Strategizing in Response to Environmental Uncertainty in the Hospitality Industry: A Data-Analytical Approach

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ABSTRACT

The hospitality industry confronts continuous challenges from external environments, such as the COVID pandemic, the proliferation of short-term rentals, and the disruptive innovations of Generative AI. For businesses, understanding these external conditions and adapting strategies accordingly is crucial yet challenging, especially considering environmental uncertainties. Therefore, this dissertation investigates the effectiveness of different strategies in navigating market, competitive, and technological uncertainties, through a big-data analytical approach. It incorporates three studies, each focusing on one specific strategy and its varying outcomes under environmental changes. These studies employ machine learning algorithms to quantify strategies and utilize econometric models to infer the causal relationships between strategies and their outcomes.

The first study examines how standardization affects short-term rental unit survival across two market conditions: pre-COVID growth and during-COVID decline. The results indicate that the risks arising from standardization are heightened under market decline. In addition, the effectiveness of standardization varies with design attributes to which the strategy is applied. Standardizing functional design boosts unit survival in the growing market but leads to a higher failure rate during the decline. Aesthetic standardization, on the other hand, negatively impacts survival in both conditions, with a stronger effect in the declining market.

The second study identifies the impacts of differentiation on unit performance in the short-term rental context in two competitive environments: local versus city-level. The findings suggest that the effectiveness of differentiation increases with competitive pressure. At the local level where firms face localized competition, differentiation enhances unit performance. Conversely, in city-level environments where direct competition diminishes, it yields negative outcomes. Moreover, competition intensity, as reflected by the number of competitors and the degree of market concentration, is found to amplify the benefits of and mitigate the drawbacks of differentiation.

The third study explores if adopting Generative AI to hotel online review response can improve customer feedback, under varying technological settings. It finds that simulated AI adoption improves customer perceptions when Generative AI models operate at high temperatures, while models with low temperatures lead to negative outcomes. The findings further underscore the importance of task-technology fit, revealing that Generative AI's effectiveness varies with review valence. Specifically, high-temperature settings for positive reviews generate significant benefits, whereas low-temperature settings lead to adverse effects. Conversely, for negative reviews, AI adoption demonstrates more stable outcomes across temperature settings, indicating balanced benefits of both low and high temperatures.

In short, this dissertation identifies that the effectiveness of standardization, differentiation, and AI adoption strategies is contingent on environmental conditions. It underscores the importance of strategic adaptation in navigating contemporary challenges.

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GENERAL AUDIENCE ABSTRACT

It is difficult to operate hospitality businesses because this industry faces constant challenges from ever-changing external conditions, including the COVID pandemic, the rise of short-term rental platforms, and the breakthroughs in technology like Generative AI. It is important but challenging for hotels and short-term rentals to understand these conditions and plan their operations accordingly. Thus, this dissertation aims to help business operators to understand how to deal with different external changes. It carries on a series of studies based on big data, using various analytical tools.

This dissertation is composed of three studies. The first one finds that, generally, it is risker for short-term rental hosts to make one property similar to his/her other properties when the whole market declines. There are differences identified between functionality and aesthetics. Keeping the functionalities, such as WIFI and coffeemaker, consistent among multiple properties will make the property more likely to survive when the market grows but it increases the likelihood of failure when the market demand decreases. When deciding property aesthetics, like color or layout, it is risky to have properties similar to each other, no matter if the market demand grows or drops.

The second study concludes that short-term rental hosts should decide the product design relative to their competitors from different scopes of areas. They are suggested to make their

properties' interior design style different from their nearby competitors to gain high revenues, especially when there are more neighboring supplies managed by a large number of hosts. On the contrary, it is more beneficial to follow the general trend of properties located in the same city when deciding one property's aesthetic style.

The third study guides hotels to apply Generative AI like ChatGPT to generate response to customer online reviews. It found that, to reply to online reviews with four- or five-star ratings, hotels should not use the default GPT model to increase the quality of customer communication. Instead, they need to use the professional OpenAI API and set the parameter called temperature to 2. However, when hotels reply to online reviews with lower star ratings, like one or two, there is no big difference between low and high temperatures (0 to 2). They can simply use the default model.

In general, there are no one-size-for-all solutions to deal with external challenges. Hospitality operators are highly recommended to adjust their operations to fit different conditions

To my parents

who love me forever with or without this dissertation ;-)

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Chapter 1. INTRODUCTION

Over the past decades, the hospitality and tourism industry has witnessed a remarkable boom, marked by a substantial increase in global travel. The number of international tourist arrivals exemplifies this growth, increasing from 680 million at the beginning of 21st century to a peak of approximately 1.46 billion in 2019 (UNWTO, 2024). Global travel spending also reached 6.41 trillion US dollars, showcasing the immense market opportunities (Statista, 2023b). Despite the dramatic growth in demand, lodging businesses are still confronted with constant pressure due to the excessive supply, which was a long-time issue in the hospitality industry (Dev & Hubbard, 1989; S. K. Lee & Jang, 2012). For example, in the United States, the number of hotels exceeded 184 thousand by 2023 and the short-term rental market supplied approximately 1.26 million listings (AirDNA, 2023; Piva, 2023). At the same time, the occupancy rate for both hotels and short-term rentals fluctuated around only 60%.

Intense competition arising from overcapacity posed great challenges for hospitality firms, highlighting the need for effective strategies to ensure exceptional and sustainable performance (J. Harrington, K. Chathoth, Ottenbacher, & Altinay, 2014; Olsen, 1991). The difficulty in strategizing hospitality businesses is amplified by the uncertainty of the environments, composed by a range of external factors (Slattery & Olsen, 1984). This difficulty keeps growing in recent years due to several contemporary changes, which bring essential changes to the industry landscape, such as the pandemic, the nascence of short-term rentals, and the disruptive innovations of Generative Artificial Intelligence (AI) technologies.

A fit to such external environments is the key premise for the effectiveness of strategies, which has been identified in many business domains including and beyond the hospitality industry (Chon & Olsen, 1990; Porter, 1980b). There is an extensive body of strategic management literature investigating the complexity and dynamism of external conditions, which has led to the identification of three key categories of environmental uncertainty: market uncertainty, competitive uncertainty, and technological uncertainty (Darvishmotevali, Altinay, & Köseoglu, 2020; DeSarbo, Anthony Di Benedetto, Song, & Sinha, 2005). Market uncertainty deals with the unpredictability of customer demands and consumptions. Competitive uncertainty involves the complexity in actions and strategies of other players in the industry. Technological uncertainty is characterized by the disruptive introduction and dynamic development of new technologies. Potential strategies in response of each type of uncertainty was explored and discussed in previous studies (DeSarbo et al., 2005; Dev & Olsen, 1989).

For each type of environmental uncertainty, the hospitality industry is confronting contemporary challenges which substantially altered the external environments and increased the difficulties of selecting and adapting strategies accordingly. In terms of market uncertainty, hospitality businesses need to deal with dramatic chansges in demand caused by pandemic, which influenced the operational and financial pressure thus shifting their strategic focus (Gössling, Scott, & Hall, 2020). Competitive uncertainty has been complicated by the emergence of new players like short-term rentals, requiring hospitality businesses to reevaluate and reset their competitive and positioning strategies (Y. Yang, Nieto García, Viglia, & Nicolau, 2022). Technological uncertainty, highlighted by the disruptive and dynamic innovations of Generative AI techniques, necessitate that firms need strategically integrate these technological advancements and explore new approaches that enhance, rather than undermines, their customer experiences (Dwivedi, Pandey, Currie, & Micu, 2023). These contemporary changes impede the application of extant knowledge drawn from broad business domains with precedent settings, especially considering the unique features of the hospitality field.

Given the contemporary environmental uncertainty and the unique features of the hospitality industry, this dissertation aims to explore a dynamic interplay between environment, strategy, and contextual features. More specifically, it first seeks to identify the effectiveness of multiple existing strategies (i.e., standardization, differentiation, and technology adoption) under recent environmental changes (i.e., pandemic, short-term rentals, and Generative AI). Second, this dissertation also targets at understanding how to adapt these strategies according to varying environmental conditions. Third, it also aims to explore how the unique features of the hospitality industry alter the selection and adaptation of strategies.

To achieve these objectives, this dissertation conducts three independent empirical studies with large-scale data on hotel and short-term rental operations based on the implementation of machine learning and econometric models. The integration of such methodological techniques provides a new perspective for understanding strategic adaptation in the hospitality industry, which differentiates from but complements extant studies that are conducted with a qualitative or survey-based approach. Detailed methodological process will be elaborated in the following chapters.

Through the exploration of these topics, this dissertation is anticipated to bring both theoretical and practical contributions. Theoretically, it adds knowledge to hospitality literature by retesting the effectiveness of traditional strategies in the contemporary settings (i.e., pandemic, short-term rentals, and Generative AI), which brings nuanced insights into the dynamic environment-strategy fit. Furthermore, it enriches strategic management literature by incorporating unique contextual features of the current hospitality landscape. The integration of contemporary and contextual settings helps refine the boundary conditions of related theories. Practically, this dissertation provides domain-specific, actionable suggestions for hospitality businesses. These suggestions are aimed at aiding industry practitioners in selecting and effectively adapting strategies to meet the challenges posed by market dynamics, competitive pressures, and technological advancements.

Therefore, the remainder of the dissertation is organized as follows. Chapter 2 provides an overview of the theoretical background concerning environmental uncertainty and adaptative strategies. Chapter 3 focuses on demand uncertainty arising from the pandemic, aiming to identify the impacts of standardization strategies conducted by short-term rental hosts on business survival at the unit level. The fourth chapter investigates how differentiation influences short-term rental listing performance at two geographical scopes: city-level vs local-level (sub-regions in a city). It also examines how the relationship between differentiation and performance varies with competition intensity. Chapter 5 simulates the adoption of Generative AI in hotel online review response, and further explores the efficacy of this new technology in finishing traditional human-based tasks as a new resource. The last chapter discusses anticipated contributions and limitations of this dissertation.

Chapter 2. CONCEPTUAL DEVELOPMENT: ENVIRONMENTAL UNCERTAINTY AND ADAPTATIVE STRATEGY

In many industries, including the tourism and hospitality field, the environment wherein businesses operate has been a pervasive topic (Miles, Snow, & Pfeffer, 1974; Slattery & Olsen, 1984). The concept of environment was introduced and defined as the "totality of physical and social factors that are taken directly into consideration in the decision-making behavior of individuals in the organization" (Duncan, 1972). These objective factors are further discussed and classified by Slattery and Olsen (1984) into two levels, general and task-related. General environments include conditions associated with technology, economy, ecology, politics, culture, and society, which are applicable to all types of organizations. Task-related environments emphasize the factors that are faced by specific organizations, such as those related to their competitors, customers, suppliers, and regulatory groups (Dess & Beard, 1984). It is critical to strategically manage these external factors as they are key determinants of a firm's economic performance, stability, growth, and long-term success (Aldrich, 2008; Bradley, Aldrich, Shepherd, & Wiklund, 2011).

This task is further complicated by the high uncertainty in environments confronted by businesses. This challenge is conceptualized as environmental uncertainty, referring to the instability and unpredictability of external elements caused by the absence of patterns or insufficient knowledge of cause-and-effect relationships (Duncan, 1972; Keats & Hitt, 1988). Given this context, it is imperative to place enough emphasis on understanding and responding to uncertain environments (Downey, Hellriegel, & Slocum Jr, 1975). Therefore, this concept has been extensively discussed and further explored under more fine-grained schemes. For example, some previous studies understand uncertainty based on different environmental factors it originated from, including market demands, competition, and technology (Darvishmotevali et al., 2020; DeSarbo et al., 2005). It resulted in three dimensions of uncertainty, namely market uncertainty, competitive uncertainty, and technological uncertainty. Monitoring, understanding, and managing each type of environmental uncertainty is continuously crucial for business success (Crawford-Welch, 1991; Olsen, 1980).

Uncertain environments often offer business opportunities for firms while also posing significant challenges to their survival and growth (Downey et al., 1975; Robert Baum & Wally, 2003). The ability of firms to respond rapidly and effectively to these environments will decide their performance and long-term viability. A key premise for effective strategic management is to ensure a fit between strategy and environmental conditions (Dev & Olsen, 1989; Venkatraman & Prescott, 1990). Achieving strategic fit not only requires a deep understanding of the environmental conditions, but also entails carefully selecting strategies that balance among multiple theoretical perspectives, such as resource-based view, institutional theory, and contingency theory (Sarta, Durand, & Vergne, 2021). In addition, the environment is inherently dynamic and ever-changing, firms need to constantly discern environmental changes and adapt their strategies to effectively meet the evolving demands from different environmental settings and stages (Hitt, Arregle, & Holmes Jr, 2021; Zajac, Kraatz, & Bresser, 2000).

The discussion revolving around environmental uncertainty, strategic fit, and adaptative strategy, has drawn extensive attention from many business domains, including the hospitality and tourism field. Pioneering studies, such as Dev and Olsen (1989), Chon and Olsen (1990), and

Jogaratnam, Tse, and Olsen (1999), explored this theme by considering the unique competitive and operational patterns of hospitality and tourism products. It becomes a vibrant topic for subsequent studies, exploring how strategic management of hospitality business shifts with varying market, competitive, and technological environments (e.g., Darvishmotevali et al., 2020; Köseoglu, Topaloglu, Parnell, & Lester, 2013). The contemporary changes happening to various environmental factors, such as market shock caused by the pandemic, new competitive landscape of short-term rentals, and disruptive technological innovations of Generative AI, have further complicated the scenario and necessitate the reexamination of strategic adaptation in the hospitality and tourism industry. The three types of environmental uncertainty and corresponding strategies will be explored in three independent studies. Table 2-1 outlines the main focus of each study, including type of environmental uncertainty, examined strategy, and context. Further conceptual development of these studies is discussed in the following subsections.

Table 2-1. Outline of three independent studies

	Environmental Uncertainty	**Strategy**	**Context**
Study 1	Market uncertainty	Standardization	Short-term rental
Study 2	Competitive uncertainty	Differentiation	Short-term rental
Study 3	Technological uncertainty	Exploration	Hotel

2.1 Market Uncertainty (Study 1)

Market uncertainty refers to the uncertainties of product demand, which stems from dynamic customer needs and consumptions (C.-M. Chen & Yeh, 2012; Souder, Sherman, & Davies-Cooper, 1998). While opening new opportunities, the market volatility simultaneously presents significant challenges for hospitality service providers as it substantially influences several fundamental aspects of operations in hospitality businesses, including primary organizational objectives, resource access, and optional strategic choices (Castrogiovanni, 1991; Jogaratnam et al., 1999). The key opportunities and challenges lying in market uncertainty are closely associated with resource availability, if it is munificent or scarce. When confronting shrinking markets with scarce resources, firms often prioritize survival as their primary goal by ensuring operational resilience to resource scarcity, such as tightened budgets. Consequently, their strategic choices are more restricted to sustaining operations, often emphasizing flexibility and risk avoidance (Burgers, Hill, & Kim, 1993; Goll & Rasheed, 2004). On the contrary, under market munificence, firms can focus on business expansion and explore diverse strategic options, shifting their emphasis from mere survival to pursuing alternative goals and opportunities (S. Song & Lee, 2020; Yasai-Ardekani, 1989).

As a cyclical industry, hospitality businesses witnessed several ups and downs in market demands associated with business and economic cycles in the past decades (J.-G. Choi, 1999). The hospitality industry displayed significant market volatility, which is much higher than traditional manufacturing industries (Crawford-Welch, 1991). Previous studies have extensively studied business operations and strategies under such market uncertainty caused by industrial lifecycle or global economic shifts (Campos-Soria, Inchausti-Sintes, & Eugenio-Martin, 2015; C.-M.

Chen, Lin, Chi, & Wu, 2016; S. Song & Lee, 2020). However, how strategies should be adapted to the significant and unprecedented market shock caused by the pandemic has not been fully explored (Redjeki, Narimawati, & Priadana, 2021).

The demand shifts caused by the pandemic are distinct from those arising from industrial or economic cycles because they are not only severe and abrupt, but also accompanied by unique characteristics, such as high unpredictability, strict governmental travel restrictions, and a rapid shift in travelers' expectations and behaviors (Gössling et al., 2020; Hitt et al., 2021). All of these present new and complex challenges for strategizing hospitality businesses to fit the transformed market environment. For example, the unpredictability of COVID-19 outbreaks and governmental regulations intensified the individual firms' inability to understand and anticipate future demand trends and subsequently plan strategies in response to the potential changes (Ozdemir, Kizildag, Dogru, & Madanoglu, 2022). This challenge is extremely acute in the short-term rental context wherein most operators are individuals with limited knowledge and experience.

When facing difficulties in understanding external environments, firms tend to treat defensive strategies as a safe choice, which seek to secure their market by efficiency and cost leadership while paying little attention to monitoring environmental changes (Justin Tan & Litsschert, 1994). This can be achieved by operations, such as providing a limited scope of product, and standardizing or streamlining their products and services (Dev & Brown, 1990). The standardization process has been validated as an effective tool in dealing with market uncertainty by minimizing return unsureness, ensuring product quality, reducing costs, and increasing organizational learning efficiency (Chiou & Droge, 2015; Sorenson & Sørensen, 2001). However, its effectiveness in the short-term rental market characterized by small business size and heterogeneous customer demands was questioned (H. Zhang, Zach, & Xiang, 2023).

2.2 Competitive Uncertainty (Study 2)

Competitive uncertainty is defined as an organization's inability to predict the competitive environment. It lies in the complexity of competitors' situations and activities (Westphal & Zhu, 2019). The actions of competitors can directly decide a firm's market position, thus affecting its market share and follow-up strategic responses (Darvishmotevali et al., 2020). As a result, firms try to reduce competitive uncertainty by actively monitoring their rivals, especially those with whom they share a high degree of inter-dependence (Burgers et al., 1993). This involves a strategic analysis of competitors' actions and decisions, focusing on aspects such as their investment, product design, and market positioning (Smit & Trigeorgis, 2017). It also necessitates differentiating among competitors based on extent of their interconnectedness, paying attention to those with close partnerships and similar customer bases (Burgers et al., 1993). By doing so, they can strategically tailor their responses, aiming to counteract the actions of these closely linked competitors and further ensure their own performance stability and growth.

This topic has been long-time investigated in the hospitality industry because of intense rivalry arising from long-term overcapacity (Köseoglu et al., 2013; S. K. Lee & Jang, 2012). The complexity of competitive environments associated with a growing number of rivals or high concentration of market shares shapes the way how hospitality businesses select and adjust their strategies (Sánchez-Pérez, Illescas-Manzano, & Martínez-Puertas, 2020; Silva, 2015). To mitigate the difficulty in monitoring and analyzing rivals' structures and activities, firms can either simplify the competitive environment by identifying a particular competitive set (Schwartz & Webb, 2022; Westphal & Zhu, 2019). Based on the possibility of analyzing and understanding external competitive environments, firms can further develop strategies to mitigate risk and build competitive advantages through several approaches, such as following their peers' practices or differentiating from the majority to avoid intense rivalry (M. Kim, Roehl, & Lee, 2020).

However, these actions are not perfectly applicable to the short-term rental sector whose competitive landscape is distinct from those of traditional hotels and restaurants (Bianco, 2023). Short-term rental hosts confront challenges in identifying their key rivals due to a lack of clear customer segmentation systems, e.g., hotel star rating (J.-y. Kim & Canina, 2011). Thus, competitive strategies in this context are more location-based (Boto-Garcia, Mayor, & De la Vega, 2021; K. L. Xie, Kwok, & Heo, 2020). Understanding how geographical scopes shape competitive conditions and decide subsequent strategic adaptation becomes particularly important.

2.3 Technological Uncertainty (Study 3)

Technological uncertainty reflects the inability to completely understand or accurately predict some aspects of the technological environment (Darvishmotevali et al., 2020; M. Song & Montoya-Weiss, 2001). It is often led by rapid and dynamic changes in technologies, such as the sudden emergence of new and breakthrough techniques (Bstieler, 2005). Different from the market and competitive dimensions, the changes in technological environment may directly drive the introduction of new services or operational solutions which will replace the existing components. As a result, technological changes offer the chance to firms to enjoy enduring competitive advantages through innovative service offerings or enhanced operations (Kerin, Varadarajan, & Peterson, 1992). However, at the same time, this process faces challenges, such as in compatibility with existing systems, thus resulting in investment risks and undesired returns (Anderson & Tushman, 1990).

The hospitality industry was long-time criticized as a slow adopter of technology innovations (Law, Lei, Zhang, & Lau, 2023). The slow adoption can be attributed to two main reasons. First, the hospitality industry is service-oriented, with a strong reliance on personal interactions between customers and service providers. Integrating new technologies into this human-centric environment can be challenging due to potential resistance from both staff and customers (W. Cai & McKenna, 2023; Christ-Brendemühl, 2022). Second, when introducing new technologies, firms need to invest extensive resources, both financial and human. The cost of acquiring new technologies, coupled with the expenses for training staff and integrating systems into existing operations, can be substantial (Williams, Rodriguez Sanchez, & Škokić, 2021). Therefore, when facing uncertain technological environments with dynamic changes, firms tend to be more cautious with innovation and technology adoption, weighing the benefits against potential disruptions to their service ethos and the substantial investment required (Grewal & Tansuhaj, 2001).

The disruptive Innovations of Generative AI in this post-pandemic era may transform technology adoption opportunities and challenges in the hospitality industry. First, the acceleration of digitalization trend caused by the pandemic has increased customer and employee openness to digital solutions, reducing potential resistance to these new technologies (Ozdemir, Dogru, Kizildag, & Erkmen, 2023; Zhong, Coca-Stefaniak, Morrison, Yang, & Deng, 2022). Second, Generative AI's cost-effective potential makes adoption more promising and attractive.

The accessibility to many advanced Generative AI platforms lowers the costs of technology development and acquisition (Dwivedi et al., 2023). In addition, the advanced tools' capabilities of generating textual content indistinguishable from that produced by humans, open opportunities of relieving labor shortage, which is an acute issue in the post-pandemic era (Kwok, 2022; Morosan & Bowen, 2022). Therefore, the transformed environment necessitates that hospitality businesses should replan their strategies, potentially turning to be more proactive in exploring the contemporary technologies in value creation.

Chapter 3. SURVIVAL OF THE FITTEST: UNDERSTANDING THE IMPACTS OF STANDARDIZATION ON SHORT-TERM RENTAL SURVIVAL UNDER SEVERE MARKET UNCERTAINTY

3.1 Introduction

Over the past two decades, the short-term rental industry has experienced unprecedented growth, catalyzed in large part by the flourishing tourism sector. The rapid adoption of online platforms such as Airbnb have further spurred the expansion of short-term rentals (Zervas, Proserpio, & Byers, 2017). This boom has led to significant economic and social benefits, including the re-allocation of housing resources and the generation of supplementary income for hosts. However, the global health crisis instigated by the COVID-19 pandemic has dealt a significant blow to the tourism industry, marked by a substantial decline in visitor arrivals (Statista, 2023a). Consequently, the precipitous decrease in demand poses substantial survival threats on lodging products, especially short-term rentals.

Survival is not a novel concept and has been extensively studied across various areas, including retail, tourism and hospitality (Lamberg, Tikkanen, Nokelainen, & Suur-Inkeroinen, 2009; Trinh & Seetaram, 2022). Prior research has investigated a multitude of factors contributing to organizational survival. Some investigations have concentrated on environmental features, including economic crises, competitive dynamics, and pandemics (Fan, Lai, Fan, & Chen, 2023; Lado-Sestayo, Vivel-Búa, & Otero-González, 2016; Lamberg et al., 2009). At the same time, other research has sought to understand the role of firm-intrinsic features, such as age, size, ownership, and strategy, in determining survival (Falk, 2013; Gemar, Soler, & Guzman-Parra, 2019; S.-C. Lin &

Kim, 2020). Among these internal factors, strategy draws enormous attention due to its potent and feasible role in ensuring a firm's survival.

Under the pandemic, managing survival strategies becomes more complicated and interesting because strategic effectiveness is highly contingent upon environmental conditions. Environmental fit, that is the degree to which a strategy meets the requirements of external conditions, is key to strategic outcomes (Haveman, 1992). Specifically, strategies previously effective may lose their potency, or even become detrimental under the altered conditions caused by significant environmental changes, such as a pandemic. Such transformations in the external environment can pose novel challenges to firms, with varying implications for survival strategies (K. Kim, Bonn, & Cho, 2021). Therefore, developing proper strategies to fit the changing environmental conditions is paramount for successful survival management, necessitating a comprehensive understanding of both the external environment and the firm's internal resources and operations. This issue is particularly critical for short-term rental properties because these units are typically managed by micro-entrepreneurs who lack experience and resources to ensure an effective environment-strategy match (D. Huang & Chen, 2021). Hence, this study primarily focusses on the strategic outcomes under varying environments in managing short-term rental unit survival.

In short-term rental operation, multiple strategies mainly implemented by professional hosts have been investigated (Gibbs, Guttentag, Gretzel, Yao, & Morton, 2018; K. Xie & Mao, 2019; H. Zhang et al., 2023). Professional hosts refer to the lodging operators who manage two or more short-term rental units. The major challenge confronted by these hosts is the increasing operational complexity as the business size grows (K. Xie & Mao, 2017b). It is particularly difficult to make proper strategies to maintain survival simultaneously for multiple units with diverse features operating within distinct markets. A safe and efficient strategy is to design units' functionalities or aesthetics by following existing templates, whether derived from substituting products (such as hotels), rival offerings, or sister units under the same host (Boto-Garcia et al., 2021; K. L. Xie & Young, 2021; H. Zhang et al., 2023). This study focuses on the practice of keeping a high consistency to other units managed by the same host, a strategy defined as standardization, given its multifaceted influence on survival.

The impact of standardization on survival is not straightforward, as it carries both positive and negative impacts. On the positive side, it enhances cost and operational efficiencies (Lawrence, 2020; Ritzer, 1992). For instance, furnishing or decorating a unit similarly to its sister units enables benefits from bulk purchasing and templated operations. Conversely, standardization may engender risk by compromising flexibility and inducing concentration risks (Tan & Wang, 2010; Tang & Jang, 2011). Specifically, maintaining a high degree of similarity to sister units could hinder the unit from meeting heterogeneous customer demands. Moreover, the financial viability of such units could be undermined in low seasons when their sister units with similar functionalities or aesthetic styles, appealing to a similar customer base, might struggle to provide financial support. It is this duality of risks and benefits that motivates the present study to empirically examine the undetermined relationship between standardization and unit survival.

In order to investigate the impact of standardization on unit survival under different environmental conditions, survival analysis is conducted on a sample of 17,375 Airbnb units in Hong Kong. We first quantify standardization by measuring the functional and aesthetic similarity between a focal unit and its sister units under the same host. The operationalization of standardization in the aesthetic dimension is based on design style scores predicted by a pre-trained machine learning model. Followingly, piecewise Cox regressions are estimated with samples from growing and declining markets respectively to provide insights into how standardization influences unit survival across two distinct environmental conditions.

This study has both theoretical and practical contributions. From the theoretical perspective, it first enriches short-term rental studies by disclosing how the micro-entrepreneurs leverage strategies to increase their units' resilience to external crises, like the pandemic. Second, it adds knowledge to survival literature by examining the joint effects of firm internal features (standardization strategy) and external environments (market growth and decline). The findings emphasize the importance of the strategy-environment match. Third, it brings nuanced understandings of standardization by elucidating its multidimensional impacts, underscoring both its benefits and potential risks and their changing relative strength under different environmental conditions. Practically, the findings provide guidance for short-term rental practitioners, short-term rental platforms, and policymakers.

3.2 Literature Review

3.2.1 Survival

Survival is a pervasive topic that has been extensively examined across multiple fields, including tourism, real estate, and hospitality sectors (Green, 1988; Josefy, Harrison, Sirmon, & Carnes, 2017; Lado-Sestayo et al., 2016). Previous studies conclude that firm survival is influenced by multiple determinants, subdivided into internal and external categories. Internal factors refer to the inherent attributes of an organization, whereas external factors underscore the prevailing environmental circumstances.

In hospitality literature, the importance of both internal and external factors has been emphasized by a comprehensive collection of prior studies. As for the internal factors, previous studies incorporate a variety of elements, including firm size (Falk, 2013; Gemar, Moniche, & Morales, 2016), location (Gemar et al., 2016; Gemar et al., 2019), resources (Kalnins & Chung, 2006), financial status (Vivel-Búa, Lado-Sestayo, & Otero-González, 2019), and strategies (S.-C. Lin & Kim, 2020). Equally significant are the external factors, with many studies examining their influence. These encompass a diverse range of variables such as economic crisis (Falk & Hagsten, 2018), market structure (Vivel-Búa et al., 2019), industrial cooperation (He, Lin, & Li, 2020), and even global phenomena like the pandemic (Fan et al., 2023).

Although previous hospitality studies have acknowledged that both internal and external factors affect firm survival, the joint impact of these factors has been insufficiently explored thus far. As is posited by the organizational ecology theory, the impact of an internal factor, such as organization strategy is largely contingent on the environmental conditions (Haveman, 1992). The alignment of the strategy with environmental conditions is crucial to its outcomes, given that the effectiveness of strategic measures is innately contingent on external factors (Nadkarni & Barr, 2008; K. G. Smith & Grimm, 1987). We argue that an environmental fit of strategies is also vital to short-term rental business survival because this unique sector is characterized by high levels of dynamism and competitive intensity (Leoni, 2020; Y. Yang & Mao, 2019). Therefore, it is crucial for strategies to adapt and respond to evolving market trends to achieve stronger resilience for short-term rental listings. These aspects form the basis for our study, which will explore the joint effect of internal strategies and external market conditions on business survival in the short-term rental context.

3.2.2 Standardization

Multiple strategies have been explored in prior survival studies in the hospitality and tourism field. These strategies range from innovation (F. J. Zach, Schnitzer, & Falk, 2021), diversification (S.-C. Lin & Kim, 2020; Park & Jang, 2022), and collaboration (He et al., 2020), to online marketing (H. Li, Chen, Liang, & Yang, 2022). However, a significant gap persists in the existing literature, with an important practice that could potentially impact the survival of lodging businesses being largely overlooked.

When strategizing hospitality offerings, the practice of utilizing other products as benchmark references is prevalent among service providers, particularly those operating within the short-term rental sector. The strategy of following existing templates emerges as a prudent choice for risk management (M. Kim et al., 2020; Winter, Szulanski, Ringov, & Jensen, 2012; H. Zhang et al., 2023). It is extremely efficacious for short-term rental hosts, often attributable to a potential deficiency in expertise and resources (K. L. Xie & Young, 2021; H. Zhang et al., 2023).

This study focuses on standardization, referring to the degree to which a unit listing is similar to other units managed by the same host. This is primarily because it is closely associated with operational efficiency, cost management, and portfolio management, which, in turn, substantially influence the survival of short-term rental units. This argument will be further extended and elaborated in Section 3. Within the strategic management domain, various dimensions of standardization have been examined, including but not limited to product functionalities and aesthetics (Gemser & Leenders, 2001; Winter et al., 2012). This study encompasses the examination of standardization in terms of functional and aesthetic perspectives, because these attributes take important roles in both customer decision-making processes and product strategizing within the short-term rental sector (Cheng, Fu, Sun, Bilgihan, & Okumus, 2019; Farmaki, Spanou, & Christou, 2021b).

3.3. Conceptual Framework and Hypotheses Development

3.3.1 Conceptual framework

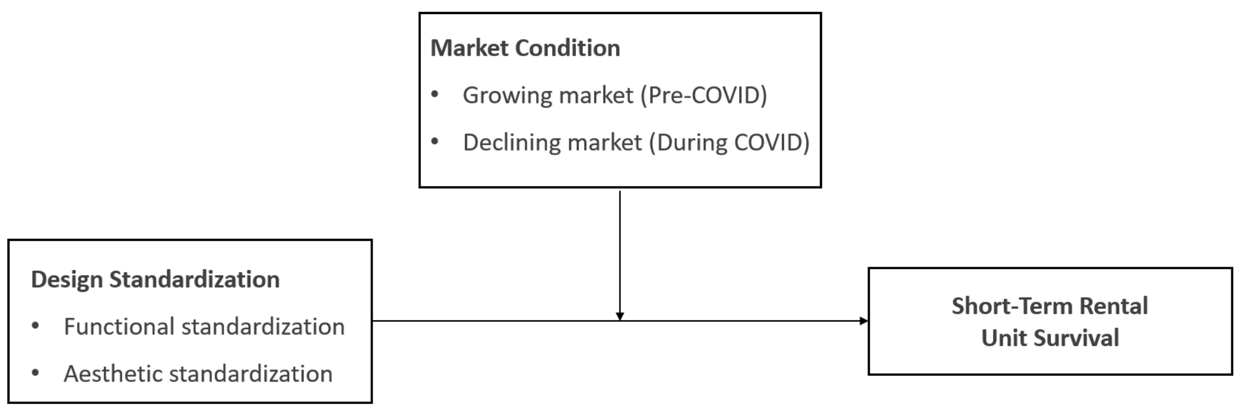


Figure 3-1. Conceptual framework

The primary objective of this research is to examine the heterogeneous impacts of standardization under varying market conditions within the context of the short-term rental sector. More specifically, this study encompasses two dimensions of standardization —functional and aesthetic—and uses unit survival as a key measure of outcome. The interrelationships between standardization and unit survival are contingent on two contrasting market conditions: a growing stage versus a declining one. The conceptual framework for this analysis is delineated in Figure 3-1.

3.3.2 Standardization and survival

In the business field, unit refers to a single business establishment, which could take the form of a restaurant, retail store, or lodging property. An organization that operates multiple such establishments simultaneously is correspondingly defined as a multi-unit organization (Woo, Cannella Jr, & Mesquita, 2019). In parallel terms, the business managed by a multi-unit host in the short-term rental context can be conceptualized as a multi-unit organization, comprised of several distinct individual units.

In the short-term rental literature, previous studies have identified that the similarity between units operated by the same host contributes to an increase in the host's managerial efficiency across these units, thereby augmenting unit quality and subsequently bolstering guest satisfaction, e.g., H. Zhang et al. (2023). However, H. Zhang et al. (2023) investigate strategic outcomes at the host level.

We argue that units with varying levels of similarity to other units under the same host possess asymmetric capabilities in leveraging the benefits of standardization. For instance, although there is a high general level of similarity among units managed by the same host, it is still hard for a unit that is distinct from its sister units to capitalize on the benefits. Hence, the focus of this study is strategic outcomes at the unit level. For each single unit, we propose that a high similarity to sister units can enhance unit survival because it allows that unit to benefit from cost efficiency and operational efficiency (Lawrence, 2020; Ritzer, 1992).

First, standardization can enhance unit survival because it allows units to improve cost efficiency via economies of scale and inter-unit collaboration. Units that are highly standardized in functional or aesthetic dimensions enable a multiunit organization (i.e., host) to engage in bulk purchasing of supplies and maintenance, or orchestrate promotional activities and management solutions (Ritzer, 1992; Silberston, 1972; H. Zhang et al., 2023). For example, if multiple units managed by the same host are furnished with the same lamps or decorated with the same styling elements, the host will have chances to build long-term partnerships with suppliers. Among these units, one with a high similarity to the majority of its sister units can enjoy these cost-effective resources while those dissimilar ones cannot (Chatterjee & Wernerfelt, 1988; Tsai, 2000). Cost-efficiency can be further translated into competitive advantages that secure unit survival (Cuypers, Hennart, Silverman, & Ertug, 2021; Pearce, 1997).

Second, standardization can potentially impact unit survival through operational efficiency. When there exists a high level of inter-unit similarity, hosts are afforded the opportunity to construct efficient process templates. This can be achieved by improving operations through multiple iterations applied to similar unit settings (Lawrence, 2020; Pennings, Barkema, & Douma, 1994). In turn, these templated processes can expedite various operations, such as equipment maintenance and the response to customer inquiries. These operational efficiencies contribute to heightened service stability, predictability, and quality (Fließ & Kleinaltenkamp, 2004). Units that share common attributes are likely to benefit from these advantages that potentially bolster their survival prospects, whereas distinct units are unlikely to experience any significant influence due to the inapplicability of the templated processes (Csaszar & Siggelkow, 2010).

Although there are tremendous benefits generated by standardization, potential risks associated with high levels of intra-organizational embeddedness cannot be overlooked. First, a unit sharing extensive common attributes or practices with others is more vulnerable to organizational inertia, consequently impairing its flexibility and adaptability which is of great value for lodging products (Tan & Wang, 2010; Zemke, Raab, & Wu, 2018a; Zuzul & Tripsas, 2020). The incapacity to effectively respond to environmental changes will ultimately increase the unit's failure rate (Hollow, 2014). Second, managing multiple units catering to similar customer segments might inadvertently amplify the failure risk, especially in sectors characterized by high seasonality such as the short-term rental industry (Coad & Guenther, 2013; D. Zhang & Xie, 2023). This risk is heightened if these units under the same host do not differentiate from each other. A dissimilar unit, however, might attain financial support in its slack season from other units that display different demand fluctuation patterns, effectively mitigating the risk.

Considering the dual nature of standardization, wherein both efficiency gains and risks coexist, the net effect on unit survival hinges on the extent to which these benefits are offset by the risks involved. For short-term rental hosts, who are largely constrained by a lack of expertise, the growing complexity associated with within-host heterogeneity presents a formidable challenge and amplifies the hosts' demands for efficiency improvements. Besides, the smallness of micro businesses operated by short-term rental hosts slacks their vulnerabilities to rigidity risks. Given such conditions, we propose the following hypotheses.

H1a: Functional standardization positively affects short-term rental unit survival.

H1b: Aesthetic standardization positively affects short-term rental unit survival.

3.3.3 Market conditions

Environmental conditions are pivotal in determining strategic outcomes, including firm survival (Carroll, 1984; T. T. Yang & Li, 2011). Prior research in the business field has examined a variety of environmental conditions, including industry evolution, policy and regulations, and market conditions (Kukalis, 1991; Shou, Yang, Zhang, & Su, 2013; Yao, Zhang, Lu, & Huang, 2020). Among these aspects, market conditions draw great attention because of the COVID pandemic (Breier et al., 2021; Yeon, Song, Yu, Vaughan, & Lee, 2021). Firms, especially those in the tourism industry, are confronted with substantial challenges due to a sharp market decline induced by the pandemic. This market shift precipitates an acute survival crisis for firms, fundamentally altering their strategic demands for survival management.

In a growing market, a heightened efficiency improvement is possible to be achieved, thus amplifying the positive impacts of standardization on short-term rental unit survival. As is suggested by resource dependence theory, the extreme market munificence offers abundant resources and development opportunities, incentivizing firms to scale up to meet the escalating market demand (Görg, Strobl, & Ruane, 2000; Pfeffer & Salancik, 2003). And the enlarged business size will, in turn, enhance firm survival (Bercovitz & Mitchell, 2007). An expanding business scale allows units to achieve more cost efficiency through a high inter-unit consistency from volume discounts, spread of fixed costs, and efficient allocation of resources (Reynolds, 1997). Furthermore, the operational complexity, exacerbated by business size, necessitates enhanced operational efficiency, facilitated by standardization. Thus, the positive impacts of standardization on survival generated through efficiency might be accentuated in a growing market due to scale of operations and operational complexity.

Conversely, in a declining market, the positive effects of standardization are more likely to downgrade owing to units' increased demands for flexibility and risk hedging. When the market declines, units face high uncertainty caused by unpredictable pandemic waves, and associated regulatory change, customer demand shifts, and economic fluctuations (Arbulú, Razumova, Rey-Maquieira, & Sastre, 2021). Given this enhanced unpredictability and dynamism, units need to be more flexible to respond to changes and adapt their design, accordingly, making high similarity to sister units less advantageous.

Intensified financial pressures in a declining market further diminish the benefits of standardization. Capital becomes more scarce in such markets, and external investors, increasingly pessimistic, are reluctant to invest (Chakrabarti, 2015). This scarcity enlarges short-term rental units' dependence on internal financial support derived from sister units' profits. However, a high similarity to sister units might limit access to internal financial support, as units sharing similar customer bases have common off seasons. In addition, under this dynamic macro environment, competition among existing players changes rapidly as firms struggle to survive. Some short-term rental units might resort to unusual or aggressive tactics, such as predatory pricing (Kourtit, Nijkamp, Östh, & Turk, 2022). Therefore, the financial support from sister units becomes increasingly critical for survival. Considering the heightened positive impacts in a growing market, and the diminished benefits in a declining market, we hypothesize that:

H2a: The positive impact of functional standardization on short-term rental unit survival is stronger in a growing market than in a declining market.

H2b: The positive impact of aesthetic standardization on short-term rental unit survival is stronger in a growing market than in a declining market.

3.4. Methodology

3.4.1 Data

We test the hypotheses with a sample of Airbnb market in Hong Kong for two reasons. First, Hong Kong is one of the most reputable and internationalized destinations in Asia, which breeds massive and diversified Airbnb supplies. It allows us to draw ubiquitous findings on short-term rental survival. Second, a sharp turn of the tourism market observed in Hong Kong offers us an ideal context to compare strategic outcomes in different market conditions.

The data used is collected from the website "Inside Airbnb", a widely used data source in short-term rental studies (Fan et al., 2023; Kakar, Voelz, Wu, & Franco, 2018). The sample includes all Airbnb units operating in Hong Kong between April 2018 and October 2021, with detailed unit information, including amenity, cover photo, location, and survival status. There are 371,318 unit-month observations comprising 27,937 units supplied by 11,336 hosts during April 2018 and October 2021 in the whole sample.

3.4.2 Market Conditions

This study aims to investigate how standardization affects unit survival under different market conditions. Variation in the size of surviving business is an important indicator of ***market condition*** (Segarra & Callejón, 2002). Figure 3-2 displays the trend of Hong Kong Airbnb supplies regardless of host type (single-unit vs multi-unit hosts). It peaked in August 2019. Hence, we categorize the time between April 2018 and August 2019 as the growing market and the time after August 2019 as the declining market. As we only focus on strategies applied by multiunit hosts, we keep 2,441 hosts with 17,375 units for the following survival analysis.

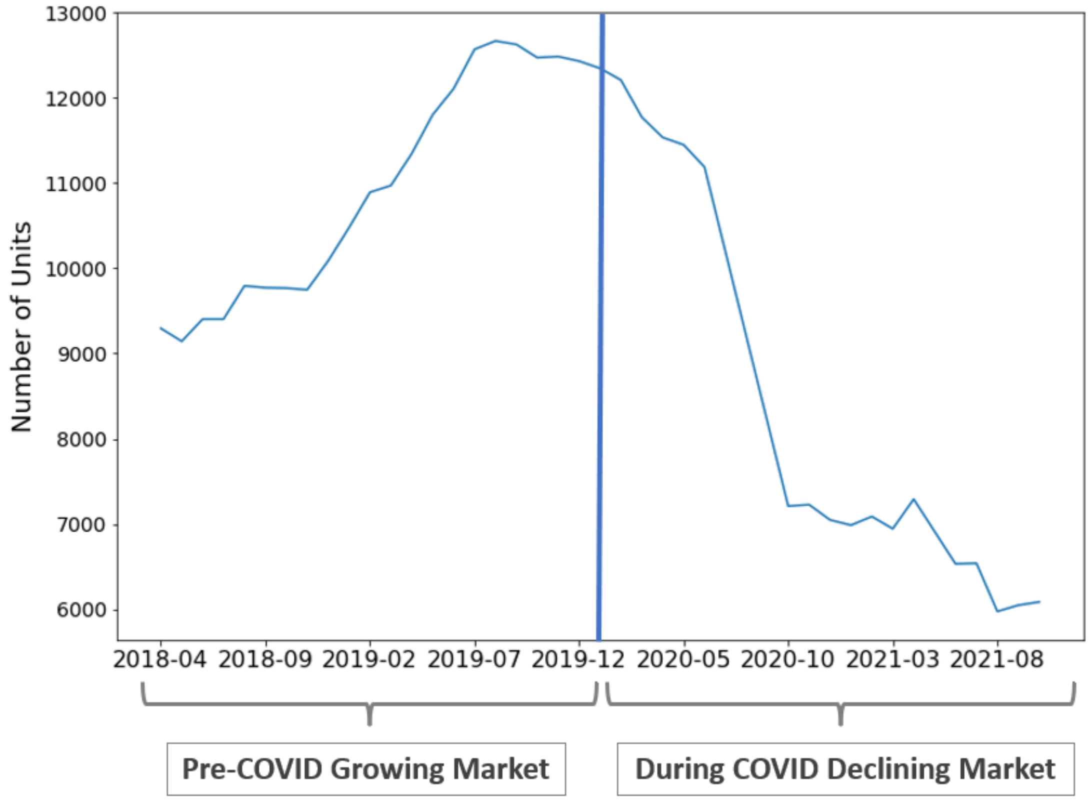


Figure 3-2. Unit supplies and market conditions

3.4.3 Standardization

This study operationalizes standardization by assessing the extent of similarity between a focal unit and other units managed by the same host. As such strategies are specific to multi-unit hosts, 253,598 observations covering 18,685 units from 2,756 multi-unit hosts are used in the following survival analysis. When measuring standardization, we first implement a pairwise comparison between the focal unit and each sister unit, then use the average similarity score of all compared pairs to denote the standardization degree of the focal unit. Standardization is measured separately across functional, aesthetic, and geographic dimensions.

Functional standardization is quantified based on amenities, such as Wi-Fi and coffee maker, as these utilitarian elements reflect the units' functionalities. Then, as depicted in Figure 3-3, the similarity degree between every two units is measured by a Jaccard Similarity Score (H. Zhang et al., 2023).

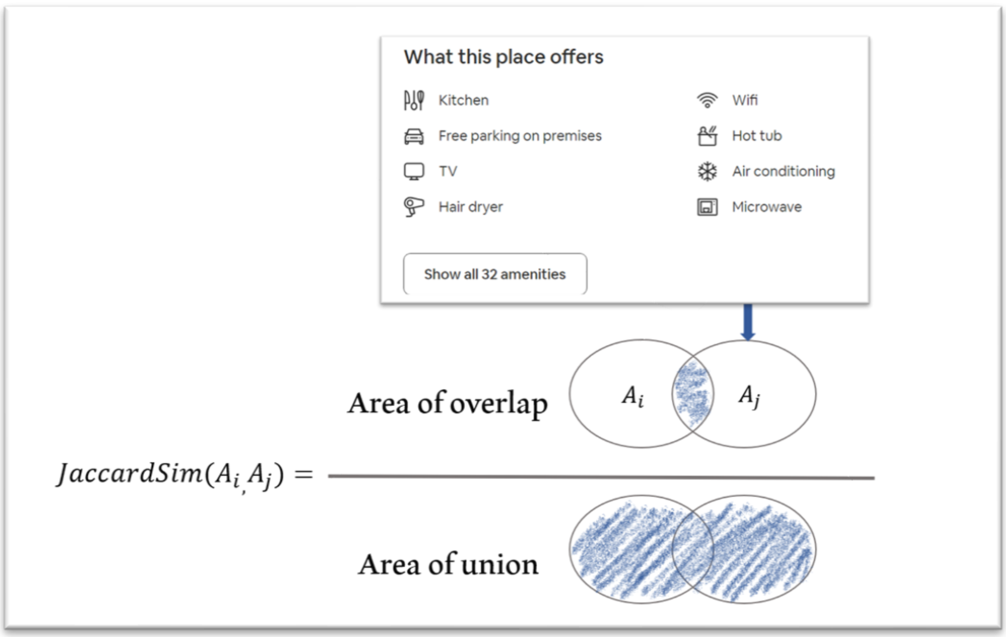


Figure 3-3. Jaccard similarity between two amenity sets

When comparing a focal unit i with n sister units managed by the same host, $Amenity_i$ denotes the Amenity set offered in unit i. The functional standardization score obtained from the following equation is between 0 and 1.

$$FuncStandardization_i = \frac{1}{n}\sum_{j=1}^{n} JaccardSim(Amenity_i, Amenity_j) \qquad (1)$$

Aesthetic standardization is measured by analyzing unit cover photos, which are considered to embed rich information reflecting unit aesthetic styles (Rahimi, Liu, & Andris, 2016).

To quantify aesthetic styles, this study implements a machine learning model VGG-16 which is pre-trained on Places365 (Simonyan & Zisserman, 2014; Zhou, Lapedriza, Khosla, Oliva, & Torralba, 2017). Places365 is a scene recognition dataset containing 10 million place images which enable the mode to capture image features relevant to physical places (Zhou et al., 2017). The model is further finetuned by a classification task with 800 images in four distinct interior design styles: casual, classic, modern, and natural (Figure 3-4).

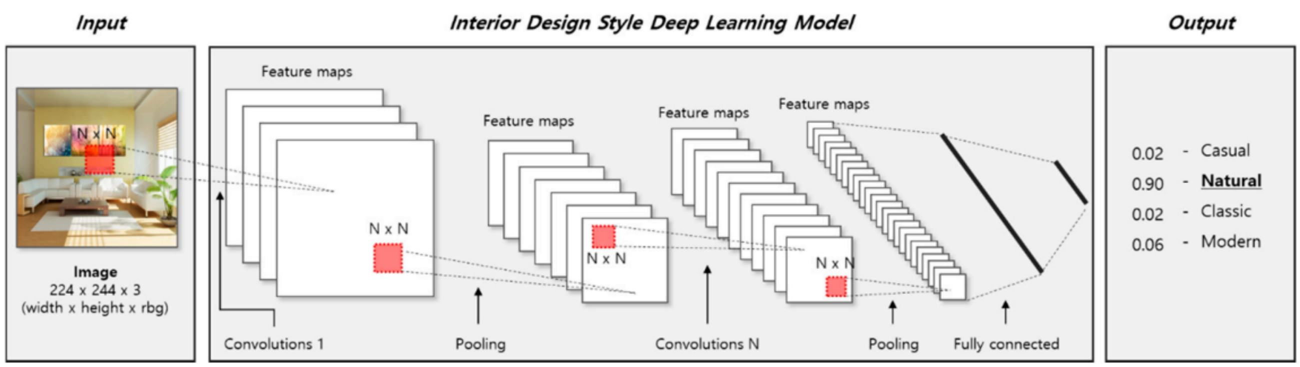


Figure 3-4. Conceptual structure of interior design style recognition model

After training, the model's design style classification accuracy reaches around 95%, comparable to human performance (J. Kim & Lee, 2020). Then, each unit cover photo is processed by the pre-trained model and represented by a probabilistic distribution over four styles, where in the score for each style is between 0 and 1. Figure 3-5 shows selected examples of predicted style scores. In the equation, $Style_i$ represented the design styles scores of unit i. When taking only non-negative values, cosine similarity equation will generate scores between 0 and 1.

$$AesStandardization_i = \frac{1}{n}\sum_{j=1}^{n} CosineSim\left(Style_i, Style_j\right) \qquad (2)$$

Figure 3-5. Examples of predicted aesthetic design distribution scores

3.4.4 Survival analysis

This study analyzes unit survival for multi-unit hosts in the Hong Kong Airbnb market. There are multiple ways to operationalize survival with different measures of mortality (Josefy et al., 2017). In this study, following previous short-term rental survival studies, we use market exit as a mortality measure (Fan et al., 2023; Leoni, 2020).

Several techniques are available for survival analysis, ranging from non-parametric to parametric models. Parametric models are not suitable for this study because they require a clear distribution of survival time, but it is challenging to predefine a survival distribution due to market fluctuations and inherent unpredictability (Kalbfleisch & Prentice, 2011). Therefore, this study applies non-parametric and semi-parametric models.

A non-parametric model, i.e., Kaplan-Meier estimator, is utilized to compare the survival function between high vs low standardization group (above median vs below median) (Kaplan & Meier, 1958). To investigate the impacts of standardization on unit survival, we also implement a semi-parametric model, that is proportional hazard regression, as known as Cox regression (Cox, 1972). This model is appropriate for this study because it is more flexible and relies less on assumptions about the shape of the hazard function or the distribution of survival times. In addition, it allows us to carry on simultaneous analysis of several time-dependent covariates. The function of hazard rate $h(t)$ is specified as:

$$h(t) = h_0(t) * e^{\sum x_i * \beta_i}$$

In this equation, $h_0(t)$ is the baseline hazard with T = 1 in April 2018 and T=44 in October 2021. The sample is right-censored and left-truncated. The present study accommodates for both right censoring and left truncation, given that many units remain active at the end of the sampling period, while the majority were already operational at the study's onset. Consequently, the survival duration is calculated based on the active time within the sample period.

In this study, we utilize a piecewise Cox regression, separately estimating the model for both the growing and declining market samples after fitting the full sample. This approach is adopted because the piecewise Cox regression allows us to compare how standardization affects unit survival in different market conditions. After removing observations with missing values, our analysis incorporates 95,294 observations from the growing market and 68,766 observations from the declining market.

We take three standardization scores as primary variables and control for the effects of relevant variables that have been identified as key determinants for unit survival in previous studies (Fan et al., 2023; Leoni, 2020). These variables include unit features and host features. Specifically, we include maximum guests, minimum nights, price, number of reviews, instant bookability, number of units, host tenure, host response time, host response rate, superhost, profile photo. Table 3-1 provides detailed descriptions for the involved variables.

Table 3-1. Variables and Descriptive Statistics

Variable	Description	Mean	Std	Min	Max
Exit	Whether a unit exits market (exit = 1, otherwise 0)	0.05	0.23	0	1
FuncStandardization	Amenity similarity between the focal unit and other units managed by the same host	0.67	0.17	0	1
AesStandardization	Aesthetic style similarity between the focal unit and other units managed by the same host	0.48	0.23	0	1
Unit type	Type of Airbnb unit (entire home/apt; private room; shared room; hotel room)	——	——	——	——
Max guests	Maximum number of guests that can be accommodated in the focal unit	1.64	1.39	1	16
Min nights	Minimum night stay required by host	8.14	15.72	1	1000
Price	Average daily price (HKD)	721.16	1725.72	0	78492
No. of reviews	Number of guest reviews per month received by the unit	25.33	46.15	0	757
Instant bookability	Whether the unit can be booked instantly (Instant bookable =1, otherwise 0)	0.49	0.50	0	1
No. of units	Number of units managed by the same host	46.83	98.69	2	524
Host tenure	Number of days since the focal unit's operator become an Airbnb host	2157.08	713.40	532	4279
Response time	Speed of response to guests' inquiries (within an hour, within a few hours, within a day, a few days or more)	——	——	——	——
Response rate	The rate of new inquiries and reservation requests a host responded to	0.94	0.16	0	1
Superhost	Whether a host has a Superhost badge (superhost = 1, otherwise 0)	0.14	0.35	0	1
Profile photo	Whether the host has a profile photo (has = 1, otherwise 0)	0.99	0.02	0	1

3.5. Results and Discussion

The main objective of this study is to assess the impact of standardization on unit survival under varying market conditions. When checking the overall supply of units, regardless of host type, two distinct market trends emerge: a growth phase and a contraction phase, with a tipping point occurring in August 2019. A similar trend and coincident peak time are observed when evaluating the monthly supply of units managed by multi-unit hosts (Figure 3-6). These observations suggest that units, managed by multi-unit hosts, participate synchronously in market expansions and contractions, aligning with the broader market dynamics.

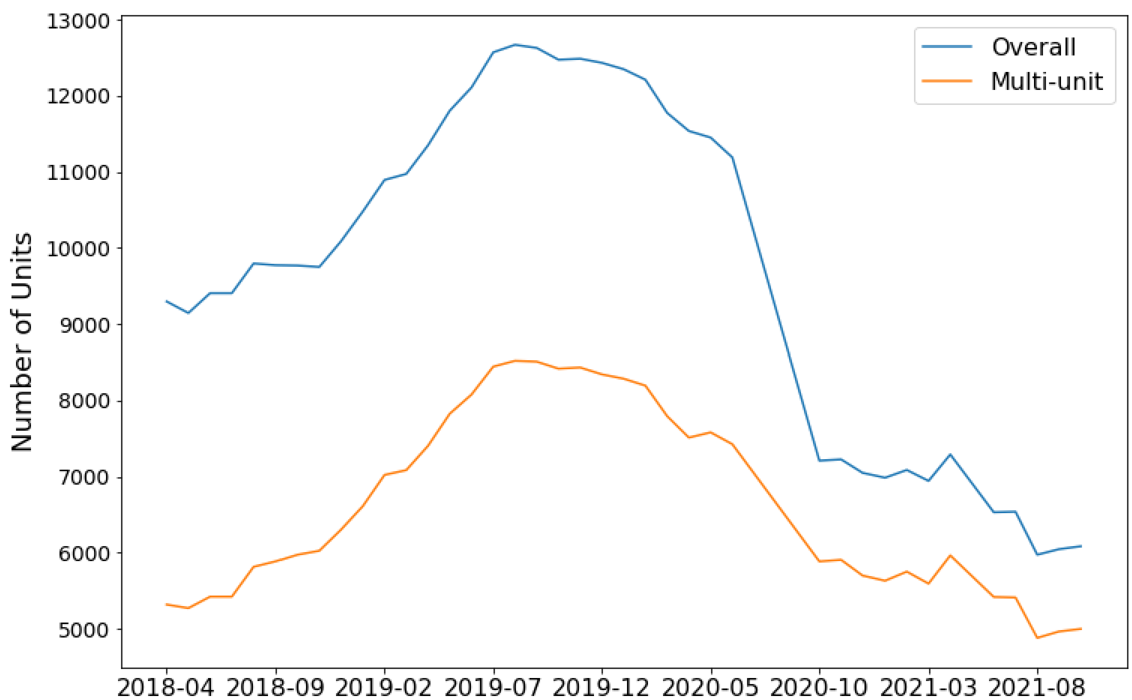


Figure 3-6. Supplies of units by multi-unit hosts

Supplementary information regarding entry, exit, and supply balance is displayed in Table 3-2. During the growing phase of the market, the quantity of units managed by multi-unit hosts escalates by 60.19%, from 5,318 in April 2018 to 8,519 in August 2019. However, this figure declines by 41.33% to 4,998 by October 2021 during the market declining phase. Intriguingly, despite an expanding total supply during the market growing phase, the number of exits remains stable, suggesting a diminishing hazard rate. In contrast, under the declining market, the number of exits exhibits notable fluctuations, signifying market instability.

Table 3-2. Lifetable of units supplied by multi-unit hosts

Time Interval	**Number of Entries**	**Number of Exits**	**Balance**
Initial State (Apr 2018)	——	——	5,318
Apr 2018 - Sep 2018	1,988	1,421	5,885
Oct 2018 - Mar 2018	2,456	1,256	7,085
Apr 2019 - Sep 2019	3,148	1,723	8,510
Oct 2019 - Mar 2019	1,468	2,184	7,794
Apr 2020 - Sep 2020	998	2,907	5,885
Oct 2020 - Mar 2020	576	710	5,751
Apr 2021 - Sep 2021	761	1,632	4,880
Oct 2021	491	373	4,998

The Kaplan Meier survival curves for short-term rental units, presented in Figures 7 and 8, depict the differences between units with high and low standardization levels, both functionally and aesthetically. A significant disparity ($p < 0.001$) in survival rates between high-standardization (above median) and low-standardization (below median) groups is observable in both figures. Intriguingly, Figure 3-7 reveals a superior survival rate for units maintaining high functional standardization in a growing market. However, in a declining market, these units are outperformed by those demonstrating a lower level of functional standardization. Therefore, these visualizations confirm the hypothesis that functional standardization exerts a positive influence on unit survival in an expanding market—a force that appears more potent than in contracting markets, thereby substantiating Hypothesis 2a (H2a).

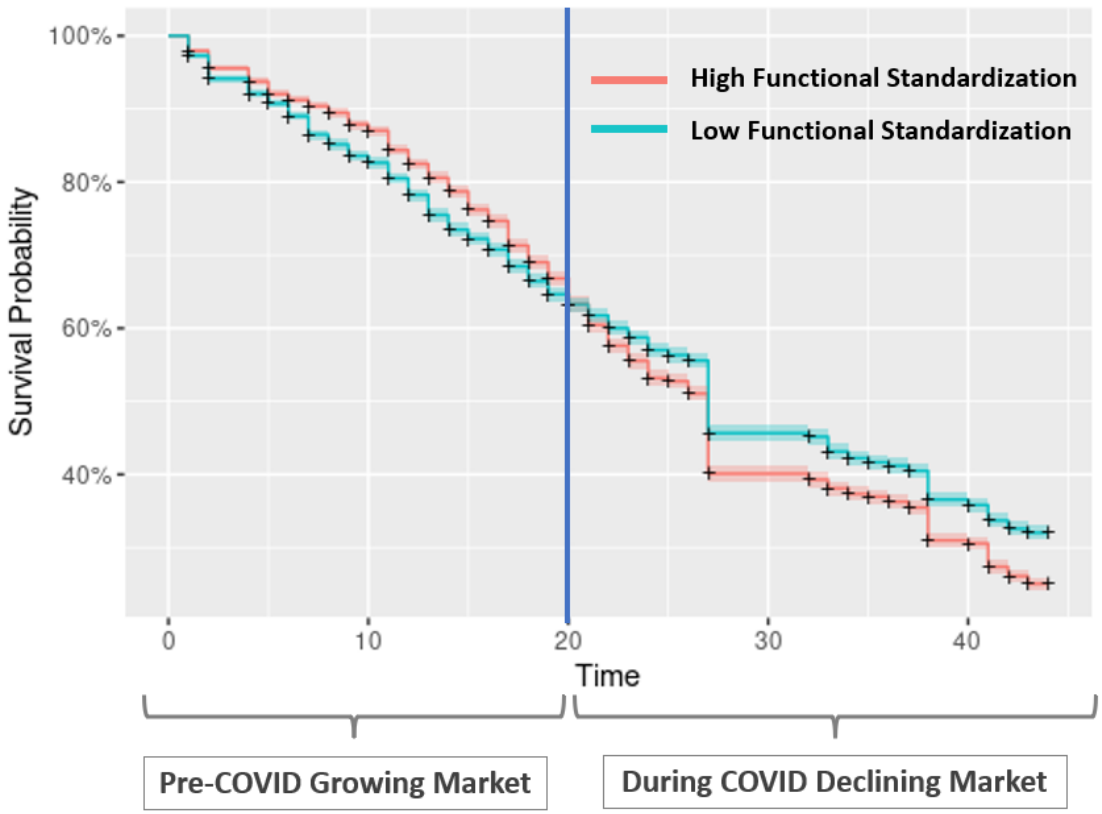


Figure 3-7. Kaplan-Meier survival curve for different levels of functional standardization

Figure 3-8 presents a less favorable survival probability for units with high aesthetic standardization under any market condition. As such, Hypothesis 1b (H1b) cannot be upheld, given the persistently negative influence of aesthetic standardization. When comparing two different market conditions, a narrower gap is discernible between the two aesthetic standardization groups in the expanding market. This suggests a mitigated negative impact, which could be interpreted as a relatively stronger positive effect. Thus, in this context, Hypothesis 2b (H2b) finds support.

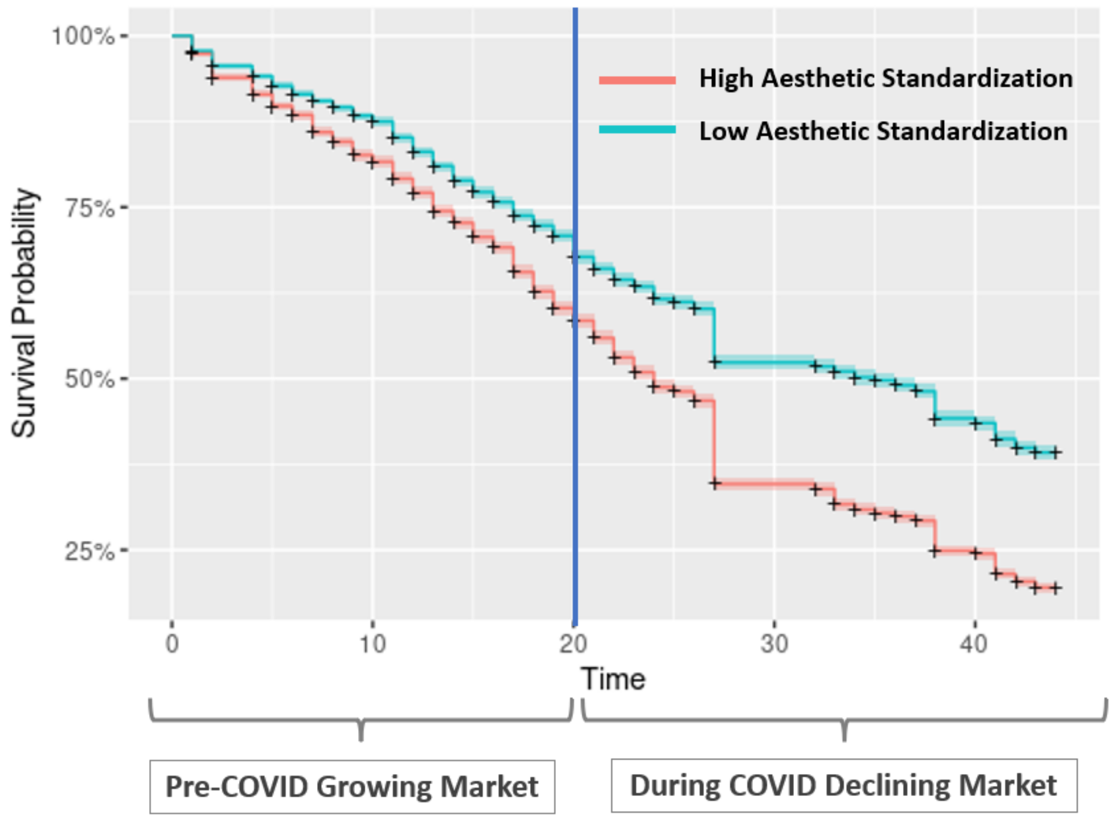


Figure 3-8. Kaplan-Meier survival curve for different levels of aesthetic standardization

The Cox regression models were subsequently estimated for the full dataset, as well as for the subsamples corresponding to growing and declining market conditions. In this step, variables including max guests, min nights, price, no. of reviews, no. of units, and host tenure are log-transformed to reduce data variability. Table 3-3 shows the findings of Cox regressions. Overall, the models exhibit good fit, as indicated by R-squared values and concordance scores; the latter suggests that the correct order in around two thirds of case pairs could be predicted. The likelihood ratio tests and score (logrank) tests further validate the goodness-of-fit. Wald tests serve to confirm the significance of individual predictors. With respect to coefficient interpretation, positive values were indicative of an increase in hazard rate, whereas negative coefficients suggested a drop.

The model outcomes, as presented in Table 3-3, largely corroborate our findings from the Kaplan Meier curves. We hypothesize that both functional and aesthetic standardization positively impact unit survival. However, analysis of the full dataset led to the rejection of both H1a and H1b. Functional standardization does not yield a significant coefficient, thus suggesting no influence on survival, rejecting H1a. Aesthetic standardization demonstrates a significant, positive coefficient ($b = 0.276$, $p < 0.001$), reflecting an increase in the hazard rate by 27.6% when the degree of aesthetic standardization grows from 0 to 1. This result rejects H1b.

The rejection of H1a and H1b suggests that, within the context of short-term rentals, the efficiency gains associated with standardization are eclipsed by the attendant flexibility costs and financial risks, subsequently impacting unit survival. This finding counters the conclusions drawn by H. Zhang et al. (2023), wherein within-host consistency in both functional and aesthetic design is identified to enhance guest satisfaction for short-term rentals - an element deemed crucial for ensuring unit survival. A plausible explanation for this discrepancy could be that the majority of observations from our study coincide with a market decline. In such scenarios, the need for flexibility and risk hedging tends to take precedence.

When checking the results of two market conditions, support for H2a and H2b is found. A significant, negative coefficient for functional standardization ($b = -0.868$, $p < 0.001$) is observed in the growing market, indicating a reduction in the hazard rate by 86.8% upon a unit increase in aesthetic standardization. However, in the declining market, the positive coefficient for functional standardization ($b = 0.272$, $p < 0.001$) pointed towards a 27.2% increase in the hazard rate as functional standardization increases from 0 to 1. This implies that the positive effect of functional standardization shrinks and turns detrimental as market conditions switch from growth to decline. Therefore, Hypothesis 2a (H2a) finds empirical support. In terms of aesthetic standardization, the negative influence is stronger in the declining market ($b = 0.278$, $p < 0.001$) than in the growing market ($b = 0.201$, $p < 0.001$), indicating an increase in the hazard rate from 20.1% to 27.8%. This result validates Hypothesis 2b (H2b).

Our findings, which highlight either strengthened positive or mitigated negative effects of standardization in a growing market, suggest that benefits derived from cost and operational efficiency are predominant in an expanding market context. This aligns with existing literature, reinforcing the notion that business expansion can bolster firm survival, particularly within a growing market. This is largely attributed to the fact that an amplified business scale enables firms to reap more substantial benefits from cost reductions and operational efficiency improvements (Görg et al., 2000; Reynolds, 1997).

By comparing the outcomes of two design dimensions, we observe distinct patterns: functional standardization exhibits a positive influence within the growing market, whereas the effect of aesthetic standardization remains negative regardless of market conditions. This result implies that aesthetic standardization sacrifices more flexibility which is valued by guests when consuming lodging products (Zemke et al., 2018a). An alternative explanation is that modifications to aesthetic elements, such as wallpaper or furniture sets, necessitate substantial effort. Conversely, functional modifications, such as the addition of a new amenity like a coffee maker, entail marginal effort. Hence, functionalities are more modifiable, enabling short-term rental units to adapt more seamlessly to environmental changes and, in turn, rendering them less susceptible to the survival risks associated with decreasing flexibility (Yu, Cheng, Yu, Tan, & Li, 2022).

Control variables, such as minimum nights, no. of reviews, no. of units, response rate and superhost, yield results consistent with previous studies (Fan et al., 2023; Kourtit et al., 2022; Leoni, 2020). However, the variable instant bookability shows an interesting pattern, improving survival probabilities in a growing market but exacerbating risks in a declining one. A potential explanation could be that units offering such hotel-like features tend to cater more to business travelers (K. L. Xie & Young, 2021). This segment is particularly vulnerable during the COVID-19 period because business trips have shifted into online videoconferencing, while leisure travel with longer trip durations emerged as a primary revenue source for short-term rentals (Guttentag, Litvin, & Smith, 2023).

Table 3-3. Cox regression results

	DV: hazard rate		
	Full sample	**Growing market**	**Declining market**
Standardization			
FuncStandardization	-0.075	-0.868***	0.272***
AesStandardization	0.276**	0.201***	0.278***
Control variables			
Unit type			
- Private room	-0.146***	-0.134***	-0.225***
- Shared room	-0.096*	-0.075	-0.389***
- Hotel room	-0.294***	——	-0.332***
Max guests (log)	0.078***	-0.023	0.072*
Min nights (log)	-0.228***	-0.213***	-0.123***
Price (log)	0.003	-0.041	-0.039*
No. of reviews (log)	0.033***	0.042***	0.031***
Instant bookability	0.122***	-0.066*	0.207***
No. of units (log)	-0.229***	-0.138***	-0.321***
Host tenure (log)	0.212***	0.014	0.208***
Response time			
- Within an hour	0.267**	0.076	0.371***
- Within a few hours	0.161	-0.143	0.349***
- Within a day	0.251***	0.187	0.347***
Response rate	-0.615***	-1.482***	-0.579***
Superhost	-0.431***	-0.351***	-0.320***
Profile photo	-0.142	-1.268***	0.132
Number of events	12,823	5,942	7,877
R^2	0.264***	0.185***	0.309***
Concordance	0.649 (se = 0.003)	0.624 (se = 0.004)	0.673 (se = 0.003)
Likelihood ratio test	3,926***	1,217***	2,915***
Wald test	3,114***	1,304***	2,275***
Score (logrank) test	3,398***	1,382***	2,503***

Note: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

3.6. Implications and Conclusion

This study examines the influence of standardization, across both functional and aesthetic dimensions, on the survival of short-term rental units within growing and declining markets. The empirical analysis is based on data from Airbnb market in Hong Kong. We identify the impacts of standardization with survival analysis models, Kaplan Meier curve and Cox regression.

The empirical findings suggest that while functional standardization does not have a significant impact, aesthetic standardization exerts a negative influence. When incorporating market conditions into consideration, the impact of functional standardization transitions from positive to negative as the market switches from growth to decline. Conversely, aesthetic standardization consistently undermines unit survival, a detrimental effect that is stronger in a declining market. The existence of either more pronounced positive impacts or attenuated negative effects on unit survival across the two design dimensions underscores the augmented benefits of standardization in a growing market. The implications of these results provide valuable contributions to the understanding of survival dynamics within the short-term rental market.

This study has both theoretical and practical contributions. First, it enhances survival and hospitality research by exploring the interaction between internal (host strategy) and external (market condition) determinants in influencing the survival of short-term rental units. By doing so, it sheds light on the nuanced interplay of firm-specific strategies and the broader market environment, thereby offering a more comprehensive understanding of survival mechanisms within the context of the short-term rental industry.

Second, the study underscores the contextual sensitivity of strategic effectiveness, particularly in relation to standardization, under varying market conditions associated with the pandemic. By elucidating the dynamic relationship between survival strategies and fluctuating environmental conditions, the study broadens the theoretical understanding of strategic adaptation and flexibility in the face of environmental turbulence.

Lastly, from a practical perspective, the study offers valuable insights for short-term rental practitioners, online platform managers, and policymakers. It provides short-term rental professional hosts with efficient and adaptive strategies, which suggest diversifying their units both functionally and aesthetically when facing market downturns. Conversely, it is recommended to enhance inter-unit consistency in functionalities but diversify aesthetic designs in a growing market.

For online platform providers like Airbnb, these findings can inform platform design. Platforms could provide features that facilitate standardization strategies, such as tools to easily replicate successful units or analytics to gauge customer preferences across different properties. Additionally, this study can help platforms in crafting policies that support hosts in navigating market fluctuations by diversifying their offerings, further promoting a stable and thriving short-term rental ecosystem. Simultaneously, it also contributes to policy-making discourse, presenting actionable insights for stabilizing short-term rental markets amid environmental disruptions such as a pandemic.

There are some limitations constraining this study. A major limitation lies in the scope of our sample selection. The hypotheses are exclusively tested using data from a single city, a factor which introduces an element of geographical bias, considering that local tourism development intricacies can significantly influence the survival patterns of short-term rentals. As such, we strongly advocate for future studies to incorporate data from a broader array of cities to re-evaluate the relationship between standardization and survival.

Additionally, our investigation is narrowly focused on market change — specifically, its growth and decline. Other nuanced market conditions such as turbulence, concentration, and life cycle stages also exert substantial influence on survival pressure and competitive dynamics. Therefore, we recommend that future research reassess this topic incorporating a more diverse set of environmental factors.

Lastly, competition within the short-term rental market does not operate in a vacuum—it also involves interplay with hotels and long-term rentals. Understanding the dynamics between long-term rental, short-term rental, and hotel supplies could provide richer insights and add an intriguing layer of complexity to this field of study. Consequently, we urge future research to explore these potential interactions.

Chapter 4. MULTI-LEVEL DIFFERENTIATION OF SHORT-TERM RENTAL PROPERTIES: A DEEP LEARNING-BASED ANALYSIS OF AESTHETIC DESIGN

4.1 Introduction

Differentiation has been a pervasive topic in many areas, including marketing, strategic management, and tourism (Deephouse, 1999; M. Kim et al., 2020; T. Levitt, 1980). It refers to the introduction of unique products which have distinctive features. There is an ongoing debate about the effects of differentiation because of the competing demands for uniqueness and legitimacy (e.g., Baum & Haveman, 1997). Being different from competitors enables products to stand out, attract specific customer segments, and avoid direct rivalry. Firms, including lodging service providers, gain competitive advantages and revenue premiums through differentiation (Sánchez-Pérez et al., 2020). However, differentiated products are vulnerable to skepticism from a diverse audience because they go against the most common forms (Deephouse, 1996). The skepticism can result in a decrease in legitimacy, thus discounting the benefits of differentiation. Such discounts are penalties that push firms to conform to their competitors (M. Kim et al., 2020). Hence, the ultimate impacts of differentiation are decided by whether differentiation benefits are offset by legitimacy penalties. We investigate short-term rental data during the COVID-19 pandemic when competition intensified due to a sharp decline in demand.

Previous differentiation studies mainly address the question of “differentiate or not” but pay little attention to the question “to whom does a firm need to compare to?” (e.g., M. Kim et al., 2020). When setting the benchmarks for positioning, previous studies utilize geographical scopes, such as rivals at the local- versus the city- level (Baum & Mezias, 1992; Yeung & Lau, 2005), whereby local is a sub-region of city. Because the strength of localized competition is contingent on geographical distances, there are significant differences between local- and city-level markets in terms of competitive pressures and market norms that decide differentiation effectiveness. This study aims to examine how city- and local-level differentiation asymmetrically affects lodging product performance. To further illustrate how competitive pressure shapes differentiation-performance relationships, we also test the moderating effects of two competition intensity indicators: number of competitors and market concentration.

In the hospitality and tourism literature, previous studies focusing on lodging products have investigated differentiation strategy in many dimensions, such as quality, size, service, amenity, and aesthetics (Baum & Haveman, 1997; Fleischer & Tchetchik, 2005; M. Kim et al., 2020). This study focuses on aesthetic design primarily for two reasons. First, our focus on visual cues is inspired by the customers' decision-making process in purchasing Airbnb stays. On the Airbnb platform, after travelers choose a destination and travel dates, they are shown a gallery of listing cover photos rather than more specific information, such as listing descriptions or amenities. As such, visual cues reflected by photos of short-term rental properties are critical for customer decision-making and host strategizing (H. Zhang et al., 2023; S. Zhang, Lee, Singh, & Srinivasan, 2022). Second, there are great differences in aesthetic designs across different levels of regions, including cities and sub-regions (X. Liu, Andris, Huang, & Rahimi, 2019). These differences across geographic levels provide a quantitative basis to further measure and distinguish differentiation degrees of aesthetic design.

The critical role of aesthetic design in strategizing lodging products has been validated for communicating product identity (Strannegård & Strannegård, 2012), differentiating product position (Lim & Endean, 2009), and boosting firm profitability (Zemke, Raab, & Wu, 2018b) (Bitner, 1992; Farmaki, Spanou, & Christou, 2021a; Lim & Endean, 2009; Strannegård & Strannegård, 2012). However, while qualitative studies (e.g., Farmaki et al., 2021a) argue that product positioning through aesthetic design is theoretically possible, there is a lack of adequate empirical evidence to support these arguments. Hence, this study aims to quantify and verify the effects of aesthetic design differentiation in the short-term rental context using a deep-learning approach to classify aesthetic design styles.

The multi-level differentiation effects under two contextual factors, number of competitors and market concentration, are tested on the longitudinal data of 96,196 Texas Airbnb listings from April 2021 to March 2022. There are several reasons why we base this empirical study on the short-term rental sector. First, short-term rental businesses provided by micro-entrepreneurs who lack sufficient resources and knowledge to compete are highly sensitive to competitive advantages and legitimacy benefits originating from either differentiation or conformity. Second, compared with traditional lodging products, short-term rentals are facing greater market dynamics. As such, this study examines how competition intensity moderates the relationship between differentiation and performance. Given such a unique context, we first quantify listing aesthetic design using photos from the Airbnb platform with a probability distribution of interior design styles obtained from a pre-trained machine learning model. Then, the impacts of aesthetic design differentiation and moderating roles of market competition intensity are examined using time-fixed effect models.

The theoretical contribution of this study is threefold. First, it contributes to hospitality literature by introducing multi-level thinking to the differentiation stream, which matters to sectors such as short-term rentals that are highly sensitive to localized competition. At the local level where there is intense localized competition, short-term rentals can benefit from differentiation because of competition avoidance. On the other hand, as localized competition fades at the city level, discounts of differentiation overwhelm. Second, this study adds knowledge to tourism literature by identifying an urgent demand for conformity at the city level, which emphasizes the importance of collaborations between destinations and service providers. Third, the moderating effects of competition intensity in shaping strategic outcomes of differentiation adds nuances that extend our understanding of the impacts of differentiation under different contingencies.

In terms of practical contributions, this study provides guidance for practitioners and destination managers. The empirical findings assist short-term rental hosts in identifying product positions using aesthetic design under different market conditions. From the perspective of destination managers, this study highlights the importance of promoting a consistent destination aesthetic identity, which serves as a source of legitimacy for short-term rental businesses within the destination.

4.2 Literature Review

4.2.1 Differentiation and conformity

Differentiation and conformity are two sides of the same coin. Differentiation is defined as the introduction of unique products which have distinctive features, while conformity refers to providing products or services similar to those supplied by other providers. The importance and effectiveness of differentiation/conformity have been widely investigated in the hospitality literature (e.g., Sánchez-Pérez et al., 2020).

A firm gains competitive advantages by differentiating from its rivals (Porter, 1980a; Sánchez-Pérez et al., 2020) in order to capture a unique position that enables it to win the favor of specific customers and stave off fierce competition (Chung & Kalnins, 2001). Previous studies empirically validate that customers with different individual characteristics, such as gender, age, and past consumption experience, have different preferences and requirements for product design such as aesthetics (Bogicevic, Bujisic, Cobanoglu, & Feinstein, 2018; Ryu & Han, 2011). Therefore, it is easier for accommodation products with features favored by a specific group of guests to capture the target market. For example, in the lodging context, home-like lodging design aesthetics help construct a "feeling at home", thus attracting particular traveler segments with high demands for a sense of control and security (Suess, Kang, Dogru, & Mody, 2020).

But, at the same time, there are contradicting findings that differentiation is sometimes useless or even harmful to lodging property performance (M. Kim et al., 2020; Yeung & Lau, 2005). It means conformity is more beneficial in some conditions. Conforming to the competitors bestows legitimacy, making the property more acceptable for target customers. Conformity also helps a firm avoid penalties associated with deviance from existing norms and achieve better performance (Abrahamson & Hegeman, 1994). K. L. Xie and Young (2021) show the improvements in short-term rental performance as a result of mimicking its substitute competitors, i.e., hotels.

One possible reason for the inconsistency in the findings related to the impacts of differentiation/conformity might be a lack of consensus on competitive set formation in prior literature. In other words, the selection of competitors to whom a focal product is compared is not clear. The competitive set scope used in previous studies of the lodging industry ranges from local-level to city-level (Baum & Mezias, 1992; Yeung & Lau, 2005). Zip code and city-level are two dominant approaches to define competition scope in hospitality literature (Kalnins & Chung, 2004; K. L. Xie & Kwok, 2017). Other studies related to competition and demand focus on local markets within the same city, such as tracts and commercial areas (Canina, Enz, & Harrison, 2005; Sánchez-Pérez et al., 2020). Among multiple ways to define competitors, there are differences in competitive dynamics and destination identities which are highly associated with how differentiation creates competitive advantages and how conformity boosts legitimacy benefits.

The importance of answering the question of “comparing to whom” is heightened within the context of our current study, particularly given our data collection period during with the COVID-19 pandemic. This scenario escalates due to the dramatic reduction in demand, leading to intensified competition among short-term rentals located in neighboring areas (Dolnicar & Zare, 2020; Milone, Gunter, & Zekan, 2023). Consequently, the urgency for these rental properties to mitigate local competition intensity while controlling legitimacy devaluation has surged. They are compelled to seek differentiation strategies, which emerge as critical survival tactics in these challenging times. We will further discuss in Section 3 how competition and legitimacy function differently at city- and local- levels and ultimately affect listing performance.

Differentiation/conformity strategy of the lodging product can be implemented in many aspects, such as quality, size, service, location, and narratives (Silva, 2015; Sonuç, 2020; Tchetchik, Fleischer, & Finkelshtain, 2008). This study focuses on differentiation in the aesthetic design dimension because aesthetic design is a crucial differentiation tool within the short-term rental market (Bitner, 1992; Candi & Saemundsson, 2011; Reimann & Schilke, 2011), while the relationship between differentiation and performance remains unclear.

4.2.2 Aesthetic design

Aesthetic design is an extensively studied topic in many disciplines, including architecture, psychology, management, as well as tourism and hospitality (Cross, 1982; Ravasi & Stigliani, 2012). It refers to the visual elements of products, which often constitute style, color, theme, layout, and symbols (H. Zhang et al., 2023). Previous studies concerning lodging property aesthetic design mainly focus on the impacts of specific aesthetic elements or perceived aesthetic quality on customer satisfaction and behavioral intention. For example, hotel guestroom color and design styles influence customer purchase intent and desire to stay (Bogicevic et al., 2018). Other works assess design holistically, for example, the relationship between perceived aesthetic design quality and behavioral intention (Heung & Gu, 2012; Ren, Qiu, Wang, & Lin, 2016).

Even though aesthetic design has been acknowledged as an effective differentiation tool (Bitner, 1992; Candi & Saemundsson, 2011; Reimann & Schilke, 2011), there are few studies validating the impacts of aesthetic design differentiation in the hospitality literature (Fleischer & Tchetchik, 2005). The theoretical underpinnings for differentiation effectiveness of aesthetic design stem from both the firm and the customer perspective, typically assessed in qualitative studies (e.g., Farmaki et al., 2021a; Lim & Endean, 2009; Strannegård & Strannegård, 2012). In an interview study with hotel managers, Lim and Endean (2009) find that hotels try to compete by offering different aesthetic features. These are indispensable components in creating their unique brand personality, such as historical, traditional, modern, or contemporary. A similar conclusion is drawn from interviews with Airbnb hosts, revealing that unique aesthetic features, such as prestigious décor and architectural design, are critical to luxury-meaning construction (Farmaki et al., 2021a). Strannegård and Strannegård (2012) investigate the communicational role of aesthetic design with an ethnographic approach. They argue that aesthetic distinctiveness is a crucial identity building block that distinguishes a hotel from its competitors.

Studies using customer interviews also revealed that differentiated design and art in hotels is an emergent mechanism to strengthen customer loyalty (Alfakhri, Harness, Nicholson, & Harness, 2018). Given the vital role of aesthetic design in developing lodging properties, conveying the properties' unique identity, distinguishing property from competitors, and creating differentiation externalities, short-term rental property performance can benefit from aesthetic design differentiation. However, a differentiation perspective that emphasizes a relative position of aesthetic design and corresponding effects remains less understood.

4.3. Conceptual framework and hypotheses development

We propose the following conceptual framework to examine the impacts of differentiation with aesthetic design on listing performance at both local and city levels (see Figure 4-1). The model also includes two factors of competition intensity – number of competitors and market concentration – to examine how the effects of aesthetic differentiation vary with market conditions.

Given the tension between legitimacy (i.e., by conforming to the market norm) and uniqueness (i.e., by differentiating from the market norm), the net benefit of differentiation is decided by two factors: first, whether, and second, to which extent, the competitive advantages of uniqueness are offset by legitimacy devaluation due to norm violation. We argue that the dynamic relationships between competitive advantages and legitimacy penalties are contingent on the geographic scope of the competitive set because of the accommodation industry's high sensitivity to location (Y. Yang, Luo, & Law, 2014). In the hospitality and tourism context, competition intensity among competitors heavily depends on geographical distances (Bianco, Singal, Zach, & Nicolau, 2023). Also, market identities or images are normally shaped and promoted at different levels of regions.

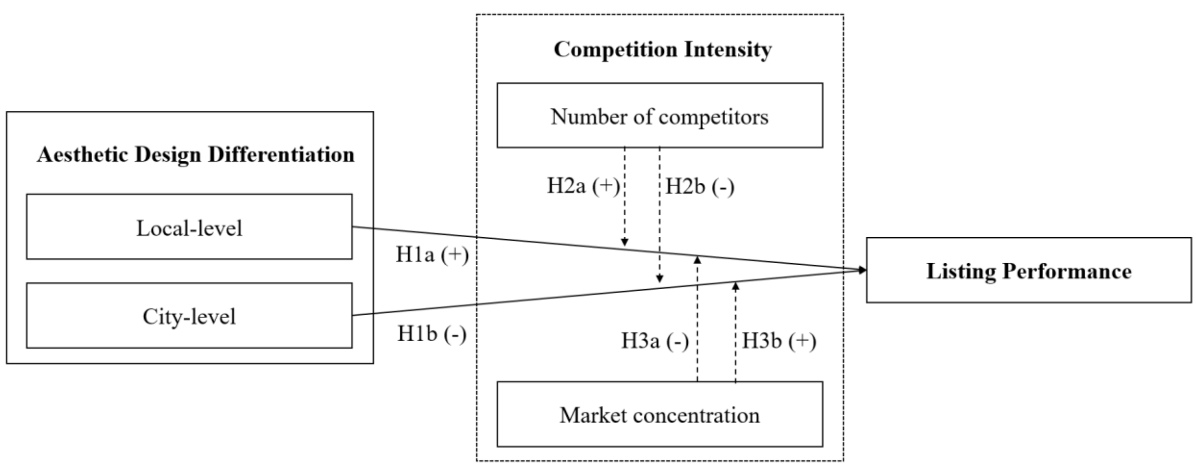


Figure 4-1. Conceptual framework of multi-level aesthetic design differentiation

4.3.1 Local-level aesthetic design differentiation

The phrase "localized competition" is conceptualized by Baum and Mezias (1992) based on spatial dependence theory, which argues that nearby competitors have stronger impacts than distant rivals (e.g., Silva, 2016). Localized competition suggests that firms with high geographic proximity pose greater threats. Therefore, lodging properties differentiating from their neighbors can avoid intense rivalry.

The benefits of differentiation from local competitors have been extensively validated in previous studies. Baum and Mezias (1992) measure size and price differentiation by comparing to competitors within a window of 50 streets, equivalent to a radius of two miles. The empirical results validate the local-level differentiation benefits with lower failure rates. Canina et al. (2005) identify tract-level differentiation benefits in size and strategic orientation dimensions for low-cost hotels in Texas. At the same time, Becerra, Santaló, and Silva (2013) found that hotels are less likely to charge a higher price when there are more similar competitors in the local market.

In this study, local-level aesthetic design differentiation refers to providing products that have aesthetic design styles different from nearby competitors. We argue that local-level aesthetic design differentiation improves listing performance because localized competition amplifies the benefits stemming from avoiding direct rivalry.

The benefits of differentiating from local competitors are also applicable to aesthetic design because lodging products compete heavily with neighbors in the aesthetic dimension. For example, hotels with more pleasing visuals are likely to charge a higher price than competitors located in the same area (Latinopoulos, 2018). Differentiated aesthetic designs thus allow lodging products to stand out from their nearby rivals. For instance, S. K. Lee and Jang (2017) argue that late movers can enjoy competitive advantages by offering newer aesthetics different from existing neighboring competitors. Hence, we hypothesize that:

H1a: Local-level aesthetic design differentiation has a positive impact on listing performance in the short-term rental context.

4.3.2 City-level aesthetic design differentiation

Differentiation benefits stem from competition avoidance at a city level is much lower than at a local level (i.e., a subregion of city-level) because city-level competition has weaker intensity. As such, the benefits of city-level differentiation decline accordingly. In addition, differentiation to a broader scope of competitors may result in performance discounts because of penalties for norm violation. For example, Blal and Graf (2013) measure the size and amenity differentiation by comparing all hotels in the same category across the United States, and their findings reveal a negative impact of differentiation on hotel prices.

City-level aesthetic design differentiation is defined as providing products that have aesthetic design different from competitors in the same city. Conforming to competitors from the same city in the aesthetic dimension can create legitimacy benefits. City is a popular type of destination studied in the tourism literature (Pike, 2002). Also, many marketing and branding activities, especially those related to accommodation, are conducted and analyzed at the city level (S. Choi, Lehto, & Oleary, 2007). Aesthetic components, including lodging property design, play an important role in building “projected” and “organic” destination identities (J. Lee, 2011; Xiao, Fang, Lin, & Chen, 2022). An identity is defined as a shared set of features representing a group of members, such as lodging suppliers in the same destination (Hardy, Lawrence, & Grant, 2005). Destination identities, including aesthetic identities, can be perceived by travelers through evaluating corresponding stakeholders and deriving their common features (Kurdoglu, Seyhan, & Bayramoglu, 2021). An example of destination aesthetic identity is that baroque is a typical style for real estate properties, including hotels, in a tourist destination (A. Smith, 2010).

Previous studies identified great differences in accommodation design styles from city to city and across different levels of destinations (X. Liu et al., 2019; Rahimi et al., 2016). A contextual fit to the city's aesthetic identity creates a consistent tourist experience, boosts recommendation intention, and adds to accommodation products' competitiveness (J. Lee, 2011; Skogland & Siguaw, 2004). Zemke et al. (2018b) also conclude that a higher social and urban integration with the environment in aesthetic elements leads to higher hotel performance. Given legitimacy benefits that are equivalent to differentiation discounts, we hypothesize that:

H1b: City-level aesthetic design differentiation has a negative impact on listing performance in the short-term rental context.

4.3.3 Moderating role of competition intensity

Previous studies suggest that the impact of differentiation is contingent on competition intensity (e.g., Miller & Eden, 2006). High competition pressure drives hospitality establishments to leverage different business strategies, including differentiation, to excel above their rivals (Becerra et al., 2013; Porter & Kramer, 2006; Y. Xu, Gong, & Law, 2022). Under strong competition intensity, a pressing task for service providers is to ease the pressure coming with competition. Hence, the benefits stemming from avoiding direct competition will expand accordingly. There is ample evidence to support the reinforcement of differentiation benefits with competition intensity (e.g., Becerra et al., 2013; Hernandez, 2011). Two dominant indicators of competition intensity are identified in these studies: the number of competitors and market concentration (Kwieciński, 2017).

The number of competitors is widely utilized to measure competition intensity in the short-term rental context (e.g., Gao, Li, Liang, Yang, & Law, 2022). An increasing number of competitors means more firms are sharing customer resources in the market, which devalues property supply (Voltes-Dorta & Inchausti-Sintes, 2021). With more neighboring competitors, firms that can stand out are more likely to gain customer attention and maximize profitability. On the contrary, the mediocre ones are probably overlooked without eye-catching features.

Previous empirical studies verify that the number of competitors strengthens differentiation benefits and mitigates differentiation discounts. Becerra et al. (2013) and Sánchez-Pérez et al. (2020) find that given high local supplies, hotels that pursue differentiation strategies can charge higher room rates in the Spanish hotel market. Kankam-Kwarteng, Osman, and Acheampong (2020) validate that competition intensity strengthens the positive impacts of differentiation strategy on restaurant performance. M. Kim et al. (2020) identify a differentiation discount on hotel performance. Their results also suggest that if there are high differentiation degrees in quality and capacity, a high location proximity of nearest neighbors, which means a higher density of competitors, can increase hotel performance. In other words, high density counteracts differentiation discounts. We thus argue that, in the short-term rental context, competition intensity amplifies differentiation benefits and mitigates differentiation discounts. Hence, we hypothesize that:

H2a: The number of competitors amplifies the local-level aesthetic design differentiation benefits in the short-term rental context.

H2b: The number of competitors diminishes the city-level aesthetic design differentiation discounts in the short-term rental context.

The number of competitors is, however, not sufficient to fully capture competition intensity because it ignores the distribution of market share, which largely shapes competitive behaviors in the market (Indounas, 2018). The extent to which market shares are concentrated among a small number of firms is defined as “market concentration” (Pan, 2005). In a highly concentrated market where the resources are taken by only a few firms, there will be less rivalry because of corporations and collusion among the dominant players (Menezes & Quiggin, 2012). These dominant players’ performance relies less on product differentiation. On the contrary, when the market is more fragmented, service providers have more chances to leverage differentiation advantages by exploiting niche markets that offer higher profitability.

How differentiation outcomes are contingent on market concentration has been extensively tested (e.g., C. B. Li & Li, 2008). A hospitality study of US urban hotel segments conducted by Graf (2011) concludes that differentiation benefits lessen when the market is highly concentrated. Given the professionalization trend of the short-term rental market, more and more big players are entering the market. Consequently, host strategies and market competition patterns are converging with traditional lodging properties (Dogru, Mody, Suess, Line, & Bonn, 2020). Therefore, we hypothesize that:

H3a: Market concentration diminishes the local-level aesthetic design differentiation benefits in the short-term rental context.

H3b: Market concentration amplifies the city-level aesthetic design differentiation discounts in the short-term rental context.

4.4. Method

4.4.1 Data

To explore the impacts of aesthetic design differentiation in the short-term rental industry, we obtained data from AirDNA.com, a credible data source for short-term rental listing performance analysis (e.g., Kwok & Xie, 2019). Our sample includes monthly data from April 2021 to March 2022 in Texas, comprising listing-level information, such as cover photos, host profiles, and performance indicators. We base this study on Texas data because many previous lodging studies concerning differentiation and competition have been conducted in the Texas market. These studies provide a basis for comparison and help identify similarities and differences in the findings across time periods (Canina et al., 2005; S. K. Lee, 2015; K. Xie & Mao, 2017a; Zervas et al., 2017).

In this study, we only include Airbnb properties from urban areas to avoid distractions for lodging products caused by agglomeration effects because nearby competitors create agglomeration externalities in rural but not urban areas (Chung & Kalnins, 2001). There are four types of listings available on the Airbnb platform, i.e., entire home/apartment, private room, shared room, and hotel room. We collect monthly observations on entire home/apartment listings because they are operated for business purposes rather than unstable sharing desires.

After excluding listings with missing values, a sample of 853,735 listing-month observations associated with 96,196 listings is used for the following regression analysis.

4.4.2 Variables

Following previous studies concerning Airbnb performance (e.g., Sainaghi, Abrate, & Mauri, 2021), we use Revenue Per Available Room (RevPAR) as the dependent variable. It is a typical performance measure used in the hospitality industry.

Aesthetic design differentiation is measured by the absolute difference between a focal listing's aesthetic design style relative to the market norm, which is the central design tendency of all listings in the corresponding market. For each listing, the aesthetic design is quantified by a probability distribution of interior design styles. The probabilistic scores of four interior design styles, casual, classic, modern, and natural, are generated by a pre-trained deep learning model after feeding the listing's cover photo. The model prediction accuracy reaches 0.94 – 0.98, which is close to human performance (J. Kim & Lee, 2020). Figure 4-2 displays examples of predicted listing style scores.

Figure 4-2. Examples of predicted listing style scores

This study compares the impacts of aesthetic design differentiation between city-level and local-level. To generate city-level aesthetic design differentiation, we compare the design scores of a listing l with the average design scores of all the listings from the same city. The differentiation degree is calculated by the following equation where $\theta_{l,s,t}$ denotes listing l's weight for style s at time t, $\bar{\theta}_{C,s,t}$ represents the average score for style s at time t among all the listings in the same city C, and abs means the absolute value.

$$CityDiff_{l,t} = \sum_{s=1}^{4} abs\left(\theta_{l,s,t} - \bar{\theta}_{C,s,t}\right)/4 \tag{1}$$

There are multiple ways to define a local market, like zip code, tract, and Airbnb neighbourhood (Coles, Egesdal, Ellen, Li, & Sundararajan, 2017; J.-Y. Kim & Canina, 2013; K. L. Xie et al., 2020; K. L. Xie & Young, 2021). Here, we use census tract, which is defined by the US Census Bureau to represent local markets for the following reasons: First, the boundary of a tract is well-defined and stable over a long time, while the boundaries for zip codes are vague, and some changes in zip codes may occur monthly (UCF, 2022). Second, census tracts are applicable to all cities, while Airbnb neighbourhood information is only available in a few cities. To obtain local-level aesthetic design differentiation, we compare a listing l to the census tract averages. The equation applied here is

$$LocalDiff_{l,t} = \sum_{s=1}^{4} abs(\theta_{l,s,t} - \bar{\theta}_{T,s,t})/4 \tag{2}$$

Here $\bar{\theta}_{T,s,t}$ refers to the average weight for style s at time t among all the listings in the same tract T.

Competition intensity is operationalized by two indicators, the number of competitors and market concentration. We measure CityComp and LocalComp by the number of Airbnb listings in the same city/local market (Sánchez-Pérez et al., 2020; Voltes-Dorta & Inchausti-Sintes, 2021). Herfindahl-Hirschman index (HHI) is a common measure of market concentration, which is the sum of the squared market shares of all competing firms in the market. We adjust room-based HHI measures used in previous hospitality studies to fit the Airbnb context (Duverger, 2013; Y. Yang, Jiang, & Schwartz, 2019). The market share of each host is represented by the number of properties managed divided by the total number of properties in the same city/local market. CityHHI and LocalHHI are used to represent city- and local-level market concentration degrees, respectively.

We also control for host and listing features and location attributes, which have been identified to have significant impacts on Airbnb performance (Deboosere, Kerrigan, Wachsmuth, & El-Geneidy, 2019; Kwok & Xie, 2019; Leoni, 2020). Host characteristics include superhost, host listing count, response time, and response rate. In terms of property characteristics, we consider instant bookability, maximum guests, minimum stay, listing age, cancellation, reviews per month, and number of photos. To identify the effects caused by differentiation strategy instead of regional features, we control for kilometre distance to the nearest airport, city centre, transit stop, and beach. They are measured by Euclidean distances from the specific locations, whose geographic information is available on the Texas Department of Transportation website (Chica-Olmo, González-Morales, & Zafra-Gómez, 2020). Detailed information on the variable description is displayed in Table 4-1. Table 4-2 displays descriptive statistics for the observations used in the following regression analysis.

Table 4-1. Variable description

Category	Variable	Description
Dependent Variables	RevPAR	Revenue per available room (USD)
Independent variables	LocalDiff	The degree to tract-level aesthetic design differentiation
	CityDiff	The degree of city-level aesthetic design differentiation
Moderators	LocalComp	Number of Airbnb listings in the same census tract
	CityComp	Number of Airbnb listings in the same city
	LocalHHI	Census tract market concentration degree
	CityHHI	City market concentration degree
Control variables	Superhost	Whether a host has a Superhost badge (superhost = 1, otherwise 0)
	Host listing count	Number of listings managed by the same host
	Response rate	The rate of new inquiries and reservation requests a host responded to
	Response time	Speed of response to guests' inquiries (within an hour, within a few hours, within a day, a few days or more)
	Instant bookablility	Whether the listings can be booked instantly (Instant bookable =1, otherwise 0)
	Maximum guests	The maximum number of guests a listing can accommodate
	Minimum stay	Minimum night stay required by the host (number of days)
	Listing age	Days since the listing was created
	Cancelation	Cancellation policy for the listing (flexible, moderate, strict, firm strict, super strict)
	Reviews per month	Number of guest reviews per month received by a listing
	Number of photos	Number of photos displayed on a listing homepage
	Transit hub	Distance from the listing to the nearest transit hub (km)
	City center	Distance from the listing to the nearest city center (km)
	Airport	Distance from the listing to the nearest airport (km)
	Beach	Distance from the listing to the nearest beach (km)

Table 4-2. Summary statistics

	Mean	Std. Dev.	Min	Max
RevPAR	696.72	1193.76	0	33283.33
LocalDiff	0.20	0.11	0	0.48
CityDiff	0.25	0.08	0	0.47
LocalComp	190.13	328.26	2	2856
CityComp	6698.11	6135.69	4	16610
LocalHHI	0.22	0.26	0.005	1
CityHHI	0.05	0.08	0.003	1
Superhost	0.16	0.37	0	1
Host listing count	496.87	1105.54	1	4155
Host response rate	0.95	0.18	0	1
Host response time – within an hour	0.82	0.39	0	1
Host response time – within a few hours	0.09	0.29	0	1
Host response time – within a day	0.06	0.23	0	1
Host response time – a few days or more	0.03	0.18	0	1
Instant bookability	0.64	0.48	0	1
Maximum guests	5.67	3.13	1	16
Minimum stay	11.81	26.75	1	1124
Listing age	649.17	630.07	1	4990
Cancelation – super strict	0.04	0.20	0	1
Cancelation – firm strict	0.04	0.19	0	1
Cancelation – strict	0.47	0.50	0	1
Cancelation – moderate	0.23	0.42	0	1
Cancelation – flexible	0.22	0.41	0	1
Reviews per month	1.18	1.87	0	204
Number of photos	22.67	15.21	0	507
Transit hub	29.91	52.65	0	338.63
City center	5.51	3.84	0.02	46.96
Airport	23.34	19.63	0.68	195.03
Beach	226.33	217.87	0.01	1128.95

4.4.3 Model specification

With the panel data, we apply the time-fixed effect model, which allows us to control the unobserved individual-specific factors that are constant over time. In the hospitality context, the time-fixed effects are often included for seasonality considerations (S. Liu, Wang, Gao, & Gallivan, 2021; Lopez Mateos, Cohen, & Pyron, 2022).

A series of models are estimated, starting with a baseline model of control variables. We then gradually include aesthetic design differentiation variables and their interaction with moderators. Accordingly, the following time-fixed effects regression tests are conducted, where μ denotes time-fixed effects and ε represents the error term.

Model 1 (Baseline):

$$\text{RevPAR} = \beta_{11}\text{Controls} + \mu + \varepsilon \tag{3}$$

Model 2 (Local-level Differentiation Effect):

$$\text{RevPAR} = \beta_{21}\text{LocalDiff} + \beta_{22}\text{Controls} + \mu + \varepsilon \tag{4}$$

Models 3&4 (Local-level Competition Intensity Moderation Effects):

$$\text{RevPAR} = \beta_{31}\text{LocalDiff} + \beta_{32}\text{LocalDiff} * \text{LocalComp} + \beta_{33}\text{Controls} + \mu + \varepsilon \tag{5}$$

$$\text{RevPAR} = \beta_{41}\text{LocalDiff} + \beta_{42}\text{LocalDiff} * \text{LocalHHI} + \beta_{43}\text{Controls} + \mu + \varepsilon \tag{6}$$

Model 5 (City-level Differentiation Effect):

$$\text{RevPAR} = \beta_{51}\text{CityDiff} + \beta_{52}\text{Controls} + \mu + \varepsilon \tag{7}$$

Models 6&7 (City-level Differentiation Effect):

$$\text{RevPAR} = \beta_{61}\text{CityDiff} + \beta_{62}\text{CityDiff} * \text{CityComp} + \beta_{63}\text{Controls} + \mu + \varepsilon \qquad (8)$$

$$\text{RevPAR} = \beta_{71}\text{CityDiff} + \beta_{72}\text{CityDiff} * \text{CityComp} + \beta_{73}\text{Controls} + \mu + \varepsilon \qquad (9)4..$$

4.5. Results and Discussion

This study aims to test the effects of two key variables, namely local- and city-level aesthetic design differentiation, on short-rental property performance. An assumption for the effects of city-level differentiation is that each city has a distinct aesthetic identity that can be perceived by the guests. The perceptions then further affect guests' expectations for and evaluations of a single listing during the purchase stage. If every city in Texas were identical in Airbnb's interior design style, the comparison to city norms would be meaningless. To offer a straightforward overview of Texas city aesthetic design norms, we display the design tendency of 10 cities with the most Airbnb listings (Figure 4-3). Large cities such as Austin, Dallas, and Houston tend to offer Airbnb properties with modern design styles. However, properties located in destinations known for their natural landscape, for example, Galveston and South Padre Island, tend to include more nature-oriented elements in aesthetic design. Given the distinct aesthetic design patterns for cities with different destination images, whether a listing meets the city norm will affect guests' choices and further influence listing performance. Similar to cities, we also observe heterogeneity in aesthetic design tendency among tracts.

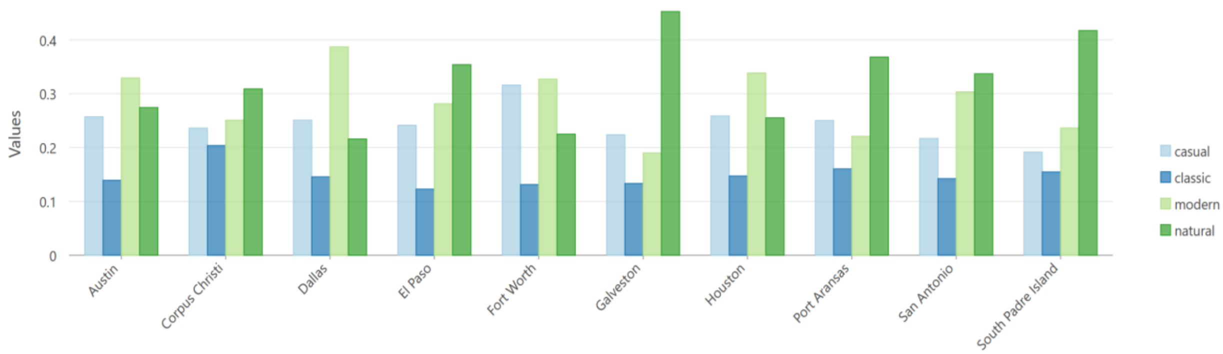


Figure 4-3. Short-term rental aesthetic design tendency of top 10 Texas cities

The next step is to test hypotheses with panel regression analysis. Following previous studies, a log transformation is applied to RevPAR to avoid regression assumption violation caused by skewness (Dogru, Mody, Line, et al., 2020). To avoid multicollinearity in estimating interaction effects, we standardize all continuous variables for further regression analysis (H. Zhang et al., 2023). The interpretation of coefficients for these variables will be that, when a predicting factor varies by one standard deviation, the RevPAR changes by corresponding percentages. Regression results are displayed in Table 4-3. Model 1 constitutes the baseline model, where we find the anticipated results for most control variables. The R2 values for all models exceed 0.331, reflecting a good model fit.

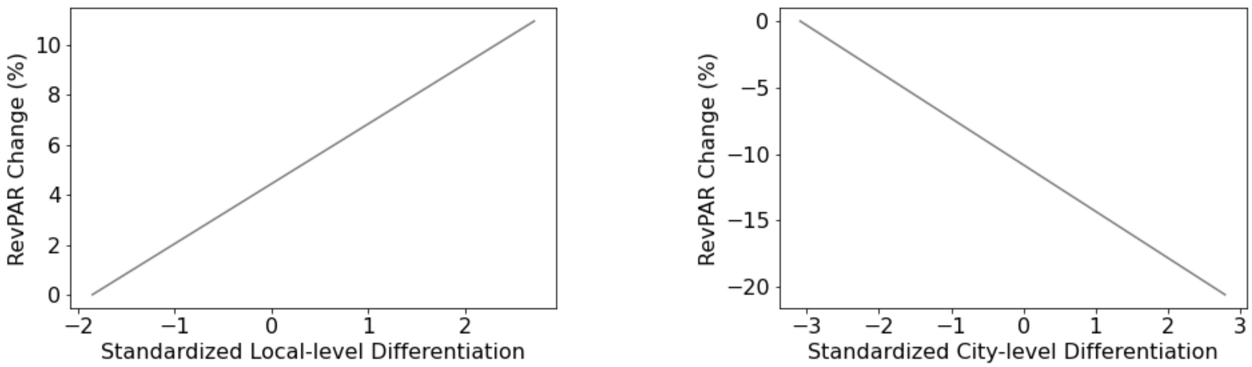
Table 4-3. Estimation results

	DV: RevPAR						
	Baseline	**Local-level differentiation**			**City-level differentiation**		
	Model 1	**Model 2**	**Model 3**	**Model 4**	**Model 5**	**Model 6**	**Model 7**
Main Effects							
LocalDiff		0.024***	0.025***	0.028***			
CityDiff					-0.035***	-0.035***	-0.034***
Moderation Effects							
LocalDiff*LocalComp			0.009*				
CityDiff*CityComp						0.019***	
LocalDiff*LocalHHI				-0.049***			
CityDiff*CityHHI							-0.018***
LocalComp	0.097***	0.095***	0.091***	0.094***	0.098***	0.099***	0.099***
CityComp	-0.203***	-0.205***	-0.205***	-0.204***	-0.200***	-0.201***	-0.200***
LocalHHI	-0.162***	-0.154***	-0.155***	-0.184***	-0.161***	-0.161***	-0.161***
CityHHI	-0.112***	-0.114***	-0.113***	-0.107***	-0.113***	-0.114***	-0.116***
Superhost	0.145***	0.146***	0.146***	0.151***	0.148***	0.148***	0.149***
Host listing count	-0.669***	-0.665***	-0.665***	-0.673***	-0.672***	-0.673***	-0.674***
Host response rate	0.146***	0.146***	0.146***	0.146***	0.145***	0.145***	0.145***
Host response time							
- within an hour	0.919***	0.919***	0.919***	0.917***	0.918***	0.919***	0.918***
- within a few hours	0.385***	0.384***	0.384***	0.380***	0.384***	0.386***	0.384***
- within a day	-0.185***	-0.185***	-0.185***	-0.188***	-0.185***	-0.184***	-0.186***
Instant booking	-0.083***	-0.083***	-0.082***	-0.080***	-0.085***	-0.085***	-0.085***
Maximum guests	0.203***	0.203***	0.203***	0.203***	0.203***	0.203***	0.203***
Minimum stay	-0.287***	-0.287***	-0.287***	-0.286***	-0.288***	-0.287***	-0.287***
Listing age	-0.261***	-0.261***	-0.261***	-0.264***	-0.260***	-0.261***	-0.260***
Cancelation							
- flexible	-1.274***	-1.274***	-1.274***	-1.272***	-1.274***	-1.274***	-1.274***
- moderate	-1.028***	-1.028***	-1.027***	-1.026***	-1.029***	-1.028***	-1.028***
- strict	-0.982***	-0.981***	-0.981***	-0.980***	-0.984***	-0.984***	-0.983***
- super strict	-0.331***	-0.330***	-0.330***	-0.331***	-0.334***	-0.335***	-0.334***
Reviews per month	1.117***	1.117***	1.117***	1.115***	1.117***	1.117***	1.116***
Number of photos	0.296***	0.296***	0.296***	0.296***	0.296***	0.296***	0.296***
Transit stop	0.041***	0.041***	0.041***	0.043***	0.042***	0.042***	0.042***
City center	-0.008*	-0.008*	-0.007*	-0.009**	-0.007*	-0.007*	-0.007*
Airport	0.187***	0.187***	0.187***	0.188***	0.185***	0.184***	0.185***
Beach	-0.105***	-0.105***	-0.105***	-0.101***	-0.105***	-0.104***	-0.105***
R^2	0.331	0.331	0.331	0.332	0.332	0.332	0.332
F test	707.74***	706.66***	706.64***	709***	707.87***	707.93***	709.39***
Hausman test	28,522***	28,538***	28,555***	28,486***	28,525***	28,538***	28,656***
LM Test	2,330,865 ***	2,323,540 ***	2,323,389 ***	2,332,175 ***	2,331,716 ***	2,332,175 ***	2,339,856 ***

Note: * p < 0.05, ** p < 0.01, *** p< 0.001. F test is included to test time effects; Hausman test is used to compare fixed effects model with random effects model; LM Test is applied to validate the necessity of time-fixed effects.

To test the effects of local-level aesthetic differentiation, we add LocalDiff to model 2 and obtain a positive and significant coefficient ($b = 0.024$, $p < 0.001$), supporting H1a. A listing with local-level aesthetically differentiated designs is predicted to generate higher revenues. An increase of one standard deviation in local differentiation degree will result in a 2.4% growth of RevPAR. Figure 4-4a visualizes the impacts of local-level aesthetic design differentiation on listing performance. The performance of a listing with the highest local-level aesthetic differentiation degree is over 10% higher than that with the lowest degree. Differentiation benefits identified at the local level align with previous studies (e.g., Baum & Mezias, 1992), which suggests that competition avoidance externalities overwhelm legitimacy penalties. This finding verifies the dominance of localized competition over legitimacy in shaping the impacts of differentiating from neighboring competitors.

On the contrary, we observe a negative impact of city-level aesthetic differentiation, providing empirical support for H1b. Model 5 shows a significant coefficient of CityDiff ($b = -0.035$, $p < 0.001$). This result suggests that RevPAR is predicted to decrease by 3.5% when the city-level aesthetic differentiation degree increases by one standard deviation. The hypothesized differentiation discount is verified. In Figure 4-4b, we can see that the performance of a listing with the highest local-level aesthetic differentiation degree is around 20% lower than that with the lowest degree. These negative impacts of differentiation, consistent with previous studies, suggest that, at the city level, legitimacy devaluation overtakes competition avoidance externalities (e.g., Blal & Graf, 2013). The benefits of conforming to city norms also validate that city-level aesthetic identity can be a source of legitimacy for individual service providers, including short-term rental listings. A more powerful influence of city-level conformity than local-level conformity might be because destination image is mainly promoted in cities. At the same time, it's rare to see tract-level destination promotion organizations.

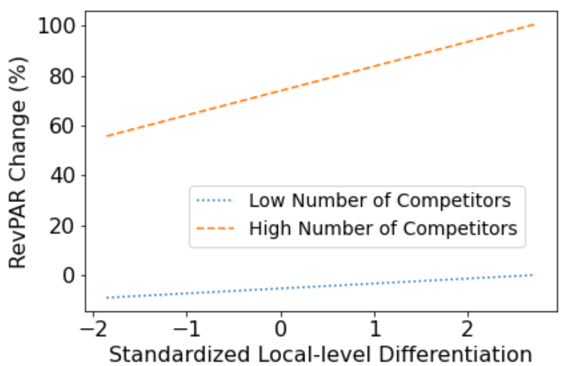


(a) (b)

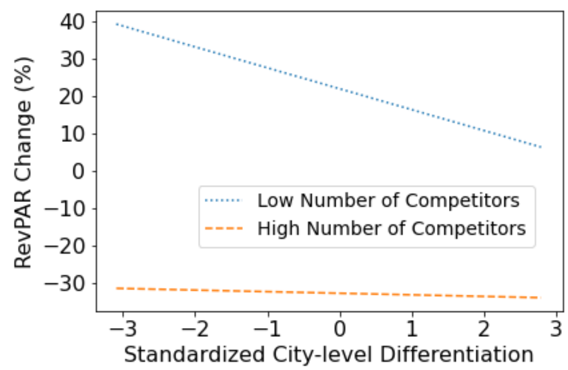
Figure 4-4. Impacts of aesthetic design differentiation

In models 3 and 6, we find that for both local- and city-level differentiation effects, the number of competitors has a positive and significant impact. These results support H2a and H2b. Model 4 predicts that the positive impact of local-level differentiation is strengthened by the number of local-level competitors (b = 0.009, p = 0.032). As is shown in Figure 4-5a, the positive effect is stronger under a high number of competitors. For a listing located in the market with the lowest number of competitors, the performance increase caused by differentiation is around 5%, but this number reaches over 40% under the condition of the highest number of competitors.

Model 6 shows that the interaction term between city-level differentiation and the number of competitors has a positive and significant coefficient (b = 0.019, p < 0.001). Thus, an increase in the number of competitors reduces the negative effects of city-level differentiation. Figure 4-5b depicts this moderation effect, where listings with the fewest competitors witness a drop of RevPAR at 30% resulting from differentiation, while listings with the most competitors only have a slight decrease.



(a)



(b)

Figure 4-5. Moderation by the number of competitors

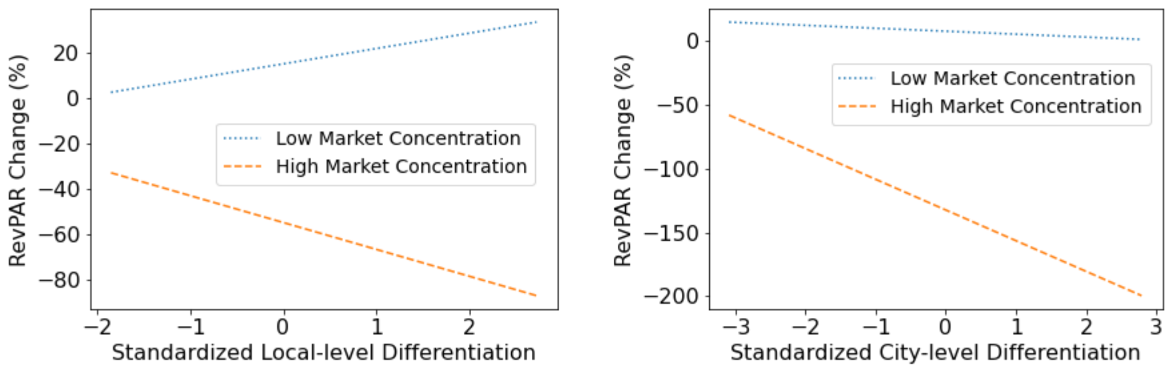
Strengthened differentiation benefits and mitigated differentiation discounts revealed in models 3 and 6 first imply that the gains stemming from avoiding intense competition increase with the number of competitors. This confirms that the effectiveness of the competitor density in moderating the effects of differentiation drawn from the hotel context is also applicable to short-term rental businesses (e.g., Sánchez-Pérez et al., 2020). Second, the results show that listings are more likely to benefit from conformity with fewer competitors. A possible explanation is that it is important for listings located in sparse destinations to shape a collective identity that can serve as a clear signal to attract target customers (Bianco, 2023; Dobrev, Ozdemir, & Teo, 2006).

At the local level, we also observe that the performance of listings located in dense tracts is generally higher than that in sparse tracts. A possible reason is that there might be tourist attractions associated with massive lodging demands, which attract a great amount of Airbnb businesses (Gutiérrez, García-Palomares, Romanillos, & Salas-Olmedo, 2017). An alternative explanation is that there are agglomeration externalities created by tract neighbors in urban areas in the short-term rental context (K. L. Xie et al., 2020). If so, this counters the findings of Chung and Kalnins (2001) based on a zip-code setting in the Texas hotel market before the internet was widely adopted, which concludes no agglomeration externalities were detected in urban areas. At the city level, this study yields opposite empirical findings. Listings from cities with a lower number of rivals tend to generate more profits, implying trivial agglomeration externalities. It might be because agglomeration advantages decay rapidly with distances, and agglomerative forces typically operate well at a geographic scale smaller than a city (Picone, Ridley, & Zandbergen, 2009; Van Soest, Gerking, & Van Oort, 2006).

Model 4 and Model 7 provide evidence for H3a and H3b. The interaction between LocalDiff and LocalHHI is negative and significant ($b = -0.049$, $p < 0.001$), supporting H3a. When a listing competes in a more concentrated market, the benefits it gains from differentiation are lower and even turn negative. Figure 4-6a reflects this flipped effect. For listings operated under the highest market concentration degree, RevPAR decreases with differentiation by at most 50%. Conversely, there is a growth in listing performance when the differentiation degree increases in a less concentrated market (over 20%).

We also observe a negative coefficient of the interaction between CityDiff and CityHHI ($b=-0.018$, $p < 0.001$). It suggests that market concentration intensifies city-level differentiation discounts and thus supports H3b. Figure 4-6b depicts this moderation effect. For a listing with low market concentration, the impact of differentiation on its performance decreases only slightly.

However, when it is in a highly concentrated market, there is a sharp drop in performance by nearly 150% from the lowest differentiation level to the highest one.



(a) (b)

Figure 4-6. Moderation by market concentration

Regardless of geographical scope, market concentration weakens differentiation benefits and amplifies differentiation discounts, which aligns with previous hotel studies (Graf, 2011). This finding implies that the short-term rental hosts cooperate to avoid direct competition, thus relying less on design differentiation. In a highly concentrated market, we also find that conformity is more profitable. Thus, if several big players dominate a market, an aesthetic design consistency among listings of the same host enhances operation efficiency (H. Zhang et al., 2023). Last, by comparing high versus low market concentration, we draw the opposite conclusion to the hotel industry: the overall short-term rental listing performance excels in a less concentrated market (Pan, 2005). The professionalism gap between short-term rental hosts and hotel management teams, which decides strategy effectiveness in leveraging market conditions, may explain this.

We carry on a series of robustness checks to validate the validity of empirical test results. We first compare the fixed effects model with pooling models, and the F test results confirm the necessity of applying fixed effects model. Then, the results of the Hausman test suggest that fixed effects model is more suitable than random effects model in this study. Third, Lagrange Multiplier tests are applied to validate the necessity of including time-fixed effects.

4.6. Implications and Limitations

Through the lens of aesthetic design, this study empirically compares the differentiation-performance relationship between two geographical competition scopes, i.e., local census tract versus city. It shows the impacts of these two geographical scopes on the effectiveness of differentiation strategy are asymmetric. Local-level aesthetic differentiation generates benefits, while city-level differentiation leads to performance discounts, decided by the alternate dominating role between competition and legitimacy within the geographic scope. The results also suggest that under high competition intensity caused by either the number of competitors or market concentration, listings can benefit more from differentiation.

This study provides several theoretical contributions. First, it contributes to the strategic management literature in hospitality and tourism by introducing multi-level thinking to the strategy of differentiation and conformity. The differences between local- and city-level reveal how localized competition influences the impacts of differentiation. The local-level differentiation gains verify the importance of spatial dependence for lodging products. The benefits of city-level conformity contribute to the destination literature by identifying the overwhelming dominance of communicating a destination aesthetic identity over rivalry, while localized competition fades with distance. We recommend subsequent studies to explore the sweet spot where the accommodation products can both benefit from city-level conformity and local competition avoidance at the same time.

Second, the findings demonstrate nuances of how differentiation-performance relationships vary with competition contingencies. The results suggest that competition intensity enhances benefits at the local level but mitigates discounts at the city level in influencing the strategic outcomes of differentiation. The opposite directions of moderation effects also emphasize the importance of competitive conditions when pursuing lodging strategies because the same strategy shows divergent patterns under different contingencies.

Third, the empirical evidence of differentiation effects adds knowledge to the hospitality literature by verifying the effectiveness of aesthetic design as a differentiating tool. The findings complement previous qualitative studies by empirically verifying the effects of aesthetic designs as differentiation tools in the hospitality industry. It may inspire future studies to explore the effects of aesthetic differentiation in more diverse visual aspects beyond interior design styles, such as color and layout.

The methodological contribution lies in quantifying lodging property aesthetics with a deep learning algorithm that offers more objectivity and interpretability than past methods, which primarily relied on qualitative assessments. As such, our approach complements extant literature based on customer perceptions to overcome bias caused by subjectivity. The design style scores can be applied to broader topics beyond differentiation, such as destination lodging image analysis, customer cognitive and affective response evaluation, and hotel aesthetic design positioning.

Several tourism stakeholders can benefit from the findings of this study. For short-term rental hosts, it is beneficial to differentiate their listings from nearby competitors by providing properties with different interior design styles. The findings of this study also suggest that hosts should not only focus on nearby competitors but also take citywide properties as references and try to align with the general design style of the city. It is also recommended to start new listings in a dense tract, a city with few listings, or a less concentrated market. Hosts are more likely to benefit from aesthetic differentiation when operating existing listings in dense regions. Following the market norm is a more profitable strategy in highly concentrated markets. Furthermore, for destination management organizations, promoting destination aesthetic images and identities and encouraging hosts to leverage related elements is an effective way to boost local short-term rental business prosperity because it can create legitimacy externalities and may help strengthen destination identity.

This study has several limitations. First, it only tests the effects of aesthetic design differentiation in Texas urban markets. We believe that the insights obtained are applicable to a wider context due to the extensive diversity across the sampled cities and tracts, thereby allowing us to capture performance variance due to differentiation. Nevertheless, the unique features of Texas markets may introduce certain biases, and we encourage further research in various geographical contexts to build upon our findings.

Second, the sample is collected during the COVID period, between April 2021 and March 2022. Although competition intensified by pandemic is a background condition in which we tested our hypotheses, how the pandemic moderates the effects of multi-level differentiation is not involved in the current study. Thus, extending the current study by testing the moderation effects of COVID on differentiation-performance relationship is recommended. We believe such studies will complement the current study in understating competitive dynamics and strategies in the hospitality context. Third, we used tract and city levels; however, other studies define competitive sets in different ways, for example, by zip code. Finally, this study only includes market competition conditions as moderators, while there are more conditional factors altering the relationship between aesthetic design differentiation and listing performance, such as host professionalism and guest demographic features.

Chapter 5. EXPLORING HOW GENERATIVE AI FITS THE TASK OF ONLINE REVIEW RESPONSE: THROUGH AN EMPIRICAL APPROACH

5.1 Introduction

Technological innovations, such as online booking systems and social media platforms, have significantly shifted the landscape of many industries including the hospitality and tourism sector (Xiang, 2018). The emergence and evolution of new technologies offer promising opportunities, yet they also pose challenges to firms. Thus, it is critical for firms to understand when and how to integrate technological innovations into their operations (F. Zach, 2016). This topic attracted great attention in 2023, due to the pivotal breakthrough of Generative AI models, like ChatGPT and DALL-E. These models demonstrate strong abilities to generate human-like content in multiple forms (e.g., text, visual, or audio).

As is posited by recent studies, Generative AI models have great potential to transform value creation in the hospitality and tourism industry (e.g., Dwivedi et al., 2023). This new technology is expected to be integrated into diverse business tasks, including content marketing, customer engagement, and travel planning (Demir & Demir, 2023; S. Shin, Kim, Lee, Yhee, & Koo, 2023). These prospects not only inspire academics to explore, but also attract industry practitioners to invest. For example, leading hospitality companies such as Expedia and Booking have pioneered in incorporating Generative AI into their services (Marr, 2023). Nevertheless, whether these firms can benefit from adopting this new technology remains unclear in both practice and academic research.

The adoption of technologies including AI techniques has been extensively studied in many domains, including the hospitality and tourism area (Pillai & Sivathanu, 2020; H. Shin, 2022). However, most previous studies focused on the factors which influence the decisions of individuals or organizations on technology adoption (Morosan & Dursun-Cengizci, 2023; Shi, Gong, & Gursoy, 2021). There is only a little research examining their outcomes (R. Cai, Wang, & Sun, 2024). Therefore, this study aims to identify the performance of Generative AI adoption in specific business tasks, specifically hotel online review engagement.

The task of online review engagement is selected for the following reasons. First, hotels' responses to online reviews are entirely text-based, which aligns well with the capabilities of Generative AI models shown by passing the Turing test (Russell & Norvig, 2010). The Turing test evaluates a machine's ability to produce text indistinguishable from that created by humans, highlighting models' promise of text-based interactions. Second, online review engagement necessitates technological advancements to assist hotel staff in processing this important yet labor-intensive task. Replying to online reviews effectively is crucial for hotel success because it enhances customer perceptions, improves subsequent interactions, and boost financial performance (Min, Lim, & Magnini, 2015). Despite the great benefits of managerial responses, only a small percentage of reviews are replied because of various reasons, particularly labor shortages (Kwok, 2022).

It is challenging to answer if online review engagement can benefit from the adoption of Generative AI models due to the complexity of online reviews and the adaptability of this technology. According to the theory of task-technology fit (Goodhue & Thompson, 1995), the effectiveness of technology implementation depends on the alignment between technological features and the demands of specific tasks. To gain deeper insights into Generative AI adoption, this study includes task conditions characterized by review valence and technological conditions influenced by model temperature setting. We distinguish between negative and positive reviews because they prioritize different response strategies (Wei, Miao, & Huang, 2013). The temperature parameter of Generative AI is included because it significantly affects the style of output texts (Lucy & Bamman, 2021), which will influence how well the generated responses meet the varying task demands. This research investigates three distinct temperature settings (0,1, and 2), wherein high temperature leads to more variations in words and generated responses (Bhavya, Xiong, & Zhai, 2022). By introducing the interaction between review valence and temperature setting, this study seeks to examine the impacts of Generative AI adoption on customer perceptions under varying task and technology conditions.

During empirical analysis, a significant challenge is to operationalize Generative AI adoption, given the limited number of hotels that have implemented this emerging technology and the difficulty in obtaining detailed data from these firms. Therefore, this study proposes a novel approach to measure AI adoption by a simulated design, which leverages historical online reviews paired with corresponding managerial responses. Specifically, we first utilize GPT 3.5 models to generate one response for each online review, then compare the existing managerial response with the AI-generated one. When one response produced by hotel staff shows similar patterns to the AI-suggested content, it is regarded as a case of simulated AI adoption. Conversely, responses that diverge from AI-suggested content are regarded as the absence of adoption. By taking the similarity between human-generated and AI-suggested responses as a proxy of AI adoption, we have the chance to further test its influences and how the influences vary with task and technological conditions. These effects were identified by negative binomial regression models based on 36090 online reviews covering 191 Houston hotels collected from TripAdvisor.com.

This study offers valuable contributions from both theoretical and practical perspectives. Theoretically, it enriches AI adoption literature by providing empirical evidence on the outcomes of adopting Generative AI, which complements prior research on antecedents. Second, this study adds knowledge to the theory of task-technology fit by retesting it in an emerging technological context. It offers insights into how task and technology align through content features and how the alignment influences the effectiveness of Generative AI. Methodologically, it introduces a novel approach to measure AI adoption, which allows the explorations of potential outcomes prior to real-world adoptions. From the practical perspective, this research offers actionable insights to hospitality practitioners, assisting them to evaluate and refine their AI-driven customer engagement strategies.

5.2 Literature Review

5.2.1 Artificial Intelligence Adoption for Business

Artificial Intelligence (AI) is defined as a system or machine that thinks humanly, acts humanly, thinks rationally or acts rationally (Russell & Norvig, 2010; Tussyadiah, 2020). The capabilities of AI systems include natural language processing, knowledge representation, automatic reasoning, machine learning, and robotics (Russell & Norvig, 2010). These capabilities allow them to act humanly, such as to read, to communicate, to remember, to conclude, to learn and adapt, and to manifest. The ability to act like humans opens the door for AI to seamlessly integrate into a wide range of business tasks, from handling routine tasks to informing decision-making processes.

AI adoption has been a pervasive topic in various business domains, including finance, marketing, and management (Babina, Fedyk, He, & Hodson, 2024; Davenport, Guha, Grewal, & Bressgott, 2020; Raisch & Krakowski, 2021). Due to AI systems' capability to assist and even replace humans in various operations, this topic is particularly important in the hospitality and tourism sector that has been persistently impacted by labor shortages (Kwok, 2022). The integration of AI-driven solutions, such as recommender systems, chatbots, and smart robots, has largely transformed the industry landscape (Pillai & Sivathanu, 2020; H. Shin, 2022; Xiang, Kim, Hu, & Fesenmaier, 2007). Therefore, there is an extensive body of literature exploring existing and potential adoption of diverse AI techniques (Law, Lin, Ye, & Fong, 2023).

Previous studies concerning AI adoption in the hospitality and tourism context, focused on two major topics: conceptual discussion and determinant investigation. Conceptual studies predominantly discuss the theoretical benefits and risks of AI. They offer insights into AI systems' potential to reshape customer experiences and organizational operations, alongside the considerations of ethical dilemmas and labor impacts (Kong, Wang, Qiu, Cheung, & Bu, 2023; Mariani, Baggio, Fuchs, & Höepken, 2018; Tussyadiah, 2020). Meanwhile, extant empirical studies mainly examine the factors influencing individuals' or organizations' decisions on whether to accept AI applications (Lu, Cai, & Gursoy, 2019; Morosan & Dursun-Cengizci, 2023; Shi et al., 2021). However, little is known about the outcomes of AI adoption, specifically if implementing AI technologies can translate into improved operational efficiency, enhanced customer perceptions, and overall competitive advantage for firms (Krakowski, Luger, & Raisch, 2023). The need for understanding AI systems' practical outcomes is further highlighted by the breakout of Generative AI due to its transformative potential to revolutionize value creation in the business domain.

Generative AI refers to a type of technology that can be used to create new content, including text, image, video, etc. A typical example is ChatGPT, a natural language generation model powered by generative pre-trained transformers (GPT) (Radford, Narasimhan, Salimans, & Sutskever, 2018; Van Dis, Bollen, Zuidema, van Rooij, & Bockting, 2023). This model is well-known for its exceptional capability of understanding human language, as well as generating relevant and realistic textual content instantly according to input text (Reisenbichler, Reutterer, Schweidel, & Dan, 2022). These abilities are deeply rooted in its sophisticated algorithms. First, ChatGPT is trained with a special natural language processing (NLP) task – next word prediction (Radford et al., 2018). Through this mechanism, the output content is formed by predicting the next word with high probabilities given the input sequence. Therefore, the output texts present a high degree of relevance to the original queries, surpassing traditional chatbots that rely on limited pre-defined question-answer pairs (Bansal, Chamola, Hussain, Guizani, & Niyato, 2024).

Second, similar to other large language models (LLM), ChatGPT is trained on massive data sets, composed of books, Wikipedia passages and other internet texts, with billions of adjustable parameters (Brown et al., 2020). The vast number of parameters allow it to understand complex language structure and styles, and consequently synthesize knowledge from multiple domains, such as marketing, finance, psychology, art, public policy, and current events (J. Yang et al., 2023). Consequently, the content generated by ChatGPT is more human-like, reflecting an accurate comprehension of the input text and an organic integration of related background knowledge (de Winter, 2023).

The ability to generate relevant and realistic content demonstrates ChatGPT's potential to enhance and even automate tasks that require human knowledge and creativity (Reisenbichler et al., 2022). It opens possibilities for scaling innovation and customization, thus shifting the value creation process (Dogru et al., 2023). This new technology has attracted great attention from business literature to explore the ways in which firms can benefit from its adoption, such as content marketing, service individualization, and customer relationship management (Demir & Demir, 2023; Reisenbichler et al., 2022; H. Shin & Kang, 2023). Therefore, understanding the practical outcomes of these applications is of great importance because it will directly influence firms' strategic decision-making, guide their allocation of resources, and ultimately decide their competitive positioning and success.

5.2.2 Online Review Response

In this digital era, consumers increasingly rely on online reviews in decision-making, especially when purchasing intangible products like hospitality and tourism services (Sparks, Perkins, & Buckley, 2013; Xiang & Gretzel, 2010). Managing online review has become an essential component of customer relationship management because reviews can significantly influence consumer perceptions and behaviors, and directly impact financial performance (Casalo, Flavian, Guinaliu, & Ekinci, 2015; Nicolau, Xiang, & Wang, 2024; Zhao, Wang, Guo, & Law, 2015). Beyond simply monitoring online reviews, many firms have been proactively engaging with customers through managerial responses with diverse strategies, facilitating two-way communications.

Response strategies involve two major decisions: whether and how to respond. In exploring the "whether" question, previous studies identified the importance of responding to online reviews regardless of their valence (e.g., W. Chen, Gu, Ye, & Zhu, 2019; K. L. Xie, Zhang,

Zhang, Singh, & Lee, 2016). There is ample empirical evidence showing the advantages of being responsive over not responding (Kumar, Qiu, & Kumar, 2018; C. H. Lee & Cranage, 2014; Lui, Bartosiak, Piccoli, & Sadhya, 2018). However, some other studies identified negative impacts of managerial responses which might be caused by ineffective response strategies (Y. Wang & Chaudhry, 2018; K. L. Xie, Zhang, & Zhang, 2014). It leads to more nuanced exploration on the "how to respond" question.

To answer the "how" question, extant literature has examined multiple factors, ranging from response source, timeliness, length, to specific content (Lopes, Dens, De Pelsmacker, & Malthouse, 2023; X. Xu & Zhao, 2022). In terms of the impact of these factors, prior studies draw divergent conclusions (e.g., C. Li, Cui, & Peng, 2017; K. Xie, Kwok, & Wang, 2017). This divergence has been further explained by the differences between positive and negative reviews, attributed to distinct customer expectations and managerial response orientations (K. L. Xie, So, & Wang, 2017; Xin Zhang, La, Huang, & Xie, 2024). When responding to reviews with heterogeneous polarities, firms are recommended with different drafting strategies. These strategies cover multiple aspects of response textual content, including inter-response variation, relevance to review texts, and linguistic characteristics (Lopes et al., 2023).

Considering inter-response variation, templated responses often fail to meet customers' expectations for personalized interaction, leading to less favorable outcomes (S. Liu et al., 2021; Z. Zhang, Li, Meng, & Li, 2019). On the contrary, customized responses can yield positive effects as they meet customers' information-seeking needs. Notably, the influence of templated responses exhibits a distinct variance between negative and positive reviews. When dealing with negative reviews, high repetitiveness in responses can intensify consumer dissatisfaction, signaling managerial evasiveness and resulting in increased negative feedback (H. Shin, Perdue, & Pandelaere, 2020; Wei et al., 2013; Xin Zhang et al., 2024). As suggested by H. Shin et al. (2020), the benefits associated with personalized responses are more pronounced for negative reviews than the positive ones. Furthermore, Wei et al. (2013) indicated that there is no significant difference between templated and personalized responses to positive reviews while it matters for negative reviews.

There are several optional approaches to tailor managerial responses, such as responding directly to the specific concerns or praises mentioned in online reviews. Responding by paraphrasing review texts can foster positive customer relations because these responses serves as verbal cues of active listening, reflecting firms' empathy and genuine care of customer voice (Palese, Piccoli, & Lui, 2021; B. Wang & Jia, 2023). Furthermore, Xiaowei Zhang, Qiao, Yang, and Zhang (2020) identified that the benefits of review-response relevance is stronger for negative reviews, where customers anticipate detailed apologies, explanations, and accommodative actions in response to service failures (Min et al., 2015). On the other hand, paraphrasing positive reviews creates less advantages or even leads to unwanted outcomes, as too specific responses to praises encounter the risk of overselling and may trigger customers' psychological reactance (Deng & Ravichandran, 2023; K. L. Xie et al., 2017).

Response strategies also vary within a single reply, regarding word selection. A response can be formed by diverse terms or more uniform terminology. High lexical diversity indicates a response covering more aspects, such as cordial greetings, appreciations, or specific service attributes. Conversely, using less redundant words shows a more focused orientation, targeting key points reflected in the review message. X. Xu and Zhao (2022) found that a low word diversity is beneficial for responses to negative reviews through a concentrated commitment to improve certain failures, but it is not significant for positive reviews.

Despite the importance of replying to online reviews, only a small proportion of them, especially the negative ones, have received responses (Lappas, Sabnis, & Valkanas, 2016). Moreover, the quality of responses remains inadequate. This deficiency may stem from several factors: a pervasive undervaluation of online review management among executives (Levy, Duan, & Boo, 2013), a lack of professional knowledge among responders (K. Xie et al., 2017), or the inherent difficulty in reading and understanding the excessive number of reviews. Given these constraints faced by hotel staff, the adoption of Generative AI provides a chance to draft responses without selection bias based on a comprehensive knowledge base and a strong capability of comprehending human languages (Reisenbichler et al., 2022). Therefore, the effectiveness of adoption Generative AI to online review management deserves further exploration.

5.2.3 Task-Technology Fit: Generative AI in Online Review Responses

When adopting technology to business operations, the effectiveness is contingent upon the degree to which the technology's features align with the requirements of the tasks. This principle, conceptualized as Task-Technology Fit (TTF) theory, posits that technology yields greater benefits when its functionalities directly support the tasks (Goodhue & Thompson, 1995). This theory has been extensively examined with various technologies and tasks in multiple fields, including the hospitality and tourism sector (Fuller & Dennis, 2009; H. H. Shin & Jeong, 2022). For example, H.-C. Lin et al. (2020) discussed how the match between the characteristics of technology (i.e., social media) and the features of task (i.e., marketing) leads to enhanced performance outcomes.

In the context of online review management, we argue that the outcomes of adopting Generative AI depend on if this new technology fits the requirements of replying to positive and negative customer feedback. Generative AI models, particularly large language models like ChatGPT, despite its pre-trained nature, provide opportunities for individuals or firms to customize some characteristics. For example, ChatGPT users can upload additional knowledge resources, connect with external Application Programming Interfaces (APIs), or simply adjust parameters like temperature, to meet their needs in diverse scenarios. Temperature here refers to a crucial hyperparameter in fine-tuning the output of large language models, that alters randomness of generated texts by manipulating the probabilities of the predicted words (Ziegler et al., 2019).

Adjusting temperature allows language generation models to balance between coherence and creativity. When a model selects the next word to form the generated text, a high temperature allows it to choose options with lower probabilities, which introduces more variation and stochasticity (Bhayana, 2024). Therefore, a high temperature tends to create more diverse and creative responses, while a low one leads to more deterministic and conservative outputs (Bhavya et al., 2022; Jablonka, Schwaller, Ortega-Guerrero, & Smit, 2024). Many previous studies have explored the optimal temperature given different tasks and settings. A lower temperature is preferred for knowledge comprehension and generation in domains such as chemistry and radiography (Mukherjee, Hou, Lanfredi, & Summers, 2023; White et al., 2023). High temperatures, however, yield better performance in tasks like analogy and story creation (Bhavya et al., 2022;

Lucy & Bamman, 2021). For tasks related to common sense or human intent which requires both logical reasoning and flexible resonating, a moderate level of temperature excels (J. Huang et al., 2022; Sahu et al., 2022; W. Xu, Zhang, Cai, & Lam, 2021). Moreover, there is insignificant influence of temperature identified when discerning evidence for social science hypotheses (Koneru, Wu, & Rajtmajer, 2023).

As a task fusing knowledge understanding and human interaction, online review management shows a challenge in selecting the optimal temperature, especially considering the heterogeneity across negative and positive reviews. Reviews with varying valence demonstrate distinct demands for the drafted response content covering three major features: variation across responses, relevance to original input, and diversity in selected words. The heterogeneous demands concluded from prior literature are summarized in Table 5-1. Based on these varying demands, the preferred temperatures change accordingly.

Table 5-1. Conceptual match between task feature and technological characteristic

Response feature	**Negative reviews**		**Positive reviews**	
	Task requirement	Preferred temperature	Task requirement	Preferred temperature
Variation across response	**High** (H. Shin et al., 2020; Wei et al., 2013)	High	**High** (H. Shin et al., 2020) or **insignificant** (Wei et al., 2013)	High
Review-response relevance	**High** (Min et al., 2015; Xiaowei Zhang et al., 2020)	Low	**Low** (Deng & Ravichandran, 2023; Xiaowei Zhang et al., 2020)	High
Lexical diversity	**Low** (X. Xu & Zhao, 2022)	Low	**Insignificant** (X. Xu & Zhao, 2022)	——

For negative reviews, considering response variability, high temperatures are more suitable because they lead to more diverse outputs (Mukherjee et al., 2023), which is needed in responding to complaints (Wei et al., 2013). However, low temperatures might be preferred because they tend to generate responses more relevant to the original reviews and tend to use more concentrated vocabulary, and the direct and specific replies are effective in addressing negative reviews (X. Xu & Zhao, 2022; Xiaowei Zhang et al., 2020). Considering there are potential benefits arising from both low and high temperatures, the optimal temperature for GPT adoption to negative reviews remains undetermined.

For positive reviews, high temperatures might be favored because they tend to generate responses less relevant to the inputs, which will help avoid the overselling risk (Ravichandran & Deng, 2023). In addition, high temperatures introduce more variations across drafted responses, which sometimes enhance customer perceptions for positive reviews (H. Shin et al., 2020). If these potential benefits of high temperatures can be transited into enhanced customer perceptions through GPT adoption deserve further exploration. Therefore, this study is designed to explore the impacts of Generative AI adoption on customer perceptions, specifically perceived helpfulness, under varying technology and task settings (Figure 5-1).

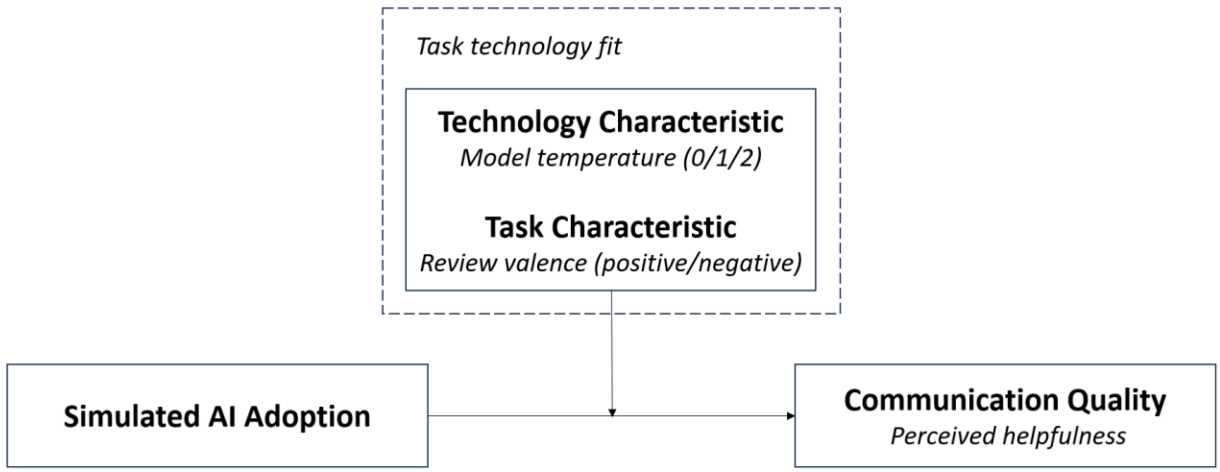


Figure 5-1. Conceptual Framework

5.3 Methodology

5.3.1 Data

This study employs online reviews and corresponding managerial responses collected in September 2023 from TripAdvisor.com, a social media platform widely used in previous studies (e.g., K. Xie et al., 2017). Our dataset comprises English reviews posted for hotels in Houston, Texas, covering detailed information on online review, managerial response, reviewer, and hotel. As this study focuses on simulated adoption of Generative AI measured based on managerial responses' similarity to AI generated content, only reviews that have received managerial responses are retained. After removing observations with missing values, 32129 observations are kept for further analysis. These observations are composed of 28397 positive reviews (with a rating of four or five) and 3742 negative reviews (with a rating of one or two). 168 unique hotels are covered, and the distribution of hotel star rating is shown in Figure 5-2.

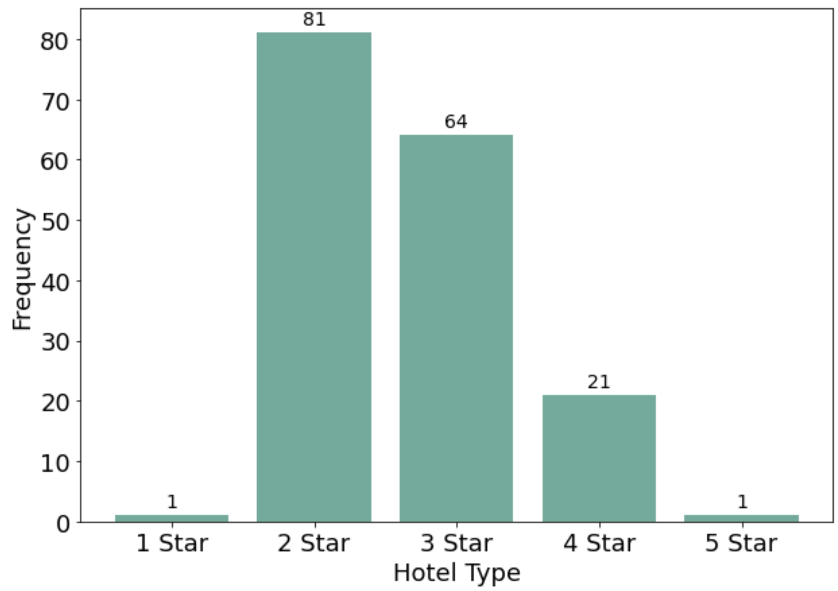


Figure 5-2. Distribution of hotel star rating

5.3.2 AI Response Generation

This study utilizes Python to access GPT-3.5 Turbo models through the chat completion component of the OpenAI API, generating AI responses to online reviews (Reisenbichler et al., 2022). To test the performance of AI adoption under varying technological settings, we conduct the generation process three times by setting the temperature parameter as 0 (lowest temperature value allowed for GPT), 1, and 2 (highest value allowed) respectively. The temperature of 1 is selected because it is the default value of GPT 3.5 model, which provides full access to users.

During each round of generation, every online review is processed individually, so that the GPT model can craft a tailored response to it. After the generation process, each online review is paired with one managerial response posted by hotel staff and one AI response generated by the GPT model. The prompt used for response generation is formed accordingly by concatenating online review title and content to a standard instruction as is shown in Figure 3. The reason why we expect the model to generate responses with around 65 words is because it is the average length of managerial responses in our dataset. Similar length distribution will make the responses from different sources, i.e., hotel staff and GPT, more comparable by avoiding distractions caused by significant differences in response length. Figure 5-3 displays the length distribution of AI-generated responses, in comparison with managerial responses from hotel staff.

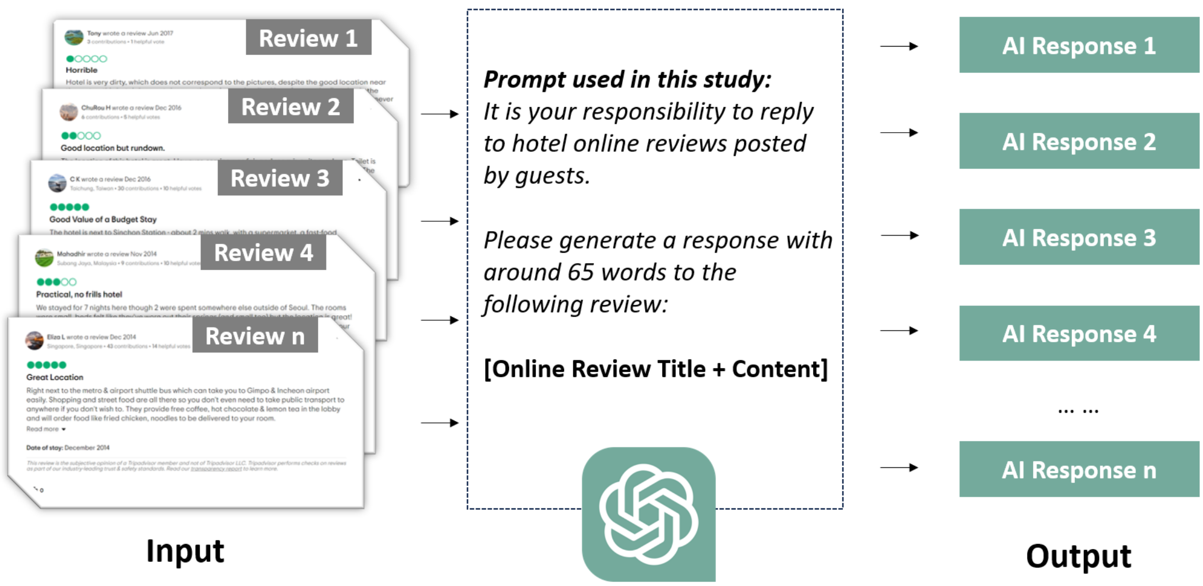


Figure 5-3. AI response generation process

5.3.3 Variables

To operationalize AI adoption, we design a novel approach wherein the similarity between managerial responses and AI-generated responses serves as an indicator of simulated AI adoption. More specifically, for each online review, if its managerial response shares similar patterns with the AI-suggested one, we treat this online review as a case of AI adoption. On the contrary, if the existing managerial response significantly diverges from the AI response, we interpret this as an instance of non-adoption.

The similarity between managerial responses and AI responses are measured through their embeddings (Carlson, 2023). Text embedding refers to a numerical representation of a textual message, which contains meaningful semantic information. Specifically, for each online review, its managerial response and AI response are converted into embeddings using Bidirectional Encoder Representations from Transformers (BERT) (Devlin, Chang, Lee, & Toutanova, 2018), a powerful method for computing document embeddings which has been widely used in business tasks (Carlson, 2023). The degree of simulated AI adoption is then quantified by the cosine similarity between the response embeddings (Figure 5-4).

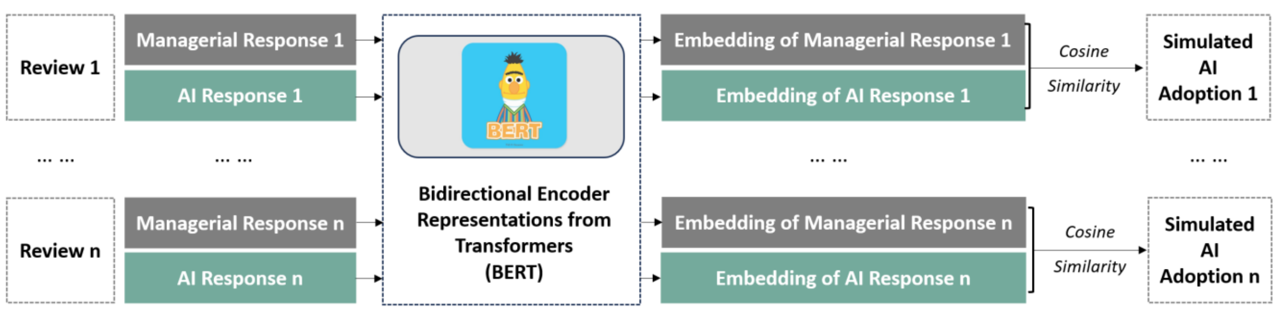


Figure 5-4. Operationalization of simulated AI adoption

Review ***helpfulness*** is used as the dependent variable for examining the performance of AI adoption for the following reasons. First, it reflects the attitudes of customers toward overall communication involving both the original review text and the managerial response. This measure is directly correlated with the effectiveness of review-response interactions (Kwok & Xie, 2016), thus can serve as a proxy for the response quality. It has been widely employed in previous studies for examining the influence of various features associated with online review responses (e.g., Xin Zhang et al., 2024). Second, this measure allows us to conduct this study at the review level, providing insights into how different types of reviews (i.e., positive vs negative) benefit asymmetrically from AI adoption.

This study also captures how task characteristics shift the effectiveness of AI adoption by taking ***review valence*** as a moderator. Review valence is measured by a binary variable which takes reviews with ratings of one or two as negative and those with ratings of four or five as positive. To ensure the validity and reliability of research findings, we also incorporate multiple control variables in the following regression analysis. These control variables include review features, such as title length, content length, readability, photo, recency, and timeliness. We further control reviewer characteristics (i.e., reviewer expertise), response features (i.e., length, readability, timeliness, and respondent level), and hotel attributes (i.e., overall rating, review volume, class, and ranking). These factors are identified as key determinants of review helpfulness (e.g., S. Shin, Du, Ma, Fan, & Xiang, 2021). Detailed descriptions and statistics of these variables are displayed in Tables 5-2 and 5-3. It is important to note that the degree of ***simulated AI adoption*** is measured separately for each temperature setting (Temp = 0, 1 or 2), as this variable varies with temperature. When the temperature setting is adjusted, the output responses vary accordingly. As a result, simulated AI adoption – quantified by the similarity between managerial response and the AI-suggested content – also changes. Meanwhile, all the other variables for each review remain constant.

Table 5-2. Variable summary

Variable name	**Variable description**
Helpfulness	Number of helpful votes received by an online review
Simulated AI adoption	Managerial response's similarity to AI generated content responding to the same online review
Review valence	A categorical variable indicating if an online review is positive or negative
Review title length	Number of words in the title of an online review
Review content length	Number of words in the content of an online review
Review readability	Gunning fog readability index of the content of an online review
Review photo	A binary variable indicating if an online review is posted with photos
Review recency	Number of months since an online review was posted
Review time lag	Number of months between the date when an online review was posted and the date of stay
Reviewer expertise	Number of reviews that have been posted by a reviewer
Response length	Number of words in a managerial response
Response readability	Gunning fog readability index of a managerial response
Response sentiment	Sentiment polarity of a managerial response
Response time lag	Number of months between the date when an online review was posted and the date when its managerial response was posted
Respondent level	A categorical variable indicating the level of respondent who generated a managerial response: Administrative, Executive, and Operational
Hotel review rating	Average rating of online reviews received by a hotel
Hotel review volume	Number of online reviews received by a hotel
Hotel class	Hotel scales: 5 - luxury hotel, 4 - above-average hotel, 3 - full-service hotel, 2 - mid-market economy hotel, 1 - budget traveler hotel
Hotel ranking	Ranking of a hotel among all hotels from the same city

Table 5-3. Variable statistics

Variable	Mean	Std. Dev.	Min	Max
Helpfulness	0.10	0.75	0	76
Simulated AI adoption (Temperature = 0)	0.88	0.05	0.61	0.98
Simulated AI adoption (Temperature = 1)	0.88	0.05	0.61	0.98
Simulated AI adoption (Temperature = 2)	0.79	0.09	0.10	0.98
Review valence – Negative	0.12	——	0	1
Review title length	4.15	2.74	0	30
Review content length	78.97	43.49	5	1258
Review readability	8.38	3.31	1.76	97.11
Review photo	0.03	0.17	0	1
Review recency	85.94	37.23	8	252
Review time lag	0.43	1.37	0	53
Reviewer expertise	80.33	579.94	0	70,083
Response length	60.76	31.75	1	412
Response readability	8.72	2.49	0.40	44.66
Response sentiment	0.35	0.19	-0.82	1
Response time lag	10.33	34.08	0	236
Respondent level – Administrative	0.75	——	0	1
Respondent level – Executive	0.02	——	0	1
Hotel review rating	4.28	0.44	1	5
Hotel review volume	1742.34	1291.74	1	4065
Hotel class	3.47	0.71	1	5
Hotel ranking	69.58	85.99	1	532

5.3.4 Regression Model Specification

As helpfulness is a count variable that exhibits overdispersion, following Xin Zhang et al. (2024), this study employs a negative binomial regression method. The regression models are estimated with the following equation, where β refers to estimated coefficient and ε_i denotes the error terms. The first equation identifies the main effect of simulated AI adoption, while the second one discloses the moderating effects of review valence.

$$Helpfulness_i = \beta_1 * AIadoption_i + \beta_2 * Controls_i + \varepsilon_i$$

$$Helpfulness_i = \beta_1 * AIadoption_i + \beta_2 * AIadoption_i * ReviewValence_i + \beta_3 * Controls_i + \varepsilon_i$$

To understand how technological characteristics shift the impact of simulated AI adoption, we estimate these regression models under each temperature setting (temperature = 0, 1, or 2) respectively.

5.4. Results and Discussion

As is argued in Section 2.3, the adjustment of temperature will lead to changes in the drafted responses concerning three aspects: variation across responses, relevance to input review, and lexical diversity within one response. We empirically examined the features of AI-generated content under varying temperature settings. A high temperature allows more randomness and flexibility in generated content, which can be described as a more creative mode. Contrarily, a low temperature can be regarded as a conservative mode because it gives priority to the words with higher probabilities, which are normally derived from logic. Followingly, we also compare the features of responses generated from different AI modes with those extracted from managerial responses posted by human.

First, following Z. Zhang et al. (2019), we measure variation across responses by comparing one response to others for the most recent five reviews from the same hotels. A high variation score indicates significant dissimilarity, suggesting the response likely deviates from a standard template. Figure 5-5 shows that the creative mode yields the highest variation across responses while the conservative mode generated the least varied content. This finding is explainable because high temperatures increase the randomness in generated texts, leading to a broader range of responses. This finding about how temperature setting influences response diversity is consistent with previous studies in natural science domains (Mukherjee et al., 2023). When comparing human responses to AI-generated content, the variation across managerial responses is higher than the conservative and default GPT models (Temp = 0 or 1), but lower than the creative mode (Temp =2). Notably, human responses display a significant difference between negative and positive reviews. According to previous studies concerning managerial responding strategies, negative reviews benefit from more particular responses while this customization is less important or significant for the positive ones (Wei et al., 2013). Humans' efforts in diversifying the responses to customer complaints may reflect that hotel staff learn from cumulated knowledge or experiences.

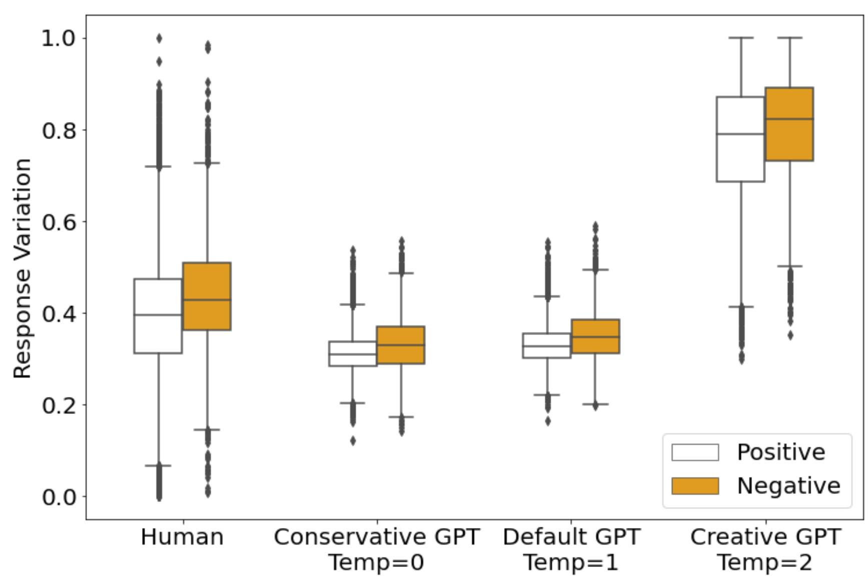


Figure 5-5. Degree of response variation from the same hotel across different sources

Second, the relevance of a response to its corresponding review is represented by the Jaccard similarity which compares their overlapped terms against the union of used terms (B. Wang & Jia, 2023). This measure indicates how closely the response content matches the key points mentioned in the review. As is displayed in Figure 5-6, responses generated by models with a high temperature show lower relevance to the review content. It is reasonable because higher temperature settings introduce more randomness and flexibility in the generated content, reducing responses' coherence to the input texts (Bhavya et al., 2022). Similar to variation across responses, human content displays a moderate level of relevance to the original review text. We also observe potential organizational learning behavior from Figure 6, because humans' replies to negative reviews show higher relevance, which is identified as a beneficial strategy to address customer complaints in previous studies (Deng & Ravichandran, 2023; K. L. Xie et al., 2017). However, GPT models fail to capture this pattern, with either equivalent or less relevant responses to the negative reviews.

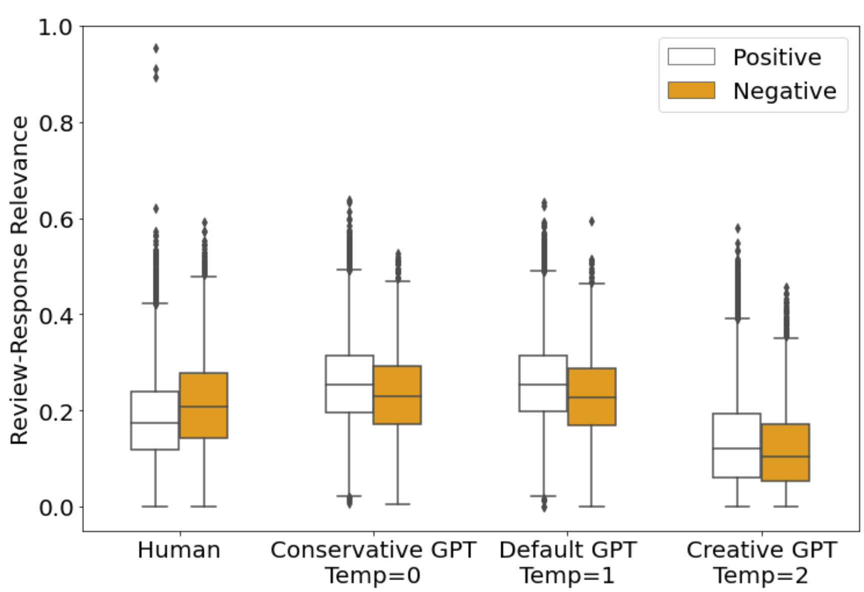


Figure 5-6. Degree of review-response relevance across different sources

Third, following X. Xu and Zhao (2022), we measure lexical diversity by the ratio of unique words to the total words in a response. Higher temperatures yield a notably diverse vocabulary in GPT-generated responses (Figure 5-7). It can be explained by the machine learning algorithm that temperature setting allows language models to select the predicted words with lower probabilities, thereby widening the range of vocabulary options (Jablonka et al., 2024). When examining the responses posted by hotel staff, they show a moderate level of lexical diversity in response to positive reviews. However, notably, their responses to negative reviews are composed of very concentrated vocabulary. It might be a sign of humans learning behavior because previous studies suggest that lower lexical diversity is beneficial for responding to negative reviews, as it indicates a focused approach to addressing specific issues raised in the customer complaints (X. Xu & Zhao, 2022).

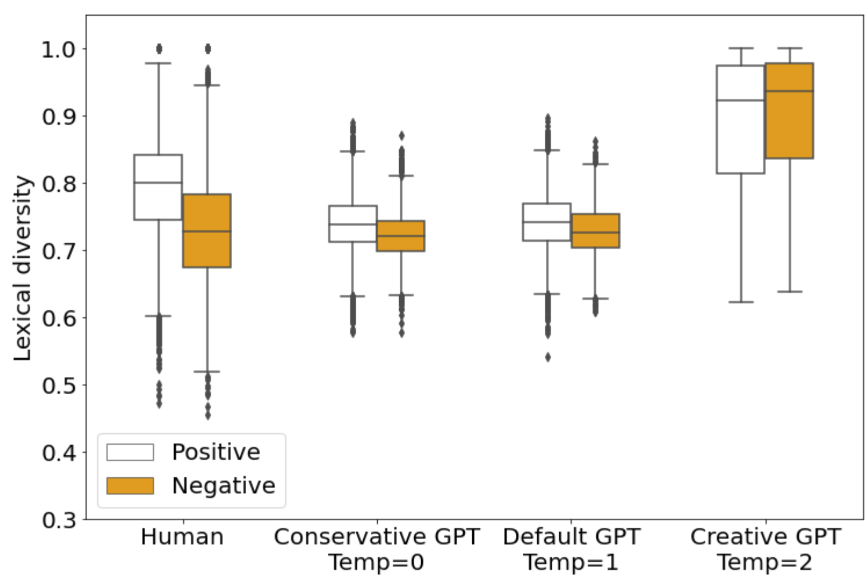


Figure 5-7. Degree of lexical diversity across different sources

To examine the effects of AI adoption with varying temperature settings, we estimated a group of regression models. They include a baseline model with only control variables and subsequent models that incorporate AI adoption and its interaction with review polarity. To mitigate the bias caused by the varying scales of variables, we standardized AI adoption and log transformed variables such as review title length and review content length. The results are displayed in Table 5-4. As is shown in Model 1, our study concludes results that are similar to previous studies, concerning the influence of several key factors like review valence, review content length, review photo, response timeliness, and respondent role (K. L. Xie et al., 2017; Xin Zhang et al., 2024).

Table 5-4. Regression Results

	DV: Helpfulness						
	Baseline	Conservative GPT Temp = 0		Default GPT Temp = 1		Creative GPT Temp = 2	
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
Simulated AI Adoption		-0.61***	-0.71***	-0.58***	-0.69***	0.18***	0.22**
Simulated AI Adoption* Negative			0.65***		0.70***		-0.19*
Review Valence – Negative	0.55***	0.72***	0.85***	0.69***	0.80***	0.61***	0.56***
Review title length (log)	0.01	0.02	0.03	0.02	0.02	0.01	0.01
Review content length (log)	0.16**	0.17**	0.17**	0.23***	0.23***	0.21***	0.22***
Review readability (log)	0.04	0.11	0.12	0.12	0.14	0.04	0.04
Review photo	0.89***	1.02***	1.04***	1.02***	1.03***	0.84***	0.83***
Review recency (log)	-1.64***	-1.42***	-1.39***	-1.43***	-1.40***	-1.63***	-1.63***
Review timeliness (log)	-0.13	-0.16*	-0.17*	-0.15*	-0.16*	-0.04*	-0.04
Reviewer expertise (log)	0.15***	0.16***	0.17***	0.15***	0.16***	0.15***	0.15***
Response length (log)	0.41***	0.20**	0.17*	0.19*	0.17*	0.41***	0.41***
Response readability (log)	-0.07	009	0.06	0.10	0.07	-0.08	-0.09
Response sentiment	-0.64***	-0.18	-0.05	-0.18	-0.07	-0.67***	-0.67***
Response timeliness (log)	-0.26***	-0.30***	-0.31***	-0.30***	-0.30***	-0.27***	-0.27***
Respondent level – Administrative	0.63***	0.34***	0.33***	0.36***	0.35***	0.61***	0.61***
Respondent level – Executive	0.60**	0.58**	0.56*	0.54*	0.52*	0.61**	0.60**
Hotel review rating (log)	0.98	-1.15*	-1.04*	-0.98*	-0.88	0.87	0.92
Hotel review volume (log)	0.33***	0.14***	0.11**	0.16***	0.13***	0.33***	0.33***
Hotel class	-0.00	0.05	0.09	0.05	0.08	-0.02	-0.01
Hotel ranking (log)	-0.02	-0.15***	-0.16***	-0.13***	-0.14***	-0.03	-0.03
Intercept	-2.72**	1.65	1.51	1.05	0.89	-2.70**	-2.82**
Pseudo R^2	0.1499	0.173	0.177	0.172	0.176	0.153	0.154

Observations	32,129	32,129	32,129	32,129	32,129	32,129	32,129

Note: * p<0.05, ** p<0.01, *** p<0.001

In general, a creative mode (Temp = 2) is more suitable for the task of responding to customer online reviews, reflected by a positive and significant coefficient of simulate AI adoption in model 6 ($b = 0.18$, $p < 0.001$). However, adopting GPT models with lower temperatures (Temp = 0 or 1) is likely to impair customer perceptions ($b = -0.61$, $p < 0.001$; $b = -0.58$, $p < 0.001$). It shows that overly predictable or formulaic replies, as produced by lower-temperature settings, might impair the perceived genuineness or authenticity of the communication. However, high temperatures lead to a high variation among responses, which signals companies' commitment to customer interactions (Wei et al., 2013). The flexibility and novelty emerging in the creative mode may facilitate more engaging communication, ultimately enhancing customer perceptions and attitudes.

The impact of AI adoption varies with task features, i.e., review valence. At lower temperatures (0 or 1), GPT models are more effective for addressing negative reviews, as shown in Figures 5-8 and 5-9. The benefits might arise from AI's inherent rationality (Yiting Chen, Liu, Shan, & Zhong, 2023). Unlike humans who might be affected by emotion and react improperly to negative reviews (Liang, Zhang, Li, Li, & Yu, 2021), AI remains unaffected by emotions, ensuring responses are constructive and focused on resolving issues. This capability helps effectively mitigate customer dissatisfaction and enhances the company's customer service reputation. However, GPT models with low temperatures are predicted to result in significant negative effects when applied to positive reviews ($b = -0.71$, $p < 0.001$; $b = -0.69$, $p < 0.001$). This finding is explainable because more conservative models tend to produce responses that are highly relevant to the original reviews, which could negatively impact customer perceptions. As is suggested by Deng and Ravichandran (2023), replying to positive reviews by paraphrasing can trigger the impression of overselling and provoke customer psychological reactance.

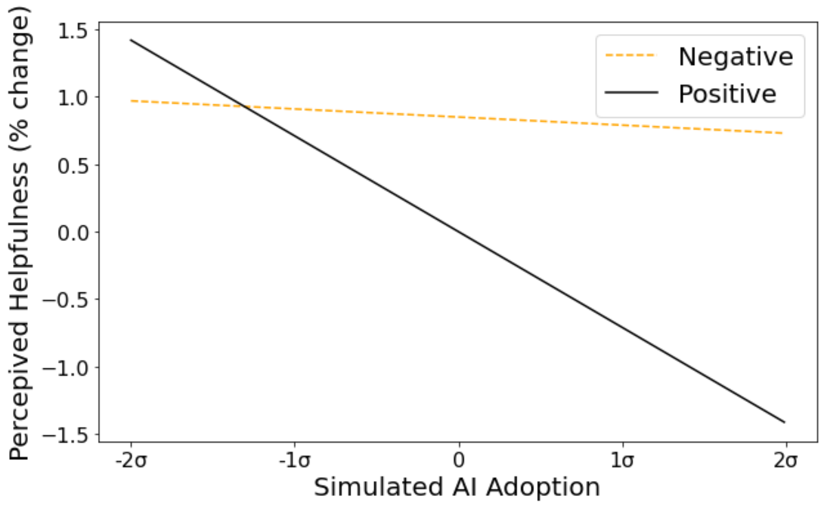


Figure 5-8. Estimated impact of simulated AI adoption – Conservative GPT (Temp = 0)

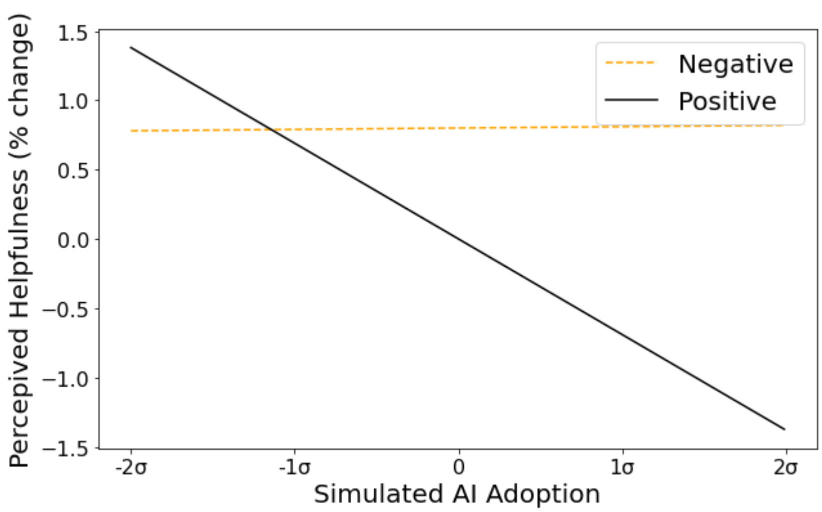


Figure 5-9. Estimated impact of simulated AI adoption – Default GPT (Temp = 1)

When set to a high temperature (Temp =2), adopting GPT models can enhance customer perceptions when addressing both positive and negative reviews, with the impact being particularly significant for positive reviews, as shown in Figure 5-10. This finding is reasonable because models with a high temperature tend to generate more diverse responses that are less relevant to the original reviews, what are effective response strategies suggested in prior literature (Deng & Ravichandran, 2023; H. Shin et al., 2020).

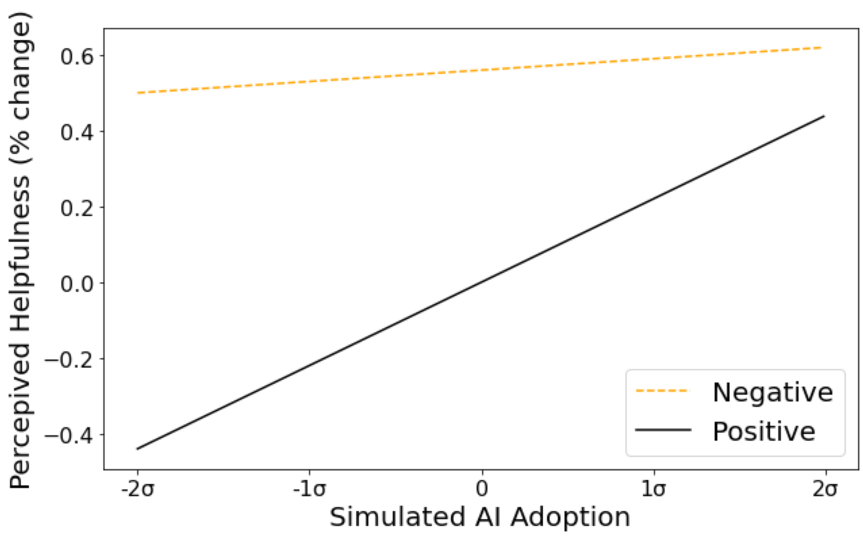


Figure 5-10. Estimated impact of simulated AI adoption – Creative GPT (Temp = 2)

The outcome of AI adoption on addressing negative reviews is more stable across different temperature settings (Figures 5-8 to 5-10). It might be because both high and low temperatures are featured with outputs that are effective for addressing complaints. High temperatures lead to a high variation among responses, which signals companies' commitment to service recovery and customer communication (Wei et al., 2013). At the same time, low temperatures can make the responses closely relevant to the original review and more concentrated on some specific points. These direct and thorough explanations improves the effectiveness of communication and persuasion (S. Yang, Zhou, & Chen, 2021; Xiaowei Zhang et al., 2020).

5.5. Implications and Limitations

This study examines the outcomes of AI adoption based on the conceptual framework, which takes task-technology fit as the theoretical foundation. Therefore, it brings contributions and implications to two streams of literature. First, this study adds knowledge to AI adoption literature, wherein previous studies mainly focused on antecedents which explain why individuals and firms decide to adopt AI techniques (e.g., Yuangao Chen, Hu, Zhou, & Yang, 2023). The findings of this study bring empirical insights into the outcomes, specifically customer perceived helpfulness, which complement prior literature to facilitate a more comprehensive understanding of this concept. For subsequent studies, it is recommended to investigate the impacts of AI adoption with more diverse metrics that are generally used for evaluating responding strategies, such as the valence and volume of subsequent reviews, hotel ranking, and financial performance (Ravichandran & Deng, 2023; K. Xie et al., 2017). These firm-level outcomes will offer a broader perspective on the strategic value of Generative AI in enhancing business performance and competitiveness.

Second, this research enriches the theory of task-technology fit. The empirical findings suggest that the performance of technology is contingent on task features and technological characteristics (Goodhue & Thompson, 1995). It validates the effectiveness of this theory in informing the adoption of a disruptive technological innovation in business tasks. In addition, this study offers explanations for the alignment between task and technology through three content features: variation across responses, review-response relevance, and lexical diversity. Different tasks (i.e., review valence) demonstrate heterogeneous demands for each content feature which could be altered through technological setting (i.e., temperature) (Bhavya et al., 2022; X. Xu & Zhao, 2022). These explanations substantiated by empirical evidence enhance the validity of the task-technology fit theory.

Considering task, technology, and the mechanisms linking them, there are three potential directions for further extending this research. Future research could explore the effectiveness of Generative AI in more diverse tasks, such as travel planning, social media content marketing, and product description (Reisenbichler et al., 2022; S. Shin et al., 2023). This would allow for a comprehensive assessment of Generative AI's adaptability to different content creation needs. For example, travel planning emphasizes the credibility of information while social media content and product description may prioritize storytelling (S. Shin et al., 2023; Taeuscher, Bouncken, & Pesch, 2021). From the technology perspective, subsequent studies are suggested to incorporate a broader range of technological settings of Generative AI models. The variation in prompt strategies (e.g., providing hotel & customer information), model choice (e.g., GPT versus Claud), and interaction modalities (e.g., voice versus text) could substantially affect the output of Generative AI models (Cao et al., 2023; Xiaoyan et al., 2023). In terms of the alignment between task and technology, it is crucial to explore how different business tasks require specific content features, such as tone, emotion, credibility, and readability (Teixeira, Wedel, & Pieters, 2012; Xiang, Du, Ma, & Fan, 2017), that could be influenced by technological settings. Pursuing these research directions will help refine the boundaries of task-technology fit in the context of

Generative AI and advance our understanding of Generative AI's capabilities in the business domain.

This research contributes to hospitality literature by validating the effectiveness of Generative AI, whose potential applications in the hospitality and tourism industry has been widely discussed in previous studies (Dwivedi et al., 2023; H. Shin & Kang, 2023). The stable performance of Generative AI in responding to negative reviews regardless of model temperature signifies the power of machine rationality in addressing customer complaints (Yiting Chen et al., 2023). At the same time, the heightened benefits of adopting high-temperature GPT for responding to online reviews, particularly the positive ones, showcase the significant potential of this emerging technology. However, the inherent risks lying in high temperatures, such as hallucination, are not covered in this study (Christensen, Hansen, & Wilson, 2024). Future research could explore if Generative AI models with high temperatures produce irrelevant or even unrealistic content when responding to online reviews and how this affects customer perceptions.

Another interesting finding emerging in the comparison between humans and AI models is about organizational learning behavior (B. Levitt & March, 1988). The strategies reflected in human drafted responses align with those suggested by prior literature, implying that hotel staff learn from accumulated organizational knowledge and experiences. Similarly, fine-tuning techniques allow machine learning models to learn and adapt to specific tasks (H. Yang et al., 2024). The similarities and differences between AI and human learning patterns deserve further exploration.

This study contributes methodologically by introducing a novel approach to measure simulated AI adoption. This method compares managerial responses against AI-suggested texts and take human responses with high similarity to AI content as instances of AI adoption. It enables the evaluation of AI's effectiveness without real-world applications, offering a new framework to examine AI technologies' potential across diverse contexts. For example, it can be applied to social media posts, advertisements, and product descriptions. Moreover, this approach can extend beyond textual analysis to include other modalities such as images and videos, based on various established methods for measuring similarity in these formats (Banerjee, Cole, & Ingram, 2023; Bekhet, Hassaballah, Ahmed, & Ahmed, 2019; H. Zhang et al., 2023).

The practical implications of this study are manifold, offering valuable insights for industry practitioners. The results showcase the potential of applying Generative AI models like GPT in business operations. By adopting GPT models, particularly at higher temperature settings, businesses can yield enhanced customer perceptions through more diverse and personalized interactions. The identified negative impacts, yet emphasize the importance of strategic AI implementation, necessitating a deep understanding of both task demands and technological features. Notably, adopting the default GPT model (Temp = 1) is predicted to impair customer perceptions. It underscores the importance of further investments in AI training and finetuning with task-specific datasets.

This study has several limitations. First, it only uses data from the Houston market, but results might differ in other regions due to varying cultural and business contexts. Therefore, it is encouraged to revisit this topic in more regions to add more nuanced understandings. Second, AI adoption is measured with a simulated approach which offers valuable insights but may not fully capture the complexity of real-world applications. For example, the decisions concerning AI adoption comprise multiples steps, such as determining which reviews to respond to with AI and updating the model based on their own database. Future studies should embrace filed experiments to better understand the nuanced implementation of Generative AI and investigate their strategic outcomes. Third, this research does not involve human modifications to the GPT generated content, while in practice, businesses often edit AI responses before publishing to ensure alignment with their brand voice and customer service standards. The synergies between AI and humans and the tension between augmentation versus automation could further enrich this topic.

Chapter 6. CONTRIBUTIONS AND LIMITATIONS

The dynamic nature of external environments requires hospitality businesses to constantly adapt their strategies in response to external pressures. The difficulty in strategizing is amplified by contemporary challenges, e.g., the pandemic, the emergence of short-term rentals, and the disruptive innovation of Generative AI. Therefore, this dissertation explores the strategic responses of hospitality businesses to these turbulent environments. It examines the effectiveness of responding strategies under multiple external conditions - market uncertainty, competitive uncertainty, and technological uncertainty - through three independent studies. Utilizing a data-analytical approach, these studies provide insights into how different strategies impact the resilience and performance of hospitality businesses and how these impacts vary with external conditions. This chapter summarizes the main findings of this dissertation, discusses its theoretical, methodological, and practical implications, and outlines both its limitations and suggestions for future research.

6.1 Summary of research findings

Overall, this dissertation identifies that strategic outcomes are contingent on market, competitive, and technological environments. Each independent study provides empirical evidence for how the external conditions distinctively influence the effectiveness of responding strategies, including standardization, differentiation, and AI adoption. The following content details the findings from each independent study and concludes with insights into strategic adaptation in the hospitality industry.

6.1.1 Standardization under market uncertainty

Chapter 3 examines the impacts of standardization on short-term rental unit survival under two market conditions: a pre-COVID growing market versus a during-COVID declining market. Standardization is operationalized in two property design dimensions: functionality and aesthetics. Generally, the findings reveal that the risks associated with standardizing short-term rental units become more prominent in the declining market in both design dimensions.

In the functional dimension, standardization is identified to enhance unit survival in the growing market. This indicates that hosts can capitalize on scaling up under market munificence, benefiting from economies of scale arising from standardization. In contrast, in a declining market, units that are highly similar to others under the same host tend to have a higher failure rate, underscoring a concentration risk. Regarding aesthetic design, standardization negatively affects unit survival in both growing and declining markets, with the impact being more pronounced in the latter. This emphasizes the increased necessity for risk hedging when market demand shrinks.

When comparing functional and aesthetic dimensions of standardization, both have negative effects on unit survival in the declining markets, yet their impacts differ in the growing markets. Functional standardization enhances survival, whereas aesthetic standardization increases the risk of failure. This discrepancy may be attributed to the relative difficulty in updating these attributes. Aesthetic updates are notably harder to implement, leading to increased rigidity and making properties less adaptable to new trends and guest preferences. Thus, despite increasing market demand, the inflexibility of aesthetic standardization can harm unit survival.

Overall, the findings of Chapter 3 suggest that standardization impairs short-term rental units' resilience to market fluctuations triggered by the pandemic. It is necessary for hosts to modify their standardization strategies in response to changing market trends, considering the design attributes of their properties.

6.1.2 Differentiation under competitive uncertainty

Chapter 4 focuses on differentiation strategies in the short-term rental context where competition relies heavily on spatial distance. This study identifies significant differences in the impacts of differentiation on unit performance across two geographical scopes: local (a subregion within a city) and city-level. It further reveals how competition intensity moderates the strategic outcomes of differentiation. The findings indicate that the benefits of differentiation are heightened in the environment of intense competition.

Differentiation through aesthetic design leads to varying outcomes across different geographical contexts, as the competitive environment changes with the scope of rivals. At the local level, differentiation enhances unit performance by mitigating localized competition. Conversely, at the city level where direct competition diminishes, this strategy negatively influences unit performance, indicating the advantage of conforming to the aesthetic designs of city-wide rivals. The alignment with the destination's aesthetic identity attracts travelers seeking a cohesive experience.

The moderation effects of competition intensity, measured by the number of competitors and the degree of market concentration, are observed at both geographical levels. At the local level, competition intensity amplifies the advantages of differentiation by highlighting the need to avoid direct competition. Similarly, at the city level, competition intensity lessens the drawbacks of differentiation, as the benefits gained from mitigating competition offset some negative effects.

In sum, differentiation alleviates the challenges posed by competition. The findings suggest that short-term rental hosts should adjust their differentiation strategy according to the competitive environments that vary with geographical scope and competition intensity.

6.1.3 AI adoption under technological uncertainty

Chapter 5 explores the implementation of Generative AI in crafting responses to hotel online reviews, considering the complexity of this disruptive technological innovation. This study reveals that the outcomes of AI adoption rely on the settings of Generative AI models. It further indicates that Generative AI’s effectiveness is contingent on how well the technological settings fit task requirements.

The impacts of AI adoption on customer perception, which is measured by review perceived helpfulness, vary with the temperature setting of Generative AI models. By analyzing the features of generated content, this study validates that high temperatures introduce more flexibility and creativity in generated content while low temperatures prioritize predictability and consistency. The findings suggest that a high temperature setting of 2 yields positive effects, possibly owing to the enhanced genuineness which is valued in customer interactions. However, low settings, including 0 and 1, lead to negative outcomes, likely attributed to the formulaic and rigid nature reflected in the replies.

The performance of AI adoption varies with the valence of online reviews, reflecting the diverse demands of positive and negative feedback. For positive reviews, high-temperature models magnify Generative AI's effectiveness, while those with lower settings lead to substantial drawbacks. That is because low temperatures tend to produce responses that paraphrase the original reviews, thereby triggering risks of overselling. Conversely, the performance of Generative AI is more stable across different temperature settings. It can be attributed to the simultaneous advantages of both high and low temperatures. The low settings craft coherent and focused explanations which can address customer complaints effectively, while higher settings introduce variability and customization in responses.

In general, Chapter 5 emphasizes the importance of understanding the dynamics of Generative AI associated with temperature settings for their effective integration into hotel operations. In addition, hotels should strategically plan the adoption of Generative AI, adapting to task-technology fit.

6.2 Contributions and Implications

This dissertation carries theoretical and methodological contributions for research, as well as implications for practitioners. From the theoretical perspective, it first enriches strategic management theories by exploring the tension between different theoretical angles and refining these theories' boundary conditions with environmental contingencies. Specifically, Chapter 3 advances our understanding of standardization by combining the theory of transaction cost economics with the financial theories on concentration risks. The findings reveal that market conditions shift the balance between these theories, highlighting cost efficiency's dominance during market growth and prioritizing risk mitigation in times of decline. Chapter 4 enriches the interplay between institutional theories and competitive strategies by incorporating spatial dynamics. It indicates that, under intense localized competition, the emphasis on avoiding competition prevails, while in less competitive settings with wider-ranging rivals, the pursuit of legitimacy dominates. Chapter 5 extends the task-technology fit theory by validating its applicability in predicting the effectiveness of an emerging technology, Generative AI. It also offers explanations by connecting technological settings to task requirements through the variations in textual content features.

Furthermore, this research enriches the literature of environmental uncertainty and strategic adaptation by focusing on three contemporary challenges. The findings confirm the fundamental role of external environments in deciding the effectiveness of standardization, differentiation, and AI adoption strategies, and guiding the continuous strategic adaptation. Moreover, by differentiating between market, competitive, and technological uncertainties and their distinct impacts on strategic outcomes, this dissertation underscores the necessity of understanding various external pressures and tailoring strategic responses accordingly.

In addition, this dissertation adds knowledge to hospitality literature by providing empirical insights into how various strategies interact with external pressures and thereby affect business resilience and performance. It complements the previous studies that have qualitatively argued for the effectiveness of these strategies and the importance of adjusting them to fit dynamic environments. It also underscores the importance of considering the unique features of the hospitality context in strategic planning, such as market demand fluctuations, spatial dependence, destination-based collective identity, and customers' expectations for authentic interactions.

The methodological contribution of this dissertation is threefold. First, it leverages extensive secondary data, where a substantial sample size reflective of real-world scenarios boosts the generalizability and external validity of the findings. Second, by integrating advanced machine learning techniques with econometric models, it allows for the efficient processing of large datasets to deliver reliable and interpretable analyses. Machine learning algorithms allow for operationalization of strategic concepts and econometrical models help identify causality between theoretical constructs based on conceptual frameworks inferred from prior literature. This integrated design can be utilized in subsequent studies to facilitate their internal validity. Third, employing this data-analytical approach not only triangulates the findings of previous studies, but also sheds light on strategies that were difficult to quantify before. Further utilization of this approach will help understand complex strategic phenomena, enhance the precision of strategic analysis, and facilitate more data-informed explorations in strategic management.

From the practical perspective, this dissertation provides domain-specific knowledge, which offers actionable guidance for industry practitioners and policymakers. Its empirical findings guide hotel managers and short-term rental hosts in tailoring and adjusting strategies to fit turbulent environments. This research also exemplifies an effective integration of advanced techniques, like machine learning and data analytic models, into business strategies. It opens opportunities for firms to further leverage these tools for making data-driven decisions, optimizing operations, and establishing industry leadership. Furthermore, this research encourages policymakers to coordinate among service providers and thus foster more resilient, collaborative, and innovative value creation.

6.3 Limitations

This dissertation faces several limitations. First, the inherent nature of secondary data may cause unavoidable bias for all three empirical studies. The data utilized in three studies were all collected through web scraping. A major concern with web-crawled secondary data is its completeness, due to inestimable variables and data points potentially missed during the crawling process. It potentially impacts the accuracy and generalizability of the findings. In addition, the third study is based on online review data, which is vulnerable to self-selection bias. This is because the people who post feedback on online review platforms are not always representative of the broader customer base. This may reduce the generalizability of the results.

Second, this research only examines limited external conditions examined while the business environments are more complicated. The first study compares pre-pandemic and during-pandemic periods, while not including the important phase of post-pandemic recovery. This temporal limitation may not fully capture the long-term impacts of the pandemic or the evolving market dynamics in the post-pandemic era. The second study investigates differentiation hypothesizes asymmetric impacts at two geographical scopes, city-level versus local-level. Exploring more fine-grained variation of geographical scope will further enrich the insights by identifying the potential turning point between negative and positive impacts. The third study is set with the background of the current technological landscape, while the advancement of Generative AI techniques and associated technical tools are evolving at a dramatic speed. Thus, it is valuable to further explore how to adapt technology adoption strategy from the contemporary background to future iterations of technological advancements.

Third, this study explores strategic adaptation across various environmental conditions, which provides specific guidance on how to navigate each type of uncertainty. However, one notable limitation is the absence of an integrative framework that combines these uncertainties to offer a holistic view of strategic adaptation. An overarching model could reveal how these uncertainties interact and collectively impact strategic decision-making. For example, technological advancements could simultaneously alter market dynamics and intensify competitive pressures, leading to complex scenarios not fully addressed by examining these factors in isolation. Addressing this gap by developing a comprehensive framework in future research could significantly enhance our understanding of strategic management in response to uncertainty. In sum, these constraints highlight the need for further research to extend upon the initial insights provided by this dissertation.

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