	257	4	Duration < median. Removed.
4	612	214	4	Duration < median. Removed.
4	643	224	4	Duration < median. Removed.

Note. Author's analysis based on Excel tool from Gaskin (2016)

Ultimately, of the 760 responses received, 635 were valid responses after the conditions were applied to filter invalid responses, as illustrated in Figure 15. Also, as per Figure 16, the breakdown of the 635 responses per experimental treatment condition was more than sufficient, at almost double the minimum cell size of 34 calculated in [§3.6](#).

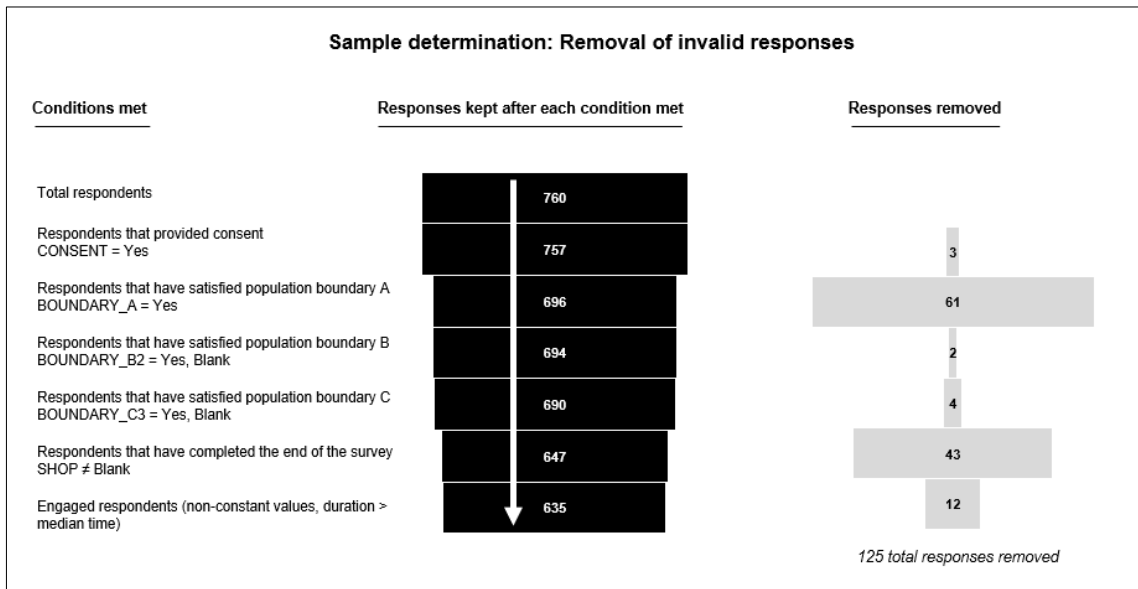


Figure 15: Conditions applied for eligibility of sample respondents
Source: Author

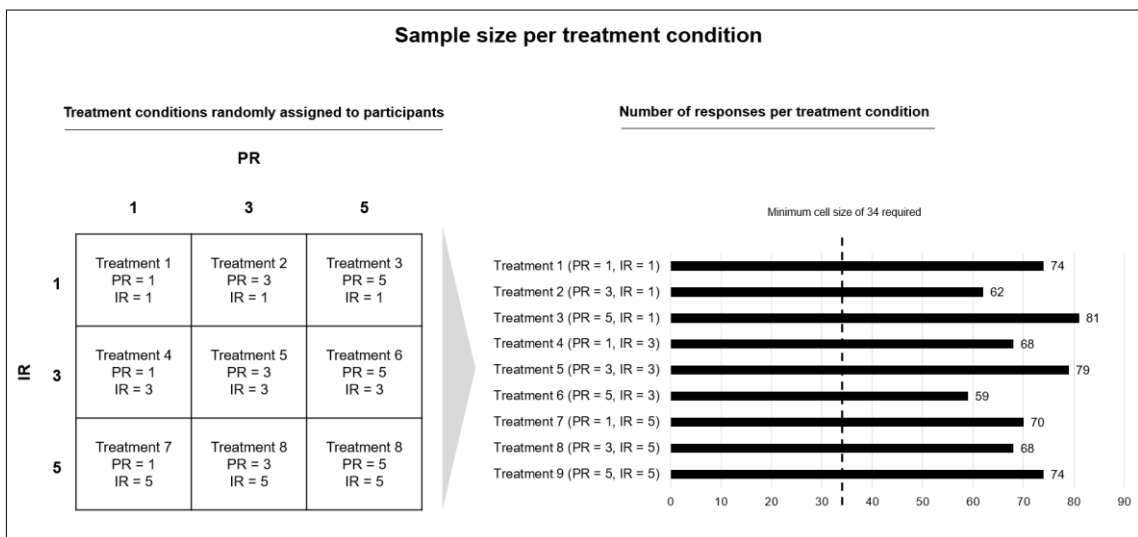


Figure 16: Number of responses per treatment condition
Source: Author

4.2.3. Data screening

Upon analysing the data, certain responses to the demographic questions were edited to match predetermined values, as outlined in Table 18. For example, for the gender question, one respondent chose the ‘please specify’ option and entered a text value of ‘elderly woman’—this response was edited to reflect as ‘female’. Similarly, for the education question, six respondents specified free-text values for the ‘other’ answer choice—these were changed to ‘Post graduate degree’ as part of the existing options.

Table 18: Demographic questions updated

Question	ID	Original answer	Updated answer
How do you currently describe your gender identity?	52	Please specify: Elderly lady	Female
	398	Other, please specify: Masters	Post graduate degree
Which category best describes your level of education?	50	Other, please specify: Busy with Post Graduate studies	Post graduate degree
	39	Other, please specify: Masters	Post graduate degree
	527	Other, please specify: Masters	Post graduate degree
	37	Other, please specify: MBA	Post graduate degree
	381	Other, please specify: Master's Degree	Post graduate degree
What is your marital status?	84	Other, please specify: Married	Married, or in a domestic partnership

Influential respondents

Cook’s distance was calculated for all of the independent variables to determine its impact on the dependent variable of PP through a standard linear regression. The Cook’s distance values were then plotted against the responses. From Figure 17, the response at the top left is still below the cut-off of 1, even though it is not clustered with the rest of the responses (Gaskin, 2016d).

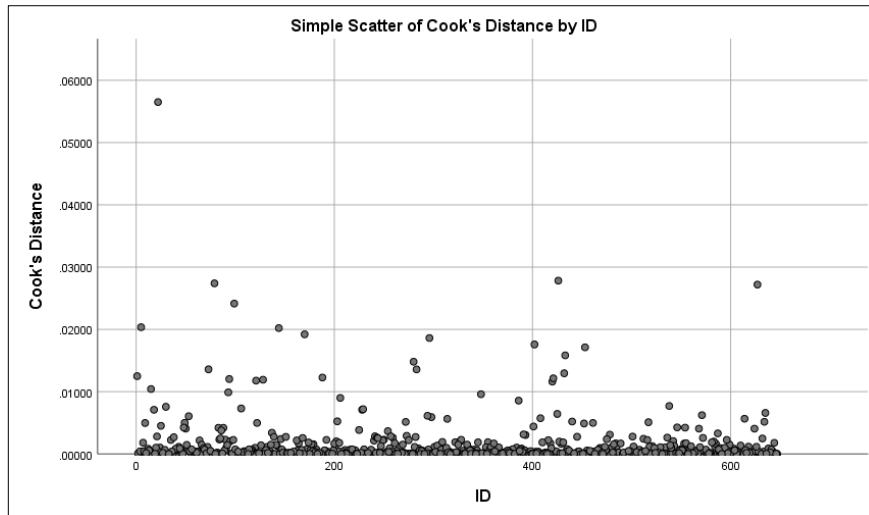


Figure 17: Cook's distance assessment
 Source: Author, SPSS

Multicollinearity

Multicollinearity was assessed by checking if the variance from the other constructs do not overlap too much in predicting the dependent variable (PP), by examining the collinearity statistics run through a linear regression. In terms of benchmarks for the collinearity statistics, tolerances above 0.1 and variance inflation factors (VIF) less than three are preferred, which has been achieved per Table 19 (Gaskin, 2016d).

Table 19: Collinearity statistics

Construct	Tolerance	VIF
TH	0.865	1.157
TP	0.419	2.388
BR	0.450	2.221

4.3 Descriptive statistics

The subsequent sub-sections are divided based on the data, such that the categorical data of the respondents form the demographics sub-section, and the Likert scale data form the last sub-section.

4.3.1. Demographics

The demographic characteristics of the 635 respondents are summarised in Figure 18, with further detail per treatment condition in [Appendix E](#). The sample had slightly more males (54.80%). Just over half (53.54%) of respondents were in the 24-39-year age bracket, followed by those between 40 and 55 years old at 39.84%. Approximately a third (32.76%) identified themselves as Indian or Asian, followed by White (30.87%) and Black African (27.56%). Most respondents had a tertiary education, with post-graduate (63.46%) and Bachelor's (22.83%) degrees. The majority (83.94%) of respondents identified as being employed full-time. Almost all respondents have purchased online per month, except for 4.88% of the sample.

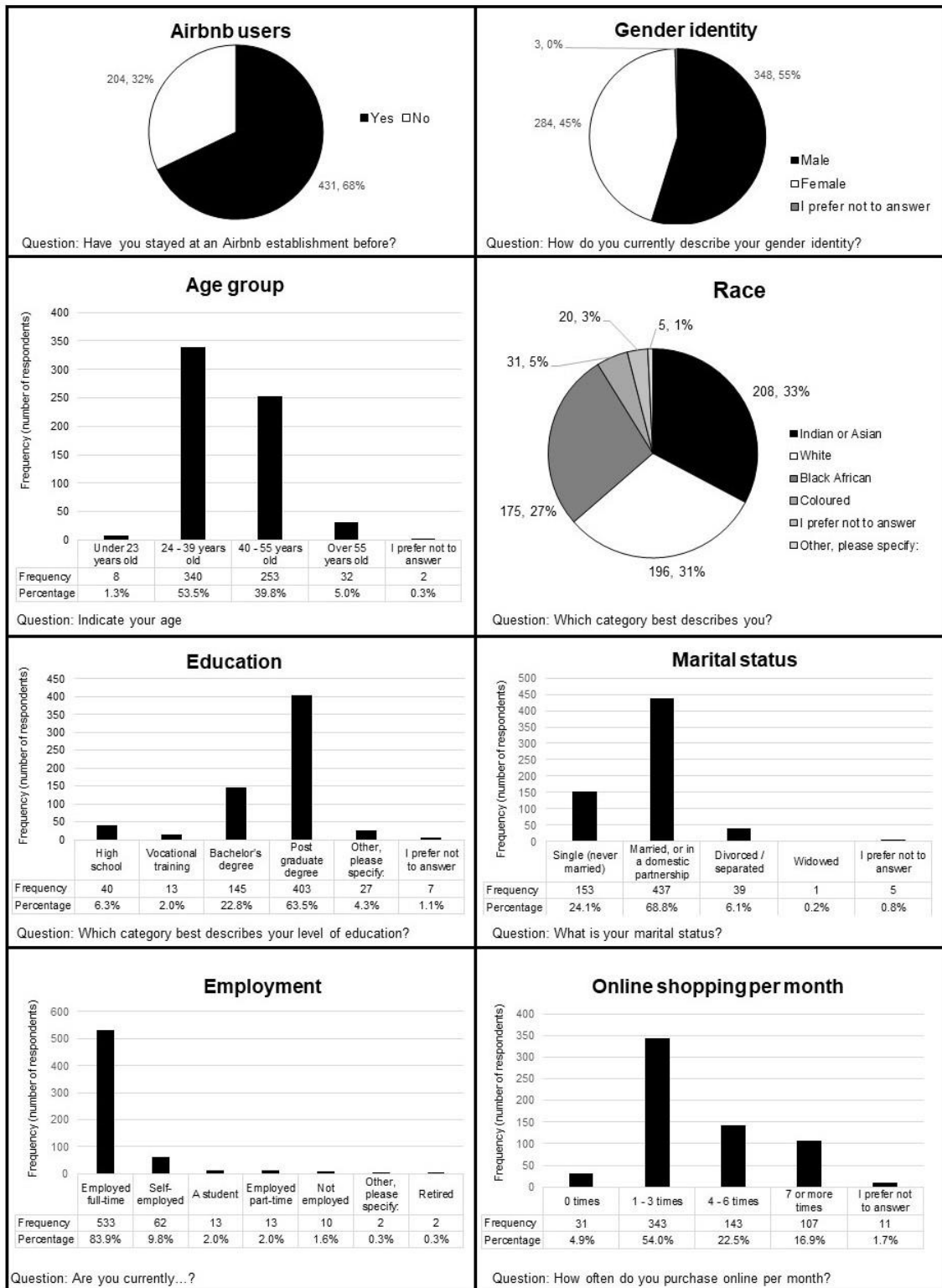


Figure 18: Summary of demographic information
Source: Author

Due to the long list of countries, the respondents' current country of residence is represented on a map (Figure 19) for ease of interpretation. The majority (83.94%) of the respondents were from South Africa followed by UK and Northern Ireland (2.99%) and Australia (1.10%). From a continental perspective, Africa dominated with the highest responses (88.41%) across 14 countries, followed by Europe (6.03%) across 10 countries.

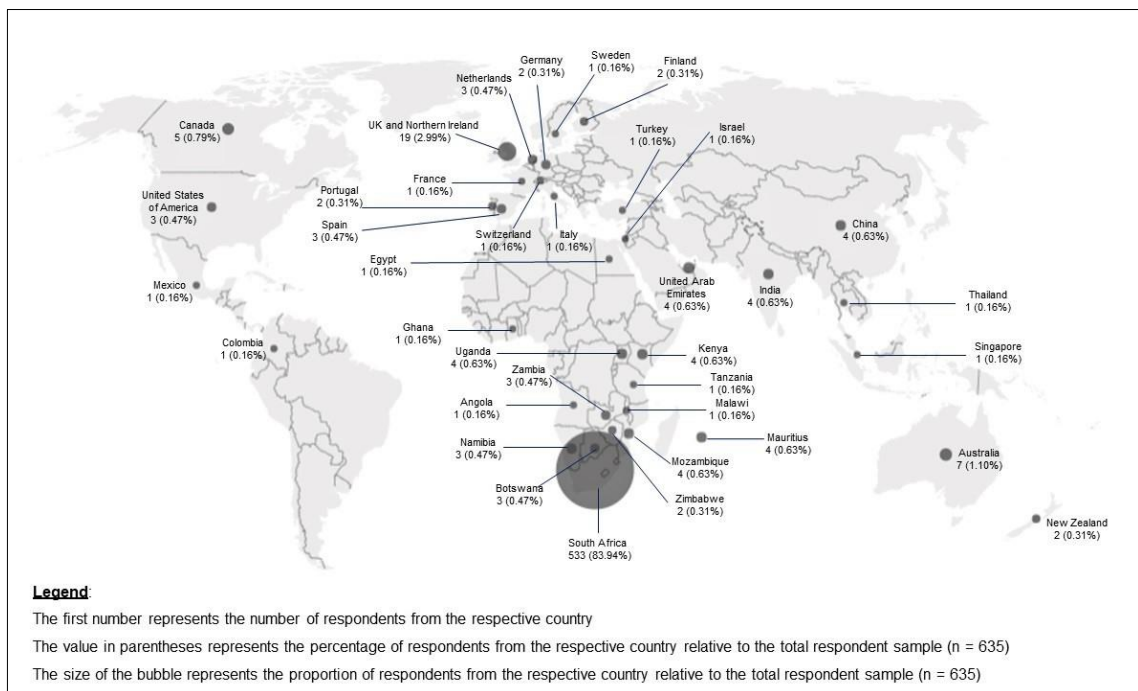


Figure 19: Representation of respondents by country
 Source: Author

Since the demographic data elements do not form part of the hypotheses stipulated in Chapter 2, insights gleaned from the demographic data are discussed in the following paragraphs, rather than Chapter 5. The following covers three insights regarding Airbnb users versus non-users, age group and the frequency of online shopping of respondents.

Although the attainment of an equal proportion of Airbnb and non-Airbnb users was attempted to ensure a non-biased sample, the majority (68%) of the respondents were Airbnb users, while almost a third (32%) did not stay at an Airbnb establishment before. This could partly be ascribed to one of the target population parameters (parameter C) that determined if respondents stayed in short-term accommodation or were considering doing so in the future. While the balance in the sample is not perfectly 50:50, the representation of some non-Airbnb users did add to the heterogeneity in the sample, which is in contrast to other similar SE studies. For example Mao et al. (2020) focussed on repeat Airbnb customers only and cited that future studies should include potential

and experienced users, which is what this research aimed to accomplish. In order to mitigate this bias, this was statistically controlled and AIRBNB_USER was shown to have a statistically significant impact (unstandardised $\gamma=0.206$) on TP in M_{MED} .

More than half (53.54%) of the respondents were between 24-39 years old, followed by respondents from the 40-55 years old age bracket (39.84%). This age distribution was similar to other SE studies, such as those conducted by Yang et al. (2019) (62.7% of respondents between 20-39) and Mao et al.(2020) (52.6% of respondents between 25-34). Moreover, millennials are a key target group for SE platforms (Amaro et al., 2019; Mittendorf et al., 2019) and Sun et al. (2020) found that tourism consumers tend to be younger, and that specifically 'Generation Y' consumers (also known as millennials) will continue to be the main consumption group. It is therefore not surprising that the sample contained a higher number of millennials. However, the 40-55-year-old respondents were shown to have a statistically significant ($p=0.014$) impact on TH (unstandardised $\gamma=0.216$) in M_{MED} , and were also controlled for in the subsequent SEM (cf. [§4.5.3](#)).

Almost all of the respondents (93.4%) identified as having purchased something online, with respondents shopping online per month between 1-3 times (54.0%), 4-6 times (22.5%) and 7 or more times (16.9%). However, those respondents that shopped 7 or more times per month (SHOP_7) were shown to have a statistically significant negative impact on TH (unstandardised $\gamma=-0.385$) in M_{MED} . This could potentially mean that consumers that have more experience with online transactions could be more suspicious of SE service providers, that is, their experience and sophistication of using online transactions creates a higher level of savvy when entrusting a SE service provider, compared to those consumers that have lower level of online transaction engagement.

4.3.2. Likert scale data summary statistics

Selected descriptive statistics were run on the fourteen Likert scale measurement indicators, which ranged from 1 (strongly disagree) to 5 (strongly agree). These are outlined in Table 20 and Table 21.

Table 20: Descriptive statistics for Likert scale measurement indicators

Likert scale measurement indicators	Central tendency		Dispersion		Kurtosis statistic	Skewness statistic
	Mean	5% Trimmed Mean	Std. Deviation	Variance		
TH1 <i>Because of the star rating from other customers, I trust the service provider (Airbnb host)</i>	3.23	3.25	1.418	2.011	-1.271	-0.379
TH2 <i>Because of the star rating from the independent tourism grading body, I trust the service provider (Airbnb host)</i>	3.08	3.09	1.346	1.811	-1.237	-0.187
TP1 <i>I trust Airbnb to continue to meet my expectations in the future</i>	3.88	3.94	0.865	0.748	0.988	-0.856
TP2 <i>I feel confident in Airbnb's brand name</i>	3.91	3.98	0.895	0.800	1.222	-0.999
TP3 <i>Airbnb's brand name guarantees satisfaction</i>	3.33	3.35	0.990	0.980	-0.476	-0.298
BR1 <i>Even if not monitored by an independent body, I would trust Airbnb to do the job right</i>	3.26	3.29	1.087	1.182	-0.875	-0.318
BR2 <i>I could rely on Airbnb's brand name to solve any problem experienced with this accommodation</i>	3.38	3.40	1.033	1.068	-0.586	-0.389
BR3 <i>Airbnb's brand name would compensate me in some way for any problem with the product or service experienced with this accommodation</i>	3.20	3.22	1.037	1.076	-0.516	-0.299
PP1 <i>Because of the star rating from other customers, I will book this Airbnb accommodation</i>	2.94	2.94	1.474	2.173	-1.493	-0.095
PP2 <i>Because of the star rating from the independent tourism grading body, I will book this Airbnb accommodation</i>	2.81	2.78	1.374	1.888	-1.333	0.034
PP3 <i>I am very likely to request a booking for this accommodation on Airbnb in the future</i>	3.10	3.12	1.333	1.778	-1.156	-0.287
PP4 <i>I would not hesitate to request a booking for this accommodation on Airbnb</i>	3.01	3.02	1.350	1.822	-1.250	-0.161
PP5 <i>I would feel comfortable requesting a booking on Airbnb for this accommodation</i>	3.13	3.15	1.382	1.909	-1.262	-0.286
PP6 <i>I would use Airbnb to request a booking for this specific accommodation</i>	3.16	3.18	1.369	1.875	-1.203	-0.349

Table 21: Correlation matrix of measures

Measures	TH1	TH2	TP1	TP2	TP3	BR1	BR2	BR3	PP1	PP2	PP3	PP4	PP5	PP6
TH1	1													
TH2	.568**	1												
TP1	.206**	.144**	1											
TP2	.189**	.167**	.711**	1										
TP3	.273**	.178**	.478**	.576**	1									
BR1	.183**	.082*	.429**	.419**	.440**	1								
BR2	.166**	.115**	.449**	.449**	.517**	.518**	1							
BR3	.130**	0.027	.293**	.309**	.363**	.362**	.628**	1						
PP1	.698**	.537**	.165**	.141**	.216**	.138**	.128**	.094*	1					
PP2	.474**	.749**	.144**	.133**	.172**	0.062	.126**	0.025	.660**	1				
PP3	.506**	.476**	.260**	.305**	.358**	.282**	.274**	.229**	.659**	.575**	1			
PP4	.499**	.476**	.193**	.261**	.313**	.227**	.225**	.175**	.668**	.561**	.825**	1		
PP5	.534**	.511**	.228**	.273**	.332**	.225**	.264**	.194**	.684**	.599**	.795**	.852**	1	
PP6	.522**	.493**	.241**	.260**	.258**	.210**	.219**	.190**	.645**	.558**	.765**	.792**	.858**	1

Notes:

** Correlation is significant at the 0.01 level (2-tailed).

* Correlation is significant at the 0.05 level (2-tailed).

From a central tendency perspective, the mean and trimmed mean values were not very divergent from each other. The trimmed mean discards 5% of outliers at either end of the distribution (Howell, 2014). Thus, the difference between the mean and trimmed mean values for each variable were well below 5%, denoting that outliers were not excessively influencing the average.

When analysing the level of variability, the standard deviation was particularly low for TP1, TP2 and TP3, that is, the data values were closely dispersed around the mean. When examining kurtosis (peaked shape of a distribution), all variables, except TP1 and TP2, were representative of a platykurtic distribution, that is flatter than the normal distribution curve.

Skewness (asymmetry around the mean) was noted for almost all the variables; however, this was not particularly concerning as the skewness values did not breach the absolute value of two. [Appendix F](#) shows box and whisker plots to visually compare each continuous variable for the entire sample, as well as per treatment condition. All variables, except for PP2, were left-skewed (denoted by the median closer to the third quartile). Box plots were generally more skewed across the treatment conditions due to the specific combinations of variables that respondents received in the vignette.

The correlation between each indicator, assessed through Pearson's correlation coefficient, indicated the strength of relationship between the measures. This served as a guide for subsequent factor analyses to ensure that similar measures had a higher correlation with each other for a specific construct (convergent validity) and that measures from different theoretical constructs were not too similar with measures from other constructs (discriminant validity).

4.4 Data validation

4.4.1. Exploratory factor analysis

In an EFA indicators across all factors are allowed to freely load together, whereas these relationship from indicator to factor are explicitly made in a CFA (Collier, 2020). Since TH1, TH2, PP1 and PP2 were created by the researcher to capture their respective constructs, an EFA was performed to determine how they loaded.

(i) Data suitability for an EFA

Firstly, the sample size requirement was sufficiently met due to the resultant sample size of 635 respondents. Secondly, both statistical measures revealed that the data was suitable for factorability through an EFA. Bartlett’s test of sphericity ($\chi^2 = 4734.473$, $df = 66$) was significant ($p < 0.001$) and the Kaiser-Meyer-Olkin measure of sampling adequacy was 0.865, which was above 0.80, thus deemed as “meritorious” (p.111) for an EFA as per Pett et al. (2003). Therefore, the data proved to be more than adequate for an EFA.

(ii) Factor extraction

While Kaiser’s criterion suggested extraction based on eigenvalues greater than 1, the initial extraction only resulted in two factors. However, changing the extraction cut-off to be greater than 0.7 as recommended by Jolliffe (Field, 2009, p. 641), resulted in four factors, which is consistent with the four factors in the hypothesised model. The four factors extracted explained 69% of the variance as shown in the penultimate column of Table 22. This was also visually determined from the scree plot (Figure 20), illustrating the four factors above the 0.7 eigenvalue. Additionally, the communalities, that is, the total variance an indicator has in common with the construct it loads on, were above 0.3 (Hair et al., 2010), with the TH2 and BR1 having the lowest communalities of 0.397 and 0.366 respectively, further demonstrating adequacy of the data for EFA after extraction.

Table 22: Total variance explained from EFA

Factor	Total Variance Explained						
	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings ^a
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	
1	5.186	43.221	43.221	2.660	22.169	22.169	4.355
2	2.377	19.805	63.026	3.108	25.897	48.066	3.092
3	.972	8.098	71.124	1.865	15.538	63.603	2.893
4	.779	6.488	77.612	.639	5.325	68.928	2.558
5	.608	5.070	82.682				
6	.524	4.365	87.047				
7	.435	3.629	90.676				
8	.325	2.706	93.383				
9	.262	2.183	95.566				
10	.244	2.034	97.600				
11	.170	1.416	99.015				
12	.118	.985	100.000				

Extraction Method: Maximum Likelihood.

a. When factors are correlated, sums of squared loadings cannot be added to obtain a total variance.

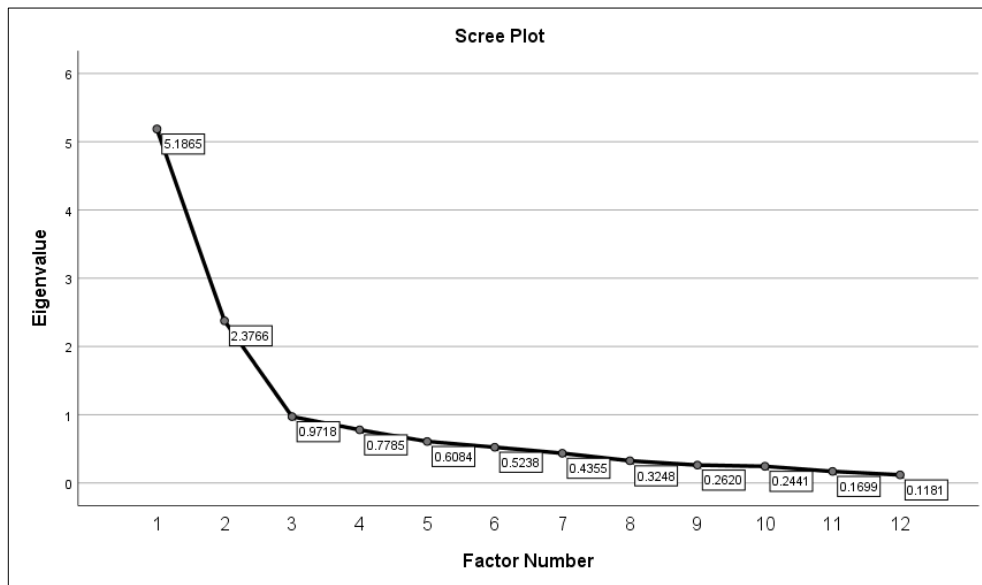


Figure 20: Scree plot

(iii) Factor rotation and interpretation

The rotated solution (pattern matrix) (Table 23) shows each indicator's contribution to a factor, with higher loadings suggestive that the specific questionnaire indicator was strongly linked to the respective factor (Hair et al., 2010). All items loaded strongly on their respective factors, when considering the minimal cut-off of 0.3 (Hair et al., 2010). The EFA rotation was conducted three times resulting in pattern matrices outlined in panels A, B and C in Table 23.

In the first pattern matrix (panel A), all indicators were included. Here, PP1 was on the borderline loading of 0.372 against factor 2 and was also cross-loaded, that is, it loaded on factors 1 and 2. Cross-loadings are acceptable if their difference is greater than 0.15 (Worthington & Whittaker, 2006); however, the difference between the cross loadings of the values for PP1 was also on the borderline at 0.154. The rotation was then rerun, but without PP1, which then created two further cross-loadings on PP2 and TH1 (panel B). Running the rotation for a third time, but with PP1 and PP2 excluded, yielded a more favourable solution (panel C). Although TH2 was cross loaded in the final iteration, it was not removed as it would then reduce one of the factors (factor 4) to only having one indicator.

Table 23: Rotated solutions (pattern matrices)

Likert scale indicators	A. Factors (all indicators)				B. Factors (excl. PP1)				C. Factors (excl. PP1, PP2)			
	1	2	3	4	1	2	3	4	1	2	3	4
TH1 <i>Because of the star rating from other customers, I trust the service provider (Airbnb host)</i>		0.443			0.325			0.381				0.989
TH2 <i>Because of the star rating from the independent tourism grading body, I trust the service provider (Airbnb host)</i>		0.888					1.037		0.349			0.377
TP1 <i>I trust Airbnb to continue to meet my expectations in the future</i>			0.758			0.771				0.759		
TP2 <i>I feel confident in Airbnb's brand name</i>			0.981			0.974				0.988		
TP3 <i>Airbnb's brand name guarantees satisfaction</i>			0.443			0.446				0.433		
BR1 <i>Even if not monitored by an independent body, I would trust Airbnb to do the job right</i>				0.406			0.405					0.423
BR2 <i>I could rely on Airbnb's brand name to solve any problem experienced with this accommodation</i>				0.958			0.949					0.929
BR3 <i>Airbnb's brand name would compensate me in some way for any problem with the product or service experienced with this accommodation</i>				0.704			0.71					0.726
PP1 <i>Because of the star rating from other customers, I will book this Airbnb accommodation</i>	0.526	0.372										
PP2 <i>Because of the star rating from the independent tourism grading body, I will book this Airbnb accommodation</i>		0.779			0.308			0.594				
PP3 <i>I am very likely to request a booking for this accommodation on Airbnb in the future</i>	0.835				0.847				0.842			
PP4 <i>I would not hesitate to request a booking for this accommodation on Airbnb</i>	0.961				0.945				0.942			
PP5 <i>I would feel comfortable requesting a booking on Airbnb for this accommodation</i>	0.938				0.944				0.948			
PP6 <i>I would use Airbnb to request a booking for this specific accommodation</i>	0.904				0.901				0.897			

Ultimately, the last pattern matrix (panel C) was the preferred factor structure of 12 indicators instead of the original 14 indicators (PP1 and PP2 were removed). Therefore, the EFA resulted in the following four factors consistent with panel C of Table 23:

- (i) propensity to participate (PP) as factor 1 with indicators PP3, PP4, PP5 and PP6;
- (ii) trust in platform (TP) as factor 2 with indicators TP1, TP2 and TP3;
- (iii) brand reputation (BR) as factor 3 with indicators BR1, BR2 and BR3; and
- (iv) trust in service provider / host (TH) as factor 4 with indicators TH1 and TH2.

In summary, while many of the indicators were adapted from prior studies, the questions relating to the ratings were novel and did not draw from prior literature, that is, TH1, TH2, PP1 and PP2. In the EFA, these indicators were shown to be somewhat problematic with lower loadings and cross-loadings. However, after two iterations, a suitable pattern matrix was produced, that necessitated the removal of PP1 and PP2. Considering that the TH construct only had two indicators, it was decided to keep them both as only having one indicator would assume that the one indicator accounted for all variance in the underlying TH construct, which is not the case in an SEM framework.

(iv) Common-method bias (CMB)

Harman's single factor test was conducted through an EFA, by constraining the number of factors extracted to one, and with no rotation. The results (Table 27) showed that the total variance explained by just one factor accounted for 37% of the variance. This is less than the cut-off of 50%.

4.4.2. Confirmatory factor analysis

This section provides the results for the CFA across the four main parts introduced in Chapter 3. Firstly, a visual CFA diagram is provided, which illustrates the measurement indicators' squared multiple correlations and factor loadings, as well as covariances between factors. The same information is tabulated to provide details on the indicators in terms of the t-values and significance levels. Secondly, model fit statistics are tabulated against thresholds. Thirdly, the internal consistency of measures is summarised to provide an indication of reliability and validity. Lastly, the results of the measurement invariance tests are provided.

(i) Construction of the CFA model

The pattern matrix (panel C from Table 23) from the EFA was used to construct the measurement model in AMOS (Figure 21), which takes the form of a CFA. At first glance, convergent validity was present for each of the standardised factor loadings, averaging above 0.5 for each of the measurement items for the specific factor. Covariances between each of the factors were less than 0.8, therefore indicating discriminant validity; however, there were fairly high values noted between PP and TH of 0.74, and between TP and PR of 0.66.

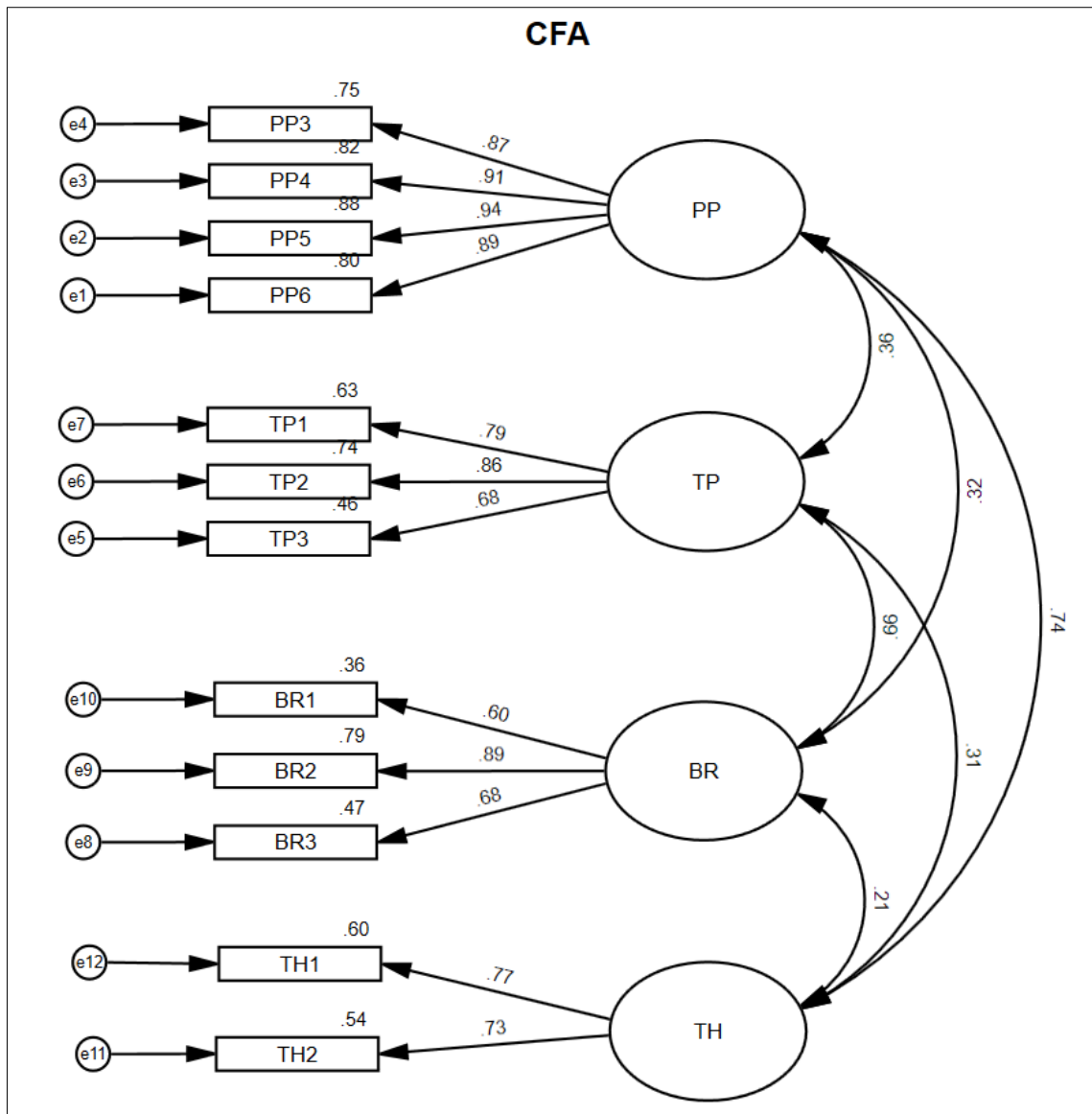


Figure 21: CFA measurement model with standardised estimates

As per, Table 24, all factor loadings were significant ($p < 0.001$) and higher than Hair et al.'s (2014) threshold of 0.5 for standardised loadings, therefore confirming convergent validity.

Table 24: Initial measurement model with standardised estimate

Constructs	Standardised factor loadings (λ)*	t-values
Trust in host (TH)		
TH1: Because of the star rating from other customers, I trust the service provider (Airbnb host)	0.773	**
TH2: Because of the star rating from the independent tourism grading body, I trust the service provider (Airbnb host)	0.735	14.703
Trust in platform (TP)		
TP1: I trust Airbnb to continue to meet my expectations in the future	0.793	**
TP2: I feel confident in Airbnb's brand name	0.862	20.293
TP3: Airbnb's brand name guarantees satisfaction	0.678	16.803
Brand reputation (BR)		
BR1: Even if not monitored by an independent body, I would trust Airbnb to do the job right	0.599	**
BR2: I could rely on Airbnb's brand name to solve any problem experienced with this accommodation	0.889	14.197
BR3: Airbnb's brand name would compensate me in some way for any problem with the product or service experienced with this accommodation	0.682	13.281
Propensity to participate (PP)		
PP3: I am very likely to request a booking for this accommodation on Airbnb in the future	0.868	**
PP4: I would not hesitate to request a booking for this accommodation on Airbnb	0.908	33.002
PP5: I would feel comfortable requesting a booking on Airbnb for this accommodation	0.939	35.444
PP6: I would use Airbnb to request a booking for this specific accommodation	0.895	31.998

Note.

* Factor loading significant at the 0.001 level

** Items constrained for identification purposes

(ii) Assessment of model fit

While the χ^2/df measure was close to 5 and significant, the other fit indices showed moderate to good fit for the CFA model (Table 25).

Table 25: CFA model fit results

Measure	Threshold	Results
Absolute fit indices		
χ^2/df *	< 3 good; < 5 adequate	4.843 (p = 0.000)
RMSEA	< 0.05 good; 0.05 – 0.10 adequate; > 0.10 poor	0.078
SRMR	< 0.05 good; 0.05 – 0.09 adequate	0.0502
GFI	> 0.90	0.942
Comparative / incremental fit indices		
CFI	> 0.90	0.961
IFI	> 0.90	0.961
NFI	> 0.90	0.951
TLI	> 0.90	0.946
RFI	> 0.90	0.933

Note. * $\chi^2 = 232.461$; $df = 48$. Threshold values adapted from "Applied structural equation modeling using AMOS: Basic to advanced techniques", by Collier, J. E., 2020, p. 66-67, New York, NY: Routledge.

(iii) Reliability and validity

As summarised in Table 26, convergent validity was obtained as the AVE per construct was above 0.5, as well as composite reliability, as the CR (as well as Cronbach's alpha) was above 0.7 per construct. Discriminant validity was achieved since the square root of the AVE (bold on diagonal) was above any of the inter-factor correlations (below the diagonal).

Table 26: Internal consistency of measures

Correlation between constructs	BR	PP	TP	TH
BR	0.734			
PP	0.319	0.903		
TP	0.658	0.363	0.781	
TH	0.214	0.737	0.309	0.754
Average variance extracted (AVE)	0.538	0.815	0.611	0.569
Composite reliability (CR)	0.773	0.946	0.823	0.725
Coefficient (Cronbach's) alpha	0.750	0.946	0.806	0.724
Maximum shared variance (MSV)	0.433	0.543	0.433	0.543

Note. Bold diagonal figures are the square root of AVE and bottom-off diagonal figures are correlations

Table 27: Harman's single factor test

Factor	Total Variance Explained					
	Total	Initial Eigenvalues		Extraction Sums of Squared Loadings		
		% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	5.186	43.221	43.221	4.466	37.221	37.221
2	2.377	19.805	63.026			
3	.972	8.098	71.124			
4	.779	6.488	77.612			
5	.608	5.070	82.682			
6	.524	4.365	87.047			
7	.435	3.629	90.676			
8	.325	2.706	93.383			
9	.262	2.183	95.566			
10	.244	2.034	97.600			
11	.170	1.416	99.015			
12	.118	.985	100.000			

Extraction Method: Maximum Likelihood.

(v) Measurement invariance

Many SEM studies evaluate measurement invariance between two groups, which AMOS is well set up for in terms of its multigroup analysis functionality. The challenge with the current research study is that the nine treatment conditions (groups) required multiple two-group analyses. This is because AMOS assesses differences as a whole across all nine groups and cannot determine differences between the groups (Collier, 2020). Therefore, measurement invariance tests were conducted 36 times for each combination of the nine treatment conditions.

As shown in Table 28, all combinations of treatment conditions (groups) showed acceptable levels of model fit, hence passing configural invariance. Of the 36 treatment condition combinations, only two were not metric invariant (TC 2 & 6; TC & 9) and one was partially metric invariant (TC 4 & 6) through the removal of the TP3 factor loading constraint. From a metric invariance perspective, only 9 treatment condition combinations were fully scalar invariant; 4 were partially scalar invariant and 21 were not scalar invariant.

Table 28: Measurement invariance results

TC pair	Configural invariance					Metric invariance			Scalar invariance		
	χ^2/df	CFI	TLI	RMSEA	Config.	χ^2	P	Metric	χ^2	P	Scalar
TC 1 & 2	2.032	0.901	0.864	0.088	✓	5.880	0.661	✓	25.797	0.173	✓
TC 1 & 3	1.933	0.922	0.892	0.078	✓	6.307	0.613	✓	58.233	0	*
TC 1 & 4	2.318	0.871	0.823	0.097	✓	5.509	0.702	✓	17.304	0.633	✓
TC 1 & 5	2.258	0.885	0.842	0.091	✓	6.961	0.541	✓	47.761	0	*
TC 1 & 6	2.032	0.901	0.864	0.088	✓	5.880	0.661	✓	25.797	0.173	✓
TC 1 & 7	1.907	0.919	0.889	0.080	✓	6.638	0.576	✓	11.173	0.942	✓
TC 1 & 8	2.183	0.875	0.829	0.092	✓	5.528	0.7	✓	54.014	0	*
TC 1 & 9	1.687	0.94	0.918	0.069	✓	6.803	0.558	✓	92.641	0	*
TC 2 & 3	1.611	0.947	0.927	0.066	✓	4.398	0.82	✓	28.646	0.095	✓
TC 2 & 4	1.996	0.898	0.86	0.088	✓	6.881	0.55	✓	33.725	0.028	*
TC 2 & 5	1.936	0.911	0.878	0.082	✓	8.801	0.359	✓	38.12	0.009	*
TC 2 & 6	1.617	0.931	0.905	0.072	✓	20.522	0.009	*			
TC 2 & 7	1.585	0.946	0.926	0.067	✓	5.2	0.736	✓	19.883	0.465	✓
TC 2 & 8	1.861	0.905	0.869	0.082	✓	6.902	0.547	✓	25.282	0.151	<i>a</i>
TC 2 & 9	1.365	0.967	0.955	0.052	✓	8.148	0.419	✓	68.514	0	*
TC 3 & 4	1.897	0.921	0.891	0.078	✓	8.9	0.351	✓	58.559	0	*
TC 3 & 5	1.836	0.93	0.904	0.073	✓	3.872	0.868	✓	40.573	0.004	*
TC 3 & 6	1.518	0.95	0.932	0.061	✓	14.881	0.062	✓	56.224	0	*
TC 3 & 7	1.486	0.96	0.946	0.057	✓	1.375	0.995	✓	25.74	0.058	<i>b</i>
TC 3 & 8	1.762	0.928	0.901	0.072	✓	7.64	0.469	✓	21.653	0.36	✓
TC 3 & 9	1.265	0.979	0.971	0.042	✓	6.544	0.587	✓	77.61	0	*
TC 4 & 5	2.222	0.882	0.838	0.092	✓	7.888	0.444	✓	62.908	0	*
TC 4 & 6	1.903	0.897	0.859	0.085	✓	12.083	0.098	<i>c</i>			
TC 4 & 7	1.871	0.918	0.887	0.080	✓	7.312	0.503	✓	16.633	0.677	✓
TC 4 & 8	2.147	0.871	0.823	0.093	✓	9.295	0.318	✓	64.182	0	*
TC 4 & 9	1.651	0.94	0.918	0.068	✓	6.165	0.629	✓	102.05	0	*
TC 5 & 6	1.843	0.911	0.878	0.079	✓	9.37	0.312	✓	28.627	0.053	<i>d</i>
TC 5 & 7	1.811	0.929	0.902	0.074	✓	2.601	0.957	✓	46.141	0.001	*
TC 5 & 8	2.087	0.887	0.844	0.087	✓	3.47	0.902	✓	22.999	0.289	✓
TC 5 & 9	1.59	0.949	0.93	0.063	✓	11.486	0.176	✓	40.938	0.004	*
TC 6 & 7	1.493	0.95	0.931	0.062	✓	13.13	0.107	✓	87.629	0	*
TC 6 & 8	1.768	0.904	0.869	0.078	✓	7.534	0.48	✓	24.844	0.129	<i>e</i>
TC 6 & 9	1.273	0.973	0.963	0.046	✓	24.108	0.002	*			
TC 7 & 8	1.736	0.926	0.898	0.074	✓	5.767	0.673	✓	44.892	0.001	*
TC 7 & 9	1.24	0.98	0.972	0.041	✓	7.326	0.502	✓	83.185	0	*
TC 8 & 9	1.516	0.949	0.93	0.061	✓	14.312	0.074	✓	60.365	0	*

Notes:

- a. Partial scalar invariance obtained by un-constraining equality of intercept for PP6.
- b. Partial scalar invariance obtained by un-constraining equality of intercept for PP6, PP5, TP2 and BR2.
- c. Partial metric invariance obtained by un-constraining equality of factor loading for TP3.
- d. Partial scalar invariance obtained by un-constraining equality of intercept for PP6 and PP5.
- e. Partial scalar invariance obtained by un-constraining equality of intercept for PP5 and PP4.

4.5 Structural equation modelling

The interpretation and discussion of the SEM results have been reserved for Chapter 5 (Discussion). In terms of the order of results presented, global tests of model fit and variance explained is presented, first, then followed by local tests (p-value) to determine support for the hypotheses (Gaskin, 2020).

4.5.1 Structural equation model (M_{SEM})

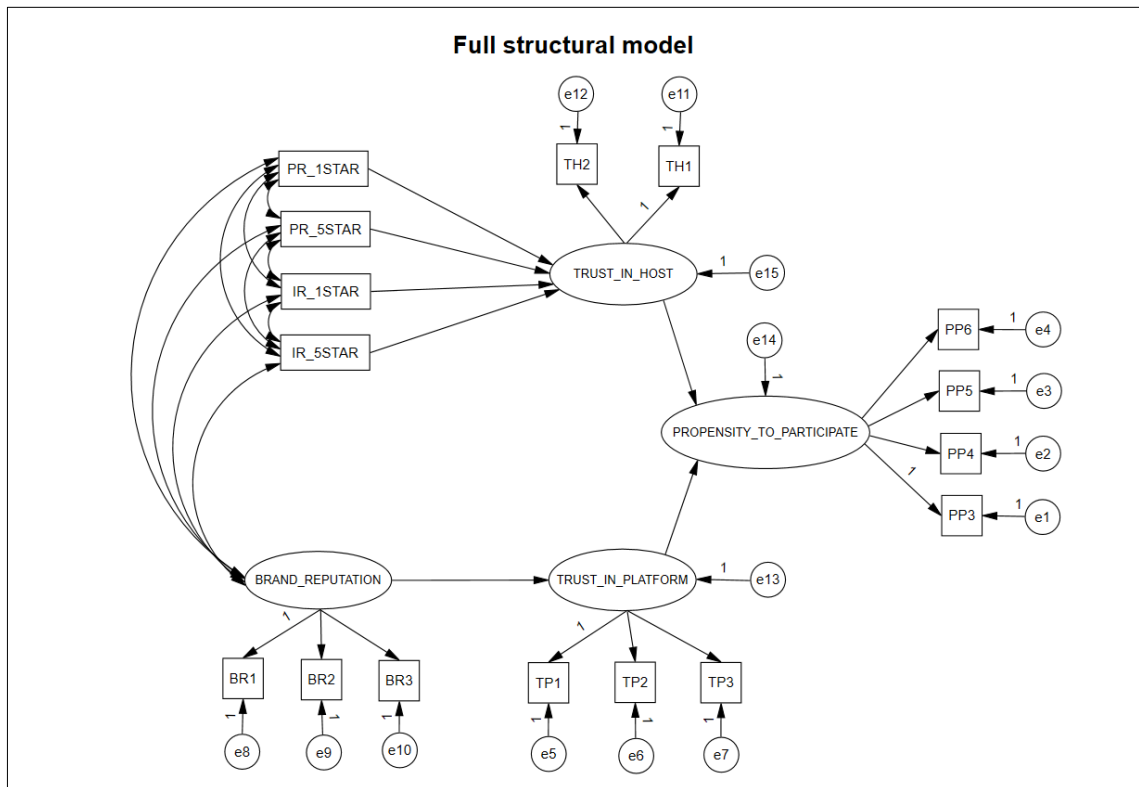


Figure 22: Full structural model

Table 29: Model fit and explained variance for full structural model

Measure	Threshold	Results
Absolute fit indices		
χ^2/df *	< 3 good; < 5 adequate	3.966
RMSEA	< 0.05 good; 0.05 – 0.10 adequate; > 0.10 poor	0.068
SRMR	< 0.05 good; 0.05 – 0.09 adequate	0.080
GFI	> 0.90	0.933
Comparative / incremental fit indices		
CFI	> 0.90	0.949
IFI	> 0.90	0.949
NFI	> 0.90	0.934
TLI	> 0.90	0.933
RFI	> 0.90	0.912
Squared multiple correlation (R²)		
TH		0.340
TP		0.437
PP		0.611

Note. * $\chi^2 = 360.943$; $df = 91$, $p = 0.000$. Threshold values adapted from "Applied structural equation modeling using AMOS: Basic to advanced techniques", by Collier, J. E., 2020, p. 66-67, New York, NY: Routledge.

Table 30: Results for full structural model

Hypothesised relationships (M_{SEM})	Standardised estimates	Unstandardised estimates *	S.E.	t-values	p-values	Result
H1: PR → TH						
H1a: 1 ★ compared to 3 ★	-0.396	-0.882	0.105	-8.402	***	Supported
H1b: 5 ★ compared to 3 ★	0.214	0.475	0.101	0.475	***	Supported
H2: IR → TH						
H2a: 1 ★ compared to 3 ★	-0.215	-0.475	0.101	-4.686	***	Supported
H2b: 5 ★ compared to 3 ★	0.031	0.069	0.100	0.692	0.489	Rejected
H4: BR → TP	0.661	0.697	0.061	11.382	***	Supported
H5: TH → PP	0.744	0.796	0.055	14.517	***	Supported
H8: TP → PP	0.243	0.399	0.057	7.017	***	Supported

Note. * Dummy variables used for 1 ★ and 5 ★ ratings necessitates the analysis of unstandardised estimates for H1 and H2. Hypotheses related to treatment conditions (H3) and mediation (H6, H7, H9) are not shown.

S.E.: Standard error

4.5.2 Structural equation model with CVs (M_{ALL CV})

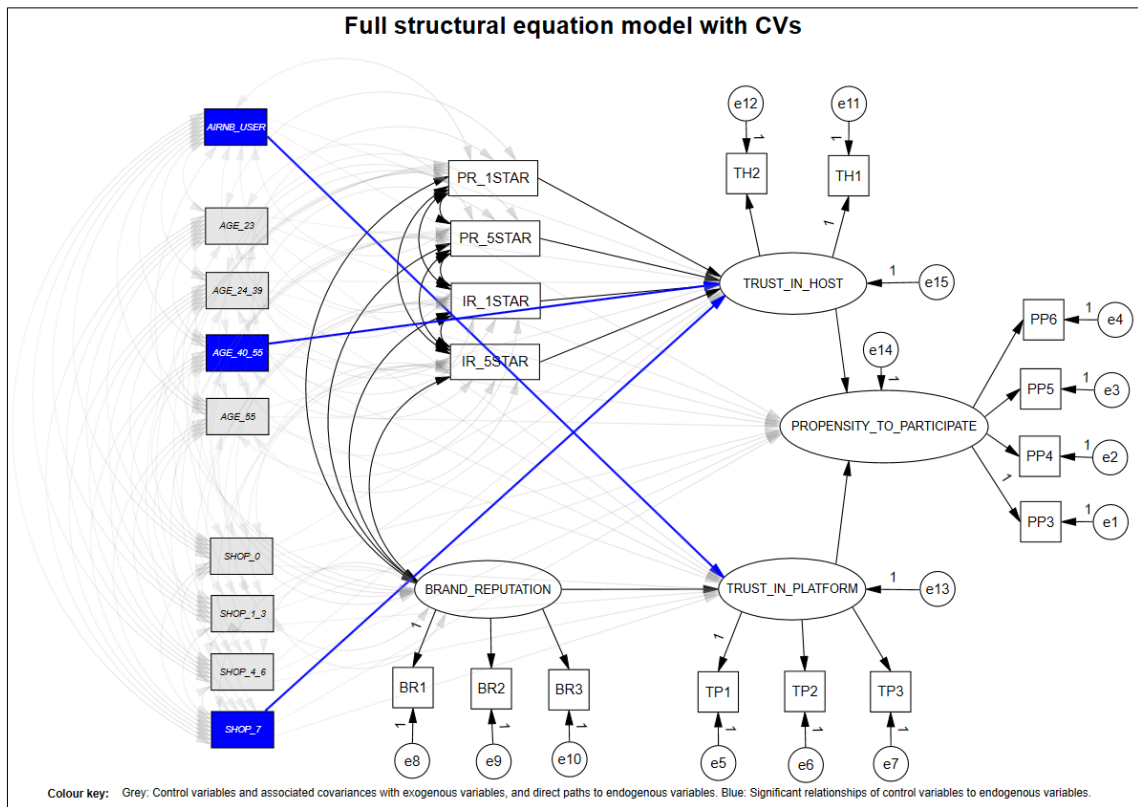


Figure 23: Full structural model with control variables
Covariances among each exogenous variable and control, as well as direct paths from controls to endogenous variables were changed to light grey in AMOS for ease of readability.

Table 31: Model fit for full structural model with CVs

Measure	Threshold	Results
Absolute fit indices		
χ^2/df *	< 3 good; < 5 adequate	2.710
RMSEA	< 0.05 good; 0.05 – 0.10 adequate; > 0.10 poor	0.052
SRMR	< 0.05 good; 0.05 – 0.09 adequate	0.0510
GFI	> 0.90	0.947
Comparative / incremental fit indices		
CFI	> 0.90	0.972
IFI	> 0.90	0.972
NFI	> 0.90	0.957
TLI	> 0.90	0.949
RFI	> 0.90	0.921
Squared multiple correlation (R²)		
TH		0.388
TP		0.474
PP		0.620

Note. * $\chi^2 = 441.729$; $df = 163$; $p = 0.000$. Threshold values adapted from “Applied structural equation modeling using AMOS: Basic to advanced techniques”, by Collier, J. E., 2020, p. 66-67, New York, NY: Routledge.

Table 32: Results for full structural model with CVs

Hypothesised relationships	Standardised estimates	Unstandardised estimates *	S.E.	t-values	p-values
H1: PR → TH					
H1a: 1 ★ compared to 3 ★	-0.393	-0.872	0.103	-8.497	***
H1b: 5 ★ compared to 3 ★	0.224	0.496	0.099	5.011	***
H2: IR → TH					
H2a: 1 ★ compared to 3 ★	-0.222	-0.489	0.099	-4.946	***
H2b: 5 ★ compared to 3 ★	0.016	0.036	0.098	0.364	0.716
H4: BR → TP	0.651	0.685	0.061	11.309	***
H5: TH → PP	0.754	0.81	0.056	14.432	***
H8: TP → PP	0.25	0.411	0.059	6.984	***
Controls					
AIRNB_USER → TH	0.037	0.084	0.09	0.89	0.374
AIRNB_USER → TP	0.149	0.218	0.06	3.989	***
AIRNB_USER → PP	-0.013	-0.032	0.09	-0.38	0.704
AGE_23 → TH	0.084	0.79	0.86	0.915	0.36
AGE_23 → TP	-0.063	-0.387	0.49	-0.795	0.427
AGE_23 → PP	-0.114	-1.15	0.75	-1.529	0.126
AGE_24_39 → TH	0.675	1.417	0.77	1.831	0.067
AGE_24_39 → TP	-0.129	-0.177	0.44	-0.407	0.684
AGE_24_39 → PP	-0.431	-0.973	0.68	-1.442	0.149
AGE_40_55 → TH	0.754	1.612	0.77	2.083	0.037
AGE_40_55 → TP	-0.115	-0.161	0.44	-0.369	0.712
AGE_40_55 → PP	-0.445	-1.022	0.68	-1.513	0.13
AGE_55 → TH	0.247	1.182	0.79	1.494	0.135
AGE_55 → TP	-0.075	-0.235	0.45	-0.528	0.598
AGE_55 → PP	-0.125	-0.641	0.69	-0.93	0.353
SHOP_0 → TH	0.049	0.236	0.38	0.617	0.537
SHOP_0 → TP	-0.025	-0.078	0.22	-0.364	0.716
SHOP_0 → PP	-0.012	-0.06	0.33	-0.181	0.856
SHOP_1_3 → TH	-0.147	-0.31	0.33	-0.934	0.35
SHOP_1_3 → TP	0.109	0.149	0.19	0.8	0.424
SHOP_1_3 → PP	0.068	0.154	0.29	0.535	0.593
SHOP_4_6 → TH	-0.142	-0.355	0.34	-1.048	0.295
SHOP_4_6 → TP	0.013	0.021	0.19	0.11	0.912
SHOP_4_6 → PP	0.069	0.185	0.30	0.627	0.531
SHOP_7 → TH	-0.252	-0.705	0.34	-2.049	0.040
SHOP_7 → TP	-0.024	-0.044	0.19	-0.227	0.821
SHOP_7 → PP	0.095	0.285	0.30	0.952	0.341

Note. * Dummy variables used for 1 ★ and 5 ★ ratings necessitates the analysis of unstandardised estimates for H1 and H2. Hypotheses related to treatment conditions (H3) and mediation (H6, H7, H9) are not shown.

S.E.: Standard error

4.5.3 Structural model with significant CVs (M_{CV})

To simplify the subsequent mediation effects and maintain model parsimony, only the significant effects of those CV categories were maintained, that is, the blue paths, which subsequently returned the revised estimates. This is aligned with Collier's (2020) recommendation to remove CVs if their effects are inconsequential. The inclusion of the significant CVs did not drastically change the first model and was therefore kept in the mediation analysis in the next sub-section.

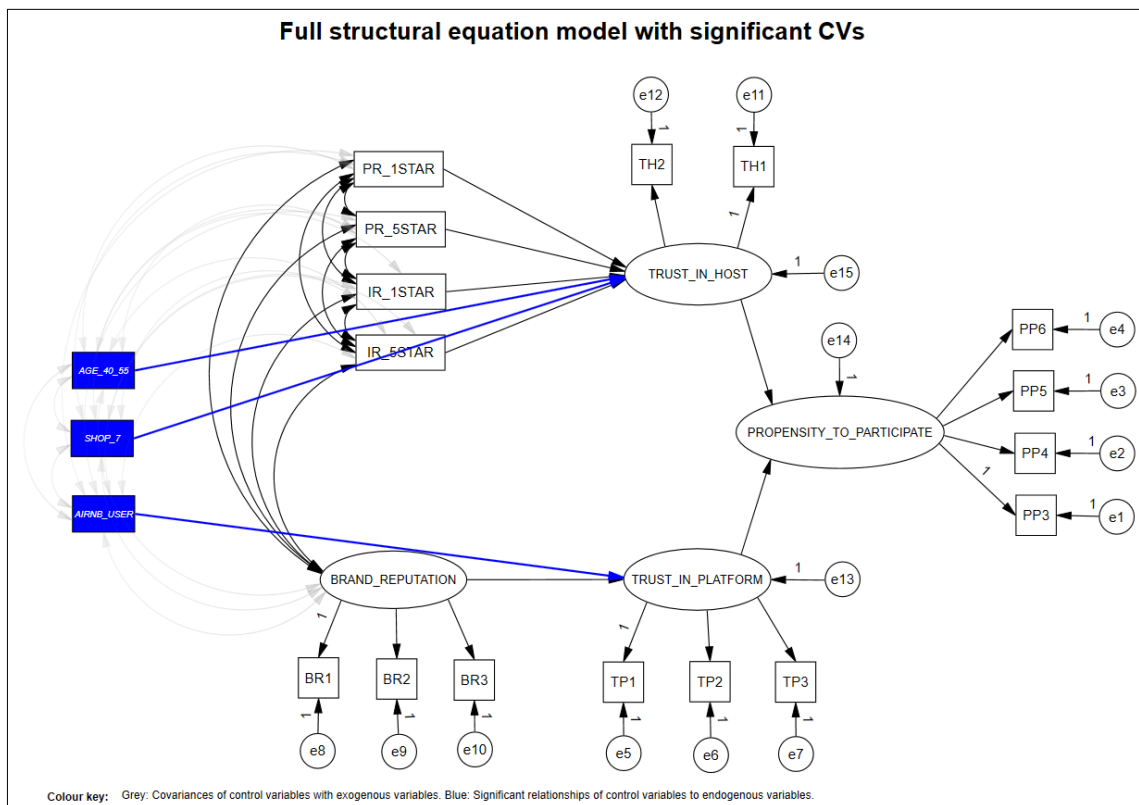


Figure 24: Full structural model with significant control variables
Covariances among each exogenous variable and control, as well as direct paths from controls to endogenous variables were changed to light grey in AMOS for ease of readability

Table 33: Model fit for full structural model with significant CVs

Measure	Threshold	Results
Absolute fit indices		
χ^2/df *	< 3 good; < 5 adequate	3.273
RMSEA	< 0.05 good; 0.05 – 0.10 adequate; > 0.10 poor	0.060
SRMR	< 0.05 good; 0.05 – 0.09 adequate	0.070
GFI	> 0.90	0.938
Comparative / incremental fit indices		
CFI	> 0.90	0.949
IFI	> 0.90	0.949
NFI	> 0.90	0.929
TLI	> 0.90	0.928
RFI	> 0.90	0.899
Squared multiple correlation (R²)		
TH		0.362
TP		0.453
PP		0.605

Note. * $\chi^2 = 396.016$; $df = 121$; $p = 0.000$. Threshold values adapted from “*Applied structural equation modeling using AMOS: Basic to advanced techniques*”, by Collier, J. E., 2020, p. 66-67, New York, NY: Routledge.

Table 34: Results for full structural model with significant CVs

Hypothesised relationships (M_{CV})	Standardised estimates	Unstandardised estimates *	S.E.	t-values	p-values
H1: PR → TH					
H1a: 1 ★ compared to 3 ★	-0.393	-0.875	0.104	-8.420	***
H1b: 5 ★ compared to 3 ★	0.220	0.488	0.100	4.860	***
H2: IR → TH					
H2a: 1 ★ compared to 3 ★	-0.216	-0.478	0.101	-4.759	***
H2b: 5 ★ compared to 3 ★	0.020	0.044	0.099	0.440	0.660
H4: BR → TP	0.636	0.671	0.060	11.177	***
H5: TH → PP	0.741	0.791	0.054	14.584	***
H8: TP → PP	0.244	0.401	0.057	7.058	***
Controls					
AIRNB_USER → TP	0.140	0.205	0.050	3.831	***
AGE_40_55 → TH	0.093	0.200	0.080	2.424	0.015
SHOP_7 → TH	-0.124	-0.347	0.110	-3.198	0.001

Note. * Dummy variables used for 1 ★ and 5 ★ ratings necessitates the analysis of unstandardised estimates for H1 and H2. Hypotheses related to treatment conditions (H3) and mediation (H6, H7, H9) are not shown.

S.E.: Standard error

4.5.4 Structural model with significant CVs and mediation (M_{MED})

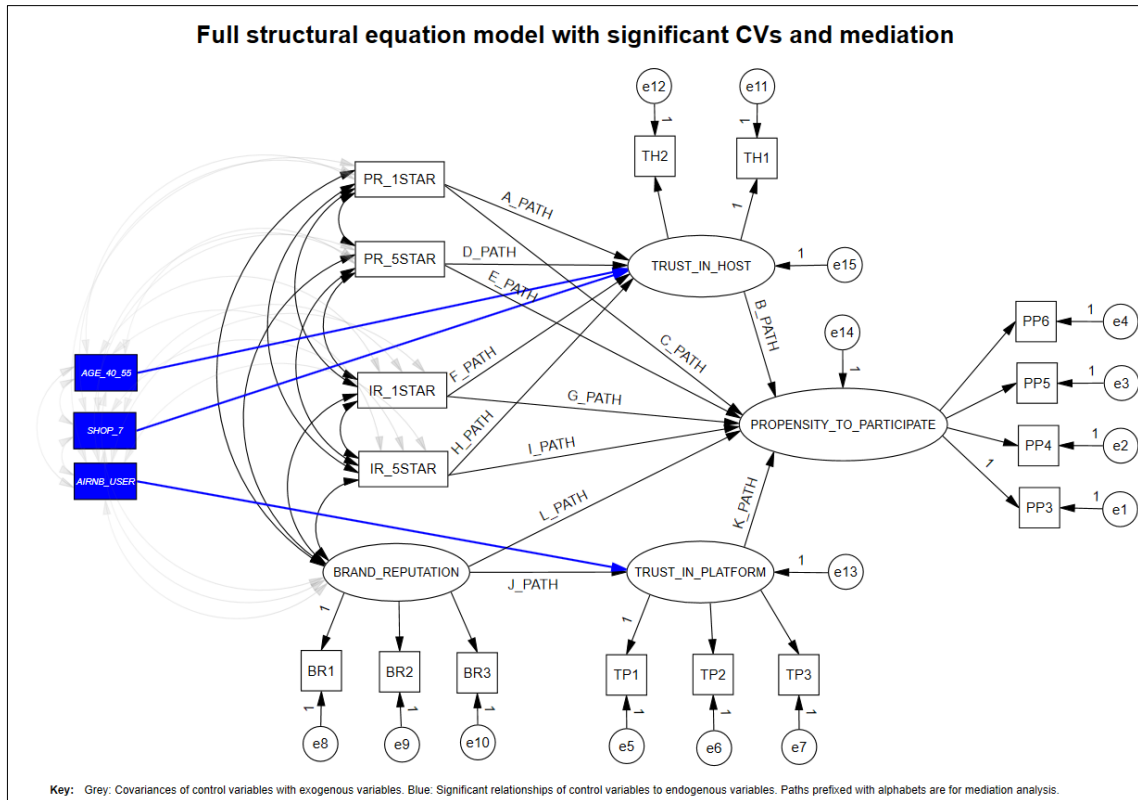


Figure 25: Full structural model with significant control variables and mediation
Covariances among each exogenous variable and control, as well as direct paths from controls to endogenous variables were changed to light grey in AMOS for ease of readability

Table 35: Model fit for full structural model with significant CVs and mediation

Measure	Threshold	Results
Absolute fit indices		
χ^2/df *	< 3 good; < 5 adequate	3.098
RMSEA	< 0.05 good; 0.05 – 0.10 adequate; > 0.10 poor	0.058
SRMR	< 0.05 good; 0.05 – 0.09 adequate	0.063
GFI	> 0.90	0.944
Comparative / incremental fit indices		
CFI	> 0.90	0.955
IFI	> 0.90	0.955
NFI	> 0.90	0.935
TLI	> 0.90	0.933
RFI	> 0.90	0.904
Squared multiple correlation (R^2)		
TH		0.298
TP		0.445
PP		0.579

Note. * $\chi^2 = 359.339$; $df = 116$; $p = 0.000$. Threshold values adapted from “Applied structural equation modeling using AMOS: Basic to advanced techniques”, by Collier, J. E., 2020, p. 66-67, New York, NY: Routledge.

Table 36: Results for full structural model with significant CVs and mediation

Hypothesised relationships (M_{MED})	Standardised estimates	Unstandardised estimates *	S.E.	t-values	p-values
H1: PR → TH					
H1a: 1 ★ compared to 3 ★	-0.339	-0.770	0.112	-6.885	***
H1b: 5 ★ compared to 3 ★	0.187	0.425	0.110	3.864	***
H2: IR → TH					
H2a: 1 ★ compared to 3 ★	-0.227	-0.512	0.110	-4.637	***
H2b: 5 ★ compared to 3 ★	0.026	0.058	0.110	0.531	0.596
H4: BR → TP	0.629	0.662	0.060	11.103	***
H5: TH → PP	0.591	0.620	0.058	10.774	***
H8: TP → PP	0.153	0.251	0.079	3.170	0.002
Controls:					
AIRNB_USER → TP	0.140	0.206	0.054	3.828	***
AGE_40_55 → TH	0.099	0.216	0.088	2.468	0.014
SHOP_7 → TH	-0.135	-0.385	0.115	-3.347	***

Notes:

* Dummy variables used for 1 ★ and 5 ★ ratings necessitates the analysis of unstandardised estimates for H1 and H2. Hypotheses related to treatment conditions (H3) and mediation (H6, H7, H9) are not shown.
S.E.: Standard error

Table 37 represents the unstandardised indirect effects, confidence interval and p-value per indirect effect. The results on the bootstrap showed that each indirect effect on PP was significant, with no confidence interval crossing over zero, except for IR_5STAR.

Table 37: Mediation test using bootstrap analysis with a 95% confidence interval

Relationships	Direct effect		Estimate	Indirect effect		p-value	Conclusion
	Estimate	P-value		Confidence interval Low	High		
H6: PR → TH → PP							
1 ★ compared to 3 ★	-0.363 (-3.797)	0.001	-0.478	-0.687	-0.300	0.000	Partial complementary mediation
5 ★ compared to 3 ★	0.210 (2.359)	0.018	0.263	0.140	0.411	0.000	Partial complementary mediation
H7: IR → TH → PP							
1 ★ compared to 3 ★	-0.003 (-0.035)	0.972	-0.317	-0.515	-0.164	0.000	Full mediation
5 ★ compared to 3 ★	-0.026 (-0.297)	0.767	0.036	-0.088	0.162	0.589	Non-significant
H9: BR → TP → PP	0.272 (3.222)	0.001	0.166	0.055	0.307	0.004	Partial complementary mediation

Note. Unstandardised coefficients reported. Values in parentheses are t-values. Bootstrap sample = 5000 with replacement.

4.5.5 Structural models with significant CVs and mediation per treatment condition

Table 38: Model fit per treatment condition

	TC 1 PR: 1 ★ IR: 1 ★	TC 2 PR: 3 ★ IR: 1 ★	TC 3 PR: 5 ★ IR: 1 ★	TC 4 PR: 1 ★ IR: 3 ★	TC 5 PR: 3 ★ IR: 3 ★	TC 6 PR: 5 ★ IR: 3 ★	TC 7 PR: 1 ★ IR: 5 ★	TC 8 PR: 3 ★ IR: 5 ★	TC 9 PR: 5 ★ IR: 5 ★
χ^2	330.396	329.709	340.959	330.144	329.405	340.644	325.855	324.511	335.282
<i>df</i>	98	98	98	98	98	98	98	98	98
χ^2/df	3.371	3.364	3.479	3.369	3.361	3.476	3.325	3.311	3.421
p-value	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
RMSEA	0.061	0.061	0.063	0.061	0.061	0.062	0.061	0.060	0.062
SRMR	0.0699	0.0712	0.0705	0.0713	0.0726	0.0721	0.0707	0.0719	0.0715
GFI	0.942	0.942	0.940	0.942	0.943	0.941	0.943	0.943	0.941
CFI	0.953	0.952	0.951	0.953	0.951	0.950	0.954	0.953	0.951
IFI	0.953	0.952	0.951	0.953	0.952	0.951	0.954	0.953	0.952
NFI	0.935	0.933	0.932	0.935	0.933	0.932	0.936	0.934	0.933
TLI	0.935	0.933	0.931	0.935	0.933	0.931	0.936	0.934	0.933
RFI	0.91	0.907	0.906	0.910	0.907	0.906	0.911	0.908	0.907

Table 39: Results per treatment condition

Hypothesised relationships	Standardised estimates	Unstandardised estimates	S.E.	t-values	p-values	Conclusion
M₁ (PR 1*,IR 1*)						
H3a: PR → TH	-0.433	-0.982	0.1	-9.773	***	Supported
H3b: IR → TH	-0.229	0.033	0.08	0.412	0.68	Rejected
H4: BR → TP	0.629	0.662	0.06	11.104	***	Supported
H5: TH → PP	0.610	0.641	0.058	11.145	***	Supported
H8: TP → PP	0.139	0.227	0.08	2.854	0.004	Supported
M₂ (PR 3*,IR 1*)						
H3a: PR → TH	0.074	0.166	0.102	1.625	0.104	Rejected
H3b: IR → TH	-0.23	-0.514	0.103	-4.999	***	Supported
H4: BR → TP	0.629	0.664	0.06	11.102	***	Supported
H5: TH → PP	0.701	0.743	0.056	13.156	***	Supported
H8: TP → PP	0.123	0.202	0.084	2.411	0.016	Supported
M₃ (PR 5*,IR 1*)						
H3a: PR → TH	0.359	0.808	0.101	8.022	***	Supported
H3b: IR → TH	-0.254	-0.569	0.099	-5.78	***	Supported
H4: BR → TP	0.629	0.663	0.06	11.095	***	Supported
H5: TH → PP	0.641	0.675	0.057	11.853	***	Supported
H8: TP → PP	0.156	0.255	0.081	3.136	0.002	Supported
M₄ (PR 1*,IR 3*)						
H3a: PR → TH	-0.437	-1.003	0.103	-9.718	***	Supported
H3b: IR → TH	0.084	0.194	0.099	1.955	0.051	Supported
H4: BR → TP	0.629	0.661	0.06	11.104	***	Supported
H5: TH → PP	0.607	0.629	0.055	11.448	***	Supported
H8: TP → PP	0.139	0.228	0.08	2.853	0.004	Supported
M₅ (PR 3*,IR 3*)						
H3a: PR → TH	0.082	0.189	0.106	1.786	0.074	Rejected
H3b: IR → TH	0.08	0.182	0.106	1.719	0.086	Rejected
H4: BR → TP	0.629	0.663	0.06	11.104	***	Supported
H5: TH → PP	0.695	0.727	0.054	13.388	***	Supported
H8: TP → PP	0.123	0.201	0.084	2.403	0.016	Supported
M₆ (PR 5*,IR 3*)						
H3a: PR → TH	0.355	0.810	0.104	7.799	***	Supported
H3b: IR → TH	0.113	0.261	0.102	2.563	0.01	Supported
H4: BR → TP	0.629	0.663	0.06	11.094	***	Supported
H5: TH → PP	0.638	0.663	0.054	12.185	***	Supported
H8: TP → PP	0.157	0.257	0.081	3.15	0.002	Supported
M₇ (PR 1*,IR 5*)						
H3a: PR → TH	-0.437	-1.008	0.103	-9.805	***	Supported
H3b: IR → TH	0.144	0.334	0.099	3.384	***	Supported
H4: BR → TP	0.629	0.662	0.06	11.104	***	Supported
H5: TH → PP	0.609	0.628	0.056	11.311	***	Supported
H8: TP → PP	0.137	0.224	0.08	2.809	0.005	Supported
M₈ (PR 3*,IR 5*)						
H3a: PR → TH	0.091	0.209	0.105	1.99	0.047	Supported
H3b: IR → TH	0.149	0.342	0.105	3.245	0.001	Supported
H4: BR → TP	0.629	0.664	0.06	11.103	***	Supported
H5: TH → PP	0.698	0.726	0.055	13.297	***	Supported
H8: TP → PP	0.122	0.2	0.084	2.388	0.017	Supported
M₉ (PR 5*,IR 5*)						
H3a: PR → TH	0.344	0.790	0.103	7.633	***	Supported
H3b: IR → TH	0.140	0.323	0.101	3.189	0.001	Supported
H4: BR → TP	0.629	0.663	0.06	11.094	***	Supported
H5: TH → PP	0.642	0.664	0.055	12.136	***	Supported
H8: TP → PP	0.153	0.251	0.081	3.079	0.002	Supported

Notes:

* Dummy variables used for star ratings necessitates the analysis of unstandardised estimates for H3a and H3b.

Hypotheses related to mediation (H6, H7, H9) are not shown.

S.E.: Standard error

Table 40: Mediation results per treatment condition

Relationships	Direct effect		Indirect effect			p-value	Conclusion
	Estimate	P-value	Estimate	Confidence interval Low High	p-value		
M₁ (PR 1*,IR 1*)							
H6: PR → TH → PP	-0.982 (-9.773)	0.001	-0.630	-0.854 -0.450	0.000	p.c.mediation	
H7: IR → TH → PP	-0.516 (-5.378)	0.001	-.331	-.516 -.187	0.000	p.c.mediation	
H9: BR → TP → PP	0.278 (3.258)	0.001	.150	.041 .289	.010	p.c.mediation	
M₂ (PR 3*,IR 1*)							
H6: PR → TH → PP	0.166 (1.625)	0.104	.123	-.015 .275	.085	Non-significant	
H7: IR → TH → PP	-0.514 (-4.999)	0.001	-.382	-.571 -.212	.000	p.c.mediation	
H9: BR → TP → PP	0.251 (2.806)	0.005	.134	.020 .273	.024	p.c.mediation	
M₃ (PR 5*,IR 1*)							
H6: PR → TH → PP	0.808 (8.022)	0.001	.546	.398 .727	.000	p.c.mediation	
H7: IR → TH → PP	-0.569 (-5.78)	0.001	-.385	-.577 -.233	.000	p.c.mediation	
H9: BR → TP → PP	0.249 (2.874)	0.004	.169	.060 .312	.003	p.c.mediation	
M₄ (PR 1*,IR 3*)							
H6: PR → TH → PP	-1.003 (-9.718)	0.001	-.631	-.842 -.461	.000	p.c.mediation	
H7: IR → TH → PP	0.194 (1.955)	0.051	.122	.006 .251	.037	p.c.mediation	
H9: BR → TP → PP	0.276 (3.231)	0.001	.150	.040 .287	.009	p.c.mediation	
M₅ (PR 3*,IR 3*)							
H6: PR → TH → PP	0.189 (1.786)	0.074	.137	-.003 .290	.056	Non-significant	
H7: IR → TH → PP	0.182 (1.719)	0.086	.133	-.019 .286	.083	Non-significant	
H9: BR → TP → PP	0.249 (2.786)	0.005	.133	.019 .273	.025	p.c.mediation	
M₆ (PR 5*,IR 3*)							
H6: PR → TH → PP	0.81 (7.799)	0.01	.537	.395 .706	.000	p.c.mediation	
H7: IR → TH → PP	0.261 (2.563)	0.001	.173	.044 .318	.007	p.c.mediation	
H9: BR → TP → PP	0.246 (2.837)	0.005	.170	.059 .311	.004	p.c.mediation	
M₇ (PR 1*,IR 5*)							
H6: PR → TH → PP	-1.008 (-9.805)	0.001	-.633	-.847 -.458	.000	p.c.mediation	
H7: IR → TH → PP	0.334 (3.384)	0.001	.209	.085 .350	.001	p.c.mediation	
H9: BR → TP → PP	0.277 (3.245)	0.001	.148	.038 .289	.010	p.c.mediation	
M₈ (PR 3*,IR 5*)							
H6: PR → TH → PP	0.209 (1.99)	0.047	.152	.008 .304	.038	p.c.mediation	
H7: IR → TH → PP	0.342 (3.245)	0.001	.248	.090 .410	.001	p.c.mediation	
H9: BR → TP → PP	0.249 (2.781)	0.005	.133	.018 .275	.024	p.c.mediation	
M₉ (PR 5*,IR 5*)							
H6: PR → TH → PP	0.79 (7.633)	0.001	.524	.383 .694	.000	p.c.mediation	
H7: IR → TH → PP	0.323 (3.189)	0.001	.214	.084 .355	.001	p.c.mediation	
H9: BR → TP → PP	0.248 (2.857)	0.004	.166	.057 .310	.005	p.c.mediation	

Notes:

Unstandardised coefficients reported. Values in parentheses are t-values. Bootstrap sample = 5000 with replacement.
p.c.mediation: partial complementary mediation

4.6 Conceptual model

Based on the aforementioned results, Table 41 summarises which hypotheses are either supported or rejected. Thereafter, Figure 26 outlines the revised conceptual model with the supported hypotheses.

Table 41: Status on hypotheses

RQ	Hypotheses		Conclusion	
1.1	H1	Platform reputation systems (ratings) affect consumers' trust in the SE service provider	PR → TH	Supported
	H1a	Low platform reputation ratings have a weaker effect on consumers' trust in the SE service provider		Supported
	H1b	High platform reputation ratings have a stronger effect on consumers' trust in the SE service provider		Supported
1.2	H2	Independent reputation systems (ratings) affect consumers' trust in the SE service provider	IR → TH	Rejected
	H2a	Low independent reputation ratings have a weaker effect on consumers' trust in the SE service provider		Supported
	H2b	High independent reputation ratings have a stronger effect on consumers' trust in the SE service provider		Rejected
1.1, 1.2	H3	The combination of platform reputation systems (ratings) and independent reputation systems (ratings) affect consumers' trust in the service provider at differing levels	PR + IR → TH	Rejected
	H3a	Main effect: There is a significant difference on trust in the SE service provider based on platform reputation systems (ratings)		Rejected
	H3b	Main effect: There is a significant difference on trust in the SE service provider based on independent reputation systems (ratings)		Rejected
	H3c	Interaction effect: There is a significant interaction effect between platform reputation systems (ratings) and independent reputation systems (ratings) in terms of trust in the SE service provider		Rejected
1.3	H4	Platform brand reputation positively affects consumer's trust in the SE platform	BR → TP	Supported
1.1	H5	Trust in the SE service provider influences consumers' propensity to participate in the sharing economy	TH → PP	Supported
	H6	The relationship between platform reputation systems (ratings) and consumers' propensity to participate in the SE is mediated by trust in the service provider	PR → TH → PP	Supported (partial complementary mediation)
1.2	H7	The relationship between independent reputation systems (ratings) and consumers' propensity to participate in the SE is mediated by trust in the service provider	IR → TH → PP	Supported (full mediation)
1.3	H8	Trust in the SE platform influences consumers' propensity to participate in the sharing economy	TP → PP	Supported
	H9	The relationship between platform brand reputation and consumers' propensity to participate in the SE is mediated by trust in the SE platform	BR → TP → PP	Supported (partial complementary mediation)

Notes:

- 1.1: What is the role of platform reputation systems in consumers' trust in the sharing economy?
 1.2: What is the role of independent reputation systems in consumers' trust in the sharing economy?
 1.3: What is the role of platform brand reputation in consumers' trust in the sharing economy?

PR: Platform reputation system
 IR: Independent reputation system
 BR: Platform brand
 TH: Trust in sharing economy service provider / host
 TP: Trust in sharing economy platform
 PP: Propensity to participate in the sharing economy

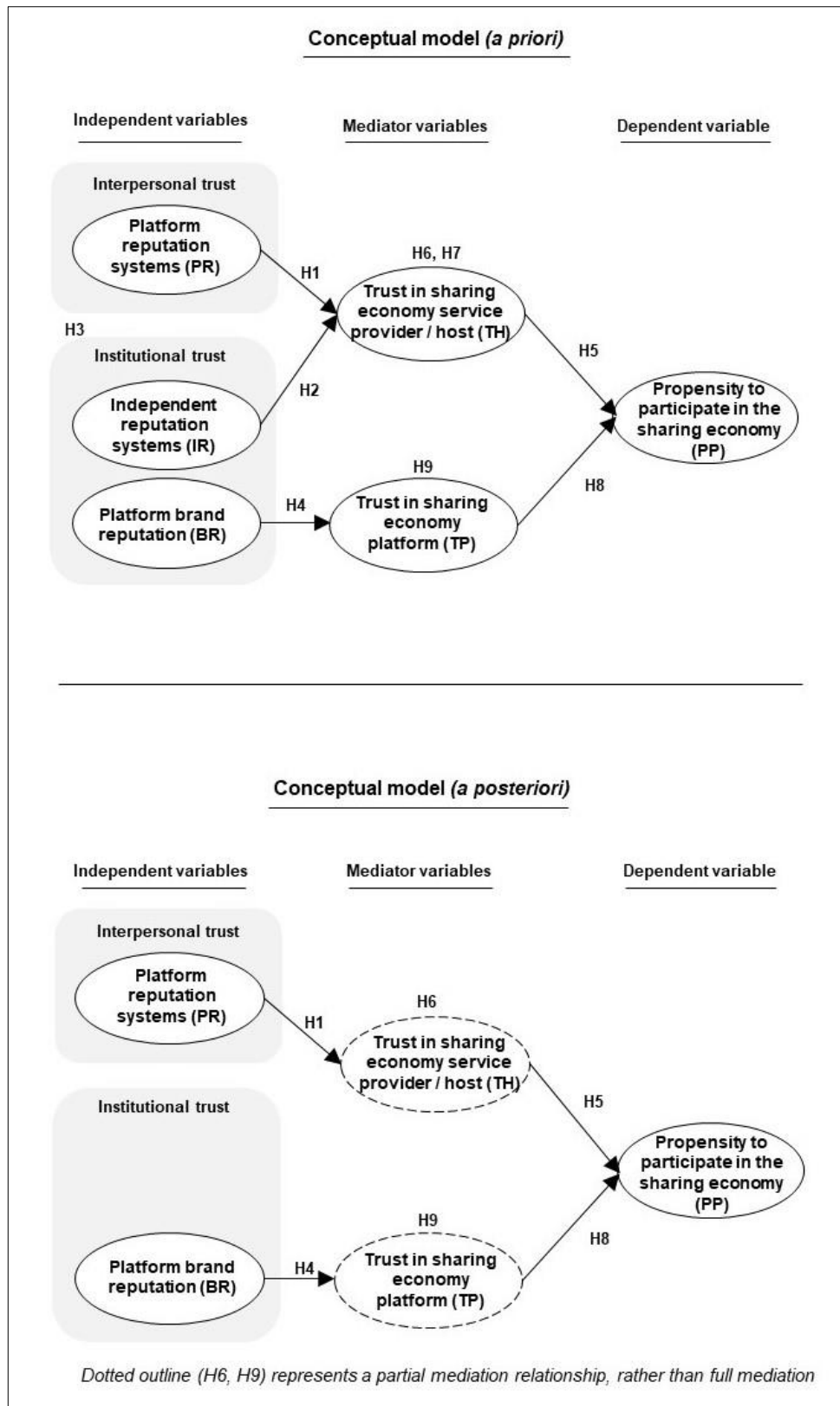


Figure 26: Revision of conceptual model

4.7 Conclusion

In this chapter the results for the various analyses were provided along the four analysis phases introduced in Chapter 3, namely, preliminary analysis (§4.2), descriptive statistics (§4.3), data validation (§4.4), and SEM (§4.5). First, in the preliminary analysis, the data was prepared, coded, cleansed and screened for outliers and multicollinearity issues. This resulted in a sample size of 635 usable responses for the subsequent analyses.

Second, descriptive statistics were run on the data to get a view of the underlying characteristics, in terms of demographics for the categorical questions and measures of central tendency, dispersion, kurtosis and skewness for the Likert-scale questions. All in all, the sample was fairly heterogenous. However, potential for homogeneity was noted as the sample included more Airbnb users (68%) and millennials (54%).

Third, as part of the data validation, the EFA resulted in two measures being removed from the analysis (PP1, PP2). The resultant EFA pattern matrix was used as input into the CFA, which showed adequate model fit, reliability and validity. In addition, all combinations of treatment conditions demonstrated configural invariance. Metric invariance was also evidenced, except for 3 treatment condition combinations (TC 2 & 6; TC & 9; TC 4 & 6). Full scalar invariance was achieved for only 9 treatment condition combinations; 4 were partially scalar invariant and 21 were not scalar invariant.

Lastly, as part of SEM, all structural models demonstrated adequate model fit and explanatory power. The outcome of the SEM resulted in the structural model with significant CVs and mediation (M_{MED}), which was carried forward into the models created for each treatment condition. The outcome from the SEM resulted in a revised conceptual model as support for certain relationships were not proven empirically, specifically for H2 and H3, whereas a partial mediation relationship was noted for H6 and H9.

The preliminary analysis, descriptive statistics and data validation (EFA, CFA) are all analyses that did not have a stated hypothesis; hence, these were interpreted and discussed in this chapter, that is, Chapter 4 (Results). The interpretation of the structural models and hypothesised relationships, as part of the SEM analysis, is discussed next in Chapter 5 (Discussion).

Chapter 5: Discussion

5.1 Introduction

Having outlined the results in the previous chapter, Chapter 5 is organised along two main sections, namely, the structural equation model fit and explanatory power ([§5.2](#)) and hypotheses ([§5.2](#)).

5.2 Model fit and explanatory power

Good model fit was evidenced as the fit indices were within the prescribed guidelines. The borderline results for chi-squared were expected since it is very sensitive to large samples and highly unlikely to be insignificant (Collier, 2020)

Considering that the structural model was iteratively built to achieve the final model, M_{MED} , it is key to note that no modification indices were utilised to improve the model fit for the different structural models. This is because the modification indices aim for better model fit amongst the relationships without an underlying theoretical base to explain why certain relationships are related. For ease of reference the model fit for each model from Chapter 4 is summarised in Table 42. In terms of explanatory power, the selected model (M_{MED}) demonstrated good squared multiple correlations

Table 42: Model fit and squared multiple correlation

Measure	Threshold	M_{SEM}	$M_{ALL CV}$	M_{CV}	M_{MED}
Absolute fit indices					
χ^2/df	< 3 good; < 5 adequate	3.966	2.710	3.273	3.098
RMSEA	< 0.05 good; 0.05 – 0.10 adequate; > 0.10 poor	0.068	0.052	0.060	0.058
SRMR	< 0.05 good; 0.05 – 0.09 adequate	0.080	0.051	0.070	0.063
GFI	> 0.90	0.933	0.947	0.938	0.944
Comparative / incremental fit indices					
CFI	> 0.90	0.949	0.972	0.949	0.955
IFI	> 0.90	0.949	0.972	0.949	0.955
NFI	> 0.90	0.934	0.957	0.929	0.935
TLI	> 0.90	0.933	0.949	0.928	0.933
RFI	> 0.90	0.912	0.921	0.899	0.904
Squared multiple correlation (R^2)					
TH		0.340	0.388	0.362	0.298
TP		0.437	0.474	0.453	0.445
PP		0.611	0.620	0.605	0.579

Note. Threshold values adapted from "Applied structural equation modeling using AMOS: Basic to advanced techniques", by Collier, J. E., 2020, p. 66-67, New York, NY: Routledge.

5.3 Hypotheses

This section is organised by hypothesis as outlined in Table 43. In summary, the main results included (i) the discovery of a floor of high PR ratings, (ii) lack of effectiveness in IR ratings relative to PR ratings (iii) and validation of BR still being important in consumers' trust in the SE platform and propensity to participate in the SE

Table 43: Summary of results per hypothesis

RQ	Hypotheses	Summary of results
1.1	H1 Platform reputation systems (ratings) affect consumers' trust in the SE service provider	<ul style="list-style-type: none"> • 1-star ratings resulted in weaker consumer's trust in the service provider relative to 3-star ratings. • 5-star ratings resulted in stronger consumer's trust in the service provider relative to 3-star ratings.
	H1a Low platform reputation ratings have a weaker effect on consumers' trust in the SE service provider	
	H1b High platform reputation ratings have a stronger effect on consumers' trust in the SE service provider	
1.2	H2 Independent reputation systems (ratings) affect consumers' trust in the SE service provider	<ul style="list-style-type: none"> • 1-star ratings resulted in weaker consumer's trust in the service provider relative to 3-star ratings. • 5-star ratings relative to 3-star ratings were not statistically significant
	H2a Low independent reputation ratings have a weaker effect on consumers' trust in the SE service provider	
	H2b High independent reputation ratings have a stronger effect on consumers' trust in the SE service provider	
1.1, 1.2	H3 The combination of platform reputation systems (ratings) and independent reputation systems (ratings) affect consumers' trust in the service provider at differing levels	<ul style="list-style-type: none"> • Low PR ratings were statistically significant, but 1-star ratings on SE platforms are almost impossible. • Medium PR ratings proved non-significant. • Zervas et al.'s (2020) study confirmed that PR ratings begin at 4.5, that is, a floor of 4.5.
1.3	H4 Platform brand reputation positively affects consumer's trust in the SE platform	<ul style="list-style-type: none"> • BR had a significant influence on TP
1.1	H5 Trust in the SE service provider influences consumers' propensity to participate in the sharing economy	<ul style="list-style-type: none"> • TH had a significant influence on PP
	H6 The relationship between platform reputation systems (ratings) and consumers' propensity to participate in the SE is mediated by trust in the service provider	<ul style="list-style-type: none"> • PR directly influenced PP and had a partial mediation effect on PP through TH.
1.2	H7 The relationship between independent reputation systems (ratings) and consumers' propensity to participate in the SE is mediated by trust in the service provider	<ul style="list-style-type: none"> • IR did not directly influence PP as the p- values were not significant, which indicated that the indirect effect was occurring fully through the TH construct. • Only the 1-star IR rating was fully mediated by TH in its effect on PP.
1.3	H8 Trust in the SE platform influences consumers' propensity to participate in the sharing economy	<ul style="list-style-type: none"> • TP had a significant influence on PP

RQ	Hypotheses	Summary of results
	H9 The relationship between platform brand reputation and consumers' propensity to participate in the SE is mediated by trust in the SE platform	• Positive partial complementary mediation

Notes:

- 1.1: What is the role of platform reputation systems in consumers' trust in the sharing economy?
- 1.2: What is the role of independent reputation systems in consumers' trust in the sharing economy?
- 1.3: What is the role of platform brand reputation in consumers' trust in the sharing economy?

PR: Platform reputation system
 IR: Independent reputation system
 BR: Platform brand
 TH: Trust in sharing economy service provider / host
 TP: Trust in sharing economy platform
 PP: Propensity to participate in the sharing economy

As demonstrated in Chapters 3 and 4, the sequence of specifying each structural model resulted in the selected model, M_{MED} , for analysis. This was also used for each treatment condition. Consequently, the discussion is based on the results from M_{MED} and the corresponding models per treatment condition, where appropriate. In framing the discussion, excerpts of the results are reproduced per hypothesis for ease of reference.

5.3.1 Hypothesis 1

Platform reputation systems (ratings) have a significant influence on consumers' trust in the SE service provider as shown in Table 44. In terms of H1a, the regression coefficient is negative and statistically significant ($\gamma = -0.770$) implying that relative to the PR reference category (3-star), the PR 1-star rating has a weaker influence on trust in the SE service provider. For H1b, the positive and statistically significant regression coefficient ($\gamma = 0.425$) meant that relative to the PR 3-star category, the PR 5-star rating has a stronger influence on trust in the SE service provider.

Table 44: Excerpt of results for H1

Hypothesised relationships (M_{MED})	Standardised estimates	Unstandardised estimates *	S.E.	t-values (critical ratios)	p-values
H1: PR → TH					
H1a: 1 ★ compared to 3 ★	-0.339	-0.770	0.112	-6.885	***
H1b: 5 ★ compared to 3 ★	0.187	0.425	0.11	3.864	***

Notes:

* The use of dummy variables for 1 ★ and 5 ★ ratings necessitates the analysis of unstandardised estimates.

The results are both intuitively and conceptually expected. Naturally, a low rating signals certain characteristics that will influence consumers to not engender trust in such service

providers, whereas a high rating will do so. While the conceptual nature of the results is consistent with prior literature, the numeric experimental operationalisation of ratings has not been studied according to the researcher’s knowledge.

That said, from the literature surveyed, the impact of reputation on a service provider was examined from a static survey perspective, that is, there were no manipulations of the rating score levels. Nonetheless, these studies found positive statistically significant results. For example, Yang et al. (2019) explained the impact of reputation on trust in service providers ($\gamma = 0.425$, $p < 0.001$) through inferring high ratings in their articulation of their survey measure: “Airbnb hosts had a *good reputation* [emphasis added] in the market” (p. 205). Similarly, Mao et al. (2020) explained the impact of cognitive-based trust on trust in service providers ($\gamma = 0.26$, $p < 0.001$) by implying the effectiveness of platform reputation scores in their survey measures of cognitive-based trust.

5.3.2 Hypothesis 2

Independent reputation systems (ratings) has an inconclusive influence on consumers’ trust in the SE service provider as shown in Table 45. The IR 1-star rating has a weaker effect on trust in the SE service provider, relative to the IR 3-star rating, because the regression coefficient is negative and statistically significant for H2a ($\gamma = -0.512$). However, the effect of the IR 5-star rating, relative to the IR 3-star rating, on the trust in the SE service provider is not statistically significant for H2b.

Table 45: Excerpt of results for H2

Hypothesised relationships (M_{MED})	Standardised estimates	Unstandardised estimates *	S.E.	t-values (critical ratios)	p-values
H2: IR → TH					
H2a: 1 ★ compared to 3 ★	-0.227	-0.512	0.11	-4.637	***
H2b: 5 ★ compared to 3 ★	0.026	0.058	0.11	0.531	0.596

Notes:

* The use of dummy variables for 1 ★ and 5 ★ ratings necessities the analysis of unstandardised estimates.

While the weakening in trust in the SE service provider is expected for the IR 1-star rating (H2a), the non-significant result for the IR 5-star rating (H2b) was not. It seems that consumers rarely rely on this rating that was determined by an independent body versus that determined by the collective experiences of other consumers. This is suggestive of the power of informal (social) as opposed to formal (regulatory) rating systems. This could also be due the effectiveness of the platform reputation system acting as an

informal certification system as suggested by Pavlou and Gefen (2004). The non-significance of H2b is corroborated by Pavlou's (2002) examination of buyers' institutional trust in sellers from perceived accreditation in online business-to-business environments, whereby he did not find support for this relationship ($\gamma = 0.06, p > 0.05$).

5.3.3 Hypothesis 3

Across the nine treatment conditions, the results vary in terms of its influence on trust in the SE service provider, as shown in Table 46.

Table 46: Excerpt of results for H3a and H3b per treatment condition

Model	PR	IR	Standardised estimates	Unstandardised estimates *	S.E.	t-values	p-values	Conclusion
H3a: PR → TH								
M ₁	1★	1★	-0.433	-0.982	0.100	-9.773	***	Supported
M ₂	3★	1★	0.074	0.166	0.102	1.625	0.104	Rejected
M ₃	5★	1★	0.359	0.808	0.101	8.022	***	Supported
M ₄	1★	3★	-0.437	-1.003	0.103	-9.718	***	Supported
M ₅	3★	3★	0.082	0.189	0.106	1.786	0.074	Rejected
M ₆	5★	3★	0.355	0.810	0.104	7.799	***	Supported
M ₇	1★	5★	-0.437	-1.008	0.103	-9.805	***	Supported
M ₈	3★	5★	0.091	0.209	0.105	1.990	0.047	Rejected
M ₉	5★	5★	0.344	0.790	0.103	7.633	***	Supported
H3b: IR → TH								
M ₁	1★	1★	-0.229	0.033	0.080	0.412	0.680	Rejected
M ₂	3★	1★	-0.230	-0.514	0.103	-4.999	***	Supported
M ₃	5★	1★	-0.254	-0.569	0.099	-5.780	***	Supported
M ₄	1★	3★	0.084	0.194	0.099	1.955	0.051	Supported
M ₅	3★	3★	0.080	0.182	0.106	1.719	0.086	Rejected
M ₆	5★	3★	0.113	0.261	0.102	2.563	0.010	Supported
M ₇	1★	5★	0.144	0.334	0.099	3.384	***	Supported
M ₈	3★	5★	0.149	0.342	0.105	3.245	0.001	Supported
M ₉	5★	5★	0.140	0.323	0.101	3.189	0.001	Supported

Notes:

* The use of dummy variables for 1 ★ and 5 ★ ratings necessities the analysis of unstandardised estimates.

5.3.3.1 H3a

At low (1-star) PR rating treatment conditions (M₁, M₄, M₇), the regression coefficients are negative and statistically significant ($\gamma = -0.982, \gamma = -1.003, \gamma = -1.008$) respectively. This is consistent with the result of H1 discussed earlier for the overall structural model (M_{MED}), where the 1-star rating is evaluated relative to its reference 3-star rating category.

However, at medium (3-star) PR rating treatment conditions (M₂, M₅, M₈), the regression coefficients are not statistically significant. While, the significance value ($p = 0.047$) for the regression coefficient in M₈ is on the borderline of the 0.05 threshold, it is decided to classify it as non-significant, as even the standardised estimate is the lowest (0.091)

relative to other significant results. It could then be concluded that the results are not statistically significant for M_2 , M_5 and M_8 treatment conditions. This could be because 3-star PR ratings are not commonplace on Airbnb. Thus, it is apparent that Airbnb ratings seem to have a floor that is higher than the 3-star rating level in practice. In a paper published in November 2020, Zervas, Proserpio, and Byers (2020) found that 95% of hosts' properties on Airbnb had an average 4.5- or 5-star PR rating and "virtually none had less than a 3.5 star-rating." (p. 1). Therefore, the findings of this research project is underscored by Zervas et al.'s (2020) findings, and it can be deduced that Airbnb ratings have a floor of 4.5. This explains the non-significance of the results for treatment conditions with 3-star PR ratings.

Lastly, at high (5-star) PR rating treatment conditions (M_3 , M_6 , M_9), the regression coefficients are positive and statistically significant ($\gamma = 0.808$, $\gamma = 0.810$, $\gamma = 0.790$). This is consistent with the result for H1 discussed earlier for the overall structural model (M_{MED}), where the 5-star rating is evaluated relative to its reference 3-star rating category.

In summary of the main effects of the platform reputation system ratings on trust in the SE service provider, while low (1-star) PR ratings are statistically significant, discovering such 1-star ratings on SE platforms, specifically Airbnb, are almost impossible. Also, medium (3-star) PR ratings prove non-significant. Lastly, while all high (5-star) PR rating treatment conditions are significant, Zervas et al.'s (2020) study confirmed that Airbnb ratings begin at 4.5 practically. Therefore, it could be contended that there is a floor on platform reputation system ratings of 4.5.

5.3.3.2 H3b

At low (1-star) IR rating treatment conditions (M_1 , M_2 , M_3), the regression coefficients are negative and statistically significant only for M_2 ($\gamma = -0.514$, $p < 0.001$) and M_3 ($\gamma = -0.569$, $p < 0.001$). This is consistent with the result discussed earlier of the overall structural model (M_{MED}), where the 1-star rating is evaluated relative to its reference 3-star rating category. However, it is interesting to note that at dual low (1-star) PR and IR ratings, the result is positive and non-significant for M_1 ($\gamma = 0.033$, $p = 0.680$).

At medium (3-star) IR rating treatment conditions (M_4 , M_5 , M_6), the regression coefficients are positive and statistically significant for M_4 ($\gamma = 0.194$, $p = 0.051$) and M_6 ($\gamma = 0.261$, $p = 0.010$), but not statistically significant for M_5 ($\gamma = 0.182$, $p = 0.086$).

At high (5-star) IR rating treatment conditions (M_7 , M_8 , M_9), the regression coefficients are positive and statistically significant ($\gamma = 0.334$, $\gamma = 0.342$, $\gamma = 0.323$). However, this is inconsistent with the non-significant result of H2b for the overall structural model (M_{MED}), where the 5-star rating is evaluated relative to its reference 3-star rating category.

5.3.4 Hypothesis 4

Platform brand has a significant influence on consumers' trust in the SE platform as shown in Table 47. The standardised regression coefficient is positive and statistically significant ($\gamma = 0.629$, $p < 0.001$).

Table 47: Excerpt of results for H4

Hypothesised relationships (M_{MED})	Standardised estimates	Unstandardised estimates	S.E.	t-values	p-values
H4: BR → TP	0.629	0.662	0.060	11.103	***

Notes:
S.E.: Standard error
*** $p < 0.001$

The results are consistent with other studies that have also conceptualised platform brand elements in influencing trust in a platform in e-commerce settings.

5.3.5 Hypothesis 5

Trust in the SE service provider (host) has a significant influence on consumers' propensity to participate in the SE, as shown in Table 48. The standardised regression coefficient is positive and statistically significant ($\gamma = 0.591$, $p < 0.001$).

Table 48: Excerpt of results for H5

Hypothesised relationships (M_{MED})	Standardised estimates	Unstandardised estimates	S.E.	t-values	p-values
H5: TH → PP	0.591	0.620	0.058	10.774	***

Notes:
S.E.: Standard error
*** $p < 0.001$

Mittendorf et al. (2019) examined the influence of consumers' trust in service providers on the consumers' intention to engage in the SE service. Interestingly, they found positive and significant results for trust towards accommodation providers on Airbnb ($\gamma = 0.384$, $p = 0.001$), but a non-significant result towards drivers on Uber

($\gamma = 0.094$, $p = 0.204$). Their reasoning in this regard is that the positive effect of consumers' trust on the intention to engage in the service is stronger for SE services that have a high degree of time, social and financial investment, such as accommodation sharing, rather than ride sharing.

5.3.6 Hypothesis 6

At the overall structural model level (M_{MED}), where the medium (3-star) ratings were used as the reference category, the mediation analysis can be interpreted by examining the direct and indirect effects for the PR \rightarrow TH \rightarrow PP relationship. This is shown in Table 49.

Table 49: Excerpt of results for H6

Relationships	Direct effect		Indirect effect		p-value	Conclusion
	Estimate	P-value	Estimate	Confidence interval Low High		
H6: PR \rightarrow TH \rightarrow PP						
1 ★ compared to 3 ★	-0.363 (-3.797)	0.001	-0.478	-0.687 -0.300	0.000	Partial complementary mediation
5 ★ compared to 3 ★	0.210 (2.359)	0.018	0.263	0.140 0.411	0.000	Partial complementary mediation

Notes:

Unstandardised coefficients reported. Values in parentheses are t-values. Bootstrap sample = 5000 with replacement

The low (1-star) PR rating relative to the 3-star rating has a negative and statistically significant effect on PP, directly from PP and indirectly through TH, indicative of the stronger 3-star reference category. The high (5-star) PR rating relative to the 3-star rating has a positive and statistically significant effect on PP, directly from PP and indirectly through TH, which indicated that the reference 3-star category is weaker. Considering that the direct and indirect effects are similar in terms of direction and statistical significance for each of the categories of PR, partial complementary mediation is present. However, the direct effects appear to be slightly weaker than the indirect effects in terms of the absolute values of the estimates.

An excerpt of Table 40 has been reproduced as Table 50 to guide the discussion of the mediation for the PR \rightarrow TH \rightarrow PP relationship across the treatment conditions.

Table 50: Excerpt of results for H6 per treatment condition

Model	PR	IR	Direct effect		Indirect effect			p-value	Conclusion
			Estimate	p-value	Estimate	Confidence interval			
						Low	High		
H6: PR → TH → PP									
M ₁	1★	1★	-0.982 (-9.773)	0.001	-0.630	-0.854	-0.450	0.000	p.c.mediation
M ₂	3★	1★	0.166 (1.625)	0.104	0.123	-0.015	0.275	0.085	Non-significant
M ₃	5★	1★	0.808 (8.022)	0.001	0.546	0.398	0.727	0.000	p.c.mediation
M ₄	1★	3★	-1.003 (-9.718)	0.001	-0.631	-0.842	-0.461	0.000	p.c.mediation
M ₅	3★	3★	0.189 (1.786)	0.074	0.137	-0.003	0.290	0.056	Non-significant
M ₆	5★	3★	0.810 (7.799)	0.010	0.537	0.395	0.706	0.000	p.c.mediation
M ₇	1★	5★	-1.008 (-9.805)	0.001	-0.633	-0.847	-0.458	0.000	p.c.mediation
M ₈	3★	5★	0.209 (1.990)	0.047	0.152	0.008	0.304	0.038	p.c.mediation
M ₉	5★	5★	0.790 (7.633)	0.001	0.524	0.383	0.694	0.000	p.c.mediation

Notes:

Unstandardised coefficients reported. Values in parentheses are t-values. Bootstrap sample = 5000 with replacement.
p.c.mediation: partial complementary mediation

At low (1-star) PR rating treatment conditions (M₁, M₄, M₇), the relationship of PR has a negative and statistically significant effect on PP, both directly and indirectly through TH. While the effects are similar in magnitude across these three models (M₁, M₄, M₇), the direct effect (-0.982, -1.003, -1.008) is stronger than the indirect effect (-0.630, -0.631, -0.633). This contrasts with the overall structural model (M_{MED}), whereby the direct effect (-0.363) is weaker than the indirect effect (-0.478) for a low (1-star) PR rating, relative to its reference 3-star category.

At medium (3-star) PR rating treatment conditions (M₂, M₅, M₈), the relationship of PR has a non-statistically significant effect on PP, both directly and indirectly, except for M₈, which is on the borderline significance value for its direct effect (p=0.047). The non-significance of the medium PR rating can be attested to the lack of such ratings in practice as discussed earlier.

At high (5-star) PR rating treatment conditions (M₃, M₆, M₉), the relationship of PR has a positive and statistically significant effect on PP, both directly and indirectly through TH. While the effects are similar in magnitude across these three models (M₃, M₆, M₉), the direct effect (0.808, 0.810, 0.790) is stronger than the indirect effect (0.546, 0.537, 0.524). This contrasts with the overall structural model (M_{MED}), whereby the direct effect (0.210) is weaker than the indirect effect (0.263) for a high (5-star) PR rating, relative to its reference 3-star category.

Therefore, from a PR rating stance, consumers' propensity to participate in the SE is partially mediated by their trust in the service provider, with the PR rating playing a stronger effect under low and high PR treatment conditions. While Mao et al. (2020) conceptually modelled the hypothesis of cognition-based trust to trust-in-hosts, and then

to behavioural intention, they did not report their mediation effects, making cross-comparison not possible.

5.3.7 Hypothesis 7

Similar to hypothesis 6, at the overall structural model level (M_{MED}), the mediation analysis can be interpreted by examining the direct and indirect effects for the IR → TH → PP relationship. This is shown in Table 51.

Table 51: Excerpt of results for H7

Relationships	Direct effect		Estimate	Indirect effect		p-value	Conclusion
	Estimate	p-value		Confidence interval	Low		
H7: IR → TH → PP							
1 ★ compared to 3 ★	-0.003 (-0.035)	0.972	-0.317	-0.515	-0.164	0.000	Full mediation
5 ★ compared to 3 ★	-0.026 (-0.297)	0.767	0.036	-0.088	0.162	0.589	Non-significant
Notes: Unstandardised coefficients reported. Values in parentheses are t-values. Bootstrap sample = 5000 with replacement							

Independent reputation system ratings does not directly influence PP as the p values are not significant for the low (1-star) ($p = 0.972$) and high (5-star) ($p = 0.767$) rating, which indicates that the indirect effect is occurring fully through the TH construct. Specifically, the low (1-star) IR rating relative to the 3-star rating has a negative and statistically significant effect on PP, indirectly through TH. This means that TH fully mediates the relationship. All other relationships were not statistically significant.

An excerpt of Table 40 has been reproduced as Table 52 to guide the discussion of the mediation for the IR → TH → PP relationship across the treatment conditions.

Table 52: Excerpt of results for H7 per treatment condition

Model	PR	IR	Direct effect		Estimate	Indirect effect		p-value	Conclusion
			Estimate	p-value		Confidence interval	Low		
H7: IR → TH → PP									
M_1	1★	1★	-0.516 (-5.378)	0.001	-0.331	-.516	-.187	0.000	p.c.mediation
M_2	3★	1★	-0.514 (-4.999)	0.001	-0.382	-.571	-.212	0.000	p.c.mediation
M_3	5★	1★	-0.569 (-5.780)	0.001	-0.385	-.577	-.233	0.000	p.c.mediation
M_4	1★	3★	0.194 (1.955)	0.051	0.122	.006	.251	0.037	p.c.mediation
M_5	3★	3★	0.182 (1.719)	0.086	0.133	-.019	.286	0.083	Non-significant
M_6	5★	3★	0.261 (2.563)	0.001	0.173	.044	.318	0.007	p.c.mediation
M_7	1★	5★	0.334 (3.384)	0.001	0.209	.085	.350	0.001	p.c.mediation
M_8	3★	5★	0.342 (3.245)	0.001	0.248	.090	.410	0.001	p.c.mediation
M_9	5★	5★	0.323 (3.189)	0.001	0.214	.084	.355	0.001	p.c.mediation

Notes:
Unstandardised coefficients reported. Values in parentheses are t-values. Bootstrap sample = 5000 with replacement.
p.c.mediation: partial complementary mediation

At low (1-star) IR rating treatment conditions (M_1, M_2, M_3), the relationship of IR has a negative and statistically significant effect on PP, both directly and indirectly through TH. While the effects are similar in magnitude across these three models (M_1, M_2, M_3), the direct effects (-0.516, -0.514, -0.569) are stronger than the indirect effects (-0.331, -0.382, -0.385).

At medium (3-star) IR rating treatment conditions (M_4, M_5, M_6), the relationship of IR has had a positive and statistically significant effect on PP, both directly and indirectly, except for M_5 .

At high (5-star) IR rating treatment conditions (M_7, M_8, M_9), the relationship of IR has a positive and statistically significant effect on PP, both directly and indirectly through TH. While the effects are similar in magnitude across these three models (M_7, M_8, M_9), the direct effects (0.334, 0.342, 0.323) are stronger than the indirect effects (0.209, 0.248, 0.214). This contrasts with the overall structural model (M_{MED}), whereby both the direct and indirect effects are non-significant for a high (5-star) IR rating, relative to its reference 3-star category.

In summary, at an overall level (M_{MED}), at low (1-star) IR ratings, relative to medium (3-star) IR ratings, consumers' propensity to participate in the SE is fully mediated by the trust in the service provider, that is, the rating provides no direct influence on such participation. While, under different treatment conditions, IR ratings plays a stronger effect under low (1-star) and high (5-star) IR treatment conditions.

5.3.8 Hypothesis 8

Trust in the SE platform has a significant influence on consumers' propensity to participate in the SE, as shown in Table 53. The standardised regression coefficient was positive and statistically significant ($\gamma = 0.153, p = 0.002$).

Table 53: Excerpt of results for H8

Hypothesised relationships (M_{MED})	Standardised estimates	Unstandardised estimates	S.E.	t-values	p-values
H8: TP → PP	0.153	0.251	0.079	3.170	0.002

Notes:
S.E.: Standard error

The results obtained are consistent with other studies that have also conceptualised consumers' trust in a platform influencing their propensity to participate. First, the results align with Mittendorf et al.'s (2019) study of trust in the SE, whereby their postulation of trust in the SE platform influenced one's intention to engage in the SE service. Here the authors also received positive and statistically significant results for this specific relationship in two SE platforms, Airbnb ($\gamma = 0.510, p = 0.001$), and Uber ($\gamma = 0.461, p = 0.001$). Second, the results are consistent with Lee et al.'s (2018) examination of consumers' intentions to participate in the SE from trust in the Uber platform, whereby the authors received positive and significant results for their endogenous (thus, β rather than γ) conceptualisation of the relationship ($\beta = 0.31, p < 0.001$). Third, the results of the present research align with Mao et al.'s (2020) assessment of consumers' trust in the Airbnb platform influencing their behavioural intention to use Airbnb ($\beta = 0.56, p < 0.001$).

5.3.9 Hypothesis 9

The direct and indirect effects for the last mediation relationship hypothesis (BR \rightarrow TP \rightarrow PP) at the overall model level (M_{MED}) are provided in Table 54.

Table 54: Excerpt of results for H9

Relationships	Direct effect		Estimate	Indirect effect		p-value	Conclusion
	Estimate	p-value		Confidence interval	Low		
H9: BR \rightarrow TP \rightarrow PP	0.272 (3.222)	0.001	0.166	0.055	0.307	0.004	Partial complementary mediation

Notes:
Unstandardised coefficients reported. Values in parentheses are t-values. Bootstrap sample = 5000 with replacement

Brand reputation has a positive and statistically significant effect on PP, both directly and indirectly through TP. Considering that the direct and indirect effects are similar in terms of direction and statistical significance, partial complementary mediation is present.

5.4 Conclusion

Based on the results obtained and extant literature, the following key results were present: (i) the discovery of a floor of high PR ratings, (ii) lack of effectiveness in IR ratings relative to PR ratings (iii) and validation of BR still being important in consumers' trust in the SE platform and propensity to participate in the SE

As outlined in [§1.4](#), the research objective has been met, that is, how consumers' trust in SE platform reputation systems, independent reputation systems and SE platform brand reputation influences their participation in the SE.

Chapter 6: Conclusion

6.1 Introduction

The structure of this final chapter draws attention to the substantive findings of the research study, the theoretical contribution, provides implications for stakeholders, limitations of the research and suggestions for future research.

6.2 Theoretical implications

The implications for theory from the research study are structured along the research questions that were introduced in Chapter 1.

RQ1: What is the role of trust in influencing consumers' participation in the SE?

In response to the overall research question, it can be concluded that trust plays a significant positive role in influencing consumers to participate and engage in services in the SE. Through a rigorous quantitative methodology, the latent construct of trust was empirically measured through an experiment, its measurement structure was verified, and it was analysed through CB-SEM. This resulted in a structural model, as an abstraction of reality, with acceptable model fit and good explanatory power. Thus, it can be claimed, that based on the conceptualisation and operationalisation of the latent constructs and its resultant model fit and predictive power, trust significantly influences consumers' participation in the SE.

The sub-research questions then disambiguated this latent construct of trust into its component parts to examine the specific trust-generating mechanisms at work in the SE.

RQ1.1: What is the role of platform reputation systems in consumers' trust in the SE?

Platform reputation systems conceptualised through prior consumers' rating of a service provider, have a significant influence on consumers' trust in the SE service provider. Specifically, in terms of the valence of these ratings, lower ratings have a negative effect

on the trust in the service provider, while higher ratings have a positive effect on the trust in the service provider.

While platform reputation systems were more effective in building trust at higher levels, this has underscored the prevalence of a higher rating floor (Zervas et al., 2020) and potential for consumers' reluctance in reporting lower ratings (Berg et al., 2020).

RQ1.2: What is the role of independent reputation systems in consumers' trust in the SE?

Independent reputation systems conceptualised through an independent regulatory body rating a service provider, have limited influence on consumers' trust in the SE service provider. While the valence of lower ratings confirmed a negative directional hypothesis on trust in the service provider, the valence of higher ratings was not statistically significant.

While Zucker (1986) characterised the formation of institutional trust in the late 19th and early 20th century, this present shift away from institutional trust could mark another milestone in the evolution of trust. Beyond the implications for theory in a business and management sense, there are fundamental underlying assumptions and epistemes that can be understood from a philosophical construction of the trust concept. Further interrogation of the trust concept, beyond a technocentric approach, may unravel further implications and opportunities for theory formulation. For example, social capital.

RQ1.3: What is the role of platform brand reputation in consumers' trust in the SE?

Platform brand has a significant positive influence on consumers' trust in the SE platform. Structural assurance factors still play a role in creating a seamless engagement for consumers. Even if they are dealing with strangers, they have trust in the structural mechanisms of the platform in the event of recourse during a problem.

6.3 Contribution

Consistent with Crane, Henriques, Husted, and Matten's (2016) dimensions of theoretical contribution, this research has contributed by means of theoretical application, that is, the application of extant theory to explain emergent phenomena. In this regard, trust theory—through sociological and technological interpretations—has been applied in explaining consumers' trust in the SE. Further, Crane et al. (2016) recommend that good theoretical work constitutes originality, in the form of incremental extensions of knowledge. Taking this into account, this research has juxtaposed two reputation systems (platform reputation and independent reputation) in a novel way.

The second contribution is methodological in nature and situates this research within the vanguard of those studies that have advanced the methodological rigour in the academic field through experimental vignette methodologies (factorial design) and SEM.

Table 55: Contribution

Contribution	Current literature	Theoretical	Methodological
First study to conceptualise and operationalise the combined effect of actual platform reputation systems and independent reputation systems in the form of star rating scores	Prior research has not determined the combined effect of platform reputation systems with independent reputation systems	✓	
Part of the vanguard in operationalising an experimental vignette methodology in a structural equation model	Existing studies include those by Breitsohl (2016, 2019); Iacobucci, Grisaffe, Duhachek, and Marcati (2003a)		✓

6.4 Implications for practice

Implications for the various stakeholders in the SE are discussed. Crane et al. (2016) endorse that besides contributing towards originality, theoretical work must also have utility beyond academia. Given this, the research offers insights to five stakeholder groups: consumers, SE service providers, regulatory bodies, incumbent accommodation providers and SE platforms.

Consumers

For the general consumer, this research provides a better understanding of what trust mechanisms will assist (and not assist) in their purchasing decision-making process in order to mitigate perceived risks that they may hold. The results of this research project corroborated the presence of skewed high platform reputation ratings as examined by (Zervas et al., 2020). Unfortunately, this also reduces the consumer's ability to differentiate between different service providers on SE platforms. Consumers should be wary in relying only on rating scores and supplement their decisions to engage in the SE service with other reputational signals, such as textual reviews and the number of reviews.

SE service providers

While the Airbnb platform has various features for hosts to differentiate themselves, it remains a crowded marketplace. Considering the skewness in ratings towards the higher valence, SE service providers should consider ways to differentiate themselves so that they are able to be selected by potential consumers.

Independent / regulatory bodies

For regulators of the SE and governmental authorities, this research provides an initial view into how consumers place greater weight on platform reputation systems (ratings) over more formal methods of independent reputation systems (ratings). Since independent reputation systems did not effectively contribute to trust in the service provider and propensity to participate in the SE, it could be surmised that instead, the platform reputation system of ratings is effective in filtering out the 'lemons' from the market.

Consistent with Botsman (2015), this is perhaps an indicator that trust is shifting from its institutional nature to an interpersonal one. Instead of enforcing Airbnb establishments to subscribe to the TGCSA rating scheme, the TGCSA should consider supplementing their rating scheme with a reputational aspect that includes consumer reviews.

Incumbent accommodation providers

The results of this research demonstrated that platform brand played a significant role in consumer's trust in the Airbnb platform. Likewise, traditional hotel brands should leverage their brand strength to diversify their portfolio in exploring business model adjacencies. In particular, by partnering with selected prosumer accommodation providers, incumbent hotels can offer a premium value proposition to consumers that is backed by the credibility of its brand through personalising a white labelled software platform for this purpose (Richard & Cleveland, 2016). In other words, hotels can carve out a niche space in the market for consumers that are seeking an authentic local experience (Birinci, Berezina, & Cobanoglu, 2018), but still value the structural assurance factors offered by traditional hotels.

Furthermore, while traditional short-term accommodation establishments may subscribe to independent reputation systems, like that of the TGCSA, they should also consider

diversifying their reputation capital to take advantage of the reputational aspects derived from communities of people, rather than a single entity.

Sharing economy platforms

There is a cliché of trust taking time to build and seconds to be broken. In the absence of independent reputation measures, this fragility of trust means that SE platforms need to rely even more on what they have at their disposal to build trust in their service offering. In particular, with the hospitality sector being severely impacted by the travel restrictions onset by COVID-19, Airbnb needs to re-position themselves in re-building trust that was broken amongst its members (service providers and consumers) when there was large-scale cancellation requests made by the consumers (Boros et al., 2020). The policies (namely relating to cancellation) were structural assurance factors that consumers trusted as part of the Airbnb platform brand. But with the pandemic, this soon became a bone of contention and distrust. While Airbnb has been revising its trust-generating mechanisms over time (Ert & Fleischer, 2019), it is nevertheless suggested that Airbnb, as well as other SE platforms, continue investing in mechanisms and marketing processes that would foster trust in and create value for its members (Dellaert, 2019). Without creating an additional reporting burden for consumers, Airbnb can also supplement its rating system with certain criteria that are used by independent bodies (such as the TGCSA).

Secondly, there are advantages for SE platforms operating in developing countries. The emerging market setting allows for the SE to help overcome development barriers such as asset scarcity (United Nations, 2020) and provides SE platforms with growth opportunities due to inaccessible ownership for many (Wallenstein & Shelat, 2017), creating opportunities for start-ups and incumbents alike. Steenkamp (2020) suggested that branded SE platforms may offer a safeguard in countries characterised by high transaction costs, weak legal systems or high corruption. Airbnb already has various mechanisms in place that serve as structural assurance factors in building institutional trust (Ert & Fleischer, 2019). As established in this research, platform brand played a significant influence in consumers' trust in the platform. Hence, fledgling SE platforms operating in developing countries should learn from Airbnb in building similar safeguards in their platforms to assuage consumers' hesitation from adopting new platforms and their requisite participation in the SE.

6.5 Limitations

Generalisability to other SE platforms

It is acknowledged that the particular commercial SE definition employed in this research is restrictive as it excludes other forms of SE platforms, specifically those that do not require the exchange of money, such as Couchsurfer. Also, the particular operationalisation of ratings used may not be generalisable to other SE settings. For example, if independent ratings existed for meter-taxi drivers, then this would be something that could be compared to the driver rating that is employed by the Uber platform for its drivers. Therefore, the ability to generalise this research model to other SE settings is dependent upon whether the service provider and platform have elements of platform and independent reputation systems that can be appropriately operationalised for the particular context.

Independent reputation systems

The current research study only evaluated the impact of ratings on trust in the SE context, rather than the traditional short-term accommodation sector. The TGCSA ratings may therefore serve other purposes that were not explicitly modelled in this research. The rating by an independent body assures customers of what they can typically expect from a given establishment. For example, such independent ratings conveys certain standard attributes that consumers can expect in a 3-star versus a 5-star hotel (Martin-Fuentes et al., 2018). By contrast, Airbnb establishments are highly heterogenous and vary in their amenities.

Timing

The context of COVID-19 would have skewed participants' trust in the SE and decision-making processes with regards to booking an accommodation during the pandemic. Firstly, from a trust in SE service provider perspective, consumers may have expected more information about the service provider with regards to cleaning protocols and COVID-19 measures implemented; however, such information was not included on the vignette for this research. Secondly, when evaluating trust in the SE platform, participants' responses may have been impacted by the recent debacle experienced with members' cancellation of reservations with Airbnb (Boros et al., 2020), which served as an implicit proxy for a structural assurance factor of the Airbnb brand.

6.6 Suggestions for future research

Future research conducted can focus on the following themes: (i) manipulation of different reputation system elements, (ii) role of platform brand in mitigating institutional voids in specific developing countries as a form of trust enhancement, (iii) extending the model to non-commercial SE platforms by including dispositional trust.

First, where suitable for comparison, different reputation system elements can be manipulated (beyond only star ratings) in assessing consumers' trust in SE service providers. Second, since platform brand strongly influenced consumers' trust in the SE platform, further research can explore to what extent platform brand mitigates institutional voids in developing country contexts. This supplements the call from Steenkamp (2020) to assess how branded SE platforms offer a safeguard in countries characterised by high transaction costs, weak legal systems or high corruption.

Lastly, by incorporating a dispositional trust construct, the model can be applied to other forms of SE platforms beyond commercial SE platforms. For example, Couchsurfer allows for travellers to spend the night on someone's couch for no fee—here the dispositional trust elements arise from interacting with the host and other 'couchsurfers' in the host's home. Also, some SE platforms are designed for sharing beyond commercial reasons, such as BlaBlaCar, whereby drivers open up their car space for passengers that are using the same route as the driver. Again, dispositional trust beyond just the driver arises in this setting.

6.7 Conclusion

With the SE upending traditional sectors and redefining paradigms (Zhang & Chang, 2020), the SE is positioned to alter long-term consumer behaviour (Kathan, Matzler, & Veider, 2016). The SE is an emerging phenomenon of academic inquiry together with understanding how consumers trust and participate in this complex arena.

This research has demonstrated the complexity of trust in the SE. Through a rigorous quantitative methodology, key insights were brought to the fore. First, platform reputation systems in the form of ratings (aggregation of other consumers' rating of a service provider) had a significant effect on consumers' trust in the service provider, also indicating the presence of a rating floor at the upper end of the rating scale. Consumers'

trust in SE service providers (who are strangers) plays a significantly bigger role in consumers' propensity to participate in the SE, compared to their trust in the faceless SE platform brand. Interpersonal trust (conceptualised through platform reputation system ratings) had a stronger influence on consumers' propensity to participate in the SE compared to institutional trust (conceptualised through independent reputation system ratings and platform brand). While independent ratings serve other purposes and may prove to be beneficial for traditional establishments in the short-term accommodation sector, they do not significantly contribute to consumers' trust in the accommodation-sharing economy.

References

- Abraham, B., Parigi, P., Gupta, A., & Cook, K. S. (2017). Reputation offsets trust judgments based on social biases among Airbnb users. *Proceedings of the National Academy of Sciences of the United States of America*, *114*(37), 9848–9853. <https://doi.org/10.1073/pnas.1604234114>
- Abramova, O., Fuhrer, A., Krasnova, H., & Buxmann, P. (2015). Understanding the sharing economy: The role of response to negative reviews in the peer-to-peer accommodation sharing network. *Twenty-Third European Conference on Information Systems (ECIS)*, (June), 1–16. Münster, Germany.
- Aguinis, H., & Bradley, K. J. (2014). Best practice recommendations for designing and implementing experimental vignette methodology studies. *Organizational Research Methods*, *17*(4), 351–371. <https://doi.org/10.1177/1094428114547952>
- Airbnb. (2018). *Airbnb in South Africa: The positive impact of healthy tourism*. Retrieved from <https://news.airbnb.com/wp-content/uploads/sites/4/2018/09/Airbnb-in-South-Africa-Positive-Impact-of-Healthy-Tourism.pdf>
- Akerlof, G. A. (1978). The market for “lemons”: Quality uncertainty and the market mechanism. *Quarterly Journal of Economics*, *84*(3), 488–500. <https://doi.org/10.1017/cbo9780511609381.002>
- Akhmedova, A., Marimon, F., & Mas-Machuca, M. (2020). Winning strategies for customer loyalty in the sharing economy: A mixed-methods study. *Journal of Business Research*, *112*(May 2020), 33–44. <https://doi.org/10.1016/j.jbusres.2020.02.046>
- Amaro, S., Andreu, L., & Huang, S. (2019). Millennials’ intentions to book on Airbnb. *Current Issues in Tourism*, *22*(18), 2284–2298. <https://doi.org/10.1080/13683500.2018.1448368>
- Aneshensel, C. S. (2013). Ruling out alternative explanations: Spuriousness and control variables. In *Theory-based data analysis for the social sciences* (2nd ed., pp. 199–222). <https://doi.org/https://dx-doi-org.uplib.idm.oclc.org/10.4135/9781506335094.n7>
- Atzmüller, C., & Steiner, P. M. (2010). Experimental vignette studies in survey

- research. *Methodology*, 6(3), 128–138. <https://doi.org/10.1027/1614-2241/a000014>
- Bagozzi, R. P., & Yi, Y. (2012). Specification, evaluation, and interpretation of structural equation models. *Journal of the Academy of Marketing Science*, 40(1), 8–34. <https://doi.org/10.1007/s11747-011-0278-x>
- Banerjee, S., Chua, A. Y. K., & Kim, J. J. (2015). Using supervised learning to classify authentic and fake online reviews. *ACM IMCOM 2015 - Proceedings*. <https://doi.org/10.1145/2701126.2701130>
- Bartlett, J. L., Pallas, J., & Frostenson, M. (2013). Reputation and legitimacy: Accreditation and rankings to assess organizations. *The Handbook of Communication and Corporate Reputation*, (April 2018), 530–544. <https://doi.org/10.1002/9781118335529.ch42>
- Basukie, J., Wang, Y., & Li, S. (2020). Big data governance and algorithmic management in sharing economy platforms: A case of ridesharing in emerging markets. *Technological Forecasting and Social Change*, 161(September 2019), 120310. <https://doi.org/10.1016/j.techfore.2020.120310>
- Becker, T. E. (2005). Potential problems in the statistical control of variables in organizational research: A qualitative analysis with recommendations. *Organizational Research Methods*, 8(3), 274–289.
- Belk, R. (2007). Why not share rather than own? *Annals of the American Academy of Political and Social Science*, 611(1), 126–140. <https://doi.org/10.1177/0002716206298483>
- Belk, R. (2014). You are what you can access: Sharing and collaborative consumption online. *Journal of Business Research*, 67(8), 1595–1600. <https://doi.org/10.1016/j.jbusres.2013.10.001>
- Bente, G., Baptist, O., & Leuschner, H. (2012). To buy or not to buy: Influence of seller photos and reputation on buyer trust and purchase behavior. *International Journal of Human Computer Studies*, 70(1), 1–13. <https://doi.org/10.1016/j.ijhcs.2011.08.005>
- Berg, L., Slette-meås, D., Kjørstad, I., & Rosenberg, T. G. (2020). Trust and the don't-want-to-complain bias in peer-to-peer platform markets. *International Journal of*

- Consumer Studies*, 44(3), 220–231. <https://doi.org/10.1111/ijcs.12561>
- Bhattacharya, R., Devinney, T. M., & Pillutla, M. M. (1998). A formal model of trust based on outcomes. *Academy of Management Review*, 23(3), 459–472. <https://doi.org/10.5465/AMR.1998.926621>
- Birinci, H., Berezina, K., & Cobanoglu, C. (2018). Comparing customer perceptions of hotel and peer-to-peer accommodation advantages and disadvantages. *International Journal of Contemporary Hospitality Management*, 30(2), 1190–1210. <https://doi.org/10.1108/IJCHM-09-2016-0506>
- Blair, E., & Blair, J. (2015). Applied survey sampling. In *Applied survey sampling*. <https://doi.org/10.4135/9781483394022.n2>
- Blunch, N. J. (2013). *Introduction to structural equation modeling using IBM SPSS Statistics and AMOS* (2nd ed.; K. Metzler, Ed.). <https://doi.org/10.4135/9781526402257.n1>
- Bollen, K., & Lennox, R. (1991). Conventional wisdom on measurement: A structural equation perspective. *Psychological Bulletin*, 110(2), 305–314. <https://doi.org/10.1037/0033-2909.110.2.305>
- Boros, L., Dudás, G., & Kovalcsik, T. (2020). The effects of COVID-19 on airbnb. *Hungarian Geographical Bulletin*, 69(4), 363–381. <https://doi.org/10.15201/hungeobull.69.4.3>
- Botsman, R. (2015). The changing rules of trust in the digital age. Retrieved January 30, 2021, from Harvard Business Review website: <https://hbr.org/2015/10/the-changing-rules-of-trust-in-the-digital-age>
- Breitsohl, H. (2016). Beyond ANOVA - A tutorial in structural equation models for experimental designs. *Academy of Management Proceedings*, 2016(1), 1–40. <https://doi.org/10.5465/ambpp.2016.12303abstract>
- Breitsohl, H. (2019). Beyond ANOVA: An introduction to structural equation models for experimental designs. *Organizational Research Methods*, 22(3), 649–677. <https://doi.org/10.1177/1094428118754988>
- Brescia, R. (2018). Finding the right “fit”: Matching regulations to the shape of the sharing economy. In N. M. Davidson, J. Infranca, & M. Finck (Eds.), *The*

- Cambridge handbook of the law of the sharing economy* (pp. 156–167). New York, USA: Cambridge University Press.
- Bryman, A., & Bell, E. (2011). *Business research methods* (3rd ed.). Oxford: Oxford University Press.
- Buccola, G. (2019). Brown wooden framed and clear glass door. Retrieved August 19, 2020, from Unsplash website: <https://unsplash.com/photos/4fGCKB4HuZQ>
- Cape Business News. (2016). SA Hospitality industry faces the double-edged sword of online platforms. Retrieved June 10, 2020, from <https://www.cbn.co.za/news/sa-hospitality-industry-faces-the-double-edged-sword-of-online-platforms/>
- Castelfranchi, C., & Falcone, R. (2010). *Trust theory: A socio-cognitive and computational model* (M. Wooldridge, Ed.). West Sussex, Uni: John Wiley & Sons Ltd.
- Chalmers, D., & Matthews, R. (2019). Good to be bad: Should we be worried by the sharing economy? *Strategic Change*, 28(6), 403–408.
<https://doi.org/10.1002/jsc.2295>
- Chan, E. S. W., & Lam, D. (2013). Hotel safety and security systems: Bridging the gap between managers and guests. *International Journal of Hospitality Management*, 32(1), 202–216. <https://doi.org/10.1016/j.ijhm.2012.05.010>
- Charness, G., Gneezy, U., & Kuhn, M. A. (2012). Experimental methods: Between-subject and within-subject design. *Journal of Economic Behavior and Organization*, 81(1), 1–8. <https://doi.org/10.1016/j.jebo.2011.08.009>
- Chasin, F., von Hoffen, M., Cramer, M., & Matzner, M. (2018). Peer-to-peer sharing and collaborative consumption platforms: A taxonomy and a reproducible analysis. *Information Systems and E-Business Management*, 16(2), 293–325.
<https://doi.org/10.1007/s10257-017-0357-8>
- Chasin, F., von Hoffen, M., Hoffmeister, B., & Becker, J. (2018). Reasons for failures of sharing economy businesses. *MIS Quarterly Executive*, 17(3), 185–199.
- Chen, Y., & Wang, L. (2019). Commentary: Marketing and the sharing economy: Digital economy and emerging market challenges. *Journal of Marketing*, 83(5), 28–31.
<https://doi.org/10.1177/0022242919868470>

- Cheng, M. (2016). Sharing economy: A review and agenda for future research. *International Journal of Hospitality Management*, 57, 60–70.
<https://doi.org/10.1016/j.ijhm.2016.06.003>
- Coffelt, T. A. (2017). Confidentiality and anonymity of participants. In M. Allen (Ed.), *The SAGE Encyclopedia of Communication Research Methods* (pp. 228–230).
<https://doi.org/10.4135/9781483381411.n86>
- Collier, J. E. (2020). *Applied structural equation modeling using AMOS: Basic to advanced techniques*. <https://doi.org/10.4324/9781003018414>
- Coltman, T., Devinney, T. M., Midgley, D. F., & Venai, S. (2008). Formative versus reflective measurement models: Two applications of formative measurement. *Journal of Business Research*, 61(12), 1250–1262.
<https://doi.org/10.1016/j.jbusres.2008.01.013>
- Cox, M., & Morris, J. (2020). Detailed listings data for Cape Town. *Inside Airbnb*. Retrieved from <http://data.insideairbnb.com/south-africa/wc/cape-town/2020-06-21/data/listings.csv.gz>
- Crane, A., Henriques, I., Husted, B. W., & Matten, D. (2016). What constitutes a theoretical contribution in the business and society field? *Business and Society*, 55(6), 783–791. <https://doi.org/10.1177/0007650316651343>
- Crane, B. (2020). Revisiting who, when, and why stakeholders matter: Trust and stakeholder connectedness. *Business and Society*, 59(2), 263–286.
<https://doi.org/10.1177/0007650318756983>
- Creswell, J. W., & Creswell, J. D. (2018). *Research design: qualitative, quantitative, and mixed methods approaches* (5th ed.). California: SAGE Publications.
- Cudeck, R. (2000). Exploratory factor analysis. In H. E. . Tinsley & S. . Brown (Eds.), *Handbook of applied multivariate statistics and mathematical modeling* (pp. 265–296). <https://doi.org/10.4135/9781446249345.n3>
- Dalberg. (2015). *Digital sharing for global growth: Sharing resources, building economies*. Retrieved from https://www.digitalsharingeconomy.com/s/DSEReport_Final_2216.pdf
- Davvetas, V., Diamantopoulos, A., Zaefarian, G., & Sichtmann, C. (2020). Ten basic

- questions about structural equations modeling you should know the answers to – But perhaps you don't. *Industrial Marketing Management*, 90(July), 252–263.
<https://doi.org/10.1016/j.indmarman.2020.07.016>
- de la Sablonnière, R., Lina, J. M., & Cárdenas, D. (2019). Rethinking current models in social psychology: A Bayesian framework to understand dramatic social change. *British Journal of Social Psychology*, 58(1), 175–195.
<https://doi.org/10.1111/bjso.12273>
- Delgado-Ballester, E., Munuera-Aleman, J. L., & Yague-Guillen, M. J. (2003). Development and validation of a brand trust scale. *International Journal of Market Research*, 45(1), 1–18. <https://doi.org/10.1177/147078530304500103>
- Delgado-Ballester, E., & Luis Munuera-Alemán, J. (2001). Brand trust in the context of consumer loyalty. *European Journal of Marketing*, 35(11/12), 1238–1258.
<https://doi.org/10.1108/eum0000000006475>
- Dellaert, B. G. C. (2019). The consumer production journey: Marketing to consumers as co-producers in the sharing economy. *Journal of the Academy of Marketing Science*, 47(2), 238–254. <https://doi.org/10.1007/s11747-018-0607-4>
- Department of Tourism. *Tourism Amendment Bill*. , Pub. L. No. Notice 235 of 2019, 4 (2019).
- Diamantopoulos, A., Riefler, P., & Roth, K. P. (2008). Advancing formative measurement models. *Journal of Business Research*, 61(12), 1203–1218.
<https://doi.org/10.1016/j.jbusres.2008.01.009>
- Diamantopoulos, A., & Winklhofer, H. M. (2001). Index construction with formative indicators: An alternative to scale development. *Journal of Marketing Research*, 38(2), 269–277. <https://doi.org/10.1509/jmkr.38.2.269.18845>
- Dobosh, M. A. (2017). Survey: Demographic questions. In M. Allen (Ed.), *The SAGE Encyclopedia of Communication Research Methods* (pp. 1702–1704).
<https://doi.org/https://dx-doi-org.uplib.idm.oclc.org/10.4135/9781483381411.n601>
- du Plessis, E., & Saayman, M. (2011). Grading and price in the accommodation sector of South Africa. *Acta Academica*, 43(1), 130–145.
- Eckhardt, G. M., Houston, M. B., Jiang, B., Lamberton, C., Rindfleisch, A., & Zervas, G.

- (2019). Marketing in the sharing economy. *Journal of Marketing*, 83(5), 5–27.
<https://doi.org/10.1177/0022242919861929>
- Ert, E., & Fleischer, A. (2019). The evolution of trust in Airbnb: A case of home rental. *Annals of Tourism Research*, 75(January), 279–287.
<https://doi.org/10.1016/j.annals.2019.01.004>
- Ert, E., Fleischer, A., & Magen, N. (2016). Trust and reputation in the sharing economy: The role of personal photos in Airbnb. *Tourism Management*, 55, 62–73.
<https://doi.org/10.1016/j.tourman.2016.01.013>
- Ertz, M., Durif, F., & Arcand, M. (2019). A conceptual perspective on collaborative consumption. *Academy of Marketing Science Review*, 9(1–2), 27–41.
<https://doi.org/10.1007/s13162-018-0121-3>
- Fang, B., Ye, Q., Kucukusta, D., & Law, R. (2016). Analysis of the perceived value of online tourism reviews: Influence of readability and reviewer characteristics. *Tourism Management*, 52, 498–506.
<https://doi.org/10.1016/j.tourman.2015.07.018>
- Fang, Y., Qureshi, I., Sun, H., McCole, P., Ramsey, E., & Lim, K. H. (2014). Trust, satisfaction, and online repurchase intention: The moderating role of perceived effectiveness of e-commerce institutional mechanisms. *MIS Quarterly: Management Information Systems*, 38(2), 407–427.
<https://doi.org/10.25300/MISQ/2014/38.2.04>
- Faulkner, P. (2015). The attitude of trust is basic. *Analysis*, 75(3), 424–429.
<https://doi.org/10.1093/analys/anv037>
- Fergusson, A., Ahlqvist, S. R., & Smith, E. (2017). *Is Airbnb safe for guests?: What causes an Airbnb stay to turn into a horror story?* Retrieved from
https://cdn3.asherfergusson.com/wp-content/uploads/2017/11/Is-Airbnb-Safe-for-Guests_-Research-Study-Method-Results-Recommendations.pdf
- Ferrari, M. Z. (2016). Beyond uncertainties in the sharing economy: Opportunities for social capital. *European Journal of Risk Regulation*, 7(4), 664–674.
<https://doi.org/10.1017/S1867299X00010102>
- Field, A. (2009). *Discovering statistics using SPSS* (3rd ed.). London: SAGE Publications Ltd.

- Finch, W. H. (2020). *Exploratory factor analysis*. <https://doi.org/10.4135/97815443399>
- Fornell, C., & Larcker, D. F. (1981). Evaluating structural equation models with unobservable variables and measurement error. *Journal of Marketing Research*, 18(1), 39–50. <https://doi.org/10.1177/002224378101800104>
- Foster, J., Barkus, E., & Yavorsky, C. (2006). *Understanding and using advanced statistics*. <https://doi.org/10.4135/9780857020154>
- Frenken, K., & Schor, J. (2017). Putting the sharing economy into perspective. *Environmental Innovation and Societal Transitions*, 23, 3–10. <https://doi.org/10.1016/j.eist.2017.01.003>
- Gasiorowski-Denis, E. (2017). New ISO solution to support the sharing economy model. Retrieved January 28, 2021, from <https://www.iso.org/news/ref2225.html>
- Gaskin, J. (2016a). DataScreen. Retrieved October 26, 2020, from Stats Tools Package website: <http://statwiki.kolobkcreations.com>
- Gaskin, J. (2016b). *SEM Series (2016) 3. Exploratory Factor Analysis (EFA)*. Retrieved from <https://www.youtube.com/watch?edufilter=NULL&v=VBsuEBsO3U8>
- Gaskin, J. (2016c). *SEM series (2016) 5c. CFA validity correction*. Retrieved from <https://www.youtube.com/watch?edufilter=NULL&v=8Sumk785Fmc%0A>
- Gaskin, J. (2016d). *SEM Series (2016) 6. Multivariate Assumptions*. Retrieved from <https://www.youtube.com/watch?edufilter=NULL&v=J2EkjleK-PE%0A>
- Gaskin, J. (2017). Categorical predictors via dummy variables SmartPLS 3. Retrieved from https://www.youtube.com/watch?edufilter=NULL&v=L-uynRF8_cg
- Gaskin, J. (2020). Structural equation modeling. Retrieved December 11, 2020, from http://statwiki.kolobkcreations.com/index.php?title=Structural_Equation_Modeling
- Gelman, A. (2018). The Failure of Null Hypothesis Significance Testing When Studying Incremental Changes, and What to Do About It. *Personality and Social Psychology Bulletin*, 44(1), 16–23. <https://doi.org/10.1177/0146167217729162>
- Gielens, K., & Steenkamp, J. B. E. M. (2019). Branding in the era of digital (dis)intermediation. *International Journal of Research in Marketing*, 36(3), 367–384. <https://doi.org/10.1016/j.ijresmar.2019.01.005>

- Görör, G. (2016). The definitions of sharing economy: A systematic literature review. *Management*, 13(2), 175–189. <https://doi.org/https://doi.org/10.26493/1854-4231.13.175-189>
- Grepperud, S., Mathisen, T. A., & Pedersen, P. A. (2019). Accreditation in a differentiated duopoly. *Managerial and Decision Economics*, 40(3), 336–349. <https://doi.org/10.1002/mde.3005>
- Grepperud, S., & Pedersen, P. A. (2020). Accreditation in regulated markets. *Managerial and Decision Economics*, 41(7), 1287–1304. <https://doi.org/10.1002/mde.3175>
- Guttentag, D. (2015). Airbnb: disruptive innovation and the rise of an informal tourism accommodation sector. *Current Issues in Tourism*, 18(12), 1192–1217. <https://doi.org/10.1080/13683500.2013.827159>
- Guttentag, D. (2019). Progress on Airbnb: a literature review. *Journal of Hospitality and Tourism Technology*, 10(3), 233–263. <https://doi.org/10.1108/JHTT-08-2018-0075>
- Hair, J. F., Black, W. C., Babin, B. J., & Anderson, R. E. (2010). *Multivariate data analysis* (7th ed.). Essex: Pearson Education.
- Hair, J. F., Ringle, C. M., Gudergan, S. P., Fischer, A., Nitzl, C., & Menictas, C. (2019). Partial least squares structural equation modeling-based discrete choice modeling: an illustration in modeling retailer choice. *Business Research*, 12(1), 115–142. <https://doi.org/10.1007/s40685-018-0072-4>
- Hair, J. F., Sarstedt, M., Hopkins, L., & Kuppelwieser, V. G. (2014). Partial least squares structural equation modeling (PLS-SEM): An emerging tool in business research. *European Business Review*, 26(2), 106–121. <https://doi.org/10.1108/eb-10-2013-0128>
- Hart, C. (2018). *Doing a literature review: Releasing the research imagination* (2nd ed.). London: SAGE Publications.
- Hawlitcshek, F., Teubner, T., & Gimpel, H. (2018). Consumer motives for peer-to-peer sharing. *Journal of Cleaner Production*, 204, 144–157. <https://doi.org/10.1016/j.jclepro.2018.08.326>
- Hawlitcshek, F., Teubner, T., & Weinhardt, C. (2016). Trust in the sharing economy.

- Die Unternehmung, Swiss Journal of Business Research and Practice*, 70(1), 26–44. <https://doi.org/10.5771/0042-059x-2016-1-26>
- Hayes, A. F. (2018). *Introduction to mediation, moderation, and conditional process analysis: A regression-based approach* (2nd ed.). New York: The Guilford Press.
- Hong, J. H., Kim, B. C., & Park, K. S. (2019). Optimal risk management for the sharing economy with stranger danger and service quality. *European Journal of Operational Research*, 279(3), 1024–1035. <https://doi.org/10.1016/j.ejor.2019.06.020>
- Hooper, D., Coughlan, J., & Mullen, M. R. (2008). Structural equation modelling: Guidelines for determining model fit. *The Electronic Journal of Business Research Methods*, 6(1), 53–60. Retrieved from www.ejbrm.com
- Howell, D. C. (2014). *Fundamental statistics for the behavioral sciences* (8th ed.). California: Wadsworth, Cengage Learning.
- Hughes, J. L., Camden, A. A., & Yangchen, T. (2016). Rethinking and updating demographic questions: Guidance to improve descriptions of research samples. *Psi Chi Journal of Psychological Research*, 21(3), 138–151. <https://doi.org/10.24839/b21.3.138>
- Iacobucci, D., Grisaffe, D., Duhachek, A., & Marcati, A. (2003a). FAC-SEM: A methodology for modeling factorial structural equations models, applied to cross-cultural and cross-industry drivers of customer evaluations. *Journal of Service Research*, 6(1), 3–23. <https://doi.org/10.1177/1094670503254271>
- Iacobucci, D., Grisaffe, D., Duhachek, A., & Marcati, A. (2003b). FAC-SEM: A Methodology for Modeling Factorial Structural Equations Models, Applied to Cross-Cultural and Cross-Industry Drivers of Customer Evaluations. *Journal of Service Research*, 6(1), 3–23. <https://doi.org/10.1177/1094670503254271>
- Jacoby, J., & Kaplan, L. B. (1972). The components of perceived risk. *Advances in Consumer Research*, (January 1972), 382–393.
- Jarvis, C. B., MacKenzie, S. B., & Podsakoff, P. M. (2003). A critical review of construct indicators and measurement model misspecification in marketing and consumer research. *Journal of Consumer Research*, 30(2), 199–218. <https://doi.org/10.1086/376806>

- Kamal, P., & Chen, J. Q. (2016). Trust in sharing economy. *Pacific Asia Conference on Information Systems, PACIS 2016 - Proceedings*, (June).
- Kang, J., Manthiou, A., Sumarjan, N., & Tang, L. (Rebecca). (2017). An Investigation of Brand Experience on Brand Attachment, Knowledge, and Trust in the Lodging Industry. *Journal of Hospitality Marketing and Management*, 26(1), 1–22.
<https://doi.org/10.1080/19368623.2016.1172534>
- Kathan, W., Matzler, K., & Veider, V. (2016). The sharing economy: Your business model's friend or foe? *Business Horizons*, 59(6), 663–672.
<https://doi.org/10.1016/j.bushor.2016.06.006>
- Kennedy, J. (2008). Confidentiality. In P. J. Lavrakas (Ed.), *Encyclopedia of survey research methods* (p. 131). <https://doi.org/https://dx-doi-org.uplib.idm.oclc.org/10.4135/9781412963947.n88>
- Kim, D. J., Ferrin, D. L., & Rao, H. R. (2008). A trust-based consumer decision-making model in electronic commerce: The role of trust, perceived risk, and their antecedents. *Decision Support Systems*, 44(2), 544–564.
<https://doi.org/10.1016/j.dss.2007.07.001>
- Krasnova, H., Spiekermann, S., Koroleva, K., & Hildebrand, T. (2010). Online social networks: Why we disclose. *Journal of Information Technology*, 25(2), 109–125.
<https://doi.org/10.1057/jit.2010.6>
- Kremelberg, D. (2011). *Practical statistics: A quick and easy guide to IBM SPSSstatistics, STATA, and other statistical software* (SAGE Publi).
<https://doi.org/10.4135/9781483385655>
- Lee, Z. W. Y., Chan, T. K. H., Balaji, M. S., & Chong, A. Y. L. (2018). Why people participate in the sharing economy: An empirical investigation of Uber. *Internet Research*, 28(3), 829–850. <https://doi.org/10.1108/IntR-01-2017-0037>
- Leedy, P. D., & Ormrod, J. E. (2005). *Practical research: planning and design* (8th ed.). New Jersey: Pearson Education International.
- Li, L., & Wang, W. (2020). The effects of online trust-building mechanisms on trust in the sharing economy: The perspective of providers. *Sustainability*, 12(5), 1717.
<https://doi.org/10.3390/su12051717>

- Luhmann, N. (1979). *Trust and power: Two works by Niklas Luhmann*. New York: John Wiley & Sons.
- Mackenzie, S. B. (2001). Opportunities for improving consumer research through latent variable structural equation modeling. *Journal of Consumer Research*, 28(June 2001), 159–166. Retrieved from <http://www.jstor.org/stable/254330>
- MacKenzie, S. B., Podsakoff, P. M., & Jarvis, C. B. (2005). The problem of measurement model misspecification in behavioral and organizational research and some recommended solutions. *Journal of Applied Psychology*, 90(4), 710–730. <https://doi.org/10.1037/0021-9010.90.4.710>
- Malhotra, N. K. (2006). Questionnaire design and scale development. In R. Grover & M. Vriens (Eds.), *The Handbook of Marketing Research*. <https://doi.org/https://dx-doi-org.uplib.idm.oclc.org/10.4135/9781412973380.n5>
- Mao, Z. (Eddie), Jones, M. F., Li, M., Wei, W., & Lyu, J. (2020). Sleeping in a stranger's home: A trust formation model for Airbnb. *Journal of Hospitality and Tourism Management*, 42(December 2019), 67–76. <https://doi.org/10.1016/j.jhtm.2019.11.012>
- Mara, C. (2020). An analysis of the opportunities and challenges of the sharing economy market in South Africa. *African Journal of Business and Economic Research*, 15(3), 115–133. <https://doi.org/10.31920/1750-4562/2020/V15N3A5>
- Marine-Roig, E. (2017). Online travel reviews: A massive paratextual analysis. In Z. Xiang & D. R. Fesenmaier (Eds.), *Analytics in smart tourism design: Concepts and methods* (pp. 1–10). https://doi.org/10.1007/978-3-319-44263-1_1
- Martin-Fuentes, E., Fernandez, C., Mateu, C., & Marine-Roig, E. (2018). Modelling a grading scheme for peer-to-peer accommodation: Stars for Airbnb. *International Journal of Hospitality Management*, 69(May 2017), 75–83. <https://doi.org/10.1016/j.ijhm.2017.10.016>
- Mauri, A. G., Minazzi, R., Nieto-García, M., & Viglia, G. (2018). Humanize your business. The role of personal reputation in the sharing economy. *International Journal of Hospitality Management*, 73(January), 36–43. <https://doi.org/10.1016/j.ijhm.2018.01.017>
- Mayer, R. C., Davis, J. H., & Schoorman, F. D. (1995). An integrative model of

- organizational trust. *Academy of Management Review*, 20(3), 709–734.
- Mazzella, F., Sundararajan, A., Butt d’Espous, V., & Möhlmann, M. (2016). How digital trust powers the sharing economy: The digitization of trust. *IESE Insight*, (30), 24–31. <https://doi.org/10.15581/002.art-2887>
- McKnight, D. H., & Chervany, N. L. (2001). What trust means in e-commerce customer relationships: An interdisciplinary conceptual typology. *International Journal of Electronic Commerce*, 6(2), 35–59. <https://doi.org/10.1080/10864415.2001.11044235>
- McKnight, D. H., Choudhury, V., & Kacmar, C. (2002). The impact of initial consumer trust on intentions to transact with a web site: A trust building model. *Journal of Strategic Information Systems*, 11(3–4), 297–323. [https://doi.org/10.1016/S0963-8687\(02\)00020-3](https://doi.org/10.1016/S0963-8687(02)00020-3)
- Mitchell, V. W. (1992). Understanding consumers’ behaviour: Can Perceived Risk Theory help? *Management Decision*, 30(3), 26–31. <https://doi.org/10.1108/00251749210013050>
- Mittendorf, C. (2016). What trust means in the sharing economy: A provider perspective on Airbnb.com. *AMCIS 2016: Surfing the IT Innovation Wave - 22nd Americas Conference on Information Systems*, 1–10. San Diego, CA.
- Mittendorf, C., Berente, N., & Holten, R. (2019). Trust in sharing encounters among millennials. *Information Systems Journal*, 29(5), 1083–1119. <https://doi.org/10.1111/isj.12237>
- Mody, M. A., Suess, C., & Lehto, X. (2017). The accommodation experiencescape: a comparative assessment of hotels and Airbnb. *International Journal of Contemporary Hospitality Management*, 29(9), 2377–2404. <https://doi.org/10.1108/IJCHM-09-2016-0501>
- Möhlmann, M. (2019). How to rebuild trust in the sharing economy. Retrieved April 25, 2020, from Warwick Business School, The University of Warwick website: <https://www.wbs.ac.uk/news/how-to-rebuild-trust-in-the-sharing-economy/>
- Möhlmann, M., & Geissinger, A. (2018). Trust in the sharing economy: Platform-mediated peer trust. In N. M. Davidson & M. Finck (Eds.), *The Cambridge Handbook on Law and Regulation of the Sharing Economy*.

<https://doi.org/https://doi.org/10.1017/9781108255882.003>

Nadeem, W., Juntunen, M., Shirazi, F., & Hajli, N. (2020). Consumers' value co-creation in sharing economy: The role of social support, consumers' ethical perceptions and relationship quality. *Technological Forecasting and Social Change*, 151(October 2019), 119786.

<https://doi.org/10.1016/j.techfore.2019.119786>

Naden, C. (2019). Sharing economy gets boost with new iso international committee. Retrieved January 25, 2021, from <https://www.iso.org/news/ref2404.html>

Newlands, G., & Lutz, C. (2020). Fairness, legitimacy and the regulation of home-sharing platforms. *International Journal of Contemporary Hospitality Management*, 32(10), 3177–3197. <https://doi.org/10.1108/IJCHM-08-2019-0733>

Newlands, G., Lutz, C., & Fieseler, C. (2019). The conditioning function of rating mechanisms for consumers in the sharing economy. *Internet Research*, 29(5), 1090–1108. <https://doi.org/10.1108/INTR-03-2018-0134>

Ody-Brasier, A., & Sharkey, A. (2019). Under pressure: Reputation, ratings, and inaccurate self-reporting in the nursing home industry. *Strategic Management Journal*, 40(10), 1517–1544. <https://doi.org/10.1002/smj.3063>

Pallant, J. (2001). *SPSS Survival manual: A step by step guide to data analysis using SPSS for Windows* (pp. 1–295). pp. 1–295. Berkshire: McGraw-Hill Education.

Pavlou, P. A. (2002). Institutional trust in interorganizational exchange relationships: The role of electronic B2B marketplaces. *Journal of Strategic Information Systems*, 11(3–4), 215–243.

Pavlou, P. A., & Fygenson, M. (2006). Understanding and predicting electronic commerce adoption: An extension of the theory of planned behavior. *MIS Quarterly*, 30(1), 115–143.

Pavlou, P. A., & Gefen, D. (2004). Building effective online marketplaces with institution-based trust. *Information Systems Research*, 15(1). <https://doi.org/10.1287/isre.1040.0015>

Pavlou, P. A., Liang, H., & Xue, Y. (2007). Understanding and mitigating uncertainty in online environments: A principal-agent perspective. *MIS Quarterly*, 31(1), 105–

136. Retrieved from <http://papers.ssrn.com/abstract=2380164>

- Penz, E., Hartl, B., Schüßler, E., & Hofmann, E. (2020). Trust building in the sharing economy – evidence from an European perspective. *EMCB 2020 Conference Proceedings: Growing Business in Emerging Markets: Challenges and Drivers for Success, Ljubljana, Slovenia, June 2-3 2020*, 52–55. Retrieved from <http://konference.ef.uni-lj.si/emcb/>
- Peterson, R. A., & Umesh, U. N. (2018). On the significance of statistically insignificant results in consumer behavior experiments. *Journal of the Academy of Marketing Science*, 46(1), 81–91. <https://doi.org/10.1007/s11747-017-0528-7>
- Pett, M. A., Lackey, N. R., & Sullivan, J. J. (2003). Assessing the characteristics of matrices. In *Making sense of factor analysis* (pp. 50–84). <https://doi.org/https://www-doi-org.uplib.idm.oclc.org/10.4135/9781412984898>
- Pickard, A. J. (2017). *Research methods in information* (2nd ed.). London: Facet Publishing.
- Querbes, A. (2018). Banned from the sharing economy: an agent-based model of a peer-to-peer marketplace for consumer goods and services. *Journal of Evolutionary Economics*, 28(3), 633–665. <https://doi.org/10.1007/s00191-017-0548-y>
- Richard, B., & Cleveland, S. (2016). The future of hotel chains: Branded marketplaces driven by the sharing economy. *Journal of Vacation Marketing*, 22(3), 239–248. <https://doi.org/10.1177/1356766715623827>
- Rindfleisch, A., Malter, A. J., Ganesan, S., & Moorman, C. (2008). Cross sectional versus longitudinal survey research: Concepts, findings, and guidelines. *Journal of Marketing Research*, 45(3), 261–279.
- Ritzer, G., & Jurgenson, N. (2010). Production, consumption, prosumption: The nature of capitalism in the age of the digital “prosumer.” *Journal of Consumer Culture*, 10(1), 13–36. <https://doi.org/10.1177/1469540509354673>
- Rousseau, D. M., Sitkin, S. B., Burt, R. S., & Camerer, C. (1998). Not so different after all: A cross-discipline view of trust. *Academy of Management Review*, 23(3), 393–404. <https://doi.org/10.5465/AMR.1998.926617>

- Rudmin, F. (2016). The consumer science of sharing: A discussant's observations. *Journal of the Association for Consumer Research*, 1(2), 198–209.
<https://doi.org/10.1086/685861>
- Sainaghi, R., Köseoglu, M. A., d'Angella, F., & Mehraliyev, F. (2020). Sharing economy: a co-citation analysis. *Current Issues in Tourism*, 23(8), 929–937.
<https://doi.org/10.1080/13683500.2019.1588233>
- Sainaghi, R., Köseoglu, M. A., & Mehraliyev, F. (2020). The intellectual structure of the sharing economy. *Tourism Economics*, 1–20.
<https://doi.org/10.1177/1354816620920434>
- Salkind, N. J. (2010). Demographics. In *Encyclopedia of Research Design* (p. 347). Retrieved from <https://dx-doi-org.uplib.idm.oclc.org/10.4135/9781412961288.n108>
- Santana, J., & Parigi, P. (2015). Risk aversion and engagement in the sharing economy. *Games*, 6(4), 560–573. <https://doi.org/10.3390/g6040560>
- Schor, J. (2016). Debating the sharing economy. *Journal of Self-Governance and Management Economics*, 4(3), 7–22.
- Schwab, D. P. (2011). A model of empirical research. In *Research methods for organizational studies* (2nd ed., pp. 11–22). Routledge.
- Shankar, V., Urban, G. L., & Sultan, F. (2002). Online trust: A stakeholder perspective, concepts, implications, and future directions. *Journal of Strategic Information Systems*, 11(3–4), 325–344. [https://doi.org/10.1016/S0963-8687\(02\)00022-7](https://doi.org/10.1016/S0963-8687(02)00022-7)
- Shaughnessy, H. (2016). Harnessing platform-based business models to power disruptive innovation. *Strategy and Leadership*, 44(5), 6–14.
<https://doi.org/10.1108/SL-07-2016-0061>
- So, K. K. F., Oh, H., & Min, S. (2018). Motivations and constraints of Airbnb consumers: Findings from a mixed-methods approach. *Tourism Management*, 67, 224–236. <https://doi.org/10.1016/j.tourman.2018.01.009>
- Sousa, F. J. (2010). Chapter 9: Metatheories in research: Positivism, postmodernism, and critical realism. In *Advances in Business Marketing and Purchasing* (Vol. 16). [https://doi.org/10.1108/S1069-0964\(2010\)0000016012](https://doi.org/10.1108/S1069-0964(2010)0000016012)
- Statistics South Africa. (2020). *Statistical release P6410: Tourist accommodation*

- (preliminary). Retrieved from
<http://www.statssa.gov.za/publications/P6410/P6410May2020.pdf>
- Steenkamp, J. B. E. M. (2020). Global brand building and management in the digital age. *Journal of International Marketing*, 28(1), 13–27.
<https://doi.org/10.1177/1069031X19894946>
- Sun, S., Law, R., & Zhang, M. (2020). An updated review of tourism-related experimental design articles. *Asia Pacific Journal of Tourism Research*, 25(7), 710–720. <https://doi.org/10.1080/10941665.2019.1699128>
- Sundararajan, A. (2016). *The sharing economy: The end of employment and the rise of crowd-based capitalism*. London: The MIT Press.
- Sundararajan, A. (2019). Commentary: The twilight of brand and consumerism?: Digital trust, cultural meaning, and the quest for connection in the sharing economy. *Journal of Marketing*, 83(5), 32–35. <https://doi.org/10.1177/0022242919868965>
- Sutherland, W., & Jarrahi, M. H. (2018). The sharing economy and digital platforms: A review and research agenda. *International Journal of Information Management*, 43(July), 328–341. <https://doi.org/10.1016/j.ijinfomgt.2018.07.004>
- Svensson, G. (2015). Contemporary process to test the theory of a research model through covariance-based structural equation modeling in business research: Is it science, quasi-science or just non-science ...? *European Business Review*, 27(4), 447–458. <https://doi.org/10.1108/EBR-08-2013-0104>
- Tabachnick, B. G., & Fidell, L. S. (2007). *Experimental designs using ANOVA*. Belmont, California.
- Tadelis, S. (2016). Reputation and feedback systems in online platform markets. *Annual Review of Economics*, 8, 321–340. <https://doi.org/10.1146/annurev-economics-080315-015325>
- Tallant, J., & Donati, D. (2020). Trust: From the philosophical to the commercial. *Philosophy of Management*, 19(1), 3–19. <https://doi.org/10.1007/s40926-019-00107-y>
- Taylor, J. W. (1974). The role of risk in consumer behavior. *Journal of Marketing*, 38(2), 54. <https://doi.org/10.2307/1250198>

- Tehseen, S., Ramayah, T., & Sajilan, S. (2017). Testing and controlling for common method variance: A review of available methods. *Journal of Management Sciences*, 4(2), 142–168. <https://doi.org/10.20547/jms.2014.1704202>
- Ter Huurne, M., Ronteltap, A., & Buskens, V. (2017). Antecedents of trust in the sharing economy: A systematic review. *Journal of Consumer Behaviour*, 16(July), 485–498. <https://doi.org/10.1002/cb.1667>
- TGCSA. (2019). *Tourism Grading Council of South Africa core grading requirements*. Retrieved from <https://www.tourismgrading.co.za/assets/Uploads/10031125-TGCSA-Grading-Criteria-Booklet-REV-20.pdf>
- TGCSA. (2020). TGCSA Membership fees effective 1 April 2019 - 31 March 2020. Retrieved December 31, 2020, from <https://www.tourismgrading.co.za/assets/Uploads/TGCSA-Grading-Fees-01-April-2019-to-31-March-2020.pdf>
- Tham, A. (2016). When Harry met Sally: Different approaches towards Uber and AirBnB—an Australian and Singapore perspective. *Information Technology and Tourism*, 16(4), 393–412. <https://doi.org/10.1007/s40558-016-0070-3>
- Tsao, W. C., Hsieh, M. T., Shih, L. W., & Lin, T. M. Y. (2015). Compliance with eWOM: The influence of hotel reviews on booking intention from the perspective of consumer conformity. *International Journal of Hospitality Management*, 46, 99–111. <https://doi.org/10.1016/j.ijhm.2015.01.008>
- Tussyadiah, I. P., & Park, S. (2018). When guests trust hosts for their words: Host description and trust in sharing economy. *Tourism Management*, 67, 261–272. <https://doi.org/10.1016/j.tourman.2018.02.002>
- United Nations. (2020). Does the sharing economy share or concentrate. In *Frontier Technology Quarterly*. Retrieved from https://www.un.org/development/desa/dpad/wp-content/uploads/sites/45/publication/FTQ_Feb2020.pdf
- Van Alstyne, M. W., Parker, G. G., & Choudary, S. P. (2016). Pipelines, platforms, and the new rules of strategy. *Harvard Business Review*, 94(4), 54–62. <https://doi.org/https://hbr.org/2016/04/pipelines-platforms-and-the-new-rules-of-strategy>

- van Damme, D. (2004). Standards and indicators in institutional and programme accreditation in higher education: A conceptual framework and a proposal. In L. Vlasceanu & L. C. Barrows (Eds.), *Indicators for Institutional and Programme Accreditation in Higher/Tertiary Education* (pp. 127–157).
- Vavilis, S., Petković, M., & Zannone, N. (2014). A reference model for reputation systems. *Decision Support Systems*, 61(1), 147–154.
<https://doi.org/10.1016/j.dss.2014.02.002>
- Wallenstein, J., & Shelat, U. (2017). What's next for the sharing economy? Retrieved April 25, 2020, from BCG Henderson Institute website: <https://www.bcg.com/en-us/publications/2017/strategy-technology-digital-whats-next-for-sharing-economy.aspx>
- Wang, Y., Asaad, Y., & Filieri, R. (2020). What Makes Hosts Trust Airbnb? Antecedents of Hosts' Trust toward Airbnb and Its Impact on Continuance Intention. *Journal of Travel Research*, 59(4), 686–703.
<https://doi.org/10.1177/0047287519855135>
- Williams, L. J., Vandenberg, R. J., & Edwards, J. R. (2009). Structural equation modeling in management research: A guide for improved analysis. *The Academy of Management Annals*, 3(1), 543–604.
<https://doi.org/10.1080/19416520903065683>
- Worthington, R. L., & Whittaker, T. A. (2006). Scale development research: A content analysis and recommendations for best practices. *The Counseling Psychologist*, 34(6), 806–838. <https://doi.org/10.1177/0011000006288127>
- Wu, X., & Shen, J. (2018). A study on Airbnb's trust mechanism and the effects of cultural values-Based on a survey of Chinese consumers. *Sustainability*, 10(9), 1–23. <https://doi.org/10.3390/su10093041>
- Xie, K., Mao, Z. (Eddie), & Wu, J. (2019). Learning from peers: The effect of sales history disclosure on peer-to-peer short-term rental purchases. *International Journal of Hospitality Management*, 76(April 2018), 173–183.
<https://doi.org/10.1016/j.ijhm.2018.05.007>
- Xu, Y. H., Pennington-Gray, L., & Kim, J. (2019). The sharing economy: A geographically weighted regression approach to examine crime and the shared lodging sector. *Journal of Travel Research*, 58(7), 1193–1208.

<https://doi.org/10.1177/0047287518797197>

- Yang, S. B., Lee, K., Lee, H., & Koo, C. (2019). In Airbnb we trust: Understanding consumers' trust-attachment building mechanisms in the sharing economy. *International Journal of Hospitality Management*, 83(October 2018), 198–209. <https://doi.org/10.1016/j.ijhm.2018.10.016>
- Yaraghi, N., & Ravi, S. (2017). The current and future state of the sharing economy. In *Brookings India IMPACT Series*. <https://doi.org/10.2139/ssrn.3041207>
- Zervas, G., Proserpio, D., & Byers, J. W. (2020). A first look at online reputation on Airbnb, where every stay is above average. *Marketing Letters*. <https://doi.org/10.1007/s11002-020-09546-4>
- Zhang, J. Z., & Chang, C.-W. (2020). Consumer dynamics: theories, methods, and emerging directions. *Journal of the Academy of Marketing Science*. <https://doi.org/10.1007/s11747-020-00720-8>
- Zhao, X., Lynch, J. G., & Chen, Q. (2010). Reconsidering Baron and Kenny: Myths and truths about mediation analysis. *Journal of Consumer Research*, 37(2), 197–206. <https://doi.org/10.1086/651257>
- Zloteanu, M., Harvey, N., Tuckett, D., & Livan, G. (2018). Digital identity: The effect of trust and reputation information on user judgement in the sharing economy. *PLoS ONE*, 13(12), 1–19. <https://doi.org/10.1371/journal.pone.0209071>
- Zucker, L. G. (1986). Production of trust: Institutional sources of economic structure, 1840-1920. *Research in Organizational Behavior*, 8, 53–111.

Appendices

Appendix A: Questionnaire



UNIVERSITEIT VAN PRETORIA
UNIVERSITY OF PRETORIA
YUNIBESITHI YA PRETORIA

Welcome! This research study seeks to understand consumers' trust in the short-term accommodation sharing economy in South Africa.

- You will be asked to answer some questions about the topic, which should take you around 8 minutes to complete.
- Your responses are confidential and will not be used to identify you, as personally identifiable information is not tracked.
- Your participation is voluntary, and you can withdraw at any time without any penalty.

If you would like to discuss this research, you may contact me or my supervisors: Dr Mthombeni (mthombenim@gibs.co.za, +27117714000) and Dr Chipp (chippk@gibs.co.za).

By selecting the consent option below, you acknowledge that your participation is voluntary, you are 18 years of age or older, and that you are aware that you may choose to terminate your participation at any time and for any reason.

Thank you,
Avikaar Ramphal (19405864@mygibs.co.za)
Master of Philosophy candidate at the Gordon Institute of Business Science (GIBS), University of Pretoria

I consent, begin the study

I do not consent, I do not wish to participate

Do you know what Airbnb offers?

Yes

No

Have you stayed at an Airbnb establishment before?

Yes

No

Have you stayed in short-term accommodation (for example, a B&B, lodge or hotel) in the past?

Yes

No

Do you plan on staying in short-term accommodation (for example, a B&B, lodge, hotel) in the future?

Yes

No

In which country do you currently reside?

South Africa ▼

Have you been to South Africa before?

Yes

No

Do you plan on visiting South Africa?

Yes

No

Carefully read the below scenario.

You are planning to go on a holiday in the near future and are browsing the Airbnb website or app, looking for a place to stay. You come across an advert, which you open up to find out more information.

- You see that the service provider (Airbnb host), has been rated **5 out of 5 stars**, on average, based on ratings by 21 other customers.
- You also notice that the property is rated **3 out of 5 stars** by the Tourism Grading Council of South Africa, which is an independent tourism grading body.

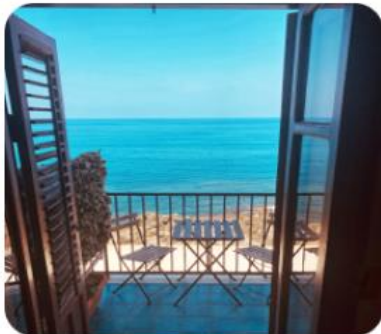
1 star is the lowest and 5 is the highest rating.



Cape Town

Nov 27 - 29

2 guests



Entire apartment in Cape Town, South Africa

Holiday beach apartment

2 guests · 1 bedroom · 1 bed · 1 bath

Free parking · TV · Housekeeping

Please select the extent to which you disagree/agree with following statements, based on the above scenario only, and not on your prior experience with Airbnb.

	Strongly disagree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Strongly agree
Because of the star rating from other customers, I trust the service provider (Airbnb host)	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Because of the star rating from other customers, I will book this Airbnb accommodation	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Because of the star rating from the independent tourism grading body, I trust the service provider (Airbnb host)	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Because of the star rating from the independent tourism grading body, I will book this Airbnb accommodation	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
I trust Airbnb to continue to meet my expectations in the future	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
I feel confident in Airbnb's brand name	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Airbnb's brand name guarantees satisfaction	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Even if not monitored by an independent body, I would trust Airbnb to do the job right	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
I could rely on Airbnb's brand name to solve any problem experienced with this accommodation	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

Airbnb's brand name would compensate me in some way for any problem with the product or service experienced with this accommodation

I am very likely to request a booking for this accommodation on Airbnb in the future

I would not hesitate to request a booking for this accommodation on Airbnb

I would feel comfortable requesting a booking on Airbnb for this accommodation

I would use Airbnb to request a booking for this specific accommodation

Before you finish, your general background information is needed to help better understand the data. This information will be reported in aggregate and cannot be used to personally identify you. Please select only one option from each of the following questions.

How do you currently describe your gender identity?

Male

Female

Please specify:

I prefer not to answer

Indicate your age

Under 23 years old

24 - 39 years old

40 - 55 years old

Over 55 years old

I prefer not to answer

Which category best describes you?

Black African

Coloured

Indian or Asian

White

Other, please specify:

I prefer not to answer

Which category best describes your level of education?

High school

Vocational training

Bachelor's degree

Post graduate degree

Other, please specify:

I prefer not to answer

What is your marital status?

- Single (never married)
- Married, or in a domestic partnership
- Widowed
- Divorced / separated
- Other, please specify:

- I prefer not to answer

Are you currently...?

- Employed part-time
- Employed full-time
- Self-employed
- Not employed
- A student
- Retired
- Other, please specify:

- I prefer not to answer

How often do you purchase online per month?

- 0 times
- 1 - 3 times
- 4 - 6 times
- 7 or more times
- I prefer not to answer



UNIVERSITEIT VAN PRETORIA
UNIVERSITY OF PRETORIA
YUNIBESITHI YA PRETORIA

Thank you for your time spent taking this survey. Your response has been recorded.

Should you know of anyone else that will want to participate in this research, please share the survey link with them: https://pretoria.eu.qualtrics.com/jfe/form/SV_4T7q6rAZxf113m5

If you have any questions, please email me on 19405864@mygibs.co.za.

Regards, Avikaar Ramphal

Appendix B: Pilot survey feedback and improvements

Actual feedback	Actions taken (updates in bold italics)
<p>Participant 1 <i>"AirBnB rating: From a personal perspective, I would not choose a place that had a 5 star rating but rather one that had many high ratings (i.e. 100 ratings averaging 4.5 stars is more important than 5 ratings that average 5 stars). This variable would probably fall out of your research parameter though</i></p> <p><i>I found some of the questions a bit confusing or unclear in how they were worded. There sometimes seemed to be very little difference in the questions. Again, not sure if this is specifically part of the design but the ambiguity might make it hard to interpret the backend results"</i></p>	<p>The average number of reviewers based on data from Cox and Morris (2020) was added as a constant in the vignette for all treatment conditions, as shown below.</p> <p>You see that the service provider (Airbnb host), has been rated [] out of 5 stars, <i>based on ratings by 21 other customers.</i></p>
<p>Participant 2 <i>"I did the survey on my mobile and thought it was very easy to follow and user friendly and was quick to complete. There were three sub-questions on the second last section of the survey questions* that you may want to rephrase but otherwise very clear."</i></p> <p>*Questions:</p> <ul style="list-style-type: none"> • Even if not monitored, I would trust Airbnb to do the job right • I could rely on Airbnb's brand name to solve the problem • Airbnb's brand name would compensate me in some way for the problem with the product or service 	<p>Updated questions:</p> <ul style="list-style-type: none"> • Even if not monitored <i>by an independent body</i>, I would trust Airbnb to do the job right • I could rely on Airbnb's brand name to solve <i>any</i> problem <i>experienced with this accommodation</i> • Airbnb's brand name would compensate me in some way for <i>any</i> problem with the product or service <i>experienced with this accommodation</i>
<p>Participant 3 <i>"I struggled to understand two questions. "I could rely on Airbnb brand name to solve the problem" - It wasn't clear what type of problem this was referring to. " Airbnb's brand name would compensate me in the same way for the problem with the product or service" - same as above."</i></p>	<p>Updated as per actions taken for participant 2.</p>
<p>Participant 4 <i>"It wasn't clear to me whether you wanted to know if I was likely to book* THIS property, or whether I was likely to request a booking via Airbnb generally."</i></p> <p>*Questions:</p> <ul style="list-style-type: none"> • I am very likely to request a booking on Airbnb in the future • I would not hesitate to request a booking on Airbnb • I would feel comfortable requesting a booking on Airbnb • I would use Airbnb to request a booking for a specific accommodation 	<p>Updated questions:</p> <ul style="list-style-type: none"> • I am very likely to request a booking <i>for this accommodation</i> on Airbnb in the future • I would not hesitate to request a booking <i>for this accommodation</i> on Airbnb • I would feel comfortable requesting a booking on Airbnb <i>for this accommodation</i> • I would use Airbnb to request a booking for <i>this</i> specific accommodation
<p>Participant 5</p>	

Actual feedback	Actions taken (updates in bold italics)
<p><i>"What worked well</i></p> <ul style="list-style-type: none"> - <i>questionnaire is short and to the point</i> - <i>a reminder of the case study is a good addition given that when the case is presented there is no context</i> <p><i>Areas of potential improvement</i></p> <ul style="list-style-type: none"> - <i>the first two questions were confusing to me, seems like double negative. You saying given this rating I will book....this got me to revert back to confirm if perhaps 1 is excellent and 5 is bad?</i> - <i>there is a typo in one of the sentences, minor but worth a tidy up</i> - <i>I answered the second part of the questionnaire on the basis of my AirBnB experience not on the case, hope that is what you expected. It felt that if I follow the case, that part is already answered in section 1."</i> 	<p>The typo was corrected, and the vignette text was updated to indicate the star rating direction, as shown below.</p> <p><i>1 star is the lowest and 5 is the highest rating.</i></p>
<p>Participant 6</p> <p><i>"The survey is easy to follow, just looks very big on PC e.g. the scale takes over the full screen. Perhaps position upfront that "the next 3 questions are based on the case study, to reduce the wording on the 3 questions related to the case.</i></p> <p><i>Can we simplify & reduce the number of options on Level of education and Marital status, unless we are trying to prove if Masters/Doctoral degree & level of singleness has different outcomes, we can probably combine some of the options."</i></p>	<p>The font size was reduced to 12 and the question order was updated to follow the vignette, rather than each being on a separate page.</p> <p>The choices for the demographic questions were consolidated:</p> <ul style="list-style-type: none"> • Education: Combined 'Master's', 'Doctorate' and 'specialised' degrees into 'Post-graduate degree'. Removed 'Some high school'. • Marital status: Combined 'divorced' and 'separated'. • Online purchases: Removed the 'Other' answer choice as choices were part of a numeric interval.
<p>Participant 7</p> <p><i>"It's quite brief."</i></p>	
<p>Participant 8</p> <p><i>"Quick to complete and easy to understand!"</i></p>	

Appendix C: Treatment conditions operationalised in Qualtrics

Survey Flow Consumers' trust in the sharing economy

The image displays two identical randomizer elements in a Qualtrics Survey Flow. Each element is a purple box with a white border, containing the following text and controls:

- Randomizer** (title)
- Randomly present 1 of the following elements
- Evenly Present Elements
- [Edit Count](#)
- Buttons: [Add Below](#), [Move](#), [Duplicate](#), [Collapse](#), [Delete](#)

Below each randomizer are three green boxes, each titled "Set Embedded Data:" and containing:

- A field name in a rounded rectangle followed by an equals sign and a value in a rounded rectangle. For the first randomizer, the field is "Airbnb rating" and the value is "1". For the second, it is "Airbnb rating" and "3". For the third, it is "Airbnb rating" and "5".
- An "Add a New Field" link.
- Buttons: [Add Below](#), [Move](#), [Duplicate](#), [Add From Contacts](#), [Options](#), [Delete](#)

Between the two randomizer elements is a green plus sign followed by the text "+ Add a New Element Here".

Appendix D: Code book

Variable	Description	Pre-defined values
Administrative		
RecordedDate	Recorded Date	
Duration	Duration (in seconds)	
ID	ID	
Population boundary		
BOUNDARY_A	Do you know what Airbnb offers?	1 = Yes 2 = No
BOUNDARY_B1	Have you stayed in short-term accommodation (for example, a B&B, lodge or hotel) in the past?	1 = Yes 2 = No
BOUNDARY_B2	Do you plan on staying in short-term accommodation (for example, a B&B, lodge, hotel) in the future?	1 = Yes 2 = No
BOUNDARY_C1	In which country do you currently reside?	Standard list of all countries from Qualtrics
BOUNDARY_C2	Have you been to South Africa before?	1 = Yes 2 = No
BOUNDARY_C3	Do you plan on visiting South Africa?	1 = Yes 2 = No
Manipulation		
PR	Platform reputation (Airbnb rating)	1 3 5
PR_1STAR	Dummy variable for 1-star rating platform reputation	If PR star rating was 1, then PR_1STAR = 1, else 0
PR_3STAR	Dummy variable for 3-star rating platform reputation	If PR star rating was 3, then PR_3STAR = 1, else 0
PR_5STAR	Dummy variable for 5-star rating platform reputation	If PR star rating was 5, then PR_5STAR = 1, else 0
IR	Independent reputation (TGCSA rating)	1 3 5
IR_1STAR	Dummy variable for 1-star rating independent reputation	If IR star rating was 1, then IR_1STAR = 1, else 0
IR_3STAR	Dummy variable for 3-star rating independent reputation	If IR star rating was 3, then IR_3STAR = 1, else 0
IR_5STAR	Dummy variable for 5-star rating independent reputation	If IR star rating was 5, then IR_5STAR = 1, else 0
TREATMENT_CONDITION	Treatment condition	Treatment 1 (PR = 1, IR = 1) Treatment 2 (PR = 3, IR = 1) Treatment 3 (PR = 5, IR = 1) Treatment 4 (PR = 1, IR = 3) Treatment 5 (PR = 3, IR = 3) Treatment 6 (PR = 5, IR = 3) Treatment 7 (PR = 1, IR = 5) Treatment 8 (PR = 3, IR = 5) Treatment 9 (PR = 5, IR = 5)
Likert (*Values: 1 = Strongly disagree; 2 = Somewhat disagree; 3 = Neither agree nor disagree; 4 = Somewhat agree; 5 = Strongly agree)		
TH1	Because of the star rating from other customers, I trust the service provider (Airbnb host)	Likert scale *
TH2	Because of the star rating from the independent tourism grading body, I trust the service provider (Airbnb host)	Likert scale *
TP1	I trust Airbnb to continue to meet my expectations in the future	Likert scale *
TP2	I feel confident in Airbnb's brand name	Likert scale *
TP3	Airbnb's brand name guarantees satisfaction	Likert scale *
BR1	Even if not monitored by an independent body, I would trust Airbnb to do the job right	Likert scale *
BR2	I could rely on Airbnb's brand name to solve any problem experienced with this accommodation	Likert scale *
BR3	Airbnb's brand name would compensate me in some way for any problem with the product or service experienced with this accommodation	Likert scale *

Variable	Description	Pre-defined values
PP1	Because of the star rating from other customers, I will book this Airbnb accommodation	Likert scale *
PP2	Because of the star rating from the independent tourism grading body, I will book this Airbnb accommodation	Likert scale *
PP3	I am very likely to request a booking for this accommodation on Airbnb in the future	Likert scale *
PP4	I would not hesitate to request a booking for this accommodation on Airbnb	Likert scale *
PP5	I would feel comfortable requesting a booking on Airbnb for this accommodation	Likert scale *
PP6	I would use Airbnb to request a booking for this specific accommodation	Likert scale *
Demographic		
AIRNB_USER	Have you stayed at an Airbnb establishment before?	1 = Yes 0 = No
GENDER	How do you currently describe your gender identity?	1 = Male 2 = Female 3 = Please specify 4 = I prefer not to answer
AGE	Indicate your age	1 = Under 23 years old 2 = 24 - 39 years old 3 = 40 - 55 years old 4 = Over 55 years old 5 = I prefer not to answer
RACE	Which category best describes you?	1 = Black African 2 = Coloured 3 = Indian or Asian 4 = White 5 = Other, please specify: 6 = I prefer not to answer
RACE_TEXT	Which category best describes you? - Other, please specify: - Text	
EDU	Which category best describes your level of education?	2 = High school 3 = Vocational training 4 = Bachelor's degree 5 = Post graduate degree 9 = Other, please specify: 10 = I prefer not to answer
EDU_TEXT	Which category best describes your level of education? - Other, please specify: - Text	
MARITAL	What is your marital status?	1 = Single (never married) 2 = Married, or in a domestic partnership 3 = Widowed 4 = Divorced / separated 6 = Other, please specify: 7 = I prefer not to answer
EMPLOY	Are you currently...?	1 = Employed part-time 2 = Employed full-time 3 = Self-employed 4 = Not employed 5 = A student 6 = Retired 7 = Other, please specify: 8 = I prefer not to answer
EMPLOY_TEXT	Are you currently...? - Other, please specify: - Text	
SHOP	How often do you purchase online per month?	1 = 0 times 2 = 1 - 3 times 3 = 4 - 6 times 4 = 7 or more times 6 = I prefer not to answer
Dummy control		
AGE_23	AGE=Under 23 years old	If under 23 years old, then AGE_23 = 1, else 0
AGE_24_39	AGE=24 - 39 years old	If 24 - 39 years old, then AGE_24_39 = 1, else 0
AGE_40_55	AGE=40 - 55 years old	If 40 - 55 years old, then AGE_40_55 = 1, else 0
AGE_55	AGE=Over 55 years old	If over 55 years old, then AGE_55 = 1, else 0
AGE_REF	AGE=I prefer not to answer	If prefer not to answer on age, then AGE_REF = 1, else 0
SHOP_0	SHOP=0 times	If shop online 0 times per month, then SHOP_0 = 1, else 0

Variable	Description	Pre-defined values
SHOP_1_3	SHOP=1 - 3 times	If shop online 1-3 times per month, then SHOP_1_3 = 1, else 0
SHOP_4_6	SHOP=4 - 6 times	If shop online 4-6 times per month, then SHOP_4_6 = 1, else 0
SHOP_7	SHOP=7 or more times	If shop online 7 or more times per month, then SHOP_7 = 1, else 0
SHOP_REF	SHOP=I prefer not to answer	If prefer not to answer on online shopping, SHOP_REF = 1, else 0
Outliers		
MAH_2	Mahalanobis Distance	
Probability_MD	Mahalanobis Distance (probability)	
Outliers	Outliers	
COO_1	Cook's Distance	

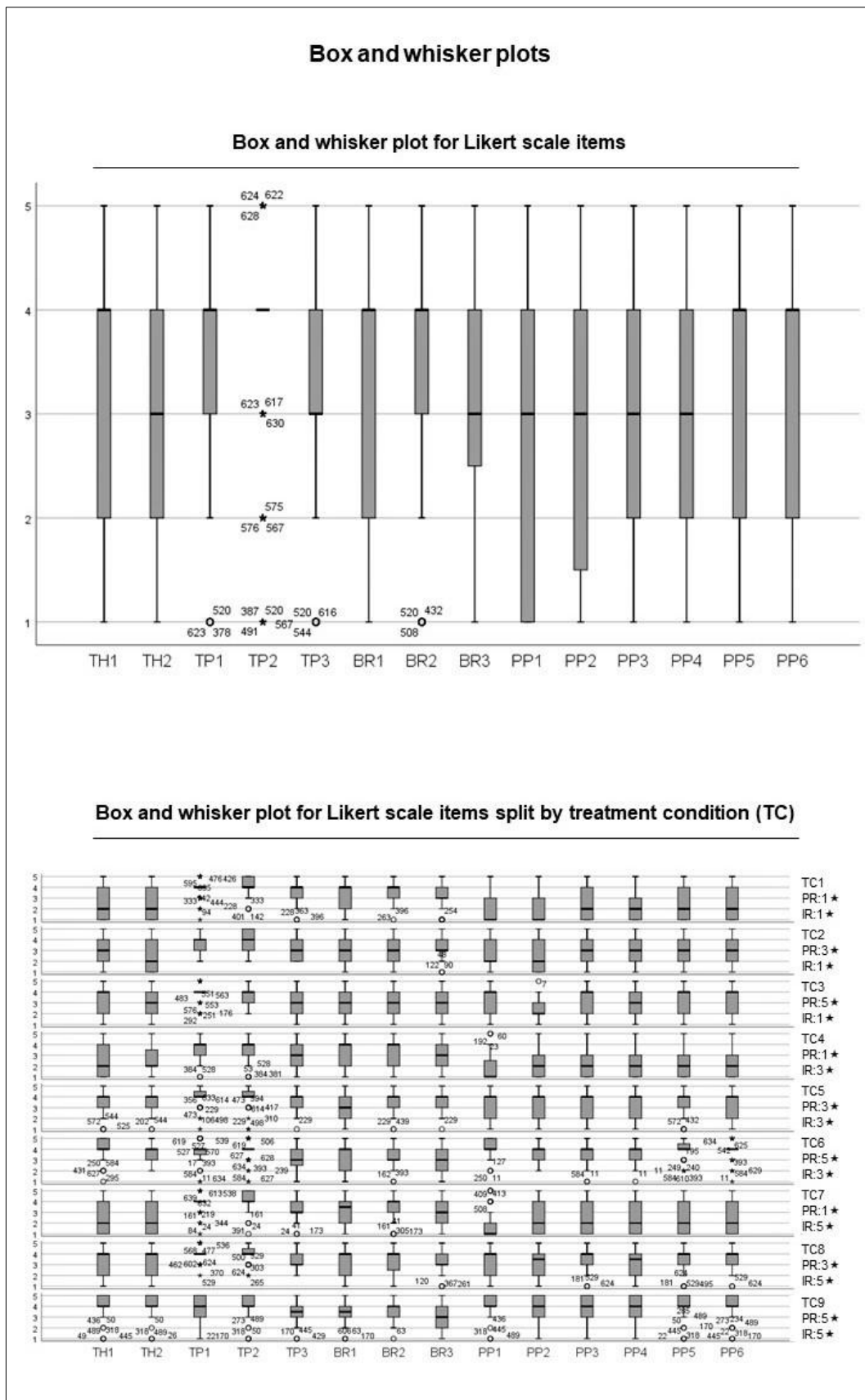
Appendix E: Demographic data per treatment condition

Table 56: Demographic data per treatment condition

Treatment condition	1		2		3		4		5		6		7		8		9		Total
	PR: 1 ★	IR: 1 ★	PR: 3 ★	IR: 1 ★	PR: 5 ★	IR: 1 ★	PR: 1 ★	IR: 3 ★	PR: 3 ★	IR: 3 ★	PR: 5 ★	IR: 3 ★	PR: 1 ★	IR: 5 ★	PR: 3 ★	IR: 5 ★	PR: 5 ★	IR: 5 ★	
	#	%	#	%	#	%	#	%	#	%	#	%	#	%	#	%	#	%	
Airbnb users																			
No	17	23%	26	42%	37	46%	25	37%	22	28%	20	34%	21	30%	17	25%	19	26%	204
Yes	57	77%	36	58%	44	54%	43	63%	57	72%	39	66%	49	70%	51	75%	55	74%	431
Gender identity																			
Female	32	43%	31	50%	38	47%	36	53%	34	43%	20	34%	30	43%	27	40%	36	49%	284
Male	40	54%	31	50%	43	53%	32	47%	45	57%	38	64%	40	57%	41	60%	38	51%	348
I prefer not to answer	2	3%									1	2%							3
Age group																			
Under 23 years old	1	1%		0%	1	1%	1	1%	2	3%		0%	2	3%		0%	1	1%	8
24 - 39 years old	51	69%	30	48%	40	49%	33	49%	37	47%	34	58%	37	53%	40	59%	38	51%	340
40 - 55 years old	18	24%	28	45%	33	41%	31	46%	34	43%	21	36%	29	41%	26	38%	33	45%	253
Over 55 years old	4	5%	4	6%	6	7%	3	4%	6	8%	3	5%	2	3%	2	3%	2	3%	32
I prefer not to answer					1	1%					1	2%							2
Race																			
Indian or Asian	27	36%	24	39%	23	28%	27	40%	20	25%	22	37%	27	39%	20	29%	18	24%	208
White	21	28%	12	19%	26	32%	18	26%	30	38%	19	32%	24	34%	18	26%	28	38%	196
Black African	23	31%	19	31%	21	26%	21	31%	22	28%	14	24%	11	16%	18	26%	26	35%	175
Coloured			3	5%	7	9%	1	1%	6	8%	2	3%	4	6%	6	9%	2	3%	31
Other, please specify:			2	3%	1	1%	1	1%			1	2%							5
I prefer not to answer	3		2	3%	3	4%			1	1%	1	2%	4	6%	6	9%			20
Education																			
High school	5	7%	6	10%	3	4%	3	4%	4	5%	4	7%	9	13%	2	3%	4	5%	40
Vocational training	4	5%	1	2%	1	1%	3	4%	1	1%	1	2%			2	3%			13
Bachelor's degree	14	19%	14	23%	19	23%	13	19%	24	30%	9	15%	19	27%	22	32%	11	15%	145
Post graduate degree	47	64%	38	61%	54	67%	43	63%	47	59%	41	69%	40	57%	39	57%	54	73%	403
Other, please specify:	2	3%	3	5%	4	5%	6	9%	1	1%	3	5%	1	1%	3	4%	4	5%	27
I prefer not to answer	2	3%							2	3%	1	2%	1	1%			1	1%	7
Marital status																			
Single (never married)	23	31%	11	18%	20	25%	22	32%	20	25%	14	24%	17	24%	12	18%	14	19%	153
Married, or in a domestic partnership	46	62%	45	73%	57	70%	42	62%	53	67%	42	71%	49	70%	50	74%	53	72%	437
Divorced / separated	4	5%	5	8%	4	5%	4	6%	6	8%	2	3%	4	6%	3	4%	7	9%	39
Widowed															1	1%			1
I prefer not to answer	1	1%	1	2%							1	2%			2	3%			5
Employment																			
Employed full-time	61	82%	48	77%	65	80%	63	93%	67	85%	50	85%	56	80%	59	87%	64	86%	533
Self-employed	9	12%	10	16%	7	9%	4	6%	8	10%	6	10%	9	13%	4	6%	5	7%	62
A student	1	1%			4	5%	1	1%	1	1%	1	2%	1	1%	2	3%	2	3%	13
Employed part-time			3	5%	1	1%			1	1%	1	2%	3	4%	2	3%	2	3%	13
Not employed	2	3%	1	2%	3	4%			1	1%	1	2%	1	1%					10
Other, please specify:					1	1%			1	1%									2
Retired	1	1%													1	1%			2
Online shopping per month																			
0 times	6	8%	5	8%	6	7%	4	6%	3	4%	3	5%	2	3%			2	3%	31
1 - 3 times	38	51%	35	56%	37	46%	36	53%	41	52%	33	56%	32	46%	47	69%	44	59%	343
4 - 6 times	20	27%	11	18%	20	25%	16	24%	18	23%	9	15%	21	30%	11	16%	17	23%	143
7 or more times	9	12%	10	16%	18	22%	12	18%	16	20%	14	24%	11	16%	8	12%	9	12%	107
I prefer not to answer	1	1%	1	2%					1	1%			4	6%	2	3%	2	3%	11
Country																			
Angola	1	1%																	1
Australia	2	3%							3	4%							2	3%	7
Botswana			1	2%					1	1%			1	1%					3
Canada											1	2%	2	3%	1	1%	1	1%	5
China			1	2%											1	1%	2	3%	4
Colombia					1	1%													1
Egypt			1	2%															1
Finland														2	3%				2
France			1	2%															1
Germany													1	1%	1	1%			2
Ghana																	1	1%	1
India							3	4%					1	1%					4
Israel									1	1%									1
Italy															1	1%			1

Treatment condition	1		2		3		4		5		6		7		8		9		Total
	PR: 1 ★		PR: 3 ★		PR: 5 ★		PR: 1 ★		PR: 3 ★		PR: 5 ★		PR: 1 ★		PR: 3 ★		PR: 5 ★		
	#	%	#	%	#	%	#	%	#	%	#	%	#	%	#	%	#	%	
Kenya	1	1%					1	1%	1	1%			1	1%					4
Malawi					1	1%													1
Mauritius	1	1%					1	1%					1	1%			1	1%	4
Mexico			1	2%															1
Mozambique	1	1%							1	1%				1	1%	1	1%		4
Namibia							1	1%					2	3%					3
Netherlands			2	3%					1	1%									3
New Zealand			1	2%					1	1%									2
Portugal							1	1%									1	1%	2
Singapore							1	1%											1
South Africa	64	86%	50	81%	76	94%	48	71%	63	80%	53	90%	62	89%	55	81%	62	84%	533
Spain	1	1%					1	1%	1	1%									3
Sweden																	1	1%	1
Switzerland													1	1%					1
Thailand							1	1%											1
Turkey			1	2%															1
Uganda					1	1%					2	3%			1	1%			4
United Arab Emirates							2	3%			1	2%			1	1%			4
United Kingdom of Great Britain and Northern Ireland	3	4%	2	3%	1	1%	5	7%	4	5%	1	2%		2	3%	1	1%		19
United Republic of Tanzania							1	1%											1
United States of America			1	2%	1	1%	1	1%											3
Zambia							1	1%			1	2%					1	1%	3
Zimbabwe									2	3%									2
Total respondents	74		62		81		68		79		59		70		68		74		635

Appendix F: Box and whisker plots



Appendix G: Operationalisation of categorical independent variables in AMOS

Avikaar Ramphal 3 weeks ago

Greetings Dr Collier. Thank you for the informative video. I am using your book and on page 244 you have a useful section on "Multicategorical Independent Variables in SEM", where "Adaptive Behavior" has three categories.

In my current research, I have another IV, also with three categories. I am doing a factorial design (experimental vignette) in AMOS and wondering if my two IVs will need to be multiplied to show their combined effect on the DV (however, I note that you use the multiplication method for moderation)?

IV1 has three categories and IV2 has three categories, resulting a 9 cells / combinations.

Show less

  REPLY

 [Hide 2 replies](#)



Joel Collier 3 weeks ago

If you have 2 multicategorical variables there is no need to form an interaction term. With categorical variables forming an interaction term can be problematic because you have dummy coded the variables. So for IV1 you will need to form two dummy coded variables and for IV2 you will need to form two dummy coded variables (see book for full description on setting up dummy variables (p. 245-246). One of your categories would need to be used as a reference for each IV). All of those variables (since they are independent variables) will have a correlation between them. This will let you account for the collective effect on your DV. Thanks for supporting the book.

Source: Collier, J. E. (2020). *How to test mediation with categorical variables in AMOS*. Retrieved from <https://youtu.be/zeTEliwEICA>