JÖNKÖPING UNIVERSITY
Jönköping International Business School

Booked or overlooked? Investigating quality signals in Airbnb reviews

A quantitative study on factors signalling quality in Airbnb Reviews in an emerging tourism market.

MASTER THESIS WITHIN: *Business Administration*
NUMBER OF CREDITS: *30ECTS*
PROGRAMME OF STUDY: *Civilekonom*
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JÖNKÖPING 2025

Master Thesis in Business Administration

Title: Booked or overlooked? Investigating quality signals in Airbnb reviews

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Date: 19/5-2025

Key terms: Airbnb, emerging market, online reviews, signals, signalling theory, quality signals

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Abstract

Background: With travel becoming more accessible, online reviews play a key role in helping consumers evaluate accommodations, especially on peer-to-peer platforms such as Airbnb. In emerging markets such as Bali, where regulatory structures are weaker and information asymmetry is higher, reviews act as important tools to assess quality. As most research focuses on hotels or mature markets, this study aims to address that gap by investigating how five quality signals in Airbnb reviews influence booking intentions in Bali. The research is grounded in signalling theory, offering insights into consumer-decisions in emerging tourism markets.

Purpose: The purpose of this study is to investigate quality signals in reviews on Airbnb and their influence on booking intentions in an emerging tourism market.

Method: A quantitative approach was used, employing an online survey distributed via Prolific and to friends and family to obtain empirical data. The data was analysed using multiple regression- and moderation analysis to examine the impact of quality signals on booking intentions.

Conclusion: The findings show that not all quality signals hold equal importance. Volume, valence, and timeliness significantly influence booking intentions, while trust and usefulness do not. Prior Airbnb experience further moderates these effects, highlighting the role of user familiarity in interpreting review content. These insights contribute to a better understanding

of consumer decision-making in emerging tourism markets and the role of online reviews in reducing uncertainty.

ACKNOWLEDGEMENTS

We would like to express our sincere gratitude to all those who supported us throughout the process of writing this thesis.

Firstly, we extend our heartfelt thanks to our supervisor, Adele Berndt, whose guidance, feedback, and encouragement were instrumental in shaping this work.

We are also grateful to our fellow students and colleagues for their insightful input and constructive feedback during the seminar sessions.

Finally, we would like to thank all the participants who generously took the time to contribute to our study. Their participation made this research possible.

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DECLARATION

We hereby declare that this thesis represents our own work.

We declare that we have obtained the necessary ethical approval (e.g., GDPR) and acknowledged our obligations and the rights of the respondents in the research.

We have read and applied the Jönköping University's current research ethics guidelines with regards to the use of artificial intelligence (AI) tool in this work as presented in the Course Guide. During the preparation of this work the authors used the following AI tools and the purpose for their use.

Endnote – Handling references
ChatGPT - Summarizing articles, handling the structure of the paper, reformulate sentences and for grammar.
Primo Search – Searching for literature
Google Scholar – Searching for literature
SPSS – Handling statistics

As authors, we have reviewed and edited the content as needed and take full responsibility for the content of the thesis.

Signature: Signature:

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1. Introduction

This paper starts with an introduction of the topic to the reader. The background provides an overview of Airbnb, reviews and Bali as an emerging market in the tourism industry. This is followed by the research problem, discussing previous research and the gap this paper intends to fill, followed by the purpose and the research questions. Lastly, key-terms are defined.

1.1 Background

Humans have always been interested in exploring the world and in today's day and age it is easier than ever to travel the world. The internet has not only transformed how people plan their trips but also how they choose where to stay. With an abundance of accommodations available worldwide, what helps travellers decide? Is it the reviews?

The rise of digital platforms has significantly impacted various industries, including tourism and hospitality. Airbnb, for instance, has become a prominent player by implementing a peer-to-peer (P2P) business model that connects property owners (hosts) with prospective renters (guests), offering an alternative to traditional hotels (Barron et al., 2018). This business model is part of the broader platform economy, where technology enables a direct exchange between individuals (Kenney & Zysman, 2016). In this context, user-generated content, such as reviews, serves as a crucial indicator of trust and quality, assisting potential guests in evaluating their accommodation options before booking (Filieri et al., 2020).

In online reviews, quality signals serve as critical indicators that help potential consumers assess the trustworthiness and value of a product or service (Spence, 1973). In the case of Airbnb, where guests cannot inspect properties in person before booking, reviews are essential when evaluating accommodations. Prior research has identified several key quality signals in online reviews, including trustworthiness, usefulness,

volume, direction, and timeliness (Filieri, 2016; Mudambi & Schuff, 2010; Zhao et al., 2015; Wen et al., 2020; Park & Nicolau, 2015).

Airbnb is unique with how they have structured their review system in comparison to other online travel agencies like Booking.com or Expedia. On Airbnb, both the host and the guest can leave a review about their experience with one another, creating a more transparent and fuller picture of the stay (Vassilikopoulou et al., 2022). This attribute of Airbnb's review system gives more dimensions than the competitors and is one of the reasons why Airbnb will be the focus of this study. That together with the platform being recognized by most as a pioneer in the sharing economy as a whole (Barron et al., 2018)

Bali Indonesia has seen a dramatic increase in the number of tourists that have visited the southeastern island over the years and the trend does not seem to stop (Bali, 2023; Airbnb, 2023). This puts Bali in a great place for this study, the market is mature enough that Airbnb is well established on the island, but it is still very much an emerging market. Which according to Yao et al., (2019) is an interesting approach to a study of this kind.

1.2 Research Problem

According to Yao et al. (2019), information asymmetry between guests and hosts is more pronounced on the P2P platform Airbnb than in traditional hotels. This means that one party holds better or more information than the other, which leads to an imbalance of power (Akerlof, 1970). Therefore, guests must sort through the information by Airbnb hosts to find trustworthy signals (Yao et al., 2019), diminish the information asymmetry and reduce uncertainty. Further, it is argued by Sthapit et al., (2019) that information overload negatively impacts booking intentions on Airbnb, stating that guests feel more satisfied when they do not need to process a large volume of information. As guests are looking towards reviews to influence their decisions, do quality signals in reviews play in the intention to book on Airbnb?

While Airbnb has become a major player in the sharing economy, (Chen & Chang, 2018; Zervas et al., 2017), booking on Airbnb comes with more uncertainty compared to hotels. Furthermore, since guests transact with individual hosts, opportunistic behaviour is possible and reputation and trustworthiness may be hard to assess (Zamani et al., 2019). Emerging markets are also important to research as they present higher degrees of risk in their economic environment, increasing integration with world markets and politics (Yang et al., 2019) According to Mckercher & Du Cros (2008), travellers engage in more strategies to reduce risks when travelling to emerging markets, which further highlights the perceived risk of emerging markets. Lastly, Abate et al., (2024) explains that access to information is important in the tourism industry, especially through digital means which is currently underutilized in emerging markets.

Research shows that electronic word-of-mouth (eWOM) strongly influences where travellers choose to stay, as reviews help reduce uncertainty and signal quality (Litvin et al., 2008; Wen et al., 2020). Existing research focus on online reviews in the hotel sector and the impact of negative versus positive reviews (Wen et al., 2020; Sidali et al., 2009; Zhao et al., 2015; Gavilan et al., 2017), Airbnb in mature markets (Yao et al., 2019) and research focusing on specific demographics (Chen & Chang 2018). Hardly any prior research has been conducted examining Airbnb reviews in an emerging market.

This presents a critical gap in the existing literature, as quality signals in the form of trustworthiness (of platform and reviews), usefulness, volume, valence (negative) and timeliness may function differently in reviews in an emerging (tourism) economy. To fill this gap, this study will focus on investigating quality signals in Airbnb reviews in a developing tourism market (Bali) and their booking intentions. The paper will further draw on signalling theory (Spence, 1973) and build upon existing research.

1.3 Purpose and Research Question

This study aims to investigate how five specific quality signals: trustworthiness, usefulness, volume, valence, and timeliness, present in Airbnb reviews influence booking intentions in an emerging tourism market, specifically Bali. In addition, the study seeks

to identify potential differences in the relative importance of these signals, providing insights into which aspects of reviews most effectively signal quality to prospective guests.

The purpose of this study is to investigate quality signals in reviews on Airbnb and their influence on booking intentions in an emerging tourism market.

By identifying which signals are most impactful, the study aims to offer actionable insights for Airbnb hosts seeking to enhance the effectiveness of their review profiles and attract more bookings.

The following research questions will be used in this study to provide guidelines in the research process when investigating the influence of quality signals on booking intentions, and if all signals hold equal importance.

RQ1: To what extent do different quality signals in Airbnb reviews influence consumer booking intentions in a developing tourism market?

RQ2: Do all factors signalling quality hold equal importance on booking intentions in a developing tourism market?

1.4 Defining Key Terms

Below is a brief set of definitions of key terms used in this paper, to ensure comprehension of the research subject. Key terms are listed alphabetically.

Airbnb: A P2P online platform offering short-term rentals where individuals can rent out their spaces. Connecting guests and hosts, Airbnb offers diverse inventory in a global setting (Guttentag 2019).

Emerging market: An emerging market is an economy with low incomes, experiencing rapid growth, economic liberalization and integration into the global economy (Hoskisson et al., 2000). In this paper, the referencing to emerging markets is

used in a tourism setting.

Online reviews: A complementing form of word-of-mouth, providing an important source of information to consumers digitally (Chevalier & Mayzlin 2006). This paper combines the use of "online reviews" and the simpler term "reviews"; however, all mentions refer to digital reviews.

Signals: Conveying information about certain qualities through observable indicators that can help reduce uncertainty in decision-making. (Spence 1973). This paper, focus on quality signals.

Signalling theory: A theory provided by Spence (1973), referring to one party conveying information to another party to mitigate information asymmetry. This concept is further developed in the literature review.

Quality signals: Signals, used to communicate quality that because of information asymmetries might be difficult to evaluate (Filieri et al., 2020). This paper assesses quality signals in the form of trustworthiness (of platform and reviews), usefulness, volume, valence (negative) and timeliness.

2. Literature Review

The purpose of this chapter is to provide a comprehensive theoretical background on quality signals in Airbnb reviews. This chapter will dive into tourism in emerging markets to understand more about emerging markets and why Bali presents an interesting case for the study. It will further continue with reviews in an online context and Airbnb as a platform and their connection. The signalling theory will be discussed along with information asymmetry as the theoretical base of the study. This will lead to quality signals and their purpose in Airbnb reviews. Additionally, the factors of quality signals will be included, discussing their relevance for the study.

2.1 Emerging Markets

Emerging markets are nations undergoing rapid economic growth and industrialization, often accompanied by progressive shifts toward more open and market-oriented economic policies (Hoskisson et al., 2000). Typically, these economies have a relatively low GDP per capita, but have a high growth potential (Li, 2010).

One of the main defining characteristics of emerging markets is the lack of supporting institutions such as a comprehensive regulatory framework, developed financial markets, and effective legal systems (Khanna & Palepu, 2010). These voids can lead to increased transaction costs and uncertainties for businesses operating within these environments (Hoskisson et al., 2000). Therefore, businesses try to use other forms to solve their issues, such as relying on personal networks and informal contacts (Meyer & Peng, 2016).

The rapid economic development in emerging markets is frequently driven by government-led initiatives aimed at economic liberalization, including deregulation, privatization, and the reduction of trade barriers (Hoskisson et al., 2000). Such actions are prioritized to increase foreign direct investment (FDI) and assist in assimilating such

economies into the world marketplace (Meyer & Peng, 2016). The speed and success of such reforms differ across regions and countries leading to different levels of economic and institutional development (Li, 2010).

Recognizing the distinct features of emerging markets is important for firms and policy makers. Rapid economic growth, along with the development of its institutional framework, creates opportunities and challenges simultaneously. While these markets have great potentials and profits, they also carry great risks which require uniquely designed strategies to be deployed relevant to the institutional context and the developmental level of each market (Meyer & Peng, 2016).

2.1.1 Emerging Market: Bali

Bali, an Indonesian island famous for its tourism, culture, and natural landscapes, has recently remapped its economy making it an emerging economy on the world stage. The economy was primarily based on agriculture, focusing mainly on rice farming, but the economy has transformed since the 1980s when tourism began to dominate (Bali, 2023).

The tourism industry of the island is booming and has successfully attracted international tourists as well as foreign investors. Bali recorded roughly 2.88 million foreign visitors in 2022, which greatly benefited the local economy of the island (Bali, 2023). This has caused a shift in the demand across several industries including real estate where there is a clear movement towards more luxurious and sustainable construction (Dwijendra et al., 2024; Suardan & Wijaatmaja, 2024).

Bali has made significant steps towards achieving economic growth but still suffers from things typical of an emerging market such as weak infrastructure and a diffused and rigid legal framework. The fast development and heavy concentration of tourists in the southern part of the island has raised a number of ecological and systematic problems which led to attempts to redistribute the tourism load and enhance sustainability across the island (Salam et al., 2024).

The evolution of the Balinese economy is an example of the constantly changing face of emerging markets, which are expanding and developing simultaneously but struggle with underlying structural and environmental issues. Tackling these problems is essential in order to ensure long term growth and protect the cultural and natural resources that make Bali such a distinct destination.

2.1.2 Tourism and Economic Development in Emerging Markets

Tourism is often described as a catalyst for economic development in emerging markets, contributing to employment, foreign exchange earnings, and infrastructure investment. According to the World Travel & Tourism Council (WTTC), tourism accounted for over 10% of global GDP in pre-pandemic years and is particularly vital in countries where alternative industries are less developed (UNWTO, 2023). For emerging economies, tourism not only drives GDP but also facilitates cross-cultural exchange, stimulates entrepreneurship, and attracts foreign direct investment (Telfer & Sharpley, 2015).

In emerging tourism markets such as Bali, the industry has transformed local economies by creating new revenue streams and integrating informal and semi-formal economic actors (Bali, 2023). However, tourism in such contexts often develops ahead of regulatory, infrastructural, and environmental capacity, leading to sustainability challenges and social displacement if not managed carefully (Salam et al., 2024).

Platforms like Airbnb introduce additional complexity. While they democratize access to tourism income, they also raise concerns about informalization, regulatory voids, and rising housing costs (Guttentag, 2015). In destinations such as Bali, Airbnb has made it easier for local and foreign property owners to monetize accommodations, expanding the tourism base but also intensifying competition with traditional hospitality providers (Tavor, 2024). This dual role of tourism as an opportunity and a challenge makes it crucial to investigate not only how consumers choose accommodations in emerging markets, but also how platforms such as Airbnb shape local economic dynamics and trust mechanisms.

2.2 Sharing economy

In a socio-economic system known as a sharing economy, people share assets that are not in use through digital platforms (Sundararajan, 2016). This model has impacted many industries such as transportation with Uber and Lyft, finance through P2P lending, or hospitality through platforms such as Airbnb. The sharing economy enables consumers to receive services on demand without fully owning a particular item, increasing the efficiency of resource use as well as benefiting the participants financially (Botsman & Rogers, 2010).

With the rise of platforms such as Airbnb, the hospitality industry has witnessed a shift in consumer preferences where they have moved away from traditional hotel stays to more unique and localized experiences (Guttentag, 2019). While traditional hospitality service providers have relied on brand loyalty and a set level of service, Airbnb greatly relies on customer reviews and trust for good business (Ert, Fleischer, Magen, 2016). The impact of this shift is particularly relevant in emerging markets, where regulatory frameworks for short-term rentals are still developing, creating both opportunities and challenges for market participants (Ikkala & Lampinen, 2015). Additionally, research suggests that consumers in the sharing economy prioritize aspects such as authenticity, local engagement, and unique experiences over standardized services (Bucher et al., 2018).

2.3 Peer-to-peer Platforms

P2P platforms are service or product marketplaces for individual users that do not require any middlemen (Einav et al., 2016). Under this model, an individual can act both as a provider and a consumer, using valuable resources that would otherwise go to waste (Sundararajan, 2016). Some examples are Uber for rides, Upwork for freelance work, and Airbnb for accommodations.

While traditional businesses with centralized management systems have policies and procedures to regulate them, P2P platforms work on user trust, technological systems, and reputation (Botsman & Rogers, 2010). Studies, however, have found issues in dealing with these systems, especially in developing countries where digital literacy and

platform saturation is considerably lower (Misra, n.d.). Trust is a very important factor in P2P dealings where business is conducted with complete strangers, and trust mechanisms such as user reviews and ratings, help in this regard.

2.4 Airbnb

Airbnb is an online P2P accommodation platform where individuals rent out their properties or spare rooms to travellers (Guttentag, 2019). Since its inception in 2008, it has evolved into one of the world's most prominent hospitality platforms, now operating in over 240 countries and regions and featuring more than eight million listings worldwide (Airbnb, 2025b). Unlike traditional hotel chains or Online Travel Agencies (OTAs) such as Booking.com or Expedia, Airbnb does not own or manage any physical properties; it operates as a digital intermediary, facilitating transactions between private individuals (Kenney & Zysman, 2016). Its core business model is based on a platform logic, where value is co-created through network interactions between hosts and guests (Sundararajan, 2016).

Airbnb's rise reflects a broader trend in the sharing economy, which emphasizes access over ownership, decentralized participation, and reputation-based trust (Belk, 2014). By relying on user-generated content, two-sided reviews, and algorithmically driven visibility, Airbnb challenges traditional notions of service quality, risk management, and hospitality standards. Its trust-based infrastructure allows participants to engage in commerce outside of formal institutions, making the platform especially influential in markets with less regulatory oversight (Zamani et al., 2019).

This platform economy model has allowed Airbnb to disrupt conventional hospitality by capitalizing on the growing demand for authentic, localized, and experience-driven travel (Guttentag, 2015; Bucher et al., 2018). Travelers are increasingly motivated by opportunities to "live like a local," engage with communities, and stay in unique accommodations that reflect cultural character. Airbnb enables such experiences through its diverse range of listings, many of which fall outside the boundaries of standardized hotel offerings.

In emerging markets such as Bali, Airbnb offers low-barrier entry for micro-entrepreneurs and flexibility for travellers, especially in areas where hotel infrastructure may be underdeveloped or unevenly regulated (Airbnb, 2019; Abate et al., 2024). Its adaptability to informal economies, combined with a scalable digital infrastructure, makes it not only a disruptor but also a platform uniquely positioned to thrive in non-traditional tourism ecosystems.

2.4.1 What Makes Airbnb Distinct from Traditional OTAs

Airbnb differs from traditional Online Travel Agencies (OTAs) in several fundamental ways. While OTAs such as Booking.com and Expedia primarily serve as intermediaries between travellers and professionally managed hotels, Airbnb is built upon a P2P model that allows individual hosts to offer short-term accommodations directly to guests. These structural and operational differences have significant implications for how consumers assess quality, trustworthiness, and risk. Consequently, Airbnb offers a distinctive context for studying perceived quality signals in digital review environments, particularly in emerging tourism markets where regulatory structures are less formalized and standardized quality metrics are lacking.

2.4.1.1 The Market Structure

Airbnb operates under a P2P framework, enabling non-professional hosts to list their properties and interact directly with guests. This model allows for a greater diversity of listings, including private homes, shared rooms, and unconventional accommodations such as treehouses and boats, which are often not available through traditional OTAs (Kenney & Zysman, 2016; Guttentag, 2015). In contrast, Booking.com and Expedia largely feature standardized, commercial properties that align with conventional hotel norms. Airbnb’s decentralized supply introduces substantial variability in quality, prompting users to rely more heavily on user-generated review content to assess value and trustworthiness (Ert et al., 2016).

2.4.1.2 Two-Sided Reputation Mechanism

Unlike most OTAs, Airbnb employs a reciprocal review system, where both guests and hosts evaluate one another. Reviews are only published after both parties have submitted feedback or after a predefined time limit. This two-way mechanism fosters a sense of mutual accountability, promoting greater trust within the platform's user community (Ikkala & Lampinen, 2015). By contrast, Booking.com and Expedia use unidirectional review systems, where only guests rate their stays. Airbnb's socially embedded design enhances the complexity and richness of the reputation system and increases reliance on review-based trust signals.

2.4.1.3 Host Autonomy and Flexible Pricing

Airbnb grant hosts considerable pricing autonomy, allowing them to set and adjust rates based on demand, availability, and personal discretion. Hosts may also use dynamic pricing tools, including Airbnb's own "Smart Pricing" feature (Wang & Nicolau, 2017). In contrast, traditional OTAs often enforce rate parity agreements with hotel partners, leading to more standardized pricing across platforms. Airbnb's flexible model supports more responsive, personalized pricing strategies and introduces greater variability in perceived value (Teubner et al., 2017). This variability makes pricing a more nuanced signal of quality, especially in the absence of formal rating systems.

2.4.1.4 User-Centric Quality Evaluation

Traditional OTAs frequently rely on institutional quality markers, such as star ratings assigned by third parties or standardized checklists. Airbnb, however, relies entirely on user-generated content, including both quantitative star ratings and qualitative narrative reviews. Guests rate experiences across multiple dimensions (e.g., cleanliness, communication, location), and these metrics form the basis of reputation and perceived reliability (Filieri, 2016; Zhao et al., 2015). This decentralized approach to quality evaluation means that subjective review signals take on greater importance in consumer decision-making.

2.4.1.5 Personal Interaction and Customization

A key differentiator of Airbnb is its facilitation of direct communication between hosts and guests, before and during the stay. Unlike OTAs, where interaction is often mediated by front-desk staff or standardized customer service protocols, Airbnb enables personalized exchanges, including custom check-in instructions, local recommendations, and flexible arrangements (Ikkala & Lampinen, 2015). This relational dynamic contributes to perceptions of authenticity and hospitality, particularly in culturally immersive destinations.

2.4.1.6 Perceived Risk and Informational Asymmetry

Airbnb bookings typically involve greater perceived risk than traditional hotel stays. This stems from a lack of formal regulation, host variability, and the non-standard nature of listings (Ert et al., 2016). As a result, users face heightened informational asymmetry, relying heavily on quality signals such as review valence, usefulness, volume, trustworthiness, and timeliness to assess the reliability of listings (Filieri, 2016). By contrast, OTAs mitigate this uncertainty through standardized amenities, brand affiliation, and professional service expectations. Airbnb's risk profile makes it a more demanding environment for review interpretation.

2.4.1.7 Narrative-Rich Reviews and Contextual Signals

Airbnb reviews are characteristically longer, more descriptive, and emotionally expressive than the concise, utilitarian reviews often found on Booking.com or Expedia. They frequently detail not only the property itself but also the host, neighbourhood, and surrounding environment (Bridges & Vásquez, 2018). This narrative richness provides contextual signals that help future guests form expectations and make informed judgments.

2.4.1.8 Regulatory and Institutional Context

Airbnb frequently operates in regulatory grey zones, especially in emerging markets where legal frameworks for short-term rentals are underdeveloped. Unlike hotels listed on OTAs, Airbnb hosts may not be subject to licensing, taxation, or regular inspections

(Guttentag, 2015). This absence of institutional safeguards increases consumer reliance on peer-generated review mechanisms to assess safety, legality, and service quality.

2.4.1.9 Cultural Relevance and Market Flexibility

In culturally diverse and tourism-dependent destinations like Bali, Airbnb offers a level of cultural customization and market adaptability that traditional OTAs often lack. Its ability to accommodate varied travel preferences ranging from budget-conscious backpackers to luxury tourists, makes it well-suited for serving fragmented markets with informal economies Mody et al. (2017). Furthermore, Airbnb expands access to tourism by allowing local homeowners to enter the hospitality sector with minimal barriers, encouraging micro-entrepreneurship.

2.4.2 Trust in the Platform Economy: Airbnb

Trust is essential in the platform economy and with regards to Airbnb, trust is divided into the platform, hosts, and reviews (Ert et al., 2016).

Trust in the Platform: Trust plays a vital part in how consumers view Airbnb's booking services. Features such as identity checks, secured payment channels, and customer care interactions further endorse trust (Zervas et al.,2017).

Trust in the Host: Guests evaluate host credibility based on factors such as response rate, profile completeness, and previous guest reviews. Superhost status for example, signal's reliability and enhances trust (Ikkala & Lampinen, 2015).

Trust in Reviews: Since Airbnb lacks a standardized quality rating system, travellers heavily rely on past guest reviews to assess the quality and legitimacy of a listing. However, the reliability of reviews may be impacted by rating inflation or review bias (Filieri, 2016).

Trust within P2P networks, and consequently the sharing economy and Airbnb, is especially important to consider within emerging markets owing to variation in level of

digital literacy and trust towards online transactions (Mckercher & Du Cros, 2008). As opposed to developed markets which have strong consumer protection frameworks, emerging markets tend to have weaker legal systems regulating peer to peer transactions which makes trust mechanisms, such as reviews, even more important for decision making (Ronteau et al., 2023). Additionally, research highlights that cultural differences influence how trust is perceived, with some societies placing greater emphasis on peer recommendations and personal networks rather than digital verification methods (Bucher et al., 2018).

2.5 Reviews

Online reviews function as a form of electronic word-of-mouth (eWOM), playing a critical role in shaping consumer behaviour, particularly in the tourism and hospitality industries (Litvin et al., 2008). As consumers are often unable to evaluate a service before purchase, reviews act as surrogate quality indicators that reduce uncertainty and perceived risk (Filieri, 2016). They deliver original, experience-based information that aids in trust formation and purchase decision-making (Dellarocas, 2003). Typically, a review contains textual feedback, a numerical star rating, and sometimes images or videos, allowing prospective customers to visualize and evaluate the product or service more effectively (Filieri, 2016).

In addition to guiding individual decisions, reviews function as market signals that help bridge the information asymmetry between service providers and consumers (Akerlof, 1970). For firms, they offer feedback that can inform quality improvements and strategic positioning. In the hospitality context, reviews are often more influential than traditional advertising, particularly in settings where trust is paramount, and services are intangible.

2.5.1 Airbnb Reviews

In the context of Airbnb, reviews take on heightened importance due to the platform's P2P structure, the diversity of listings, and the lack of standardized service benchmarks. Instead of hotel brands offering guaranteed levels of service, Airbnb users evaluate

individual hosts and properties, creating a higher dependency on review-based trust mechanisms (Ert et al., 2016). As one of the most review-intensive platforms in the sharing economy, Airbnb integrates reviews as core components of both search ranking algorithms and user decision-making processes (Guttentag, 2019).
Airbnb's two-sided review system, in which both guests and hosts evaluate one another adds a layer of transparency and accountability (Vassilikopoulou et al., 2022; Ikkala & Lampinen, 2015). Reviews are only published once both parties have submitted their evaluations, or a designated time period expires, reducing retaliatory behaviour and ensuring participation from both sides. This reciprocal design distinguishes Airbnb from traditional OTAs such as Booking.com or Expedia, where only guests review their stays.

However, the system is not without flaws. Scholars have noted the tendency toward review inflation, wherein users avoid leaving negative feedback due to social norms, fear of retaliation, or concerns about disrupting platform harmony (Filieri, 2016). As a result, the majority of Airbnb reviews are overwhelmingly positive, which may diminish the discriminatory power of the rating system and lead consumers to rely more on qualitative signals, such as narrative tone, level of detail, and recency when interpreting review content (Bridges & Vásquez, 2018).

The reliance on reviews is even more pronounced in emerging markets like Bali, where formal regulations may be less developed, and consumer trust depends heavily on community feedback mechanisms (Christiaens, 2025; Ronteau, 2019; Yang, 2019). In such contexts, review credibility and transparency are essential for maintaining trust, mitigating uncertainty, and facilitating informed decision-making (Filieri, 2015).

2.5.2 Fake Reviews and Airbnb's Verification Mechanisms

As with any user-generated content platform, Airbnb faces challenges related to fake or misleading reviews. However, it employs several strategies to mitigate manipulation and maintain trust in its review system. Firstly, only users who have completed a reservation are permitted to leave reviews, which limits fraudulent input from non-participants (Airbnb, 2025a). Additionally, both guests and hosts have a 14-day window

post-checkout to submit their reviews. These reviews are mutually blind, meaning neither party can see the other's feedback until both have submitted, which helps reduce retaliatory or coercive behaviour.

Airbnb also uses automated fraud detection tools and machine learning algorithms to identify suspicious review patterns, such as review swarms, duplicate text, or coordinated manipulation. Although these systems are not foolproof, their presence underscores Airbnb's commitment to ensuring review authenticity. The platform also encourages users to report any review that appears false or violates community guidelines, and it reserves the right to remove reviews that breach these terms (Airbnb, 2025a).

Despite these protections, the subjectivity of Airbnb's trust-based model leaves room for bias, exaggeration, and omission, making it all the more important to understand how consumers interpret and respond to review signals. Research continues to call for greater transparency and oversight in reputation systems, particularly in the P2P economy, where institutional safeguards are minimal compared to traditional hospitality environments (Zamani et al., 2019).

2.6 Signalling Theory

Signalling theory is a framework about understanding how parties with asymmetric information communicate signals to reduce uncertainty in decision-making (Spence 1973). This theory is relevant in situations where one party holds more information than the other which is called information asymmetry (Akerlof, 1970).

Signalling theory explains how information is conveyed in decision-making to reduce uncertainty. The theory was introduced by Spence (1973) in the labour market, where education signals worker-productivity to employers. Spence stresses that providers have an information advantage relative to users regarding the services being offered, and it becomes important for providers to convince the user of the service quality. The conviction is done through signals such as education, signalling worker-productivity in Spences (1973) paper. Further, the author explains that signals that cost more are also

more reliable indicators of quality, as higher-quality sellers can afford them, while lower-quality sellers cannot. While originally developed in the labour market, the theory has been widely applied in various areas such as finance, marketing, management and entrepreneurship (Connelly et al., 2011).

Signalling theory outlines three key components: the signaller, the signal, and the receiver (Connelly et al., 2011). The signaller is the insider with knowledge of the true quality of an individual, product, or organization. The signal represents the positive or negative information that the signaller intentionally conveys to the outsider. Finally, the receiver is the party that receives this information but lacks direct insight into the actual quality of the individual, product, or organization (Connelly et al., 2011).

Recent research highlights how signals have evolved across various domains, including organizational behaviour, strategic management, and digital markets. Studies now examine the increasing complexity of signals, their interactions with feedback mechanisms, and the role of new actors within signalling systems. Looking ahead, future research directions focus on assessing the costs associated with signalling, developing generalized models of signalling theory, and most importantly, expanding its application to a broader range of contexts (Connelly et al., 2024).

Signalling theory (Spence, 1973) is the most suitable framework for this study as it effectively addresses the issue of information asymmetry between Airbnb hosts and guests. In online marketplaces, where buyers cannot inspect a product or service before purchasing, quality signals play a critical role in decision-making (Yao et al., 2019). Therefore, the theory is particularly relevant as uncertainty and risk are higher in online- than offline purchases, making it more challenging to assess the seller's reliability and product quality (Schlosser et al., 2006: Mitra & Fay, 2010). Airbnb's P2P structure amplifies this asymmetry, making reviews a primary means for guests to assess trustworthiness and service quality.

Signalling theory has been widely applied in digital markets, where consumer decisions rely heavily on perceived indicators of quality, such as reviews, ratings, and host credibility (Zubair Ali Shahid et al., 2024; Zhao et al., 2015). Unlike alternative

theories, such as the Elaboration Likelihood Model (Petty & Cacioppo, 1986), which focuses on cognitive processing, signalling theory provides a direct explanation of how guests interpret quality signals to reduce uncertainty (Yao et al., 2019). Signalling theory is a widely validated theory, as it has been used in many research papers in various areas, including, though not limited to, economics (Connelly et al., 2024).

Given the unique challenges of emerging markets, where regulatory frameworks are weaker and consumer trust is more fragile (Rua & Nunes, 2012), signalling theory offers a robust foundation for understanding how Airbnb reviews function as quality indicators in booking decisions.

2.7 Information Asymmetry

The assumption of perfect information has been assumed in many economic models of decision-making processes. Stiglitz (2002) writes “The reason that models with imperfect information were not developed earlier was that it was not obvious how to do so...” (s. 468). However, everyone does not know the same things, hence, information asymmetry exists in many cases (Stiglitz 2002).

Information asymmetry was identified by Akerlof (1970). Asymmetric information occurs when one party possesses better or more information than the other, in an economic transaction. It can further lead to market failure as a result of the imbalance of power in the economic transaction.

Two broad and important types of information where asymmetry plays a significant role are information about quality and information about intentions, which can lead to selection problems and moral hazard problems (Stiglitz 2000). The author explains that selection problems arise when one party lacks knowledge of another party’s characteristics and qualities, making it difficult to make an informed decision. Moral hazard problems arise when one party is uncertain about another party’s intentions. The selection problem is resolved by signals, and the moral hazard problem through incentives (Mavlanova et al., 2012: Kirmani & Rao, 2000).

The presence of information asymmetry creates challenges for buyers in assessing product or service quality, making trust a crucial factor in decision-making. To navigate this uncertainty, sellers utilize quality signals as key differentiators in the market (Bergh et al., 2019). These can guide consumers toward informed choices while discouraging low-quality providers from misrepresenting their offerings (Kirmani & Rao, 2000).

2.8 Quality Signals

Quality signals are observable indicators that firms or individuals use to convey the quality of what they offer to potential buyers (Kirmani & Rao, 2000).

Quality signals can be categorized into default-independent and default-contingent signals (Kirmani & Rao, 2000). Default-independent signals, such as branding and advertising, require upfront investment and expects this investment to be recovered in the future. In contrast, default-contingent signals, such as customer reviews or refund policies are costless once transmitted and impose costs only if the promised quality is not met. Kirmani & Rao (2000) explains that the information problem regarding quality disappears as the buyer buys the product or service and learns the quality. It is therefore important for a high-quality seller to communicate quality through signals, while low-quality sellers can be better off by not signalling quality. The authors explain that false quality signals would lead to negative consequences once the buyer learns the quality. Therefore, low-quality sellers and high-quality seller benefit differently from signalling quality.

Lastly, signals through marketing such as pricing and advertising convey quality directly while nonmarketing quality signals such as third-party reviews provide independent validation, often perceived less biased and more credible (Akdeniz et al., 2013).

2.8.1 Signals or Cues?

Cues and signals both play a role in communication and decision-making, particularly in contexts involving information asymmetry. However, they differ in their

intentionality. Cues are incidental pieces of information that consumers use to infer quality, but they are not necessarily intended by the provider to convey a specific message (Kirmani & Rao, 2000). While signals can be referred to as intentionally communicated cues meant to convey quality, cues are also indicators of quality, although unintentionally communicated (Donath, 2011).

This paper focuses on signals and the intent to communicate quality instead of hidden cues. It can be argued that reviews are intentional, as previous guests actively take the time to write about their experiences and their opinions. As reviews are intentional, signals present a better fit for this study compared to cues. While "cues" are mentioned in this paper, it is mentioned in contexts where the difference between signals and cues does not matter. Other than this, the paper focuses only on quality signals.

2.8.2 Quality Signals in Airbnb Reviews

In the context of Airbnb, where guests and hosts interact in a P2P marketplace, information asymmetry is more pronounced compared to traditional hotels (Yao et al., 2019). Unlike hotels, who provide standardized accommodation, Airbnb offers a wide range of individual hosts and accommodations that differentiates it in the hospitality industry (Ding et al., 2024). With the popularity of the internet, customers now have access to a wider range of information sources, especially through various platforms that have revolutionized tourism (Buhalis & O'Connor (2005). As reviews are important when booking hotels (Wen et al., 2020: Litvin et al., 2008), it can be argued that reviews might be even more important for a platform like Airbnb as a result of the higher information asymmetries and many options provided by Airbnb.

Many researchers have investigated different quality components of reviews in Airbnb (Ert et al., 2016: Yao et al., 2019: Wang & Nicolau, 2017: Teubner et al., 2017: Xie & Mao 2017). Ert et al., (2016) found that host pictures can increase the booking probability of Airbnb accommodations as well as listings, information on the host, pricing and house rules (Yao et al., 2019). Further, factors such as host attributes, services, amenities, property attributes and review ratings are also shown to be quality signals (Wang & Nicolau, 2017). Lastly, another quality signal is the duration that a

host operates through Airbnb that can influence the trust of guests and the reputation of the host, where a host who has been on the platform longer can command higher prices (Teubner et al., 2017: Xie & Mao 2017). This past research highlights the importance and some different types of quality signals in Airbnb.

Online reviews function as default-contingent signals (Kirmani & Rao, 2000), meaning that a cost will occur if a host misrepresents quality. Therefore, if the reviews are not aligned with the quality of the accommodation, once the prospective guest finds out the quality, it can have a negative consequence for the host. It is then important to investigate the quality signals in reviews, to avoid misrepresented quality. Yao et al., (2019) further found that the effect of signal attributes in listings declines as online reviews increases (reducing information asymmetry), highlighting that consumers rely more on reviews when they are present.

Baek et al., (2012) writes "However, the influx of online consumer reviews has caused information overload, making it difficult for consumers to choose reliable reviews." (p. 99). Information overload refers to the situation where the vast amount of potentially useful information becomes an obstruction instead of helpful (Bawden & Robinson 2020). This highlights the need to research quality signals in Airbnb reviews to avoid the information overload of too many signals. In the context of Airbnb, the signaller is the previous guests, the signal is the content of the reviews, and the receiver is the guest.

2.9 Booking intentions

Purchase intentions is widely discussed in consumer behaviour that aims to predict buying behaviours among consumers (Morwitz, 2014). Lien et al., (2015) & Ho et al., (2023) instead, researches purchase intentions in the hospitality industry using "Booking intentions" to refer to a consumer's likelihood or willingness to reserve a particular accommodation after evaluating available options. In the context of Airbnb, understanding booking intentions is crucial due to the platform's unique characteristics within the sharing economy.

Analysing booking intentions help in understanding the decision-making process of consumers in the sharing economy (Kim & Liu, 2023). This includes many factors such as the influence of social media, familiarity with the platform and perceived risk (Kim & Liu, 2023). Another reason for the importance of booking intentions, is the perceptions of trust and safety (Ho et al., 2023). For example, concerns such as neighbourhood safety, privacy and security assurance can decrease the likelihood of a consumer choosing Airbnb accommodations (Ho et al., 2023). Further, understanding booking intentions can inform discussions on Airbnb's impact on local housing markets, tourism dynamics and community relations (Hati et al., 2021). This shows the importance of booking intentions in Airbnb in many different ways as it directly influences the platforms success.

There are many previous studies that research what factors influence booking intentions in the hospitality industry, such as brand familiarity, price, online reviews (Wen et al., 2021), online ratings (Gavilan et al., 2018), trust and reputation (Ert et al., 2016), etc. Showing the many aspects that might influence booking intentions in the broad industry that is hospitality.

2.10 Conceptual Model

Considering quality signals in reviews instead of quality signals in Airbnb, previous studies have identified multiple key quality signals in reviews that have been adopted to the case of this paper, including trustworthiness (Rosenthal et al., 2020: Gavilan et al., 2018: Sidali et al., 2009), usefulness, volume, valence and timeliness (Zhao et al., 2015). Most of the items used in this paper are adapted from Zhao et al., (2015), though this paper excludes "reviewer expertise" and "comprehensiveness of online reviews". "Reviewer expertise" is ignored as the information about the previous guests on Airbnb is limited, and arguing for what characteristics makes a good reviewer is outside the scope of this paper. "Comprehensiveness of online reviews" is also ignored as it is similar to "usefulness" and will therefore be included in that factor.

Tabel 1.

Author	Trust in Reviews	Trust in Platform	Usefulness	Volume	Valence	Timeliness	Additional Signals
Cheung et al. (2008)			✓			✓	Completeness, Accuracy
Chevalier & Mayzlin (2006)	✓			✓	✓		Review text depth
Ert et al. (2016)		✓			✓		Attractiveness
Ert et al. (2016)		✓			✓		Attractiveness
Filieri (2016)	✓		✓		✓		Reviewer Expertise
Gavilan et al. (2018)	✓	✓		✓	✓		Social Influence
Harvard Business Review (1990)	✓	✓					
Höpken et al. (2009)		✓	✓				Community engagement
Lien et al. (2015)		✓					Price, Brand Image
Mao & Lyu (2017)					✓		Perceived risk, Value
Parasuraman et al. (1985)		✓	✓				Reliability, Responsiveness
Park & Lee (2009)	✓		✓				Consumer susceptibility
Richins (1983)	✓				✓		Complaint behavior
Rosenthal et al. (2020)		✓			✓		Perceived service quality
Sidali et al. (2009)	✓	✓					Expertness, Style, Brand familiarity
Tandon et al. (2020)	✓		✓		✓	✓	Length, Readability
Torres et al. (2015)				✓	✓		Ranking
Wen et al. (2020)	✓	✓			✓		Price, Brand familiarity
Willemsen et al. (2011)	✓	✓	✓		✓		Review diversity
Xie & Mao (2017)				✓	✓		Superhost status, Responsiveness
Zhao et al. (2015)	✓	✓	✓	✓	✓	✓	Comprehensiveness

2.10.1 Trustworthiness

Filieri (2016) writes “A trustworthy review can be defined as a review that is perceived by the reader as the honest, sincere, truthful, and non-commercial opinion of a customer who has experienced a product or a service” (p. 47-48). The author also concludes that the higher the trustworthiness of the review, the higher the chances are that a review is taken into consideration in the decision-making process. Further, Filieri (2016) finds that the primary cues to assess trustworthiness of reviews are the message content and style, review extremity and valence. Customer trust is especially crucial in the online environment as consumers depend on the internet for information and purchases (Filieri 2016).

Trustworthiness is a factor that has been applied in previous studies’ scales (Rosenthal et al., 2020: Gavilan et al., 2018: Sidali et al., 2009), where Rosenthal et al., (2020) measures reputation cues as signals, Gavilan et al., (2018) analyse trust as a mediating effect between ratings and the selection of a product or service and Sidali et al., (2009) investigates the determinants of trust in reviews. A limitation for previous research is that they operate with trust as a factor in the reviews, ignoring the potential effect of trust in the platform (Rosenthal et al., 2020: Sidali et al., 2009). Therefore, this paper includes both trust in reviews and trust in the platform (Airbnb).

In the platform Airbnb’s case, features such as secure payments, identity verification, and customer support contribute to platform trust, reducing perceived risk (Ert et al., 2016). Platform trust has also been shown to mediate the relationship between user experience and booking intentions (Mao & Lyu, 2017) and is especially important in P2P markets where traditional systems are not enough. Without trust in the platform, even credible reviews may have limited influence on consumer behaviour.

Trust plays a fundamental role in online booking decisions, as consumers must rely on digital information to assess accommodations they cannot inspect in person (Filieri, 2016). Reviews serve as a crucial mechanism for building trust, with their perceived credibility directly influencing consumer reliance. In the context of the platform Airbnb, trust reduces perceived risk and increases confidence in booking decisions (Ert et al., 2016). A higher level of trust in reviews and the Airbnb platform itself leads to stronger

booking intentions, as consumers are more likely to choose listings that appear reliable and reputable (Gavilan et al., 2018). The items for the factor of trustworthiness have been adapted from Gavilan et al., (2018) and Sidali et al., (2009).

Hence, this study proposes the following:
H1. The trustworthiness of Airbnb reviews will positively influence booking intentions on an Airbnb accommodation in Bali.
H2. The trustworthiness of the platform Airbnb will positively influence booking intentions on an Airbnb accommodation in Bali.

2.10.2 Usefulness

The second factor is the usefulness of the review. Park & Lee (2009) define the perceived usefulness of online reviews as the extent to which consumers perceive the review as helpful in guiding their purchase decision. Usefulness also refers to the extent to which a review offers valuable and relevant information and the perceived helpfulness that it provides for prospective consumers (Mudambi & Schuff, 2010).

It is a reasonable assumption that consumer expectations will be influenced by the usefulness of a review as travellers mainly search for information to help plan their trip (Zhao et al., 2015). Furthermore, Willemsen et al., (2011) proposed that when evaluating online reviews, the usefulness of the reviews is the key factor that consumers consider. The perceived usefulness of online reviews also positively influences how frequently consumers use reviews (Park & Lee 2009). In the context of Airbnb, usefulness is crucial as travellers seek relevant and detailed information to mitigate uncertainty before booking (Zhao et al., 2015). Research suggests that the more useful a review is perceived to be, the more likely it is to influence booking intentions, as consumers rely on structured, informative, and credible content to evaluate accommodations (Oliveira, 2020). This suggests that the practical value of information directly shapes consumer behaviour in online booking environments.

It is therefore relevant to include usefulness of the review as a factor in this paper, as it is suggested to have a significant influence on consumers' decisions to utilize the

review (Cheung et al., 2008). A previous study by Zhao et al., (2015), include usefulness of online reviews in their scale, developed to investigate how hotel booking intentions are influenced by online reviews. The items for the factor of usefulness have been adapted from Zhao et al., (2015).

Hence, this study proposes the following:
H3. The usefulness of Airbnb reviews will positively influence booking intentions on an Airbnb accommodation in Bali.

2.10.3 Volume

This factor relates to the number of online reviews. Volume is a fundamental attribute of word-of-mouth (WOM) communication, referring to the total number of customer reviews a product or service receives (Liu, 2006: Duan et al., 2008).

Numerous studies highlight the positive relationship between the number of online reviews and better business performance (Liu, 2006: Duan et al., 2008: Torres et al., 2015). Torres et al., (2015) found that a higher number of reviews and improved review quality can serve as indicators of both a hotel's quality and popularity, showing that the relationship also exists in the hospitality industry. The author further states that it is possible that extreme reviews make less of an impact with a greater number of reviews.

The volume of online reviews plays a crucial role in consumer decision-making, as a higher number of reviews increases visibility and awareness (Davis & Khazanchi 2008). This author, however, argue that the impact on consumer decision-making is not by volume alone. Research also suggests that variations in review volume indicate disparities in consumer attention, meaning that not all reviews are perceived equally (Zhao et al., 2015). Lastly, while previous research highlights the positive aspect of larger volume of reviews (Liu, 2006: Duan et al., 2008: Torres et al., 2015: Davis & Khazanchi 2008), Kim et al., (2015) found the effect of volume to be insignificant when investigating if the number of reviews is positively related to hotel performance.

Volume makes an interesting factor to investigate in the context of Airbnb reviews, as there are constructing findings for and against volume having an effect. The items measuring the factor of volume were adapted from Zhao et al., (2015).

Hence, this study proposes the following:
H4. The volume of Airbnb reviews will positively influence booking intentions on an Airbnb accommodation in Bali.

2.10.4 Valence

The fourth factor, valence refers to product attributes through either the positive aspect (benefits gained) or the negative aspect (benefits lost) (Maheswaran & Meyers-Levy 1990). The valence of the review is in this paper used to assess negative reviews.

Multiple studies have found negative reviews to have the bigger effect rather than positive reviews in the hotel industry (Wen et al., 2020: Zhao et al., 2015: Gavilan et al., 2018: Filieri et al., 2020), and in general as well (Lee et al., 2008: Chevalier & Mayzlin 2006: Chen et al., 2022). It is important to lessen the gravity of negative information based on negative experiences (Hart et al., 1990), as negative information have a tendency to spread and be used as a reason for consumers to switch brands and complain, which may be lasting effects (Richins, 1983).

Baek et al., (2012) found that people find the use of negative words to be one of the most helpful indicators in reviews and that consumers tend to develop a more unfavourable attitude towards the product as the proportion of negative online reviews increases. However, Maheswaran & Meyers-Levy (1990) found positive framing to be more persuasive than negative framing, except when the consumer is highly involved. Another study by Lei et al., (2023) found that there is a confirmation bias in the information-evaluation stage of reviews, meaning that consumers find positive content more helpful when “exposed to the actual content of individual reviews” (p. 1166).

Despite the large number of previous studies investigating the larger effect of negative reviews (Wen et al., 2020: Zhao et al., 2015: Gavilan et al., 2018: Filieri et al., 2020:

Lee et al., 2008: Chevalier & Mayzlin 2006: Chen et al., 2022: Baek et al., 2012), research also shows the importance of positive reviews (Maheswaran & Meyers-Levy 1990: Lei et al., 2023: Liu & Park, 2015). Therefore, this paper includes valence as a factor. The items for valence in this study were also adapted from Zhao et al., (2015).

Hence, this study proposes the following:
H5. Negative Airbnb reviews will negatively influence booking intentions on an Airbnb accommodation in Bali.

2.10.5 Timeliness

The last factor refers to the specific time stamp that is associated with each piece of information (Zhao et al., 2015). Cheung et al., (2008) explains timeliness as timely, current and up-to-date information.

Tandon et al., (2020) found that recently posted eWOM is more important rather than old eWOM. Newer reviews might reflect the current state of the listing such as cleanliness and amenities which may change over time. Keeping a website updated along with changing and using accurate information has shown important in e-commerce (Madu & Madu, 2002). It is therefore also relevant to consider it regarding eWOM. Zhao et al., (2015) also found evidence supporting the positive influence of newer reviews on bookings.

However, Cheung et al., (2008) found that timelines in eWOM hold no significant importance. Moreover, Baek et al., (2024) introduced the concept of the "Cost of Newest First," indicating that displaying the most recent reviews first can cause negative reviews to remain prominent longer, which may have negative consequences. This highlights how timeliness of reviews may affect consumer behaviour.

The limited research on timeliness in reviews makes it a valuable aspect to explore in this paper. Timeliness is meant to capture the difference between recently posted and older reviews, potentially affecting consumer behaviour. Further, there is plenty of

research on the other factors, which makes timeliness even more interesting. The items measuring the factor of timeliness were adapted from Zhao et al., (2015).

Hence, this study proposes the following:
H6. The timeliness of Airbnb reviews will positively influence booking intentions on an Airbnb accommodation in Bali.

2.11 The Moderating Effect of Previous Experience with Airbnb

Consumers' previous experience with Airbnb might play a role in how they interpret and rely on quality signals in Airbnb reviews in Bali.

Consumers with less experience, might face higher uncertainty (Weathers et al., 2007) and conveying information about certain qualities through signals can help reduce uncertainty in decision-making (Spence 1973). Bae et al., (2017) found that shared experiences such as previous Airbnb stays can decrease uncertainty and that travellers share their experiences when they have strongly positive or negative experiences. Further, Filieri (2016) found that the moderating variable of experience influences how consumers evaluate trustworthiness. Moreover, previous research on online travel platforms shows that consumers with more experience engage in more selective information processing and are better at distinguishing between helpful and less helpful reviews (Park & Kim, 2008.

However, further research is needed to specifically examine how prior experience with Airbnb influences consumers' evaluation of Airbnb reviews in Bali.

Hence, this study proposes the following:
H7. Respondents previous experience with Airbnb has a moderating effect on the importance of the factors in Airbnb Reviews.

3. Research Methodology

The third chapter serves the purpose of determining and explaining the methodology, sampling and data collections to the reader. The chapter starts with the methodological reasonings, discussing research- philosophy, approach, design, strategy and method as well as the sampling strategy and selection of the primary data. Thereafter this chapter discusses the data collections for the study, including the gathering of information, data analysis and discussion of the quality, reliability and validity of the data. This chapter aims to explain the rationale of the study and the collection of information for the empirical results.

3.1 Methodological Reasoning

3.1.1 Research Philosophy

The term research philosophy builds on certain assumptions regarding the creation and comprehension of knowledge within a particular study. It serves as the basis for the research's design, data collection, and analysis (Saunders et al., 2019). Carefully developed research philosophies and approaches differ according to their ontological (nature of reality) and epistemological (nature of knowledge) assumptions. It is well established that business and social science research dualism rests on the ontology of positivism and interpretivism. The Research Onion model (Saunders et al., 2019) gives a coherent description for different philosophies of research and methodological practices with philosophy being on the outermost layer since it shapes all subsequent decisions.

This study takes a positivistic approach because of the adoption of a positivist research philosophy which assumes that reality exists independently of human beings. The world as understood within the positivist philosophy is based upon empirical evidence, described and explained using systematic observation, and has a quest for generalization

(Bell et al., 2022). This philosophical stance aligns with the study's aim to analyse quality signals in Airbnb reviews in an emerging tourism market by identifying patterns and testing hypotheses. Positivist research is commonly associated with quantitative methods, structured data collection, and statistical analysis, all of which are central to this study.

Another alternative research philosophy, interpretivism, is quite popular in qualitative research where it emphasizes subjective and individual experiences (Easterby-Smith et al., 2015). However, interpretivism does not suit this research as its focus on socially constructed knowledge and insights which are non-generalizable undermines the purpose of the research, which is to determine the objective quality signals that alter consumer behaviours on Airbnb. Given that this research aims at establishing some quantifiable causative linkage between quality signals and booking intentions, a positivist stance is a better choice (Saunders et al., 2019).

Positivism further justifies adoption because it is consistent with already established theories and organizational paradigms. The study employs the signalling theory as a framework (Spence, 1973), which posits that signals can be taken to represent the presence of certain qualitative attributes. This belief rests within the positivist paradigm where phenomena are assumed to be tested through systematic data analysis rather than being explored via interpretation (Ghauri et al., 2010).

Adopting a positivist approach enables this study to offer scientific accuracy, neutrality and reproducibility thereby making the results applicable to wider groups. A positivist approach also reduces the bias of the researcher as it is governed by structured predetermined data collection strategies and hypothesis testing (Hair et al., 2019).

3.1.2 Research Approach

The research approach refers to the way knowledge is constructed in a study. It specifies whether the inquiry originates from an assembly of data to a generalized theory (inductive approach) or develops from a considered theory to an empirical observation (deductive approach) (Saunders et al., 2019).

This research takes a deductive approach, hence the use of the signalling theory as the starting point to generate the hypotheses which are subsequently tested against collected data. Deduction is commonly associated with positivism, as it emphasizes structured hypothesis testing, statistical analysis, and objective validation of theoretical assumptions (Bell et al., 2022). The study is able to utilize the deductive approach for a number of reasons:

Research Based on Hypotheses: It is said that deductive research strategies fit best where plausible hypotheses tend to be based on original theories or principles. (Collis & Hussey, 2021). This study attempts to understand how trustworthiness, usefulness, volume, valence as well as timeliness in a review are utilized as quality signals in Airbnb which in essence is an application of signal theory (Spence, 1973).

Causal Relationships: The purpose of deductive research is to describe cause-and-effect relationships among the elements (Easterby-Smith et al., 2021). In this study, the effort was made to understand how different signals of quality affect the decision of a consumer when booking, thus deduction makes the most sense.

Generalization and Replicability: The findings from this study can be generalized beyond this sample and replicated in future studies of its nature, which is a hallmark of deduction (Hair et al., 2019). This is made possible because an organized form of data collection and statistical analysis is used. An alternative inductive approach would entail gathering data without any pre-formulated theory and creating a theory based on the data structure that emerges (Saunders et al., 2019). As much as the inductive approach is useful in exploratory studies, this particular study which seeks to test some established theory within a context does not benefit from it. Inductive approaches are more prevalent in qualitative research, where themes and concepts are developed from interviews or other forms of observations (Ghauri et al., 2020).

Since this research is not exploring new concepts but rather applying and testing established theories, deduction is the most appropriate research approach. Therefore, the most suitable research approach would be deduction. The guaranteed structure allows the methodology to empirically either affirm or rebut the theoretical stance in question

and add to the body of knowledge pertaining to quality signals in emerging markets with an emphasis on Airbnb Reviews.

3.1.3 Research Design

The research design serves as the overall framework for this study, ensuring a structured approach to the purpose. A good design is necessary to obtain accurate results, organize and plan the research process based on the research questions and hypotheses (Toledo-Pereyra, 2012). The design of this study was best described as a descriptive research design.

There are multiple different research designs that one can categorize their work in, for example: exploratory (Brink & Wood, 1998), descriptive (Siedlecki, 2020) and explanatory (casual) (Baskerville & Pries-Heje, 2010) designs are commonly used. Descriptive research seeks to provide a precise representation of events, individuals, or situations, whereas exploratory studies focus on uncovering new insights by posing open-ended questions on a given topic (Saunders et al., 2019). Descriptive studies are also often extensions or forerunners to explanatory research which focuses on investigating cause-and-effect relationships between variables. Explanatory research aims to investigate why certain phenomena occur by testing hypotheses derived from theoretical frameworks (Saunders et al., 2019).

This study was descriptive, as it sought to investigate quality signals in Airbnb reviews in an emerging market. While explanatory research focuses on causality between variables, descriptive research allows for the possibility to draw some correlations among the variables. A big component of explanatory research is manipulating variables in an experimental setting which was not the case here. It is neither exploratory as it does not ask open-ended questions to gain rich and detailed insights. This paper was therefore categorized as descriptive due to the describing of the relationships between the quality signals and booking intentions and the possibility of some correlations.

3.1.4 Research Strategy

As mentioned, this paper followed a positivistic philosophy, deductive and descriptive approach, and regarding the type of data, research is typically quantitative or qualitative. Quantitative research focuses on numerical data and statistical analysis to answer "what?" questions, identify relations and generalize findings (Barnham, 2015; Lim, 2024). In contrast, qualitative research is more about the "why?" questions, aiming to explore in-depth meanings, behaviours and experiences (Barnham, 2015). Qualitative research also provides rich, contextual insights through various interviews (Barnham, 2015) while a quantitative approach is preferrable when testing hypotheses, making casual inference and relations between variables (Lim, 2024).

We chose a quantitative approach to investigate answers to our research questions. A quantitative approach was appropriate as it allows for the measurement of relationships between variables, and the findings could also lead to statistically generalizable insights (Lim, 2024). The quantitative approach also allows for testing hypotheses, statistical values and measuring through scales (Lim, 2024), which were appropriate for the target of the study and in alignment with a deductive approach. Given this quantitative approach, a structured, web-based, survey was used which enabled the collection of larger and standardized data (Lim, 2024).

Furthermore, previous studies regarding online reviews in the hospitality industry have predominantly used quantitative methods to answer their research questions (Chen & Chang, 2018; Gavilan et al., 2018; Sidali et al., 2009; Wen et al., 2021; Zhao et al., 2015). Since this study also sought to investigate the moderating effect of prior experience with Airbnb, a quantitative approach allowed for statistical techniques such as a regression and moderation analysis which was useful for the hypotheses (Lim, 2024).

Thus, by adopting a quantitative approach, this study aimed to be objective, reliable and acquire scalable findings, aligning with similar, previous research.

3.1.5 Research Method

After having established what type of research this paper aimed for, and the terms to define it, the next part was to focus on the research method. Goundar (2012) explains that the research method refers to the techniques and procedures used to conduct research into a topic or subject. This is not to be confused with the research methodology that involves the entire research process while the method is a subset, referring to a specific part of the study (Goundar, 2012).

Surveys, laboratory experiments, structured equations modelling and simulations are examples of a quantitative research method (Goundar, 2012). This study chose to use an online, web-based survey. Ruel (2019) explains that a survey is a research method used to gather data from a broad audience to address specific research questions. It involves designing a questionnaire, selecting an administration method, determining the collection, contact and conviction of respondents. This research tool is one of the most commonly used quantitative methods as it is interdisciplinary and adaptable (Ruel, 2019).

Surveys can also be done online, proving useful because of the possibility of larger samples, speedy responses, low costs, efficiency, direct and rapid data gathering and its wide geographic reach (Sue & Ritter, 2016; Nunan et al., 2020). On the other hand, online surveys also possess challenges such as coverage and sampling bias, reliance on software, digital survey fatigue, low engagement, incomplete responses, spam, and privacy concerns (Sue & Ritter, 2016; Nunan et al., 2020).

However, we considered that the positive characteristics outweigh the negative for this study, especially due to the short time frame for this study. The rapid data collection, low costs, large audience and wide reach were also deemed beneficial. The reliance on software was not deemed an issue and non-completed surveys could be cleaned. Further, this study did not require such a large sample that the issue of non-interested possible respondents would present a significant risk. Regarding privacy issues, this could be battled by ensuring anonymity, that answers were only used for academic use, avoiding non-public communities mailing lists and avoiding prenotification e-mails and follow-up notes (Andrews et al., 2003).

Lastly, previous research conducting similar research to that of this paper, have also made use of questionnaires (Chen & Chang, 2018; Sidali et al., 2009; Zhao et al., 2015), further showing that this research tool presented a good research method for our research questions and hypotheses.

3.2 Data collection

3.2.1 Secondary Data

Secondary data can be defined as existing data being analysed and applied to a topic other than the original one but also as re-analysing existing data for updated techniques or new research questions (Smith, 2008). There are many types of secondary data, such as large-scale surveys, longitudinal studies and administrative records, which are all data already gathered by someone else (Smith, 2008). Secondary data was collected for this study to increase reliability by leveraging data within our research objectives.

The main use of secondary data was in the literature review along with complimentary information in the entire paper. Beginning with a workshop to gathering secondary data, provided by Jönköping International Business School, we got tips on how to find credible data. The main database used was Primo, which is the library of Jönköping University. We also made use of the databases Scopus, JSTOR and ProQuest along with using Google Scholar as a complimentary base when Primo, Scopus, JSTOR and ProQuest were not enough. Lastly, Statista was used for certain information regarding statistics.

To start the collection of data, we firstly aimed to find academic articles similar to what we were going to research through Primo, which could guide us in what additional data needed to be collected. Key words that we commonly used were “Airbnb”, “Reviews”, “Booking intentions”, “Online reviews”, “Emerging markets”, “Bali” and various combinations of these. We adopted a strategy of examining through sources of other credible academic articles and through that, a sort of snowballing effect took place. This

strategy proved useful in gathering qualitative and useful sources. Additionally, we put great stress in selecting articles that are peer-reviewed to confirm high quality data. Lastly, we also used ChatGPT to find us academic sources for information proven hard to find and searched these sources on the other databases to make certain of their quality.

3.2.2 Primary Data

The primary data refers to the data gathered firsthand by researchers and intentionally accumulated for the purpose of the investigation (Rabianski, 2003). This is often gathered through observation or questioning, such as observing a workplace or interviewing people (Rabianski, 2003). The primary data collected for this paper was through an online survey.

The survey was conducted to gather data specifically related to our research questions and to answer our hypotheses. Therefore, the main purpose of the survey was for respondents to answer questions regarding the factors of quality signals. The questionnaire was conducted online using Qualtrics as it was efficient and easy to send and answer. Qualtrics is an online, cloud-based platform that allows users to create and distribute surveys, collect responses and analyse the gathered data (Qualtrics, n.d.). The license we had for Qualtrics allowed for a maximum of 30 questions.

The questionnaire was firstly designed with an information introduction, stating the purpose of the survey, a brief description of the content as well as a statement on the respondent's anonymity, the insurance of privacy and the handling of their data. After the brief information, a link was included that led to a participant information sheet. This sheet explained more thoroughly the purpose of the survey, what rights the participants had and the way JIBS handles their data. After the introduction and the starting information of the questionnaire, the last information on the front page was a statement that stated if the respondent continued beyond the first page, they are consenting to their data being collected and used in our thesis. If consent was given, the next question was a filter question to filter out unwanted participants. The filter question was necessary to ensure the participant knew of Airbnb and had previously booked an

accommodation through any online website. This was included to ensure the respondents could understand the survey questions. A filter question regarding the respondent's familiarity with Bali was not necessary as the focus was not on knowledge or perceptions of Bali itself, but rather quality signals in Airbnb reviews influencing booking intentions in an emerging tourism market, where Bali served as the contextual example.

Once the participants read the information, completed the consent and filter question, they were introduced to statements about the factors. Each factor was designed with three statements, whereas the factor of trustworthiness had six statements, three regarding trust in reviews and three regarding trust in the platform. These two versions of trustworthiness were treated as two separate factors. Each factor was addressed in their own page, resulting in three statements per page. At the start of each page, we also included a clarification note regarding what we meant with the word "accommodation", to avoid misinterpretations.

All statements were asked using the Likert scale. The Likert scale measures attitudes where a statement is made, and the respondent can indicate their level of agreement on a five- or seven-point scale (Joshi et al., 2015). For example, statement X states, "I believe recently posted reviews are important" and the Likert scale presents seven options the respondents can choose from, ranging from 1 – Strongly disagree to 7 – Strongly agree, with the in-between numbers being various degrees of agreement. The Likert scale was also used for the second question regarding the respondent's attitude towards their experience or experiences with Airbnb. Here they could choose 1 – Very negative to 7 – Very positive and various degrees of attitudes in between. We chose the seven-point scale as it is generally better than a five-point scale in terms of precision, reliability and validity (Joshi et al., 2015). We also included an attention check in the survey to make certain participants were keeping attention and not answering randomly. Then we addressed the questions regarding booking intentions. We chose three items to ensure reliability that stated different versions of whether they are likely to book an Airbnb accommodation in Bali with the help of reviews. The attention check and the booking intentions also used the Likert scale.

Thereafter, when the factors and booking intentions had been addressed, three questions were asked regarding the respondent's previous experience with Airbnb, addressing their previous number of stays and whether their experience was positive or negative. The last question regarding previous experience was a voluntary open-ended question where they could explain their reasoning for their previous stays being positive or negative. An open-ended question was included to gather qualitative data. While this paper is quantitative, a qualitative question could help gather more in-depth information. These questions were asked to investigate the moderating role of previous experience with Airbnb and see if it influenced their answers on the factors.

Lastly, a few demographic questions were asked, regarding the respondents age, gender and yearly income. Age and gender were included to get a better overview on who our respondents were, and the yearly income was included to see if it possibly moderates our findings. We deemed that these were the most interesting aspects to include. Once all statements regarding the factors and questions regarding the moderating role and demographics were done, the final page included a debriefing. The debriefing thanked the participants and concluded the survey. The survey was open for four days after the pre-test to give time for the collection of data. Table 2 shows the factors chosen and their Cronbach's alphas from previous studies, see appendix 1 for the final survey.

Table 2.

Source	Factor	Nr of items	Cronhach's alpha
Gavilan et al. (2018)	**Trust in Airbnb Reviews**	2	0.820
Sidali et al. (2009)		1	Not included
Gavilan et al. (2018)	**Trust in the platform Airbnb**	2	0.820
Sidali et al. (2009)		1	Not included
Zhao et al. (2015)	**Usefulness**	3	0.874
Zhao et al. (2015)	**Volume**	3	0.776
Zhao et al. (2015)	**Valence**	3	0.782
Zhao et al. (2015)	**Timeliness**	3	0.710
Zhao et al. (2015)	**Booking intentions**	3	Not included

3.2.3 Pre-Test

Once the questionnaire had been finalised, a pre-test was conducted. A pre-test was conducted to ensure that the questionnaire was comprehensive and easy for prospective respondents to follow. This was important to include to avoid problems when collecting the real data.

The finished survey was given out to ten people, including our friends and relatives. Friends and relatives were chosen to partake in the pre-test due to the convenience and rapid feedback. After the respondents answered the survey, they were given five questions to answer regarding the survey (see appendix 2). From these questions, no major issues were encountered and almost all respondents answered that everything was clear. One respondent explained that they thought that the statements "I believe Airbnb is trustworthy" and "I believe Airbnb is responsible" were unclear whether they indicated Airbnb as a platform or Airbnb as a company, their listings, the hosts etc. Therefore, we addressed this concern by adding "as a platform" to both statements. Another respondent explained that they thought the survey was too short. Due to the limit of 30 questions on Qualtrics, this feedback could not be addressed as the limit was met.

No other feedback was given except that everything was clear, nothing was confusing, no technical issues, good length and no suggestions for improvement.

3.2.4 Sampling Strategy

This study employed a non-probability sampling strategy, combining convenience sampling with elements of judgmental sampling. Convenience sampling was selected for its efficiency and accessibility, especially in contexts where the population is not fully known or a probability-based method is impractical (Etikan, Musa, & Alkassim, 2016). It enabled the researchers to collect data from two channels: Prolific Academic and personal networks, which allowed for timely and cost-effective recruitment of respondents.

Judgmental sampling, also known as purposive sampling, was integrated by including a screening question to ensure that only participants with relevant background knowledge were included. At the beginning of the survey, respondents were asked: *"Are you familiar with the accommodation platform Airbnb and making reservations for accommodations through online booking sites? (such as Booking.com, Airbnb, Expedia etc)"*. Only those answering *"yes"* were allowed to proceed. This approach is aligned

with recommendations in research methodology literature, which suggests purposive criteria help ensure that the sample is aligned with the research objectives (Palinkas et al., 2015). The combination of both methods provided both practicality and conceptual rigor, ensuring the study reached appropriate respondents while maintaining internal consistency.

3.2.5 Sample Selection

A total of 223 responses were initially collected. Participants were eligible to participate if they were at least 18 years old, fluent in English, and confirmed familiarity with online booking platforms via the screening question. These inclusion criteria ensured that respondents possessed the requisite background to interpret review-based signals and evaluate booking intentions within the context of platforms such as Airbnb (Bell et al., 2022).

In line with established practices in survey-based research, data cleaning procedures were implemented to ensure the reliability and validity of the dataset (Hair et al., 2019). Participants were excluded from the final sample if they:

- Answered “no” to the filter question
- Did not complete the full survey
- Failed an embedded attention check
- Exhibited straight-lining behaviour, defined as selecting identical responses across Likert-scale items.

In total, 23 responses were removed based on these criteria, resulting in a final sample of 200 participants. This process aligns with established recommendations in the literature that advocate for the removal of low-effort or inattentive responses to protect the integrity of the data (Berinsky et al., 2014).

3.2.6 Survey Distribution and Use of Prolific

The survey was distributed through two channels: Prolific Academic, an online platform designed specifically for academic research, and personal networks (friends and family). The majority of responses (147 out of 200) came from Prolific. This platform was selected for its ability to pre-screen participants based on demographics and behavioural characteristics, offer fast response rates, and deliver high data quality (Peer, Brandimarte, Samat, & Acquisti, 2017). Prolific also enforces participant quality through reputation scores, attention check support, and fraud detection, features that are widely endorsed in academic literature as best practices in online survey research (Palan & Schitter, 2018).

Nonetheless, some limitations of Prolific should be acknowledged. The use of monetary compensation may introduce bias if participants are primarily motivated by financial reward rather than genuine interest (Chandler, Rosenzweig, Moss, Robinson, & Litman, 2020). There is also the risk of "professional respondents," who may have high familiarity with survey formats, potentially affecting authenticity or response variance (Fricker, 2008).

To complement Prolific, the survey was also shared within personal networks. While this distribution method helped increase participation in the early phases, a higher proportion of responses from this group had to be excluded during the cleaning process due to ineligibility or low engagement. This supports existing concerns in the literature that convenience sampling through personal connections may result in lower data reliability (Fricker, 2008).

The combination of structured, compensated responses from Prolific and unpaid, informal responses from personal networks allowed for a more diversified sample, while the screening and cleaning procedures helped ensure that only valid responses informed the final analysis.

3.2.7 Open-Ended Question

Although this study follows a quantitative research design, one open-ended question was included at the end of the survey to complement the close-ended items. The purpose of this addition was to allow respondents to elaborate on their previous experiences with Airbnb stays and provide context for their evaluation of those experiences. Specifically, participants were asked: *"Why would you describe your previous experience/experiences as such? (negative/positive)"*. This qualitative component served an exploratory function within the broader quantitative framework, offering the opportunity to identify potential themes or influencing factors not captured through structured survey items.

Including open-ended questions in survey-based research is supported in the methodological literature as a means of enabling greater respondent expression, reducing response bias, and enhancing data richness (Reja et al., 2003). While the primary aim was not to conduct a formal qualitative analysis, the open-ended responses functioned as a secondary data source to verify that no major dimensions influencing booking intentions were omitted during survey development. This strategy aligns with the principle of methodological complementarity, where qualitative input is used to triangulate or contextualize quantitative data (Jick, 1979).

The responses were reviewed post-collection and grouped thematically to assess the presence of any recurring concepts or unaddressed concerns. This process did not involve formal coding or content analysis but was intended to serve as a qualitative check on the comprehensiveness of the structured survey instrument. As such, this open-ended item provided methodological value by supporting the internal validity of the study's design and offering direction for future research development.

3.3 Data Analysis

Data analysis is crucial for the research process as it helps to uncover certain patterns, relations, and statistical significance in the collected data (Hair et al., 2019). With this said, this study is designed using descriptive research method within the boundaries of a

positivistic paradigm hence a quantitative approach was employed to understand the effects of quality signals within Airbnb reviews on the intention to book.

The study employed both descriptive and inferential statistical techniques to summarize the dataset and test the hypotheses. Data analysis was performed using #SPSS, following a structured sequence of data cleaning, validation, and statistical testing. The analysis techniques used are explained in detail below.

3.3.1 Data Quality

In order to get dependable results, high-quality data is required. Consequently, data cleaning measures must be carried out prior to analysis, as poor-quality data can lead to biased conclusions being drawn (Saunders et al., 2019).

The dataset was scrutinized for missing values, as full survey completion is essential for accurate results. Surveys with more than 10% missing responses were excluded to prevent inconsistencies (Pallant, 2020). Outliers were identified using boxplots and standard deviation, as extreme values can distort statistical outcomes. Any outlier deemed faulty or irrelevant to the study was removed or adjusted to reduce its impact (Field, 2018). Additionally, inattentive response patterns such as straight-lining where respondents select the same option across all Likert items, were examined. Low-quality responses were either removed or appropriately transformed appropriately (Podsakoff et al., 2003).

Through these quality control measures, the study ensures that the dataset is accurate, complete, and statistically robust, thereby strengthening the reliability of findings.

3.3.2 Attention Check

To ensure that participants were engaged and provided thoughtful responses, an attention check question was embedded mid-survey. Attention checks are widely used in survey-based research to filter out inattentive respondents, thereby improving overall data quality and response validity (Berinsky, Margolis, & Sances, 2014). The attention

check used in this study stated: *"It is important that you pay attention. In this question, please answer 'somewhat agree.'"* Participants who failed to provide the correct response were excluded from the final dataset. This approach helped identify and remove cases of satisficing or careless answering behaviour, phenomena known to threaten the reliability and interpretability of self-report data (Hauser & Schwarz, 2016). The inclusion of this quality control measure ensured that the dataset used for analysis reflected the views of attentive and conscientious respondents.

3.3.3 Validity

Validity refers to how well the study measures what it aims to investigate, and whether the findings are meaningful and applicable to the context (Saunders et al., 2019). Establishing validity is important to ensure that the conclusions drawn from the data are trustworthy.

To ensure content validity, the survey questions were based on established academic literature related to quality signals in online reviews. This helped make sure that the questionnaire accurately reflected the key concepts and was relevant for the purpose of the study.

To support predictive validity, the research design included regression analysis to test whether the selected quality signals could be used to predict booking intentions. This approach was chosen to assess if the variables identified in the literature had practical relevance when applied to the context of Airbnb.

By incorporating these validity tests, the study ensures that its research instrument is accurate, theoretically grounded, and capable of producing meaningful insights.

3.3.4 Reliability

Reliability refers to the consistency and stability of the measurement instrument across different instances of data collection (Collis & Hussey, 2021). In other words, repeating a reliable study under the same conditions should produce the same results.

In survey-based research, establishing measurement reliability is essential to ensure the consistency and stability of scale-based responses across items designed to measure the same underlying construct (Collis & Hussey, 2021). For this purpose, internal consistency reliability was assessed using Cronbach's alpha (α), the most widely used coefficient for evaluating the reliability of multi-item scales (Hair et al., 2020).

Cronbach's alpha values range from 0 to 1, where higher values indicate stronger internal consistency. A threshold of $\alpha \geq 0.70$ is generally accepted for explanatory research. However, values between 0.60 and 0.70 may be considered acceptable in behavioural and social science research, particularly when dealing with newly adapted or context-specific scales (Hair et al., 2019; Nunnally & Bernstein, 1994). This has been supported in similar studies on Airbnb using comparable constructs; for example, Zhao et al. (2015) accepted α values slightly above 0.60 in their analysis of signal attributes in Airbnb listings.

The reliability analysis was conducted in IBM SPSS Statistics using the "Reliability Analysis" function. Each factor was assessed independently to determine the degree to which its items formed a consistent scale. The output also included the "Cronbach's alpha if item deleted" statistic, which was reviewed to identify items that weakened internal consistency. This informed any necessary scale refinement in accordance with established guidelines (DeVellis, 2017).

One construct in this study yielded an alpha of 0.621, which was retained based on both theoretical relevance and its consistency with literature in the same field. This decision reflects the principle that moderately reliable constructs may still offer meaningful insight when supported by sound scale development and alignment with existing studies (Zhao et al., 2015).

All constructs were evaluated using this procedure, and final alpha values were deemed sufficient for use in subsequent inferential analyses. By ensuring high reliability, the

study strengthens its trustworthiness and replicability, making it more useful for future research and practical applications.

Below is a table demonstrating the reliability between our two samples and the whole dataset.

Table 3.

	TrustReviews	TrustPlatform	Usefulness	Volume	Valence	Timeliness	BookingIntentions
Prolific	0.611	0.901	0.726	0.730	0.641	0.362	0.720
Friends and Family	0.478	0.864	0.610	0.813	0.591	0.486	0.623
Complete dataset	0.583	0.892	0.700	0.763	0.621	0.371	0.708

3.3.5 Regression Analysis

To examine how the identified review-based quality signals influence consumers' booking intention, a multiple linear regression analysis was conducted. This technique allows for the evaluation of the relationship between a single dependent variable and several independent variables, while accounting for the simultaneous contribution of each predictor (Pallant, 2020). In the context of this study, booking intention served as the dependent variable, and the independent variables included the six quality signals: trust in reviews, trust in the platform, usefulness, volume, valence, and timeliness.

The analysis was conducted using IBM SPSS Statistics, applying the standard method in which all predictors were entered into the model simultaneously. This approach is appropriate when each independent variable is theoretically relevant and the goal is to assess their individual and combined explanatory power (Field, 2018; Hair et al., 2019).

To ensure the accuracy and validity of the regression results, multicollinearity diagnostics were performed by examining tolerance values and variance inflation factors (VIF). VIF values indicate how much the variance of a regression coefficient is increased due to multicollinearity. Values above 5.0 are typically considered problematic, while tolerance values below 0.10 also suggest multicollinearity concerns (Pallant, 2020). In this study, both diagnostics were examined for each moderation model to confirm the stability and interpretability of the regression coefficients.

These indicators help to detect whether any of the predictor variables are too highly correlated with one another, which could otherwise distort the interpretation of the regression coefficients. All values were reviewed to confirm that multicollinearity was not present to a degree that would compromise the model.

This regression approach provided a basis for testing the core hypotheses of the study by quantifying the influence of each quality signal on booking intention while controlling for the others.

3.3.6 Moderation Analysis

To assess whether the relationship between individual review-based factors and booking intention is influenced by users' previous platform familiarity, a moderation analysis was conducted. Specifically, the analysis examined whether the number of previous Airbnb stays moderated the effect of each factor on consumers' booking intention. Moderation occurs when the strength or direction of an independent variable's effect on a dependent variable change depending on the level of a third variable, referred to as the moderator (Hayes, 2018; Hair et al., 2019).

The moderation analysis followed a hierarchical multiple regression approach using IBM SPSS Statistics. For each factor, a separate moderation model was estimated. The analysis involved three key steps. First, an overall mean score was computed for each factor, based on the average of the corresponding Likert-scale items. Next, mean-centring was applied to both the independent variable and the moderator (number of previous Airbnb stays). Centring was done by subtracting the overall sample mean of each variable from each respondent's score. This step reduces the potential for multicollinearity between the main effects and their interaction term, and it improves the interpretability of regression coefficients (Pallant, 2020; Field, 2018).

An interaction term was then computed for each model by multiplying the centred factor with the centred moderator (e.g., *Valence_Centred* × *Experience_Centred*). These interaction terms were used to test whether previous experience significantly moderated the relationship between the respective factor and booking intention.

Each regression was conducted in two steps. In Step 1, the centred independent variable and the centred moderator were entered. In Step 2, the interaction term was added. This approach allowed for the assessment of both main effects and conditional (moderating) effects.

To ensure that multicollinearity did not threaten the validity of the regression models, VIF and tolerance values were reviewed.

Prior to running each moderation model, descriptive statistics were examined for the factors and their corresponding interaction terms to ensure acceptable distribution properties and identify potential outliers. This step helped confirm that the input variables for the models fell within reasonable and interpretable ranges.

While the survey included an item capturing participants' general attitude toward Airbnb, number of previous stays was selected as the moderating variable. This decision was based on the conceptual distinction between behavioural experience and attitudinal perception. Research suggests that prior usage provides a more objective and cognitively accessible frame for interpreting platform signals, such as reviews, compared to general attitude (Bettman, Luce, & Payne, 1998). Moreover, experience-based familiarity is typically more predictive of decision-making behaviours and can be measured with greater reliability than subjective attitudes (Hair et al., 2019). Therefore, the number of previous Airbnb stays was considered the most appropriate and theoretically grounded moderator for this study. This process was repeated for each of the five factors.

3.3.7 Descriptive Statistics

Descriptive statistics were used to summarize the central tendencies and distribution characteristics of each factor in the study. These initial analyses provided insight into the structure of the data and helped assess whether assumptions required for further statistical testing were met (Pallant, 2020).

For each factor and for the dependent variable, the minimum and maximum values were reviewed to confirm that responses fell within the expected range of the 7-point Likert scale. The mean was calculated to indicate the average response across all participants for each factor, reflecting the overall level of agreement or perception.

The standard deviation (SD) was used to measure the extent to which responses were dispersed around the mean. A low standard deviation indicates that responses were clustered closely around the average, suggesting consistency in how participants evaluated the factor. A high standard deviation indicates greater variability in responses and a broader range of perspectives (Pallant, 2020; Field, 2018). For 7-point Likert scales, the following thresholds are commonly used to interpret the extent of variability:

- SD below 0.70: low variability
- SD between 0.70 and 1.00: moderate variability
- SD above 1.00: high variability

These thresholds serve as general guidelines in social science research using multi-point Likert scales (Boone & Boone, 2012; Hair et al., 2019).

To assess the distributional characteristics of the data, skewness and kurtosis were calculated for each factor, along with their respective standard errors. Skewness indicates the symmetry of the distribution. A skewness value near zero suggests a relatively symmetric distribution, while positive or negative values indicate asymmetry. The standard error of skewness helps determine whether the skewness is statistically significant.

Kurtosis evaluates the peaked-ness of the distribution. A kurtosis value close to zero indicates a distribution similar to the normal curve, while positive values suggest a more peaked distribution with heavy tails (leptokurtic), and negative values indicate a flatter distribution with lighter tails (platykurtic). As with skewness, the standard error of kurtosis is used to assess whether deviations from normality are statistically meaningful (Field, 2018; Hair et al., 2019).

These statistical measures were complemented by frequency histograms, which visually represented the distribution of responses for each factor. Since the study applied parametric tests such as multiple regression, it was important to assess the assumption of normality. A normal distribution ensures that estimates of central tendency and inferential statistics are robust and interpretable. According to the central limit theorem, the sampling distribution of the mean approaches normality when the sample size is sufficiently large, typically around 30 or more cases. With a sample size of 200, this condition is more than adequately met, and minor deviations from normality are unlikely to affect the validity of the results (Field, 2018; Pallant, 2020).

Together, the descriptive statistics and distributional assessments ensured that the dataset was suitable for subsequent inferential analysis and that the factors were appropriately interpreted at the group level.

3.3.8 Hypothesis Testing

To test the study's hypotheses, a series of multiple linear regression models were used. Each hypothesis proposed a relationship between a specific factor (independent variable) and booking intention (dependent variable). The statistical significance and direction of these relationships were assessed using the coefficients table generated in IBM SPSS Statistics.

Hypotheses were evaluated based on the p-value associated with each standardized regression coefficient (β). The p-value indicates the probability of obtaining the observed effect if no actual relationship exists between the variables. A significance threshold of p-value < 0.05 was used. If the p-value for a given factor was below this threshold, the null hypothesis of no effect was rejected, and the research hypothesis was considered supported. If the p-value was equal to or greater than 0.05, the hypothesis was not supported.

The standardized beta coefficient (β) was also reviewed to determine the direction and relative magnitude of the relationship. A positive β indicates a positive association, while a negative β reflects an inverse one. Standardized coefficients enable meaningful

comparisons across predictors because they are measured on a common scale (Pallant, 2020).

In addition to significance testing, the explanatory power of the regression models was evaluated using the coefficient of determination (R^2). R^2 indicates the proportion of variance in booking intentions that can be explained by the signals. Following Cohen's (1988) guidelines, R^2 values can be interpreted as follows:

- 0.02 to 0.12: small effect
- 0.13 to 0.25: medium effect
- 0.26 and above: large effect

These thresholds help assess the practical significance of the models beyond statistical significance. All predictors were entered into the regression models simultaneously using SPSS's default enter method, which includes all variables in a single step to assess their unique contribution while controlling for the others. Before interpreting results, assumptions required for multiple regression, including normality, linearity, and multicollinearity, were checked and addressed in earlier steps to ensure the robustness of the hypothesis testing process. Each hypothesis was tested through a consistent approach across all regression models.

3.3.9 Model Fit and Regression Output Interpretation

To evaluate the strength and validity of each regression model used to test the study's hypotheses, several output components generated by SPSS were reviewed. These components assess the model's overall performance and provide insight into how well the set of predictors explains variation in the dependent variable.

The ANOVA (Analysis of Variance) table tests the statistical significance of the regression model as a whole. Specifically, it examines whether the model explains a significantly greater proportion of variance in the dependent variable than would be expected by chance (Pallant, 2020). This is evaluated using an F-statistic and an associated p-value. If the p-value is below the commonly used threshold of 0.05, the

model is considered statistically significant, indicating that the independent variables, as a group, reliably predict the outcome (Field, 2018).

Another key output is the coefficient of determination (R^2), which indicates the proportion of variance in the dependent variable that is explained by the independent variables. An R^2 value of 0.30, for example, would indicate that 30% of the variability in booking intention can be accounted for by the included factors (Hair et al., 2019).

The standard error of the estimate is another important model-level diagnostic. It indicates how far, on average, the observed values deviate from the regression line. A smaller standard error suggests that the model's predictions are more precise, while a larger standard error indicates greater unexplained variance in the outcome (Field, 2018).

Together, these output elements provide a comprehensive view of model fit and are necessary for interpreting the quality and explanatory power of each regression analysis.

3.3.10 Correlation Analysis

To examine the linear associations between the study's variables, Pearson correlation coefficients were computed. Correlation analysis is a foundational method in quantitative research and is used to assess the strength and direction of relationships between pairs of continuous variables (Pallant, 2020). In this study, correlations were calculated between the five factors and booking intention to identify patterns of association and support the interpretation of subsequent regression results.

The Pearson product-moment correlation coefficient (r) measures the degree to which two variables are linearly related. Its value ranges from -1 to +1, where:

- +1 represents a perfect positive linear relationship,
- -1 represents a perfect negative linear relationship, and
- 0 indicates no linear association (Field, 2018).

In addition to the correlation coefficient itself, statistical significance is assessed using a p-value, which estimates the probability that the observed correlation occurred by chance. A correlation is considered statistically significant if the p-value falls below a pre-established threshold, typically $p < 0.05$. In this study, both the 0.05 and 0.01 significance levels were used.

In the SPSS output, significance levels are indicated by asterisks next to the correlation coefficients:

- A single asterisk (*) indicates the correlation is significant at the $p < 0.05$ level.
- A double asterisk (**) indicates the correlation is significant at the $p < 0.01$ level.

These notations provide a quick visual reference to identify which relationships are statistically significant and at what level of confidence. However, statistical significance alone does not indicate the practical importance of a relationship. Therefore, the strength of the correlation is also considered using common interpretative guidelines (Cohen, 1988):

- 0.10 to 0.29: small (weak) correlation,
- 0.30 to 0.49: moderate correlation,'
- 0.50 and above: large (strong) correlation.

Before computing Pearson correlations, assumptions of scale-level measurement, linearity, and normality were considered. The variables used were either interval-level or treated as such due to the use of composite means from Likert-scale items, a common and accepted practice in behavioural and consumer research (Field, 2018; Hair et al., 2019). Scatterplots and descriptive statistics were used to confirm that relationships between variables were approximately linear and suitable for Pearson's method.

The analysis was performed in IBM SPSS Statistics using the bivariate correlation function. While correlation does not imply causation, it serves as a valuable tool to explore relationships between variables, identify patterns that warrant further testing, and support the interpretation of multivariate results.

3.3.11 Common Method Bias and Additional Considerations

As the study relies on self-reported data collected through a single survey instrument, common method bias (CMB) was recognized as a potential methodological concern. CMB occurs when variance is attributable to the measurement method rather than the constructs being measured, potentially inflating or distorting observed relationships between variables (Podsakoff et al., 2003).

To mitigate this risk, several procedural controls were applied during the survey design. First, participants were assured of anonymity and confidentiality, which is known to reduce social desirability bias, a form of CMB where respondents may provide answers, they believe to be more socially acceptable (Saunders, Lewis, & Thornhill, 2019). Second, a mid-survey attention check was embedded to identify inattentive respondents and ensure engagement with the content (Berinsky, Margolis, & Sances, 2014).

In addition, the survey included clear instructions and explanatory notes to reduce ambiguity and ensure consistent interpretation of key concepts. For example, the term *"accommodation"* was defined as *"any short-term rental option (hotel, hostels, vacation rentals etc.)"* to standardize understanding. Participants were also instructed to *"respond as if you are hypothetically booking an Airbnb in Bali"*, which helped establish a shared mental context across respondents. These framing techniques help reduce random measurement error and support the internal consistency of responses (Aguinis & Bradley, 2014).

While no statistical tests for CMB were conducted, the above design choices contribute to reducing the risk of method bias and enhance the overall credibility of the data collection process.

3.4 Ethical Considerations

In research, ethical measures are to be strictly followed so that the rights, privacy, and wellbeing of the participants of the study are taken care of (Saunders et al., 2019). This

study followed all ethical principles relevant to academic institutions and GDPR to ensure regulation of transparency, confidentiality, and informed consent were followed correctly.

Before commencing the study, respondents were given a thorough briefing on the purpose of the study, the processes involved, and their personal rights regarding the study. Participants were also informed that if they agree to participate, it is voluntary, and they can withdraw at any point of time without any need to explain their decision. In order to guarantee confidentiality, personally identifiable information (PII) is not stored, and all responses are kept in secured encrypted drives. Access to data was limited to the research team, while the information is only used for academic purposes.

The survey maintained a neutral non-intrusive design that ensure all questions asked did not offend or distress the respondent in any way. Even though respondents are put at the centre of investigation, ethical research should respect the dignity of all participants in order to achieve the primary objective of reporting inaccuracy free and unbiased results. The above approach enables the study and research to be conducted in a proper manner and the objectives achieved in an academically ethical acceptable way.

4. Empirical Findings and Analysis

The following chapter presents the findings of the data collected. The findings chapter starts with the profile of the respondents to explain the demographics of the sample. Afterwards, we discuss the reliability of the scales and multicollinearity. Further, we present the findings for descriptive statistics, to summarize the central tendencies and distribution characteristics. The chapter continues with the Regression and Moderation analyses to test our various hypotheses and then the regression model to test the fit. Lastly, we present what correlations could be seen and the attitudes regarding previous experience with Airbnb, representing more qualitative data.

4.1 Profile of Respondents

Out of the total of 223 responses collected, the number of responses considered was 200. There were 15 respondents who failed the filter questions, five respondents who failed the attention check and three responses that were our own when double-checking the finished version of the survey. These responses were removed, making the final number of responses, 200.

Regarding the age of our respondents, the biggest group consisted of people aged 18 – 24, closely followed by the group of people aged between 25 – 34. The frequency of responses was less and less the older the age group. The frequency and percentage of the respondents and their age are summarized in table 4.

Table 4.

	Frequency	Percent
18-24	76	38.0
25-34	65	32.5
35-44	35	17.5
45-54	16	8.0
55-64	5	2.5
65+	3	1.5
Total	200	100

The second demographic asked was what gender the respondents identified with. The majority of respondents were female and 28 respondents less, identified as male. There was also one respondent who identified as non-binary/third gender, and one who chose "prefer not to say". The gender of the respondents is also summarized below in table 5.

Table 5.

	Frequency	Percent
Male	85	42.5
Female	113	56.5
Non-binary/third gender	1	0.5
Prefer not to say	1	0.5
Total	200	100

The last demographic addressed was the yearly income of the participants. The results showed that the majority of participants made between 10,000 - 25,000 EUR yearly. The groups of people who made under 10,000 EUR and the ones that made 25,000 - 49,000 EUR were the second and third biggest groups respectively, closely following. Fewer participants had a bigger yearly income than that, which can be seen in table 6.

Table 6.

	Frequency	Percent
Under 10,000 EUR	53	26.5
10,000 – 24,999 EUR	62	31.0
25,000 – 49,000 EUR	48	24.0
50,000 – 74,999 EUR	21	10.5
75,000 – 99,999 EUR	8	4.0
100,000 EUR or more	8	4.0
Total	200	100

While the demographics showed many different profiles, there were still certain groups bigger than others, such as being younger and female.

4.2 Reliability of the Scales

The reliability of the items on the survey where the first set of statistics aside from descriptives conducted. The reliability of the items was tested through a reliability analysis on SPSS to compute Cronbach's alpha on the factors, including the reliability if item deleted. The reliability scores can be seen in table 7.

Table 7.

	Cronbach's alpha	Nr of Items
TrustReviews	0.583	3
TrustPlatform	0.892	3
Usefulness	0.700	3
Volume	0.763	3
Valence	0.621	3
Timeliness	0.371	3
BookingIntentions	0.708	3

As seen in table 7, the factors of trust in reviews and timeliness did not result in acceptable values. The first factor of trust in reviews showed a Cronbach's alpha of 0.583 which was below the acceptable level of 0.6 (Hair et al., 2019; Nunnally & Bernstein, 1994). Table 8 shows the different Cronbach's alphas if items in the factors of trust in reviews and timeliness are deleted. This shows the greatest value of 0.716 if

item 2 is deleted. Therefore item 2 was deleted, and the factor has a Cronbach's alpha above the acceptance level. The last factor of timeliness had the lowest Cronbach's alpha of 0.371, which was also not acceptable. Out of the items, the second item was found to be the issue, resulting in a value of 0.665 if item 2 is deleted. Therefore, item 2 was removed and not used in the subsequent analysis.

Table 8.

(items)	Cronbach's alpha if item deleted
TrustReviews1	0.194
TrustReviews2	0.716
TrustReviews3	0.351
Timeliness1	0.273
Timeliness2	0.665
Timeliness3	-0.081

Next, the trust in the platform showed a high value of 0.892 which was above the acceptable level (Hair et al., 2019; Nunnally & Bernstein, 1994). Therefore, the items in this factor were all kept. Usefulness ($\alpha = 0.700$), volume ($\alpha = 0.763$), and valence ($\alpha = 0.621$) also met acceptable reliability levels, and no items were removed. Lastly, booking intentions showed a Cronbach's alpha of 0.708, supporting the retention of all items in that scale as well.

4.3 Multicollinearity

4.3.1 Regression Analysis

Table 9 presents the results of the multicollinearity check for the regression analysis. All independent variables showed VIF values well below the common threshold, indicating no strong multicollinearity (Pallant, 2020). Usefulness had the highest VIF (2.066), suggesting only low to moderate overlap with other variables, while valence had the lowest (1.069), indicating minimal correlation. The remaining VIFs ranged from 1.2 to 1.7, reflecting weak but non-problematic correlations. Tolerance values were all

well above 0.10, further confirming the absence of significant multicollinearity (Pallant, 2020).

Table 9.

	Collinearity Tolerance	VIF
TrustReviews	0.654	1.529
TrustPlatform	0.600	1.666
Usefulness	0.484	2.066
Volume	0.815	1.227
Valence	0.936	1.069
Timeliness	0.786	1.272

4.3.2 Moderation Analysis

In each model, predictors were mean centred to avoid multicollinearity before computing the interaction terms for the moderation analysis.

As shown in table 10, all VIF values were quite low. The highest and lowest values are shown for the interaction items with valence at 1.061 and trust in reviews and usefulness at 1.011. This indicates that there were no issues with multicollinearity. In accordance with this, the collinearity tolerance showed all values well above 0.10 (Pallant, 2020).

Table 10.

	Collinearity Tolerance	VIF
TrustReviews	0.990	1.011
TrustPlatform	0.969	1.032
Usefulness	0.989	1.011
Volume	0.985	1.015
Valence	0.943	1.061
Timeliness	0.956	1.046

4.4 Descriptive statistics

Descriptive statistics were calculated to provide an overview of the central tendencies and dispersion for each of the factors. This includes the mean, minimum, maximum, standard deviation, skewness and kurtosis and frequency distribution.

These findings suggest that all measured quality signals were positively perceived by the sample, with relative agreement among the respondents. All variables also displayed negative skewness indicating that responses were generally skewed towards higher value on the 7-point Likert scale. Participants tended to agree or strongly agree with the statements across all variables. Overall, the kurtosis values indicated that most variables exhibited moderately peaked distributions, with responses clustering around the mean.

Table 11.

	N	Minimum	Maximum	Mean	Standard Deviation	Skewness	Kurtosis
TrustReviews	200	1.00	7.00	6.090	0.775	-2.377	10.165
TrustPlatform	200	1.67	7.00	5.800	0.929	-1.305	2.963
Usefulness	200	3.00	7.00	6.008	0.715	-0.913	1.417
Volume	200	2.67	7.00	5.697	0.969	-0.695	0.032
Valence	200	1.67	7.00	5.538	0.960	-1.005	1.811
Timeliness	200	2.50	7.00	6.023	0.889	-1.137	1.374
BookingIntention	200	1.33	7.00	5.663	0.973	-0.898	1.377

4.4.1 Factors and Booking Intentions

The mean value for trust in reviews was 6.09, indicating that participants generally perceived Airbnb reviews as highly trustworthy. The minimum and maximum showed that there were responses across the entire Likert scale and the standard deviation was also quite moderate at, 0.78 (Boone & Boone, 2012; Hair et al., 2019). Trust in reviews showed a strong negative skew of -2.38 and high kurtosis of 10.17. This means that responses were heavily concentrated at the high end of the scale with very little variation.

Trust in the platform showed a moderately high mean (5.80), slightly lower than trust in reviews. Responses ranged from 1.67 to 7.00, indicating variation in trust levels. The standard deviation was 0.93, suggesting moderate variability and the distribution was skewed toward agreement (skewness = -1.31) with a relatively peaked distribution (kurtosis = 2.96).

Usefulness had a high mean of 6.01, indicating that respondents generally found Airbnb reviews very useful. Responses ranged from 3 to 7, with no strong disagreement. It also showed the least variation (SD = 0.72), with general agreement (skewness = -0.91) and a moderately peaked distribution (kurtosis = 1.42).

Volume had a mean of 5.70, suggesting moderate to high importance placed on the number of reviews. With a minimum of 2.67 and a maximum of 7, few respondents disagreed. It showed one of the highest variations among the factors, though still moderate (SD = 0.97), the lowest skewness (-0.70), and near-zero kurtosis (0.03), indicating a more symmetrical and normally distributed response pattern.

Valence had the lowest mean (5.54), indicating general agreement on the importance of negative reviews. The minimum and maximum showed that there were responses across the entire Likert scale. Variation was moderate (SD = 0.96), with skewness toward agreement (skewness = -1.01) and a moderately peaked distribution (kurtosis = 1.81).

Timeliness also showed a high mean of 6.02, indicating its importance and there were varied responses across the Likert scale. The variation was also moderate with a standard deviation of 0.89. Timeliness showed a moderate to high skewness of -1.14 and kurtosis of 1.37, suggesting a tendency toward more agreement and in a moderate distribution.

Booking intention had a mean of 5.66, indicating a generally positive willingness to book Airbnb in Bali. It was the second lowest mean, with responses ranging across the Likert scale. Variation was one of the highest among the variables (SD = 0.97), though

still moderate. The distribution was skewed toward agreement (skewness = -0.90) with a moderate peaked distribution (kurtosis = 1.38).

4.4.2 The Moderating Effect of Previous Experience with Airbnb

Lastly, the descriptive statistics regarding the previous experiences with Airbnb is displayed in table 12. This excludes the open-ended question.

Table 12.

	N	Minimum	Maximum	Mean	Standard Deviation	Skewness	Kurtosis
NrStays	200	1	5+	3.55	1.496	-0.479	-1.232
PrevExperience	200	3	7	5.97	0.847	-1.236	2.522

The average number of stays was 3.55 which is quite a lot (frequences can be seen in the appendix). It is noteworthy though that the survey did not include the option to answer 0, which may affect our findings. The standard deviation was 1.50, indicating a moderate to high level of variation, with responses slightly skewed toward more frequent stays (skewness = -0.48). The distribution was relatively flat (kurtosis = -1.23), suggesting responses were spread out.

The attitude toward their previous experiences had a mean of 5.97 indicating that the experiences were overall positive and no responses below 3. This implies that no participant reported negative experiences with Airbnb. The standard deviation was quite low at 0.85 reflecting general agreement for their attitudes. Skewness and kurtosis showed values of -1.24 and 2.52 indicating more respondents having positive previous experiences and more peaked distribution. Overall, these results reflect that participants were familiar with Airbnb and had mainly positive past experiences.

4.5 Hypothesis Testing

The statistics conducted to test the hypothesis was a multiple regression analysis, using SPSS. The calculated p-values of all factors can be seen in Table xx and the significance level threshold is 0.05 (Pallant, 2020).

Table 13.

	Sig
TrustReviews	0.931
TrustPlatform	0.012
Usefulness	0.193
Volume	<0.001
Valence	<0.001
Timeliness	0.010

4.5.1 Trustworthiness

First, addressing the hypothesis of trustworthiness. Trust in reviews showed a p-value of 0.931. The p-value is therefore higher than our significance level, $p > 0.05$ and we reject our hypothesis, H1. Our findings do not show evidence that trust in Airbnb reviews positively influence booking intentions on Airbnb accommodation in Bali. H1 is not supported.

Trust in platform, however, showed a p-value of 0.012 which is less than our significance level, $p < 0.05$. Hence, we accept our hypothesis that trust in the platform positively influences booking intentions on Airbnb accommodation in Bali. The evidence suggests support for H2.

4.5.2 Usefulness

The factor of usefulness showed a p-value higher than our significance level, calculated to 0.193. As $p > 0.05$ we do not find evidence supporting H3. Our hypothesis regarding the usefulness of reviews positively influencing booking intentions on Airbnb accommodation in Bali is not supported and we reject H3.

4.5.3 Volume

The p-value for volume was calculated to < 0.001 which is well below the significance level of 0.05. Since this factor showed $p < 0.05$, our hypothesis can be accepted.

Therefore, the findings show that the volume of Airbnb reviews positively influence booking intentions on Airbnb accommodation in Bali. H4 is supported.

4.5.4 Valence

The resulting p-value for valence was as volume, also < 0.001 which is well below the significance level. As valence resulted in a $p < 0.05$, our hypothesis can be accepted. Therefor the findings suggest that negative Airbnb reviews negatively influence booking intentions on Airbnb accommodation in Bali. H5 is supported.

4.5.5 Timeliness

Lastly, timeliness showed a computed p-value of 0.010 which is below the significance level of 0.05. Since this factor resulted in $p < 0.05$, our hypothesis can be accepted. These findings show that the timeliness of Airbnb reviews positively influence booking intentions on an Airbnb accommodation in Bali. H6 is supported.

4.5.6 The Moderating Effect of Previous Experience with Airbnb

To test the moderating effect of previous experience with Airbnb for H7, we used a moderation analysis. “Number of stays” was used to determine if previous experience moderates the relations between the factors and booking intentions. In all model analysis tests, the factor and previous number of stays with the additional interaction term are tested in isolation of the other variables. H7 is partially supported.

Table 14.

	Model	R	R Square	R Square Change	Sig. F Change	Interaction coefficient
TrustReviews	1	0.295	0.087	0.087	<0.001	-0.204
	2	0.358	0.128	0.041	0.003	
TrustPlatform	1	0.375	0.141	0.141	<0.001	-0.092
	2	0.386	0.149	0.008	0.170	
Usefulness	1	0.409	0.168	0.168	<0.001	-0.118
	2	0.426	0.181	0.014	0.072	
Volume	1	0.429	0.184	0.184	<0.001	0.001
	2	0.429	0.184	0.000	0.994	
Valence	1	0.309	0.095	0.095	<0.001	0.159
	2	0.345	0.119	0.024	0.022	
Timeliness	1	0.372	0.139	0.139	<0.001	-0.042
	2	0.374	0.140	0.002	0.536	

4.5.6.1 Trustworthiness

Table 14 presents the moderation analysis results. In model 1, trust in reviews and number of stays together explained a significant portion of the variance in booking intentions ($R^2 = 8.7\%$, $p < 0.001$). Model 2 included the additional interaction term between trust in reviews and previous experience, which significantly improved the model ($R^2 = 12.8\%$, R^2 change = 4.1%, $p = 0.003$). Further, the interaction coefficient was negative ($\beta = -0.204$), indicating that the positive effect of trust in reviews on booking intentions weakens as experience increases. This reflects a significant negative moderation ($p < 0.05$), and therefore, H7 is partially supported.

Secondly, trust in platform showed that model 1 (including trust in platform and number of stays) explained 14.1% of the variance in booking intentions, proving significant as $p < 0.001$. Model 2, which added the interaction term, showed only a small increase ($R^2 = 14.9\%$, R^2 change = 0.8%) that was not statistically significant as $p = 0.170$ and above the significance level of 0.05. Thus, there is no evidence that previous experience moderates the relationship between trust in platform and booking intentions. As a result, H7 is not supported in this case.

4.5.6.2 Usefulness

Table 14 shows that usefulness and number of stays explained 16.8% of the variance in booking intentions ($p < .001$), indicating a significant effect. Adding the interaction term in Model 2 increased the explained variance to 18.1% (R^2 change = 1.4%), however this change was not statistically significant as $p = 0.072$. Thus, there is no evidence that previous experience moderates the relationship between usefulness and booking intentions, and H7 is not supported in this case.

4.5.6.3 Volume

Model 1 showed that the variance, R^2 in booking intentions was 18.4%. This was also shown to be statistically significant as p-value was < 0.001. Model 2 displayed a variance of 18.4% as well and no increase once the interaction term was added. This was unlike Model 1 not statistically significant with p calculated to 0.994. Hence, previous experience does not moderate the relationship between volume and booking intentions. H7 is not supported through the factor of volume.

4.5.6.4 Valence

Table 14 shows that valence and number of stays significantly predicted booking intentions ($R^2 = 9.5\%$, $p < .001$). Adding the interaction term in Model 2 increased the explained variance to 11.9% (R^2 change = 2.4%, $p = 0.022$), indicating a significant moderation effect. The positive interaction coefficient ($\beta = 0.159$) suggests that as experience increases, the impact of negative reviews on booking intentions becomes stronger. Hence, H7 is partially supported through valence.

4.5.6.5 Timeliness

Lastly, Model 1 indicated that timeliness and number of stays together accounted for 13.9% of the variances in booking intentions, showing statistical significance ($p < 0.001$). Model 2, where the additional interaction term is present, showed an increase in R^2 by 0.2% making it in total 14.0%. This increase in the variance is not statistically significant, as $p = 0.536$. This means that there is no moderation effect from previous

experience on the relationship between timeliness and booking intentions. H7 is not supported through timeliness.

4.6 Regression Model

The multiple regression analysis further resulted in an ANOVA table and a Model Summary (table 15 and 16). The results in table 15 indicated that the model was statistically significant, as $p < 0.001$ which is well below the acceptance level of 0.05 (Pallant, 2020). This suggests that the combination of predictors; trustworthiness, usefulness, volume, valence, and timeliness collectively explain a significant proportion of variance in consumers' booking intention (Cohen, 1988).

The correlation (R) between predicted and actual values of booking intention shows a value of 0.586, indicating a strong correlation (Cohen, 1988). R^2 was 0.344, meaning that approximately 34.4% of the variance in booking intention was explained by the model, a relatively large explaining power (Cohen, 1988). The standard error of the estimate was 0.80, suggesting a moderate level of deviation between the predicted and actual booking intention scores (Boone & Boone, 2012; Hair et al., 2019).

Table 15.

	Sum of Squares	df	Mean Square	F	Sig
Regression	64.787	6	10.798	16.853	<0.001
Residual	123.655	193	0.641		
Total	188.442	199			

Table 16.

Model	R	R Square	Std Error of the Estimate
1	0.586	0.344	0.800

The next table shows all model summaries from the factors in isolation (table 17).

Table 17.

	Model	R	R Square	Std Error of the Estimate
TrustReviews	1	0.258	0.067	0.942
TrustPlatform	1	0.357	0.128	0.911
Trustworthiness	1	0.385	0.148	0.903
Usefulness	1	0.392	0.154	0.898
Volume	1	0.418	0.175	0.886
Valence	1	0.260	0.068	0.942
Timeliness	1	0.362	0.131	0.909

4.6.1 Trustworthiness

Each factor was also tested individually against booking intention through a simple linear regression model. Starting with trust in Airbnb reviews in isolation from the other factors, table 17 indicates that this factor has a limited influence when considering booking intentions. The correlation is fairly weak at 0.258 and the variance of booking intentions caused by trust in reviews is only 6.7%. Out of all factors, this shows the weakest variance and correlation when ignoring the other factors.

Regarding trust in the platform, both R and R^2 is slightly higher. This shows a moderate correlation of 0.357 and a variance of 12.8% in booking intentions from trust in platform. This indicates that this factor is better at explaining booking intentions, however it is still a medium explainer in isolation (Cohen, 1988).

When considering trustworthiness (both trust in reviews and trust in platform together) as a factor in isolation from the other factors we get the values in table 17. Here, we found that the correlation between trustworthiness and booking intentions shows a moderate value of 0.385. The variance was found to be 14.8% showing that trustworthiness as a whole explains booking intentions slightly better than trust in reviews and trust in platform separately. The correlation and variance are however, in general medium.

4.6.2 Usefulness

R, the correlation between usefulness and booking intentions and R^2, the variance in booking intentions caused by usefulness were calculated to 0.392 and 15.4% respectively. This indicates that in isolation, usefulness is a good predictor of booking intentions, compared to the other factors individually. However, in general it is still medium.

4.6.3 Volume

The volume factor shows the largest R at 0.418 and R^2 of 17.5%. This means that in isolation, this factor has the strongest correlation with booking intentions and explains the biggest amount of variance among all factors. These findings indicate that a greater number of reviews mediumly explains booking intentions.

4.6.4 Valence

The correlation for valence is 0.260 which indicates a quite weak correlation between valence and booking intentions. Among the factors, valence has the second weakest correlation in isolation. The same applies for the variance in booking intentions caused by valance, which is the second weakest at 6.8%. This suggests a medium effect.

4.6.5 Timeliness

Lastly, the R and R^2 in table 17 was calculated to 0.362 and 13.1%. The values for the correlation and variance indicate a moderate influence of timeliness on recent reviews in booking intentions. In general, however, these are also quite medium values.

4.7 Pearson Correlation

A Pearson correlation analysis was conducted to assess the linear relationships between the five quality signals, trustworthiness (trust in reviews+ trust in platform), usefulness, volume, valence, and timeliness and booking intention. Correlation coefficients (r)

indicate the strength and direction of association between variables, while significance levels determine the statistical relevance of the relationships (Cohen, 1988).

The results show that all factors were positively and significantly correlated with booking intention at the $p < 0.01$ level. However, the strength of the relationships varied, ranging from weak to moderate.

All inter-factor correlations were likewise positive and significant, indicating internal consistency among the quality signals. However, none of the bivariate correlations exceeded thresholds that would suggest multicollinearity concerns (i.e., $r > 0.80$).

Table 18.

	Booking intention	Trust Reviews	Trust Platform	Usefulness	Volume	Valence	Timeliness
Booking intention	1.0						
Trust reviews	0.258**	1.0					
Trust Platform	0.357**	0.349**	1.0				
Usefulness	0.392**	0.536**	0.607**	1.0			
Volume	0.418**	0.296**	0.326**	0.369**	1.0		
Valence	0.260**	-0.058	-0.109	0.037	0.051	1.0	
Timeliness	0.362**	0.382**	0.242**	0.353**	0.280**	0.133	1.0

In addition to analysing the relationship between each factor and booking intention, Pearson correlation coefficients were examined to assess the linear associations among the five factors themselves. All inter-factor correlations were found to be positive and statistically significant at the $p < 0.01$ level, except for correlations involving valence, which demonstrated weak or negative associations with other factors.

The strongest inter-factor correlation was observed between trust in platform and usefulness ($r = 0.607$), indicating a strong positive relationship. This suggests that respondents who perceived the platform as trustworthy also tended to rate the reviews as more useful. Similarly, trust in reviews correlated strongly with usefulness ($r = 0.536$) and moderately with timeliness ($r = 0.382$). Weaker positive correlations were noted between volume and other factors, such as trust in reviews ($r = 0.296$) and timeliness ($r = 0.280$).

Contrarywise, valence showed negligible or negative correlations with most factors, including a slight negative correlation with trust in reviews (r = -0.058) and trust in platform (r = -0.109). These values indicate that perceptions of review valence were largely independent of other quality signals in this dataset.

4.8 Reflections on Previous Airbnb Experience- Open Ended Survey Question

To complement the structured survey items, respondents were asked an open-ended question regarding their previous experiences with Airbnb: *"Why would you describe your previous experience/experiences as such? (negative/positive)"*. A total of 169 responses were collected and thematically reviewed to identify recurring sentiments and ensure no major influencing factors were overlooked.

Of these responses, 152 were provided by participants recruited via Prolific, while 17 came from the unpaid friends and family group. The high engagement and detailed answers from Prolific participants further support the platform's reliability in generating attentive and thoughtful data.

Most respondents reflected on their Airbnb stays in positive terms, frequently citing themes such as accuracy of listings, effective communication, and cleanliness. Comments like *"the place matched the description"* and *"host was responsive and helpful"* were common, reinforcing the importance of trust and timeliness as key quality signals.

While some participants used the open-ended question to express minor frustrations or unrelated concerns such as general travel inconveniences, the overarching sentiment remained favourable towards Airbnb. Negative remarks were typically isolated and focused on occasional discrepancies or unmet expectations, as illustrated by statements like *"the property was not as clean as expected"*.
In summary, the open-ended responses confirmed that the structured survey successfully captured the main factors influencing booking intentions. The qualitative input served as a validation check, indicating that no significant themes were

overlooked, and highlighted the generally positive outlook respondents held towards their Airbnb experiences.

5. Discussion

There are various key findings presented in the previous chapter, including findings regarding the hypotheses and the overall model used for the test. The results provide a better overview of which signals in Airbnb reviews matter to prospective guests when considering Bali as the destination. The hypotheses we could accept were H2, H4, H5, H6 and partially H7, while the hypotheses rejected were H1, H3 and partially H7. This chapter discusses all factors one by one, followed by the moderating effect of previous experience with Airbnb and the overall model.

5.1 Trustworthiness

The first hypothesis rejected was H1, regarding trust in reviews. Contrary to expectations and previous literature (e.g., Filieri, 2016; Sidali et al., 2009), trust in reviews did not significantly impact booking intentions in the full regression model. One potential explanation is the overall high mean rating of this factor, which may have led to ceiling effects and reduced variance. This could have limited its explanatory power, even though participants generally rated it as important. Additionally, phenomena such as review inflation (Bridges & Vásquez, 2018) may have caused scepticism, particularly among experienced users. In saturated digital platforms like Airbnb, overly positive or biased reviews might be discounted, leading guests to rely on other more quantifiable or objective signals.

Notably, the moderation analysis revealed that trust in reviews declined in importance among more experienced guests. This supports previous research (Wheathers et al., 2007; Park & Kim, 2008), which suggests that experienced users are more adept at identifying potentially biased or uninformative content. For novice users, review trustworthiness may still play a meaningful role, but repeated exposure may reduce its perceived value. This finding is reflected in the negative moderation coefficient (β = -

0.204), indicating that experience weakens the positive relationship between trust in reviews and booking intentions.

Contrarywise, trust in the Airbnb platform (H2) significantly and positively influenced booking intentions, confirming findings by Ert et al. (2016) and Gavilan et al. (2018). In contexts with weaker institutional structures, such as emerging tourism markets like Bali, platform-level trust is particularly critical (Rua & Nunes, 2012). Airbnb's systems for identity verification, secure payments, and mutual feedback help reduce perceived risk in the absence of formal regulation (Zervas et al., 2017; Ikkala & Lampinen, 2015). These platform-based trust mechanisms create a baseline of credibility that supports the platform's role in enabling commerce between strangers (Zamani et al., 2019).

This distinction between trust in reviews and trust in the platform aligns with signalling theory (Spence, 1973). Trust in the platform functions as an institutional signal that facilitates participation in P2P markets, while review-based trust operates at the level of individual listings. The current findings suggest that as consumers become more experienced, institutional signals may be prioritized over peer-generated ones.

In emerging markets, where formal standards are often lacking, additional signals such as host responsiveness, profile photos, and Superhost status become more salient (Ert et al., 2016; Rua & Nunes, 2012). These visual and behavioural indicators provide reassurance when traditional regulatory protections are limited.

5.2 Usefulness

Usefulness of reviews (H3) was also rejected as a significant predictor of booking intentions. This contrasts with earlier studies that positioned perceived usefulness as a key driver in consumer decision-making (Park & Lee, 2009; Oliveira, 2020; Mudambi & Schuff, 2010). One explanation could be the multidimensional nature of usefulness itself. In this study, usefulness may have been interpreted as a compound concept, influenced by other signals such as volume, trust, and timeliness. Notably, usefulness correlated moderately with trust in reviews ($r = 0.536$), trust in the platform ($r = 0.607$),

and volume (r = 0.369), suggesting it may function more as a mediating perception shaped by other review qualities rather than an independent driver (table 18).

Although usefulness showed a respectable explanatory power in simple regression (R^2 = 15.4%), it was not a significant predictor once controlling for other variables in the full regression model. This pattern suggests some overlap with other predictors, particularly volume and trust. Supporting this interpretation, the VIF value for usefulness was the highest among all predictors (2.066), indicating moderate multicollinearity. While not exceeding critical thresholds, this overlap suggests that usefulness shares explanatory variance with volume and trustworthiness, thereby weakening its unique predictive contribution.

Another consideration is the role of information overload. In environments with vast amounts of user-generated content, consumers may rely less on their subjective judgment of usefulness and more on heuristic signals such as volume or recency (Baek et al., 2012; Bawden & Robinson, 2020). Furthermore, usefulness is inherently subjective and varies based on user experience and information needs (Park & Kim, 2008). This is supported by the study's descriptive results: 43% of participants had five or more Airbnb stays, suggesting that more experienced users may interpret and evaluate review content differently than novices.

Despite H3 being rejected, the strong correlations between usefulness and several other quality signals support its continued relevance. From a signalling theory perspective (Spence, 1973), usefulness enhances signal clarity, enabling potential guests to better interpret reviews in light of their own expectations and uncertainties. It may not always act as a direct driver of behaviour but instead supports other perceptions that shape final decisions.

In Bali's emerging market context, peer-generated reviews often substitute for formal guidance (Rua & Nunes, 2012). While usefulness did not emerge as a significant standalone factor, the ongoing importance of relevant, clear, and recent review content remains evident. Prior research (Tandon et al., 2020; Zhao et al., 2015) also suggests

that attributes such as review length and specificity can increase perceived usefulness, even if not explicitly isolated in the current study.

5.3 Volume

Volume (H4) was found to be a significant predictor of booking intentions, in line with earlier studies highlighting the importance of review quantity in shaping perceptions of credibility and popularity (Liu, 2006; Duan et al., 2015; Torres et al., 2015). Among all signals tested, volume showed the strongest isolated explanatory power ($R = 0.418$, $R^2 = 17.5\%$), indicating a moderate but leading influence on booking behaviour. This suggests that while not decisive on its own, volume is a central factor in early-stage decision-making.

Volume acts as a heuristic that reduces uncertainty in P2P markets (Chevalier & Mayzlin, 2006; Zhao et al., 2015). In fragmented markets like Bali, where accommodation quality varies and formal certifications are rare, the number of reviews provides a clear signal of a listing's reliability and prior engagement (Rua & Nunes, 2012; Ert et al., 2016). Volume therefore compensates for information gaps, helping users identify listings that are more likely to meet expectations.

From the perspective of signalling theory (Spence, 1973; Connelly et al., 2011), volume serves as a visible indicator of prior market behaviours, signalling that many others have transacted successfully with a given host. As Baek et al. (2012) note, consumers often use volume as a filtering mechanism, excluding listings with few or no reviews before even engaging with detailed content.

Although volume was the strongest predictor in this study, its effect remains moderate, and it likely operates in conjunction with other signals such as timeliness and/or trust. Some studies suggest that review volume may face diminishing returns once it surpasses a certain threshold, after which users shift attention to content quality (Mudambi & Schuff, 2010). Additionally, users with higher platform experience may use volume as a baseline criterion rather than a decisive factor, instead relying on content specifics to finalize decisions (Filieri, 2016; Park & Kim, 2008).

The correlation results support this interpretation (table 18), showing moderate associations between volume and usefulness (r = 0.369) and between volume and trust in the platform (r = 0.326). This suggests that volume contributes to building a general perception of reliability but is rarely the sole driver of consumer action.

In conclusion, volume plays a visible and influential role in shaping booking intentions, especially in early-stage screening. Its strength lies in reducing uncertainty efficiently, particularly in markets where formal indicators of trust are absent.

5.4 Valence

Valence (H5) emerged as a significant predictor of booking intentions, supporting the hypothesis that the emotional tone of reviews influences consumer behaviour. The findings revealed that more negative review content negatively impacts booking intentions, with a statistically significant p-value below 0.001. This result aligns with previous literature emphasizing the strong emotional influence of review valence (Zhao et al., 2015; Filieri, 2016; Mudambi & Schuff, 2010).

Valence serves as a clear and immediate signal of consumer sentiment, allowing potential guests to quickly assess the perceived quality of an accommodation. In line with signalling theory (Spence, 1973; Connelly et al., 2011), valence operates as a simple yet powerful signal that helps travellers reduce information asymmetry without requiring deep engagement with all available review content. Positive reviews offer reassurance, while negative reviews act as risk amplifiers, potentially outweighing other positive signals due to negativity bias (Filieri, 2016). This cognitive bias leads consumers to place greater emphasis on negative information when evaluating choices, particularly in high-stakes or uncertain environments like P2P marketplaces.

In the context of Bali's emerging tourism market, valence may hold even more weight. Given the general tendency for review positivity and possible review inflation (Bridges & Vásquez, 2018), negative reviews could stand out more sharply, drawing consumer attention and influencing perceptions more strongly. When formal guarantees or

institutional quality standards are absent, emotional signals such as review valence become especially critical for managing perceived risk (Rua & Nunes, 2012).

While valence is often considered a subjective signal, Airbnb's structured 5-star rating system provides a standardized framework that reduces ambiguity. A one-star or two-star rating clearly conveys dissatisfaction, even if the emotional tone of the accompanying text is open to interpretation. This formalized scoring mechanism positions valence as a hybrid signal, blending emotional expression with a numerical rating, making it more reliably interpretable across users and cultures.

Still, individual preferences may influence how much weight is placed on specific types of negative feedback. For example, what one traveller considers a drawback, such as limited Wi-Fi access or a remote location, may not hold the same relevance for another. This subjectivity highlights the nuanced way in which valence interacts with consumer expectations and personal travel priorities.

Moreover, the moderation analysis revealed that the effect of valence on booking intentions became stronger for more experienced users. This indicates that as guests accumulate more Airbnb stays, they become even more sensitive to negative reviews. The positive interaction coefficient from the moderation model supports the interpretation that experienced users react more negatively to unfavourable review content compared to less experienced users.

5.5 Timeliness

Timeliness (H6) was found to significantly influence booking intentions, with a p-value of 0.010 and an R^2 of 13.1%, showing a statistically significant contribution to explaining booking behaviour. This supports prior research suggesting that the recency of reviews plays a key role in shaping consumer perceptions of relevance and reliability (Zhao et al., 2015; Tandon et al., 2020). On a platform like Airbnb, where listing conditions and host behaviour can change rapidly, recent reviews help guests assess current service quality more effectively than older reviews.

In emerging markets such as Bali, where regulatory oversight is limited, and accommodations often operate outside formal quality control mechanisms (Rua & Nunes, 2012), the importance of recent feedback becomes even more pronounced. In such settings, recent reviews reduce uncertainty by signalling that the host and listing remain active and trustworthy under current conditions. From a signalling theory perspective (Spence, 1973), timeliness increases the credibility and informativeness of review content, offering more accurate signals about potential risk.

The role of timeliness is further supported by its positive correlations with other signals (Table 18), including usefulness (r = 0.353**), trust in reviews (r = 0.382**), trust in the platform (r = 0.242**), and booking intention (r = 0.362**). These relationships suggest that timeliness reinforces the effectiveness of other quality signals, rather than functioning in isolation. Prior literature supports this, with Zhao et al. (2015) and Tandon et al. (2020) arguing that recent reviews are more likely to be perceived as useful precisely because of their recency. While this study assessed timeliness as an independent construct, these findings highlight its interconnected role within the broader evaluation of review quality.

Importantly, timeliness was one of the few signals whose impact did not vary significantly across different levels of user experience. Unlike trust in reviews and valence, which were both moderated by experience, timeliness maintained a consistent influence. This suggests that both novice and experienced users value recent information when evaluating listings. In an environment characterized by high information availability, timely reviews may function as a useful filter to avoid information overload (Baek et al., 2012; Bawden & Robinson, 2020).

A strength of this study was treating timeliness as a distinct factor rather than folding it into broader constructs like usefulness. This allowed the analysis to isolate its unique contribution. However, it is noteworthy that timeliness was assessed through general perceptions of recency rather than exact time frames.

In conclusion, timeliness emerged as a relevant and reliable quality signal in Airbnb reviews, particularly in emerging markets where other safeguards are weak or absent.

While not the strongest signal overall, its consistent effect and correlation with multiple other signals highlight its importance in reducing uncertainty and aiding booking decisions.

5.6 The Moderating Effect of Previous with Airbnb

The study also proposed that previous Airbnb experience would moderate the influence of quality signals on booking intentions. The results partially support H7, showing significant moderation for trust in reviews and valence.

For trust in reviews, a negative moderation was observed where experienced guests relied less on this signal when booking. This aligns with Park & Kim (2008) who argue that experienced consumers develop selective processing skills, and perhaps then have less dependence on trust. This is interesting considering that trust in reviews did not show to significantly influence booking intentions. The relationship between trust in reviews and booking intention is not the same across different experienced guests. For less experienced guests, trust in reviews may still have a weak effect on booking intentions while for more experienced guests, the factor does not influence booking intentions. When averaged out, this opposite pull might cancel out the overall effect. The moderation analysis captures that variation which the overall regression cannot.

In contrast, valence showed a positive moderation, indicating that experienced guests are more sensitive to negative reviews. This supports findings by Baek et al. (2012) and Wen et al. (2020), who highlight the stronger impact of negative information. In emerging markets such as Bali, where perceived risk is higher (Rua & Nunes, 2012), experienced guests may treat negative reviews as key risk indicators.

No moderation was found for platform trust, usefulness, volume, or timeliness, suggesting these signals are consistently important across guests. This reinforces the idea that certain heuristics, such as volume and timeliness, are universally relied upon to manage information overload (Baek et al., 2012)

5.7 Overall Model

The regression model explained 34.4% of the variance in booking intentions, indicating that quality signals play a meaningful but not exclusive role in Airbnb booking decisions in Bali (see table 16 in findings). This aligns with research suggesting other factors such as price and photos also influence consumer choices (Yao et al., 2019; Ert et al., 2016) and not exclusively Airbnb reviews. The model's significance ($p < 0.001$) confirms the importance of quality signals in Airbnb reviews to reduce uncertainty in emerging markets. This also highlights that booking behaviour in the sharing economy remains complex and shaped by multiple factors beyond reviews alone.

6. Conclusion

Lastly, chapter six provides a conclusion of the research. The aim for this chapter is to highlight the key aspects of the study and answer our research questions. This, followed by the implications of the research, specifically theoretical, managerial and societal. Lastly, chapter six discusses the limitations encountered during the study-process and future research to provide clarity and opportunities for continued research.

6.1 Purpose and Research Questions

This study aimed to investigate how five specific quality signals (trustworthiness, usefulness, volume, valence, and timeliness) present in Airbnb reviews influence booking intentions in an emerging tourism market, specifically Bali. Guided by signalling theory, the study also sought to examine whether all signals are perceived as equally influential, thereby addressing gaps in existing research on the varying impact of user-generated review content in P2P platforms.

The findings offer clear answers to the proposed research questions. Concerning RQ1: "*To what extent do different quality signals in Airbnb reviews influence consumer booking intentions in a developing tourism market?",* the results show that volume, valence, and timeliness significantly influence booking intentions, whereas trust in reviews and usefulness do not exhibit statistically significant effects. These outcomes suggest that certain signals are more effective in reducing information asymmetry and fostering booking confidence in a digital hospitality context. Addressing RQ2: "*Do all factors signalling quality hold equal importance on booking intentions in a developing tourism market?",* the data indicate that the five quality signals do not hold equal importance. Volume emerged as the strongest predictor, followed by timeliness, which proved influential across all user groups. Valence also had a positive effect, particularly for users with prior Airbnb experience, while the signals of trust and usefulness appear to be less decisive in shaping booking behaviour.

Beyond addressing the research questions, the study highlights the moderating effect of prior experience with the platform. Among experienced users, trust in the overall platform appears to substitute for trust in individual reviews, shifting the consumer's reliance from micro level heuristics to broader platform level assessments. This insight contributes to ongoing academic discussions on how experience shapes signal interpretation in P2P contexts.

Methodologically, the study adopted a positivist stance with a structured, quantitative design, enabling the identification of statistically testable relationships. The use of Prolific as a distribution channel provided access to a diverse and high-quality sample, while scale reliability was critically assessed and adjusted to ensure internal consistency. These considerations enhanced the methodological robustness of the research and demonstrate a transparent and well considered research process.

Taken together, this thesis provides a clearer understanding of how different quality signals in Airbnb reviews shape booking intentions in developing tourism markets. By demonstrating that certain signals carry more weight than others, and that their impact varies depending on user experience, the study reinforces the importance of context in digital trust formation. These insights contribute to both academic and practical efforts to improve decision-making and trust-building in peer-to-peer accommodation.

6.2 Theoretical Implications

This study extends the application of signalling theory (Spence, 1973) by examining how quality signals in Airbnb reviews influence booking intentions in an emerging tourism market. While prior research has largely focused on mature, regulated markets (e.g., Zhao t al., 2015; Filieri, 2016), this study confirms that signalling theory remains relevant in high-uncertainty context such as Bali, where formal trust mechanisms are limited (Salam et al., 2024).

Importantly, the findings challenge the assumption that all signals are equally effective. While prior studies often treat review components such as trustworthiness, usefulness,

and volume as uniformly impactful (e.g., Mudambi & Schuff, 2010; Zhao et al., 2015), our results show variation in their perceived importance in emerging markets and depending on prior experience. This supports the view that signal interpretation is context-dependent and challenges the generalizability within the signalling literature that signals have consistent meaning across markets and user groups (Kirmani & Rao, 2000).

By introducing prior Airbnb experience as a moderating factor, the study also contributes to signalling theory by showing that signal interpretation depends not only on the signal itself but also on the receiver's background. Experienced users appeared less influenced by certain trust-based signals, aligning with earlier findings that experience leads to more selective information processing (Park & Kim, 2008).

This study also adds to the literature by distinguishing trust in the platform from trust in reviews, an aspect overlooked in prior research. The findings indicated that trust in the platform significantly influenced booking intentions, whereas trust in the reviews did not show a similar effect.

Overall, the study reaffirms signalling theory's usefulness but emphasizes the need to account for market context and user familiarity when assessing the effectiveness of review-based signals in digital platforms.

6.3 Managerial Implications

6.3.1 From Hosts to Superhosts: Leveraging Review Signals to Build Trust

The findings offer several actionable insights for Airbnb hosts operating in emerging tourism markets such as Bali. Given that review volume and timeliness significantly influenced booking intentions, hosts should actively encourage guests to leave reviews promptly after their stay. A high and recent review count can act as a persuasive quality signal, especially in markets where formal certifications are lacking (Zhao et al., 2015; Tandon et al., 2020; Torres et al., 2015; Davis and Khazanchi, 2008). In addition to

encouraging more frequent and timely reviews, hosts can benefit from designing guest experiences that naturally elicit positive feedback. This may include personalized welcome notes, offering local recommendations, maintaining consistent cleanliness and communication standards, and exceeding expectations through small gestures such as refreshments on arrival or flexible check-in times.

Valence, or the tone of reviews, was also among the strongest predictors of booking intentions. While trust in individual reviews did not significantly influence booking decisions and was even less relied upon by experienced users, valence remains a key indicator of perceived quality, particularly for newer guests. Hosts should therefore monitor review content and respond thoughtfully to feedback. Responding to negative reviews in a constructive and professional manner can signal service recovery, transparency, and accountability, which contribute to perceived reliability (Filieri, 2015; Park and Kim, 2008).

6.3.2 Platform Trust Infrastructure: Designing for Confidence in Uncertain Markets

The results highlight the importance of platform-level trust mechanisms. Trust in the Airbnb platform itself, rather than in individual reviews, was found to be a significant predictor of booking intentions. This points to the need for ongoing investment in visible system-level trust features such as identity verification, secure payment systems, and accessible customer support (Ert et al., 2016; Mao and Lyu, 2017). These mechanisms help reduce uncertainty, especially in emerging markets where formal institutional safeguards may be weaker (Hoskisson et al., 2000).

For individual hosts, credibility-enhancing signals such as Superhost status and timely guest communication can complement platform-level trust. Airbnb may also consider emphasizing trustworthy listing elements in the user interface, such as verification badges, responsiveness indicators, or AI-powered summaries of recent positive reviews. Making trust-enhancing signals more prominent may strengthen guest confidence and improve overall conversion rates.

6.3.3 Guest Segmentation: Adapting Trust Signals to Experience Levels

The study reveals that guests interpret review signals differently depending on their prior experience with the platform. First-time users tend to rely more on broad trust indicators, such as five-star ratings or verified host credentials (Xie and Mao, 2017; Teubner et al., 2017; Filieri et al., 2021). For this group, high valence and visible structural trust mechanisms play an outsized role in booking decisions. In contrast, experienced users are more critical of review content and less influenced by surface-level trust signals. They may prioritize transparent listings, recent reviews, and detailed property information.

These findings suggest that hosts and platforms alike may benefit from tailoring content and visual signals based on guest experience levels. For example, platforms could experiment with adaptive interfaces that highlight different types of information depending on whether a user is new or returning. Hosts, similarly, may want to ensure that listing descriptions are detailed and transparent for experienced guests while using trust-building elements like high ratings and visual storytelling for first-time users.

6.4 Societal Implications

This study's findings have several broader societal implications, particularly in the context of digital tourism, platform capitalism, and emerging travel markets like Bali. While the study is grounded in consumer behaviour and quality signals, it also raises questions about how P2P platforms shape social and environmental dynamics.

One societal concern relates to the environmental consequences of increased travel demand. Platforms like Airbnb have lowered barriers to entry for accommodation, potentially contributing to overtourism and higher carbon emissions. Even though Airbnb markets itself as a more sustainable alternative to hotels, the ease of access to accommodation options can stimulate long-distance travel and place additional strain on local ecosystems. In destinations like Bali, this includes pressure on water resources, waste management systems, and land use, issues that are rarely visible in user reviews and thus not factored into the booking decision.

Another critical issue is the risk of digital colonialism and cultural homogenization. Many travellers on platforms like Airbnb come from wealthier Western countries and bring with them implicit expectations and norms that can influence host behaviour. The review system, which relies on public ratings and written feedback, often reflects Western-centric standards of service, communication, and cleanliness. This may marginalize local ways of hosting and subtly enforce conformity to globalized hospitality expectations, leading to a dilution of cultural uniqueness in places like Bali.

In addition, Airbnb operates within a platform capitalism model, where user-generated data, including reviews, becomes a form of unpaid labour that enriches a global corporation. While travellers and hosts contribute content and interactions that build trust on the platform, the financial and strategic benefits are largely centralized. This raises ethical concerns about data ownership and economic inequality, particularly in emerging markets where local hosts may be heavily dependent on a platform over which they have little control.

The findings also highlight how review systems reinforce social norms and biases, which can have societal consequences. As shown in the study, signals like valence and timeliness heavily influence consumer decisions. However, these signals may not always reflect objective truth. Hosts from minority or marginalized backgrounds may be disproportionately affected by subjective reviews shaped by implicit bias. Furthermore, the tendency toward review inflation where users leave overly positive feedback can create unrealistic expectations and reduce the transparency needed for fair competition and informed decision-making.

Overall, this study sheds light on how trust mechanisms in P2P platforms do more than reduce uncertainty, they actively shape social behaviours, economic dependencies, and cultural norms. These societal implications underline the need for ongoing critical reflection on the broader role of digital platforms in tourism and the communities they affect.

6.5 Limitations

This research has experienced a few limitations which are important to consider when interpretating the results. The challenges have varied in importance and are acknowledged to provide clear and transparent research for the readers. By providing a section regarding limitations, this paper hopes to present opportunities for future research.

First, technical issues within Qualtrics restricted certain design choices. For example, a typographical error by the authors resulted in a demographic question listing "49,000 EUR" instead of the intended "49,999 EUR," which may have influenced responses related to income categorization. Additionally, the limit of 30 questions on Qualtrics prevented the inclusion of an active consent question and the separation of filter questions, potentially affecting respondent clarity and engagement. This also restricted the survey to ask for more demographics which could have provided a more comprehensive overview of our participants.

Another limitation was the suboptimal reliability that two factors originally resulted in, which then required certain items being deleted. This was surprising considering our use of previous studies for the scales. The responses from friends and family also demonstrated slightly lower reliability compared to the paid responses on prolific, highlighting that data gathered through personal connections may be less reliable (Fricker, 2008). It was also observed that respondents with more Airbnb experience placed less emphasis on trustworthiness in reviews. This combined with the possible use of Prolific, may suggest the presence of “professional respondents”, who are familiar with online surveys and possibly more critical or less influenced by review-based signals (Fricker, 2008).

Lastly, there was an assumption regarding participants familiarity with Bali and the exclusion of the possibility for respondents to answer “0” on the number of previous stays with Airbnb. Participants might not have been informed regarding Bali as a travel-destination which may have affected their answers. The exclusion of “0” also became an assumption that everyone who knew about Airbnb also had stayed at Airbnb which may have not been the case for some respondents. This may have affected the generalizability and accuracy of the research.

6.6 Future Research

There are several opportunities for further investigation revealed throughout this study. Firstly, future research could incorporate additional quality signals not included in this model (see table 1), such as the length of the reviews and review diversity, which may influence the decision-making (Tandon et al., 2020; Willemsen et al., 2011). This could offer more insights into what signals quality in reviews and might increase the explanation power in booking intentions.

Further, comparative studies across mature and emerging markets could help determine whether the effectiveness of quality signals is context-dependent (Yao et al., 2019). While previous research focused on mature markets and this study focused on an emerging market, comparative studies could reveal how they differ from each other. Likewise, cross-cultural studies could examine how nationality or cultural background affects the signal interpretation in Airbnb reviews. This, to increase understanding into how demographics might play a role in signal interpretation and booking intentions (Bucher et al., 2018).

Lastly, specific factors could also be of interest. For instance, timeliness could examine how guests interpret specific time intervals in reviews such as one month old review versus six months old review, and whether this affects booking intentions. Similarly, a deeper understanding of the other factors might offer further insights especially as consumers face information overload and the challenge of finding reliable reviews (Baek et al., 2012).

7. Reference list

Abate, M., Christidis, P., & Gkoumas, K. (2024). Digitalization in tourism in emerging economies. *Journal of Travel Research*.

Abate, Y. A., Ukpabi, D. C., & Karjaluoto, H. (2024). Investigating digital marketing readiness among tourism firms: an emerging economy perspective. *Current issues in tourism*, 1-20. https://doi.org/10.1080/13683500.2024.2358047

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. (2023). *Report: Airbnb's contribution to the Indonesian economy post pandemic*. Airbnb. https://news.airbnb.com/report-airbnbs-contribution-to-the-indonesian-economy-post-pandemic/

Airbnb. (2025a). *Airbnb's Reviews Policy*. Airbnb. https://www.airbnb.com/help/article/2673

Airbnb. (2025b). *Fast Facts*. Airbnb Newsroom. https://news.airbnb.com/about-us/

Akdeniz, M. B., Calantone, R. J., & Voorhees, C. M. (2014). Signaling Quality: An Examination of the Effects of Marketing- and Nonmarketing-Controlled Signals on Perceptions of Automotive Brand Quality. *The Journal of product innovation management*, *31*(4), 728-743. https://doi.org/10.1111/jpim.12120

Akerlof, G. A. (1970). The Market for "Lemons": Quality Uncertainty and the Market Mechanism. *The Quarterly journal of economics*, *84*(3), 488-500. https://doi.org/10.2307/1879431

Andrews, D., Nonnecke, B., & Preece, J. (2003). Electronic Survey Methodology: A Case Study in Reaching Hard-to-Involve Internet Users. *International journal of human-computer interaction*, *16*(2), 185-210. https://doi.org/10.1207/S15327590IJHC1602_04

Assimakopoulos, C., Papaioannou, E., Sarmaniotis, C., & Georgiadis, C. K. (2015). Online reviews as a feedback mechanism for hotel CRM systems. *Anatolia : an*

international journal of tourism and hospitality research, *26*(1), 5-20. https://doi.org/10.1080/13032917.2014.933707

Ba, S, Pavlou, & P, A. (2002). Evidence of the effect of trust-building technology in electronic markets: Price premiums and buyer behavior. *A. (2002). Evidence of the effect of trust-building technology in electronic markets: Price premiums and buyer behavior. MIS Quarterly*.

Bae, S. J., Lee, H., Suh, E.-K., & Suh, K.-S. (2017). Shared experience in pretrip and experience sharing in posttrip: A survey of Airbnb users. *Information & management*, *54*(6), 714-727. https://doi.org/10.1016/j.im.2016.12.008

Baek, H., Ahn, J., & Choi, Y. (2012). Helpfulness of Online Consumer Reviews: Readers' Objectives and Review Cues. *International journal of electronic commerce*, *17*(2), 99-126. https://doi.org/10.2753/JEC1086-4415170204

Baek, J., Dinev, A., & Lykouris, T. (2024). Social Learning with Bounded Rationality: Negative Reviews Persist under Newest First. https://doi.org/10.48550/arxiv.2406.06929

Bali, P. (2023). *Provinsi Bali Dalam Angka 2023*. Bps.go.id; Badan Pusat Statistik Provinsi Bali https://bali.bps.go.id/publication/2023/02/28/b467b61cc7b43c86916a11db/provinsi-bali-dalam-angka-2023.html

Banerjee, S., & Chua, A. Y. K. (2019). Trust in online hotel reviews across review polarity and hotel category. *Tourism Management*

Barnham, C. (2015). Quantitative and Qualitative Research: Perceptual Foundations. *International journal of market research*, *57*(6), 837-854. https://doi.org/10.2501/IJMR-2015-070

Bart, Y., Shankar, V., Sultan, F., & Urban, G. L. (2005). Are the Drivers and Role of Online Trust the Same for All Web Sites and Consumers? A Large-Scale

Exploratory Empirical Study. *Journal of marketing*, *69*(4), 133-152. https://doi.org/10.1509/jmkg.2005.69.4.133

Baskerville, R., & Pries-Heje, J. (2010). Explanatory Design Theory. *Business & information systems engineering*, *2*(5), 271-282. https://doi.org/10.1007/s12599-010-0118-4

Bawden, D., & Robinson, L. (2020). Information overload: An overview. City, University of London. https://openaccess.city.ac.uk/id/eprint/23544/

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

Bell, E., Harley, B., & Bryman, A. (2022). *Business Research Methods* (6 ed.). Oxford University Press.

Bergh, D. D., Ketchen, D. J., Orlandi, I., Heugens, P. P. M. A. R., & Boyd, B. K. (2019). Information Asymmetry in Management Research: Past Accomplishments and Future Opportunities. *Journal of management*, *45*(1), 122-158. https://doi.org/10.1177/0149206318798026

Berinsky, A. J., Margolis, M. F., & Sances, M. W. (2014). Separating the Shirkers from the Workers? Making Sure Respondents Pay Attention on Self-Administered Surveys. *American journal of political science*, *58*(3), 739-753. https://doi.org/10.1111/ajps.12081

Black, W., Babin, B. J., & Sarstedt, M. (2019). *Multivariate Data Analysis: Its Approach, Evolution, and Impact.* In (pp. 121-130). Springer International Publishing. https://doi.org/10.1007/978-3-030-06031-2_16

Boone, H., & Boone, D. (2012). Analyzing Likert Data. *Journal of extension*, *50*(2). https://doi.org/10.34068/joe.50.02.48

Botsman, R., & Rogers, R. (2010). *What's Mine Is Yours: The Rise of Collaborative Consumption*. HarperCollins.

Bridges, J., & Vásquez, C. (2018). If nearly all Airbnb reviews are positive, does that make them meaningless? *Current Issues in Tourism*, *21*(18), 2057-2075.

Brink, P. J. (1998). Exploratory designs. *Advanced design in nursing research*, *2*(1), 141-160.

Bryman, A, Bell, & E. (2022). *Business research methods (6th ed*).

Bucher, E., Fieseler, C., & Lutz, C. (2018). What's mine is yours (for a nominal fee): Exploring the motives for internet-mediated sharing. *Computers in Human Behavior*, *62*, 316-326. https://doi.org/10.1016/j.chb.2016.04.007

Buhalis, D., & O'Connor, P. (2005). Information Communication Technology Revolutionizing Tourism. *Tourism recreation research*, *30*(3), 7-16. https://doi.org/10.1080/02508281.2005.11081482

Chandler, J., Rosenzweig, C., Moss, A. J., Robinson, J., & Litman, L. (2019). Online panels in social science research: Expanding sampling methods beyond Mechanical Turk. *Behavior research methods*, *51*(5), 2022-2038. https://doi.org/10.3758/s13428-019-01273-7

Chapman, S. J. (2018). Review of Discovering Statistics Using IBM SPSS Statistics, 4th Edition. In (Vol. 14, pp. 145-147). Abingdon: Routledge.

Chatterjee, P. (2001). Online reviews: do consumers use them?

Chen, C.-C., & Chang, Y.-C. (2018). What drives purchase intention on Airbnb? Perspectives of consumer reviews, information quality, and media richness. *Telematics and informatics*, *35*(5), 1512-1523. https://doi.org/10.1016/j.tele.2018.03.019

Chen, T., Samaranayake, P., Cen, X., Qi, M., & Lan, Y.-C. (2022). The Impact of Online Reviews on Consumers' Purchasing Decisions: Evidence From an Eye-Tracking Study. *Frontiers in psychology*, *13*, 865702-865702. https://doi.org/10.3389/fpsyg.2022.865702

Cheung, C. M. K., Lee, M. K. O., & Rabjohn, N. (2008). The impact of electronic word-of-mouth: The adoption of online opinions in online customer communities. *Internet research*, *18*(3), 229-247. https://doi.org/10.1108/10662240810883290

Chevalier, J. A., & Mayzlin, D. (2006). The effect of word of mouth on sales: Online book reviews. *Journal of marketing research*, *43*(3), 345-354.

Christiaens, T. (2025). Trust and power in Airbnb's digital rating and reputation system: Trust and power in Airbnb's digital rating and reputation system. *Ethics and information technology*, *27*(2), 18. https://doi.org/10.1007/s10676-025-09825-6

Cohen, J. (2013). *Statistical power analysis for the behavioral sciences*. routledge.

Collis, J., & Hussey, R. (2021). *Business research: A practical guide for students*. Palgrave Macmillan.

Connelly, B. L., Certo, S. T., Ireland, R. D., & Reutzel, C. R. (2011). Signaling Theory: A Review and Assessment. *Journal of Management*, *37*(1), 39-67. https://doi.org/10.1177/0149206310388419

Davis, A., & Khazanchi, D. (2008). An empirical study of online word of mouth as a predictor for multi-product category e-commerce sales. *Electronic markets*, *18*(2), 130-141.

Dellarocas, C. (2003). The digitization of word-of-mouth: Promise and challenges of online feedback mechanisms. *Management Science*, *49*(10), 1407-1424.

Donath, J. (2007). Signals, cues and meaning. *Signals, Truth and Design*.

Duan, W., Gu, B., & Whinston, A. B. (2008). The dynamics of online word-of-mouth and product sales—An empirical investigation of the movie industry. *Journal of retailing*, *84*(2), 233-242. https://doi.org/10.1016/j.jretai.2008.04.005

Dwijendra, N. K. A., Prasiani, N. K., Pranajaya, I. K., Dewi, N. M. E. N., & Hendrawan, F. (2024). Optimizing Materials and Building Design for The Circular Economy in Bali: A Case Study of Architectural Projects.

Easterby, S., M, Thorpe, R, Jackson, & P. (2021). *Management and business research* (6th ed). SAGE Publications Ltd.

Easterby-Smith, M., Thorpe, R., & Jackson, P. R. (2015). *Management and Business Research* (5th ed.). SAGE Publications Ltd.

Einav, L, Farronato, C, Levin, & J. (2016). Peer-to-peer markets. *(2016). Peer-to-peer markets. Annual Review of Economics*. 615–635. https://doi.org/10.1146/annurev-economics-080315-015334

Einav, L., Farronato, C., & Levin, J. (2016). Peer-to-Peer Markets. *Annual review of economics*, *8*(1), 615-635. https://doi.org/10.1146/annurev-economics-080315-015334

Ert, E., Fleischer, A., & Magen, N. (2016). Trust and reputation in the sharing economy: The role of personal photos in Airbnb. *Tourism management (1982)*, *55*, 62-73. https://doi.org/10.1016/j.tourman.2016.01.013

Etikan, I. (2016). Comparison of Convenience Sampling and Purposive Sampling. *American Journal of Theoretical and Applied Statistics*, *5*(1), 1. https://doi.org/10.11648/j.ajtas.20160501.11

Field, A. (2024). *Discovering statistics using IBM SPSS statistics*. Sage publications limited.

Filieri, R. (2015). What makes online reviews helpful? A diagnosticity-adoption framework to explain informational and normative influences in e-WOM. *Journal of business research*, *68*(6), 1261-1270. https://doi.org/10.1016/j.jbusres.2014.11.006

Filieri, R. (2016). What makes an online consumer review trustworthy? *Annals of tourism research*, *58*, 46-64. https://doi.org/10.1016/j.annals.2015.12.019

Filieri, R., Raguseo, E., & Vitari, C. (2021). Extremely Negative Ratings and Online Consumer Review Helpfulness: The Moderating Role of Product Quality Signals. *Journal of travel research*, *60*(4), 699-717. https://doi.org/10.1177/0047287520916785

Fradkin, A., Grewal, E., & Holtz, D. (2018). The determinants of online review informativeness: Evidence from field experiments on Airbnb. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.2939064

Gavilan, D., Avello, M., & Martinez-Navarro, G. (2018). The influence of online ratings and reviews on hotel booking consideration. *Tourism management (1982)*, *66*, 53-61. https://doi.org/10.1016/j.tourman.2017.10.018

Gong, X. Y., Huang, T., & Choo, W. C. (2024). Recommend or not: A comparative analysis of customer reviews to uncover factors influencing explicit online recommendation behavior in peer-to-peer accommodation. *European research on management and business economics*, *30*(1), 1-18. https://doi.org/10.1016/j.iedeen.2023.100236

Goundar, S. (2012). *Chapter 3: Research methodology and research method*. Victoria University of Wellington. https://www.researchgate.net/publication/333015026_Chapter_3_-_Research_Methodology_and_Research_Method

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*(4), 814-844. https://doi.org/10.1108/JHTT-08-2018-0075

Hair, J. F., Black, W. C., Babin, B. J., & Anderson, R. E. (2020). *Multivariate data analysis*. Cengage Learning.

Hair Jr, J., Page, M., & Brunsveld, N. (2019). *Essentials of business research methods*. Routledge.

Hart, C. W. L., Heskett, J. L., & Sasser, W. E., Jr. (1990). The profitable art of service recovery. *Harvard Business Review, 68*(4), 148–156.

Hati, S. R. H., Balqiah, T. E., Hananto, A., & Yuliati, E. (2021). A decade of systematic literature review on Airbnb: The sharing economy from a multiple stakeholder perspective. *Heliyon, 7*(10), e08222. https://doi.org/10.1016/j.heliyon.2021.e08222

Hauser, D. J., & Schwarz, N. (2016). Attentive Turkers: MTurk participants perform better on online attention checks than do subject pool participants. *Behavior research methods, 48*(1), 400-407. https://doi.org/10.3758/s13428-015-0578-z

Ho, C.-I., Chen, T.-S., & Li, C.-P. (2023). Airbnb's negative externalities from the consumer's perspective: How the effects influence the booking intention of potential guests. *Sustainability, 15*(11), 8695. https://doi.org/10.3390/su15118695

Holman, D. (2005). Business research methods. In D. Partington (Ed.), *Essential skills for management research* (pp. 266–268). Sage Publications Ltd.

Hoskisson, R. E., Eden, L., Lau, C. M., & Wright, M. (2000). Strategy in Emerging Economies. *Academy of Management journal, 43*(3), 249-267. https://doi.org/10.5465/1556394

Hunziker, S., & Blankenagel, M. (2024). *Research Design in Business and Management: A Practical Guide for Students and Researchers* (Second edition ed.). Springer Gabler. in Springer Fachmedien Wiesbaden GmbH. https://doi.org/10.1007/978-3-658-42739-9

Ikkala, T., & Lampinen, A. (2015). Monetizing network hospitality: Hospitality and sociability in the context of Airbnb. *Proceedings of the 18th ACM Conference on Computer Supported Cooperative Work & Social Computing (CSCW '15)*, 1033–1044. https://doi.org/10.1145/2675133.2675274

Jick, T. D. (1979). Mixing qualitative and quantitative methods: Triangulation in action. *Administrative Science Quarterly, 24*(4), 602–611. https://doi.org/10.2307/2392366

Joshi, A., Kale, S., Chandel, S., & Pal, D. K. (2015). Likert scale: Explored and explained. *British Journal of Applied Science & Technology*, *7*(4), 396–403. https://doi.org/10.9734/BJAST/2015/14975

Kenney, M., & Zysman, J. (2016). The rise of the platform economy. *Issues in science and Technology*, *32*(3), 61-69.

Khanna, T., & Palepu, K. G. (2010). Winning in Emerging Markets: A Road Map for Strategy and Execution. *NHRD Network journal (Online)*, *3*(3), 75-75. https://doi.org/10.1177/0974173920100316

Kim, J., & Liu, W. E. (2023). Airbnb purchase intentions: How familiarity and social media impacts millennials. *Journal of Global Hospitality and Tourism*, *2*(2), 183-202.

Kim, W. G., Lim, H., & Brymer, R. A. (2015). The effectiveness of managing social media on hotel performance. *International journal of hospitality management*, *44*, 165-171. https://doi.org/10.1016/j.ijhm.2014.10.014

Kirmani, A., & Rao, A. R. (2000). No Pain, No Gain: A Critical Review of the Literature on Signaling Unobservable Product Quality. *Journal of marketing*, *64*(2), 66-79. https://doi.org/10.1509/jmkg.64.2.66.18000

Lee, J., Park, D.-H., & Han, I. (2008). The effect of negative online consumer reviews on product attitude: An information processing view. *Electronic commerce research and applications*, *7*(3), 341-352. https://doi.org/10.1016/j.elerap.2007.05.004

Lei, Z., Yin, D., & Zhang, H. (2023). Positive or Negative Reviews? Consumers' Selective Exposure in Seeking and Evaluating Online Reviews. *Journal of the*

Association for Information Systems, *24*(4), 1162-1183. https://doi.org/10.17705/1jais.00823

Li, P. P. (2010). Toward a learning-based view of internationalization: The accelerated trajectories of cross-border learning for latecomers. *Journal of International Management*, *16*(1), 43-59. https://doi.org/10.1016/j.intman.2009.01.003

Lien, C.-H., Wen, M.-J., Huang, L.-C., & Wu, K.-L. (2015). Online hotel booking: The effects of brand image, price, trust and value on purchase intentions. *Asia Pacific management review*, *20*(4), 210-218. https://doi.org/10.1016/j.apmrv.2015.03.005

Lim, W. M. (2024). What Is Quantitative Research? An Overview and Guidelines. *Australasian marketing journal*. https://doi.org/10.1177/14413582241264622

Litvin, S. W., Goldsmith, R. E., & Pan, B. (2008). Electronic word-of-mouth in hospitality and tourism management. *Tourism management (1982)*, *29*(3), 458-468. https://doi.org/10.1016/j.tourman.2007.05.011

Liu, Y. (2006). Word of Mouth for Movies: Its Dynamics and Impact on Box Office Revenue. *Journal of marketing*, *70*(3), 74-89. https://doi.org/10.1509/jmkg.70.3.074

Liu, Z., & Park, S. (2015). What makes a useful online review? Implication for travel product websites. *Tourism management (1982)*, *47*, 140-151. https://doi.org/10.1016/j.tourman.2014.09.020

Luca, M., & Zervas, G. (2016). Fake it till you make it: Reputation, competition, and Yelp review fraud. *Management Science*, *62*(12), 3412-3427. https://doi.org/10.1287/mnsc.2015.2304

Madu, C. N., & Madu, A. A. (2002). Dimensions of e-quality. *The International journal of quality & reliability management*, *19*(3), 246-258. https://doi.org/10.1108/02656710210415668

Maheswaran, D., & Meyers-Levy, J. (1990). The Influence of Message Framing and Issue Involvement. *Journal of marketing research*, *27*(3), 361-367. https://doi.org/10.1177/002224379002700310

Mao, Z., & Lyu, J. (2017). Why travelers use Airbnb again?: An integrative approach to understanding travelers' repurchase intention. *International journal of contemporary hospitality management*, *29*(9), 2464-2482. https://doi.org/10.1108/IJCHM-08-2016-0439

Mavlanova, T., Benbunan-Fich, R., & Koufaris, M. (2012). Signaling theory and information asymmetry in online commerce. *Information & management*, *49*(5), 240-247. https://doi.org/10.1016/j.im.2012.05.004

McKercher, B, Du, C., & H. (2008). Cultural tourism: *The partnership between tourism and cultural heritage management.* Haworth Hospitaility Press

McKercher, B., & Du Cros, H. (2008). A Comparison of International Travel Between an Emerging and a Mature Source Market. *Asia Pacific journal of tourism research*, *13*(3), 265-280. https://doi.org/10.1080/10941660802280406

Meyer, K. E., & Peng, M. W. (2016). Theoretical foundations of emerging economy business research. *Journal of international business studies*, *47*(1), 3-22. https://doi.org/10.1057/jibs.2015.34

Mitra, D., & Fay, S. (2010). Managing Service Expectations in Online Markets: A Signaling Theory of E-tailer Pricing and Empirical Tests. *Journal of retailing*, *86*(2), 184-199. https://doi.org/10.1016/j.jretai.2010.02.003

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

Morrison, D., Walker, K. D., Tunison, S., & Okoko, J. M. (2023). Online Focus Groups. In (pp. 359-364). Springer International Publishing AG. https://doi.org/10.1007/978-3-031-04394-9_55

Morwitz, V. (2014). Consumers' purchase intentions and their behavior. *Foundations and Trends® in Marketing*, *7*(3), 181–230. https://doi.org/10.1561/1700000036

Mudambi, S. M., & Schuff, D. (2010). What makes a helpful online review?: a study of customer reviews on Amazon.com. *MIS quarterly*, *34*(1), 185-200. https://doi.org/10.2307/20721420

Oliveira, R. d. C., Baldam, E. C. G. D. R., Costa, F. R. d., & Pelissari, A. S. (2020). The effect of perceived usefulness of online reviews on hotel booking intentions. *Revista Brasileira de Pesquisa Em Turismo*, *14*, 30-45.

Palan, S., & Schitter, C. (2018). Prolific.ac—A subject pool for online experiments. *Journal of behavioral and experimental finance*, *17*, 22-27. https://doi.org/10.1016/j.jbef.2017.12.004

Pallant, J. (2020). *Ebook: SPSS Surival Manual: A Step by Step Guide to Data Analysis using IBM SPSS* (7th ed.). McGraw-Hill Education (UK).

Park, C., & Lee, T. M. (2009). Antecedents of Online Reviews' Usage and Purchase Influence: An Empirical Comparison of U.S. and Korean Consumers. *Journal of interactive marketing*, *23*(4), 332-340. https://doi.org/10.1016/j.intmar.2009.07.001

Park, D.-H., & Kim, S. (2008). The effects of consumer knowledge on message processing of electronic word-of-mouth via online consumer reviews. *Electronic commerce research and applications*, *7*(4), 399-410. https://doi.org/10.1016/j.elerap.2007.12.001

Peer, E., Brandimarte, L., Samat, S., & Acquisti, A. (2017). Beyond the Turk: Alternative platforms for crowdsourcing behavioral research. *Journal of experimental social psychology*, *70*, 153-163. https://doi.org/10.1016/j.jesp.2017.01.006

Podsakoff, P. M., MacKenzie, S. B., Lee, J. Y., & Podsakoff, N. P. (2003). Common method biases in behavioral research: A critical review of the literature and

recommended remedies. *Journal of Applied Psychology*, *88*(5), 879–903. https://doi.org/10.1037/0021-9010.88.5.879

Rabianski, J. S. (2003). Primary and secondary data: concepts, concerns, errors, and issues. *The Appraisal journal*, *71*(1), 43-55.

Reja, U. a., Manfreda, K. L., Hlebec, V., & Vehovar, V. (2003). Open-ended vs. close-ended questions in web questionnaires. *Developments in applied statistics*, *19*(1), 159-177.

Richins, M. L. (1983). Negative Word-of-Mouth by Dissatisfied Consumers: A Pilot Study. *Journal of marketing*, *47*(1), 68. https://doi.org/10.2307/3203428

Ronteau, S., Muzellec, L., Saxena, D., & Trabucchi, D. (2022). *Digital Business Models: The New Value Creation and Capture Mechanisms of the 21st Century*. De Gruyter. https://doi.org/10.1515/9783110762556

Rosenthal, S., Tan, J. Y. C., & Poh, T. F. (2020). Reputation Cues as Signals in the Sharing Economy. *Social sciences (Basel)*, *9*(4), 49. https://doi.org/10.3390/socsci9040049

Rua, M, Nunes, & P. (2012). The role of trust in the decision-making process for accommodation choices: A comparative study of Portugal and Brazil. *(2012). The role of trust in the decision-making process for accommodation choices: A comparative study of Portugal and Brazil. International Journal of Tourism Research*.

Rua, A., & Nunes, L. C. (2012). A wavelet-based assessment of market risk: The emerging markets case. *The Quarterly review of economics and finance*, *52*(1), 84-92. https://doi.org/10.1016/j.qref.2011.12.001

Rua, O. L., & Nunes, T. (2012). Innovation and entrepreneurship in small service firms. *Service Business*, *6*(3), 299-309.

Ruel, E. (2019). What Is a Survey? In (pp. 3-3). SAGE Publications, Inc. https://doi.org/10.4135/9781506348803.n5

Salam, R., Samudra, A. A., Suradika, A., & Sumada, I. M. (2024). Future policy implementation to balance growth and sustainability: Managing the impact of mass tourism in Bali. *Journal of Infrastructure, Policy and Development, 8*(9), Article 7927. https://doi.org/10.24294/jipd.v8i9.7927

Saunders, M., Lewis, P., & Thornwill, A. (2019). *Research Methods For Business Students* (8th ed.). Pearson Education Limited.

Schlosser, A. E., White, T. B., & Lloyd, S. M. (2006). Converting Web Site Visitors into Buyers: How Web Site Investment Increases Consumer Trusting Beliefs and Online Purchase Intentions. *Journal of marketing*, *70*(2), 133-148. https://doi.org/10.1509/jmkg.70.2.133

Senecal, S., & Nantel, J. (2004). The influence of online product recommendations on consumers' online choices. *Journal of retailing*, *80*(2), 159-169. https://doi.org/10.1016/j.jretai.2004.04.001

Shahid, Z. A., Tariq, M. I., Paul, J., Naqvi, S. A., & Hallo, L. (2024). Signaling theory and its relevance in international marketing: a systematic review and future research agenda. *International marketing review*, *41*(2), 514-561. https://doi.org/10.1108/IMR-04-2022-0092

Sidali, K. L., Schulze, H., & Spiller, A. (2009). The impact of online reviews on the choice of holiday accommodations. In W. Höpken, U. Gretzel, & R. Law (Eds.), *Information and Communication Technologies in Tourism 2009* (pp. 87–98). Springer. https://doi.org/10.1007/978-3-211-93971-0_8

Siedlecki, S. L. (2020). Understanding Descriptive Research Designs and Methods. *Clinical nurse specialist*, *34*(1), 8-12. https://doi.org/10.1097/NUR.0000000000000493

Smith, E. (2008). *Using secondary data in educational and social research* (1st ed.). Open University Press.

Sparks, B., So, K. K. F., & Bradley, G. L. (2013). Consumer trust in tourism and hospitality: A review of the literature. *International Journal of Hospitality Management*, *31*(1), 1-9. https://doi.org/10.1016/j.ijhm.2011.04.011

Spence, M. (1973). Job Market Signaling. *The Quarterly journal of economics*, *87*(3), 355-374. https://doi.org/10.2307/1882010

Sthapit, E., Del Chiappa, G., Coudounaris, D. N., & Bjork, P. (2020). Determinants of the continuance intention of Airbnb users: consumption values, co-creation, information overload and satisfaction. *Tourism review (Association internationale d'experts scientifiques du tourisme)*, *75*(3), 511-531. https://doi.org/10.1108/TR-03-2019-0111

Stiglitz, J. E. (2000). The Contributions of the Economics of Information to Twentieth Century Economics. *The Quarterly journal of economics*, *115*(4), 1441-1478. https://doi.org/10.1162/003355300555015

Stiglitz, J. E. (2002). Information and the Change in the Paradigm in Economics. *The American economic review*, *92*(3), 460-501. https://doi.org/10.1257/00028280260136363

Suasa Real Estate. (2023). The future of Bali's real estate market: Trends to watch in 2023. *Suasa Real Estate*. https://www.suasarealestate.com/the-future-of-balis-real-estate-market-trends-to-watch-in-2023/

Sue, V. M., & Ritter, L. A. (2016). *Conducting online surveys* (Second edition. ed.). SAGE.

Sundararajan, A. (2017). *The sharing economy: The end of employment and the rise of crowd-based capitalism*. MIT press.

Tandon, A., Aakash, A., Aggarwal, A. G., & Kapur, P. K. (2021). Analyzing the impact of review recency on helpfulness through econometric modeling. *International journal of system assurance engineering and management*, *12*(1), 104-111. https://doi.org/10.1007/s13198-020-00992-x

Tavor, T. (2024). Analyzing the influence of Airbnb announcements in the Asia Pacific Region: a sectoral perspective on travel, tourism, and real estate. *Eurasian economic review*, *14*(4), 873-905. https://doi.org/10.1007/s40822-024-00289-5

Teubner, T., Hawlitschek, F., & Dann, D. (2017). Price determinants on Airbnb: How reputation pays off in the sharing economy. *Journal of Self-Governance and Management Economics*, *5*(4), 53-80. https://doi.org/10.22381/JSME5420173

Toledo-Pereyra, L. H. (2012). Research Design. *Journal of investigative surgery*, *25*(5), 279-280. https://doi.org/10.3109/08941939.2012.723954

Torres, E. N., Singh, D., & Robertson-Ring, A. (2015). Consumer reviews and the creation of booking transaction value: Lessons from the hotel industry. *International journal of hospitality management*, *50*, 77-83. https://doi.org/10.1016/j.ijhm.2015.07.012

Vassilikopoulou, A, Siomkos, G, Chatzipanagiotou, K, & Pantouvakis. (2022). The influence of electronic word-of-mouth on consumer trust: A study of Airbnb. *(2022). The influence of electronic word-of-mouth on consumer trust: A study of Airbnb. Journal of Travel & Tourism Marketing*.

Vassilikopoulou, A., Kamenidou, I., & Constantinos-Vasilios, P. (2024). Negative Airbnb reviews: an aspect-based sentiment analysis approach. *EuroMed journal of business*, *19*(2), 191-207. https://doi.org/10.1108/EMJB-03-2022-0052

Vassilikopoulou, A. I., Siomkos, G. J., & Chatzipanagiotou, K. (2022). Enhancing trust in the sharing economy: Insights from Airbnb. *Journal of Strategic Marketing*, *30*(1), 23-39.

Wang, D., & Nicolau, J. L. (2017). Price determinants of sharing economy based accommodation rental: A study of listings from 33 cities on Airbnb.com. *International journal of hospitality management*, *62*, 120-131. https://doi.org/10.1016/j.ijhm.2016.12.007

Wen, J., Lin, Z., Liu, X., Xiao, S. H., & Li, Y. (2021). The Interaction Effects of Online Reviews, Brand, and Price on Consumer Hotel Booking Decision

Making. *Journal of travel research*, *60*(4), 846-859. https://doi.org/10.1177/0047287520912330

Willemsen, L. M., Neijens, P. C., Bronner, F., & de Ridder, J. A. (2011). "Highly Recommended!" The Content Characteristics and Perceived Usefulness of Online Consumer Reviews. *Journal of computer-mediated communication*, *17*(1), 19-38. https://doi.org/10.1111/j.1083-6101.2011.01551.x

Wright, K. B. (2005). Researching Internet-Based Populations: Advantages and Disadvantages of Online Survey Research, Online Questionnaire Authoring Software Packages, and Web Survey Services. *Journal of computer-mediated communication*, *10*(3), 00-00. https://doi.org/10.1111/j.1083-6101.2005.tb00259.x

Xie, K. L., Zhang, Z., & Zhang, Z. (2014). The business value of online consumer reviews and management response to hotel performance. *International Journal of Hospitality Management*, *43*, 1–12. https://doi.org/10.1016/j.ijhm.2014.07.007

Xie, K., & Mao, Z. (2017). The impacts of quality and quantity attributes of Airbnb hosts on listing performance. *International journal of contemporary hospitality management*, *29*(9), 2240-2260. https://doi.org/10.1108/IJCHM-07-2016-0345

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*, 198-209. https://doi.org/10.1016/j.ijhm.2018.10.016

Yao, B., Qiu, R. T. R., Fan, D. X. F., Liu, A., & Buhalis, D. (2019). Standing out from the crowd – an exploration of signal attributes of Airbnb listings. *International journal of contemporary hospitality management*, *31*(12), 4520-4542. https://doi.org/10.1108/IJCHM-02-2019-0106

Zamani, E. D., Choudrie, J., Katechos, G., & Yin, Y. (2019). Trust in the sharing economy: the AirBnB case. *Industrial management + data systems*, *119*(9), 1947-1968. https://doi.org/10.1108/IMDS-04-2019-0207

Zervas, G., Proserpio, D., & Byers, J. W. (2017). The Rise of the Sharing Economy: Estimating the Impact of Airbnb on the Hotel Industry. *Journal of marketing research*, *54*(5), 687-705. https://doi.org/10.1509/jmr.15.0204

Zhao, X., Wang, L., Guo, X., & Law, R. (2015). The influence of online reviews to online hotel booking intentions. *International journal of contemporary hospitality management*, *27*(6), 1343-1364. https://doi.org/10.1108/IJCHM-12-2013-0542

8. Appendix

8.1 Survey

Dear Participant,

Thank you for participating in our Master's thesis survey in Business Administration. This study investigates how travelers perceive Airbnb reviews when booking an accommodation in Bali. You'll rate your agreement with statements and answer a few questions about your Airbnb experiences and yourself. Please respond as if you are hypothetically booking an Airbnb in Bali.

The survey takes about 10 minutes and is anonymous and voluntary. You may withdraw anytime without a reason. Data is used solely for academic purposes, with no identifying information collected. For more information on how your data will be handled, see: https://docs.google.com/document/d/1vxsd-toD94RI8WmI4dALuC6cGTTAoCNXxcIJ9gZnlqU/edit?usp=sharing

By moving forward to the next page, you are agreeing to take part in our thesis study and consent to JIBS processing personal data in accordance with current data protection legislation and the data delivered.

End of Block:

1.

Start of Block: Filter questions

Note: "Accommodation" refers to any short-term rental option (hotel, hostels, vacation rentals etc.)

Are you familiar with the accommodation platform Airbnb and making reservations for accommodations through online booking sites? (such as Booking.com, Airbnb, Expedia etc.)

9. No
10. Yes

End of Block: Filter questions

2.

Start of Block: Trust in Airbnb reviews

Please respond as if you are hypothetically booking an Airbnb in Bali

I believe Airbnb reviews are trustworthy

11. Strongly disagree
12. Disagree
13. Somewhat disagree
14. Neutral
15. Somewhat agree
16. Agree
17. Strongly agree

Before booking an Airbnb, I read the reviews

18. Strongly disagree
19. Disagree
20. Somewhat disagree
21. Neutral
22. Somewhat agree
23. Agree
24. Strongly agree

I have confidence in Airbnb reviews

25. Strongly disagree
26. Disagree
27. Somewhat disagree
28. Neutral
29. Somewhat agree
30. Agree
31. Strongly agree

End of Block: Trust in Airbnb reviews

3.

Start of Block: Trust in Airbnb

Please respond as if you are hypothetically booking an Airbnb in Bali

I believe Airbnb is trustworthy as a platform

32. Strongly disagree
33. Disagree
34. Somewhat disagree
35. Neutral
36. Somewhat agree
37. Agree
38. Strongly agree

I believe Airbnb is responsible as a platform

39. Strongly disagree
40. Disagree
41. Somewhat disagree
42. Neutral
43. Somewhat agree
44. Agree
45. Strongly agree

I have confidence in the platform Airbnb

46. Strongly disagree
47. Disagree
48. Somewhat disagree
49. Neutral
50. Somewhat agree
51. Agree
52. Strongly agree

End of Block: Trust in Airbnb

4.

Start of Block: Usefulness

Please respond as if you are hypothetically booking an Airbnb in Bali

Airbnb reviews are useful

53. Strongly disagree
54. Disagree
55. Somewhat disagree
56. Neutral
57. Somewhat agree
58. Agree
59. Strongly agree

Airbnb reviews are relevant when planning a trip

60. Strongly disagree
61. Disagree
62. Somewhat disagree
63. Neutral
64. Somewhat agree
65. Agree
66. Strongly agree

Airbnb reviews are genuine

67. Strongly disagree
68. Disagree
69. Somewhat disagree
70. Neutral
71. Somewhat agree
72. Agree
73. Strongly agree

End of Block: Usefulness

5.

Start of Block: Volume

Please respond as if you are hypothetically booking an Airbnb in Bali

I care more about Airbnb accommodations that have larger amount of reviews

74. Strongly disagree
75. Disagree
76. Somewhat disagree
77. Neutral
78. Somewhat agree
79. Agree
80. Strongly agree

The amount of reviews relates to the popularity of an Airbnb accommodation

81. Strongly disagree
82. Disagree
83. Somewhat disagree
84. Neutral
85. Somewhat agree
86. Agree
87. Strongly agree

I am more likely to book an Airbnb accommodation with a large amount of reviews compared to one with few

88. Strongly disagree
89. Disagree
90. Somewhat disagree
91. Neutral
92. Somewhat agree
93. Agree
94. Strongly agree

End of Block: Volume

6.

Start of Block: Attention check

Attention check: It is important that you pay attention. In this question, please answer "Somewhat agree"

95. Strongly disagree

96. Disagree

97. Somewhat disagree

98. Neutral

99. Somewhat agree

100. Agree

101. Strongly agree

End of Block: Attention check

7.

Start of Block: Valence

Please respond as if you are hypothetically booking an Airbnb in Bali

I pay more attention to negative reviews than positive reviews

102. Strongly disagree

103. Disagree

104. Somewhat disagree

105. Neutral

106. Somewhat agree

107. Agree

108. Strongly agree

The volume of negative reviews is important

109. Strongly disagree
110. Disagree
111. Somewhat disagree
112. Neutral
113. Somewhat agree
114. Agree
115. Strongly agree

Negative reviews will negatively affect my willingness to book an accommodation

116. Strongly disagree
117. Disagree
118. Somewhat disagree
119. Neutral
120. Somewhat agree
121. Agree
122. Strongly agree

End of Block: Valence

8.

Start of Block: Timeliness

Please respond as if you are hypothetically booking an Airbnb in Bali

Recently posted reviews are important

123. Strongly disagree
124. Disagree
125. Somewhat disagree
126. Neutral
127. Somewhat agree
128. Agree
129. Strongly agree

I do not pay attention to old reviews

130. Strongly disagree
131. Disagree
132. Somewhat disagree
133. Neutral
134. Somewhat agree
135. Agree
136. Strongly agree

Recent reviews reflect up-to-date information

137. Strongly disagree

138. Disagree

139. Somewhat disagree

140. Neutral

141. Somewhat agree

142. Agree

143. Strongly agree

End of Block: Timeliness

9.

Start of Block: Booking intentions

Please respond as if you are hypothetically booking an Airbnb in Bali

I rely on Airbnb reviews when booking an Airbnb accommodation in Bali

144. Strongly disagree

145. Disagree

146. Somewhat disagree

147. Neutral

148. Somewhat agree

149. Agree

150. Strongly agree

I am likely to book an Airbnb accommodation based on the reviews

151. Strongly disagree
152. Disagree
153. Somewhat disagree
154. Neutral
155. Somewhat agree
156. Agree
157. Strongly agree

Airbnb reviews are my main information channel when booking an Airbnb accommodation in Bali

158. Strongly disagree
159. Disagree
160. Somewhat disagree
161. Neutral
162. Somewhat agree
163. Agree
164. Strongly agree

End of Block: Booking intentions

10.

Start of Block: Previous experience

How many times have you previously booked an Airbnb accommodation?

165. 1
166. 2
167. 3
168. 4
169. 5+

How would you describe your overall previous experience/experiences with Airbnb?

170. Very negative
171. Negative
172. Somewhat negative
173. Neither negative nor positive
174. Somewhat positive
175. Positive
176. Very positive

Why would you describe your previous experience/experiences as such? (negative/positive)

_____

_____

_____

_____

_____

End of Block: Previous experience

11.

Start of Block: Demographics

What is your age?

177. 18-24

178. 25-34

179. 35-44

180. 45-54

181. 55-64

182. 65+

What gender do you identify as?

183. Male

184. Female

185. Non-binary / third gender

186. Prefer not to say

Which of the following categories best describes your yearly income?

187. Under 10,000€

188. 10,000€ - 24,999€

189. 25,000€ - 49,000€

190. 50,000€ - 74,999€

191. 75,000€ - 99,999€

192. 100,000€ or more

End of Block: Demographics

12.

8.2 Pre-Test Feedback Sheet

Hi! Thanks for helping us pre-test our survey. Your feedback is super valuable and will help us improve it before we send it out to a larger audience.

Please take a couple of minutes to answer the questions below:

1. **How clear were the survey instructions?**

- Very clear
- Somewhat clear
- Not clear
- Comments (optional):

2. **Did any questions seem confusing, unclear, or difficult to understand?**

- Yes
- No
- If yes, which ones and why?

3. **Did you encounter any technical issues while completing the survey (e.g., layout, buttons, loading)?**

- Yes
- No
- If yes, please explain:

4. **How long did it take you to complete the survey (roughly)?**

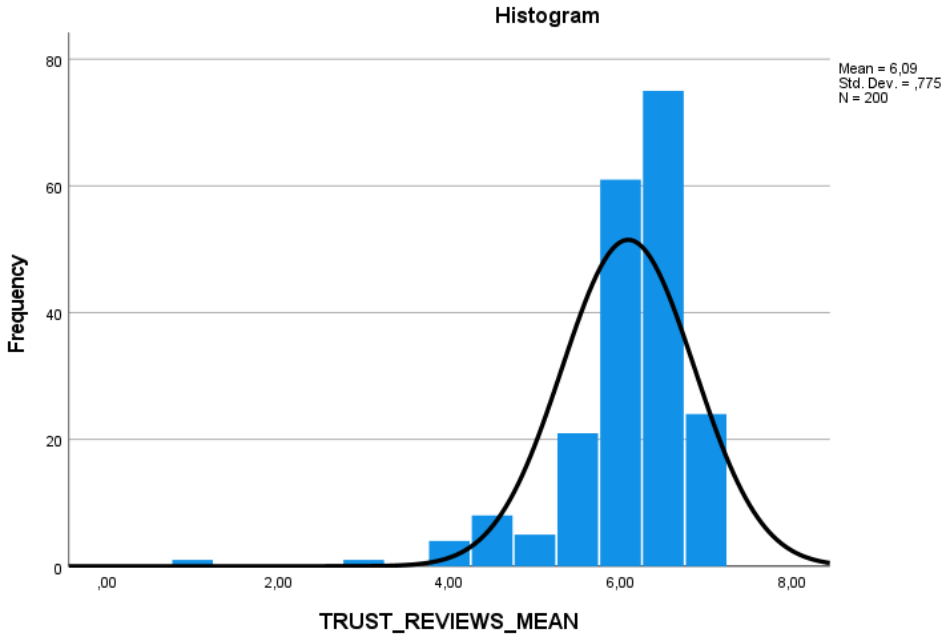
5. **Was the survey too long, too short, or just right?**

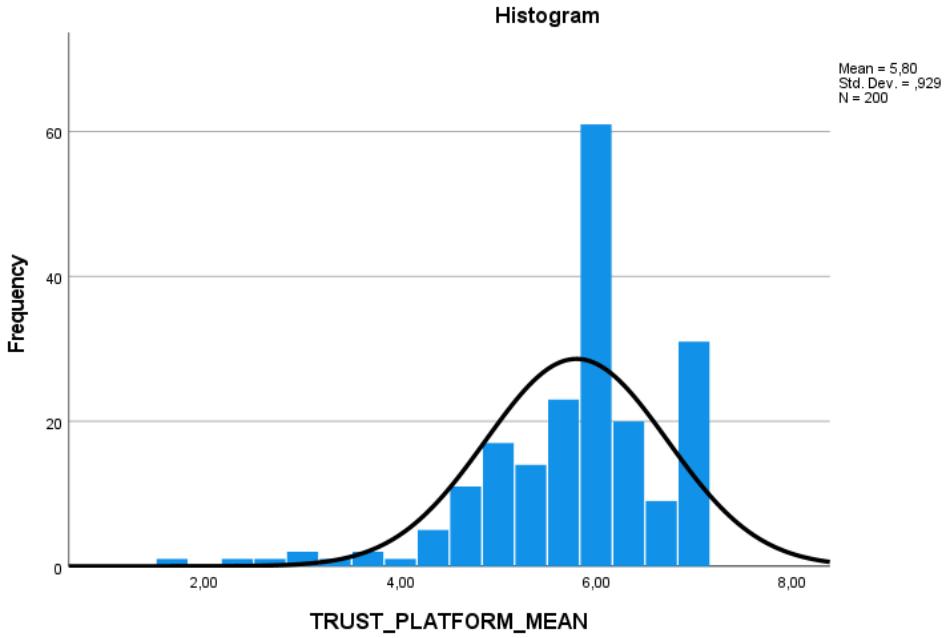
- Too long
- Too short
- Just right
- Comments (optional):

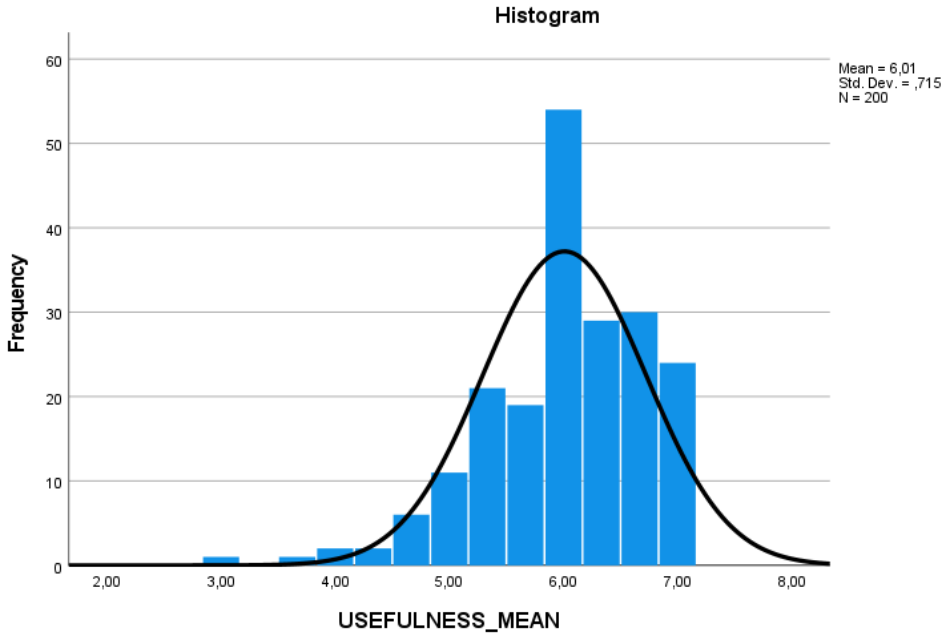
6. **Do you have any suggestions for improvement?**

(e.g., wording changes, additional questions, flow of the survey)

8.3 Distribution of Survey-responses



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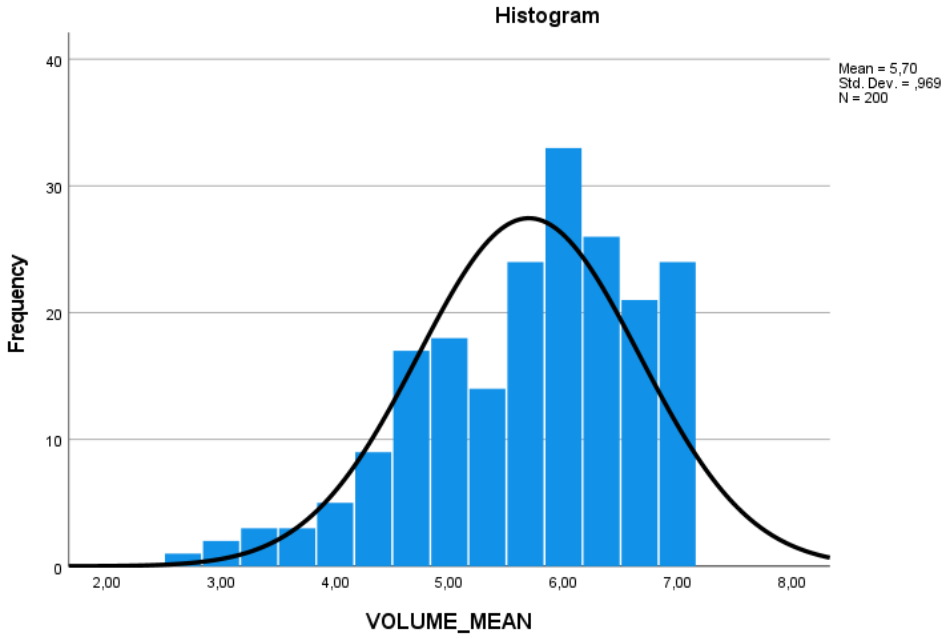
50
40
30
20
10
0
2,00
3,00
4,00
5,00
6,00
7,00
8,00
USEFULNESS_MEAN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3,00
4,00
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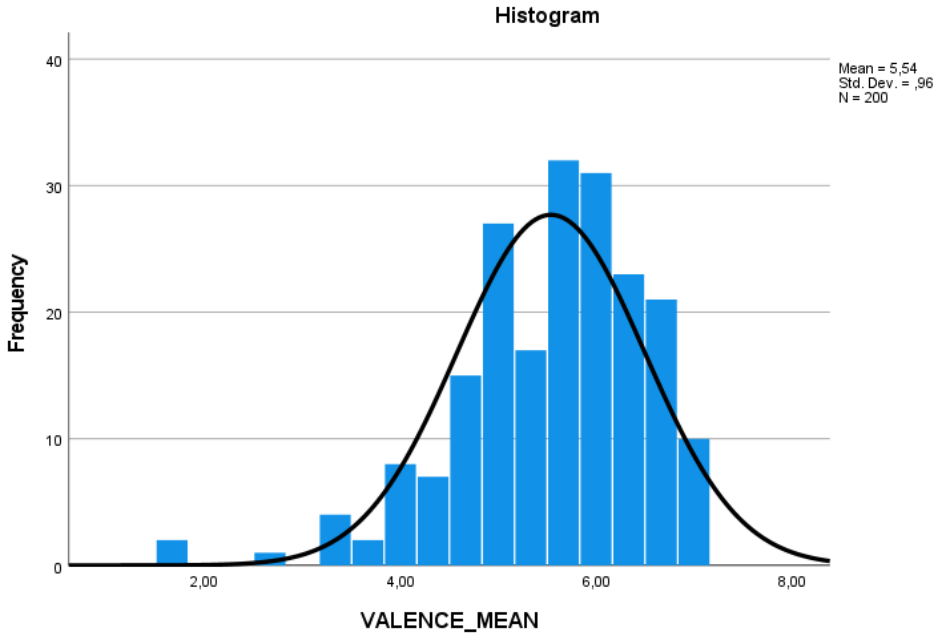
6,00
7,00
8,00
VOLUME_MEAN


Histogram
Mean = 5,54
Std. Dev. = ,96
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Frequency
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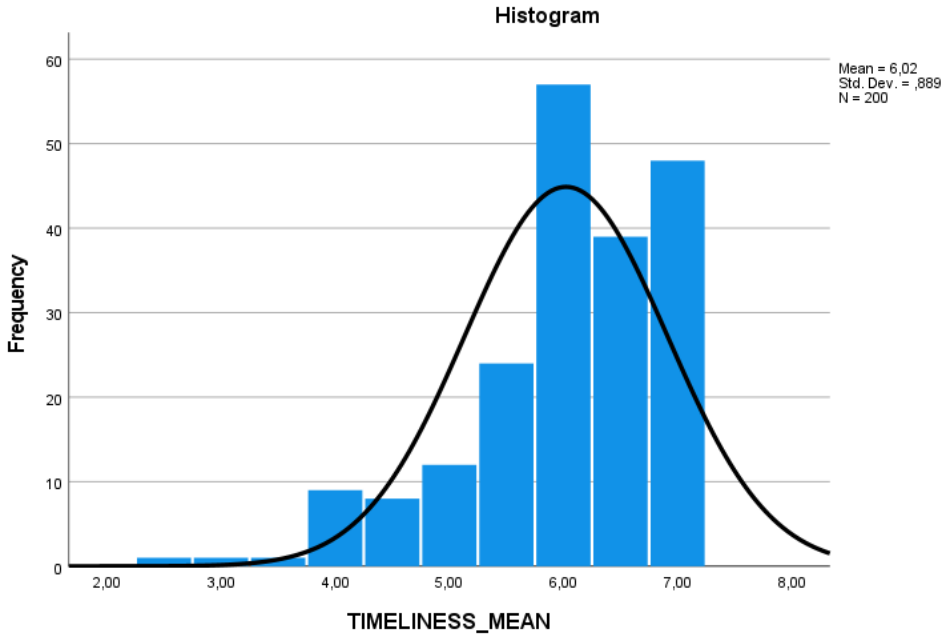
30
20
10
0
2,00
4,00
6,00
8,00
VALENCE_MEAN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Frequency
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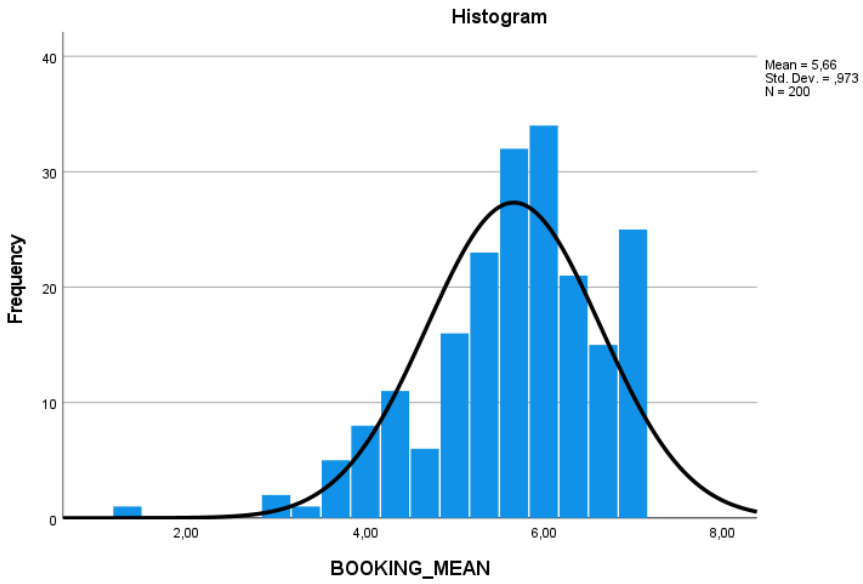
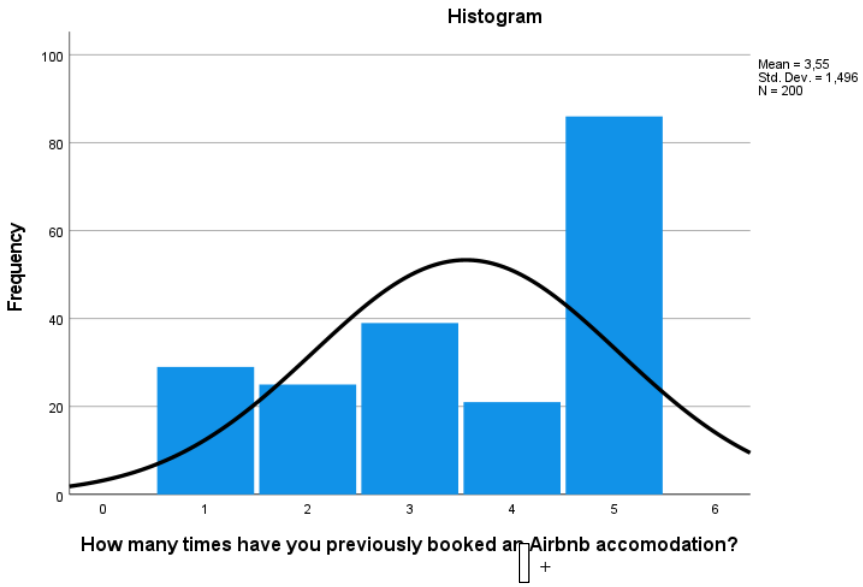
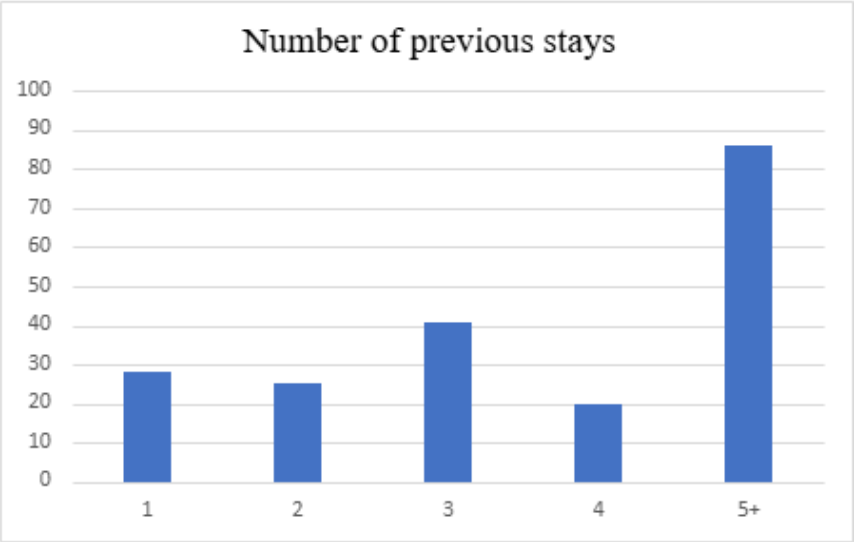
7,00
8,00
TIMELINESS_MEAN





8.4 Frequencies of Number of Stays


Number of previous stays
100
90
80
70
60
50
40
30
20
10
0
1
2
3
4
5+