

The Effects of Novel & Creative Pricing Strategies

A qualitative study on partitioned pricing strategies' impact on repurchase intention and brand reputation

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Abstract

Partitioned pricing strategies, dividing a product's final price into multiple mandatory components, has become increasingly common and is an important and growing part of a firm's total revenue, especially within certain business segments of the retail industry. Previous research has rendered contradictory findings on the effectiveness of exercising partitioned pricing strategies, as a way of gathering more or less favorable evaluations. However, previous research is scarce on partitioned pricing's effect on repeat purchasing behavior and brand reputation. This study examines 5 570 online customer reviews gathered from eight firms within the hotel and ticket sales industry, seeking to gauge whether and how the use of partitioned pricing has an impact on consumers repurchase intention and brand reputation. Reviews were gathered from Trustpilot, a large and established review website, and analyzed using a qualitative framework, extracting key concepts and themes from reviews. A large language model (LLM) was used to support the textual analysis, highlighting a novel research approach, allowing for analysis with a broader dataset. In large, multiple datasets were created with firms using either all-inclusive pricing or partitioned pricing within the hotel or ticket sales industry. The datasets were analyzed and compared to identify whether and how partitioned prices impacted repurchase intention and brand reputation. This study found that partitioned pricing negatively influenced brand reputation and repurchase intention for firms using them within the ticket sales industry. However, there was no link between partitioned pricing and negative evaluations within the hotel industry. Thus, no link between partitioned pricing and decreased repurchase intention and brand reputation could be made for hotel companies.

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1. Introduction

1.1 Background

The notion of partitioned pricing, the act of dividing a product's final price into one or multiple mandatory parts, was first introduced by Morwitz et al. (1998). The all-inclusive price of a product is typically divided into two components: the base price, which is the initial price displayed and marketed to the customer before checkout, and one or more surcharges. In a digital shopping context, these surcharges may include shipping costs, handling charges, mandatory additional purchases, or miscellaneous fees, collectively known as the partitioned price component. These additional costs are commonly revealed to the customer at or after the checkout.

Partitioned pricing strategies are currently commonplace, yet have become more sophisticated. For instance, during 2016, hotels in the U.S. gathered an estimated \$2bn from partitioned pricing strategies in the form of mandatory resort fees, up 35% from the previous year (Young, 2016). Likewise, the rate of destination fees, a type of after-service fee, in the automotive industry increased by more than 2.5 times inflation between 2011 and 2020, highlighting the pervasiveness of partitioned prices (Monticello, 2021).

The increased adoption of complex partition pricing strategies has raised concerns about consumer protection and the effects these strategies may have on purchasing behavior (Greenleaf et al., 2015). In response to these concerns, the Biden-Harris administration directed all U.S. agencies to eliminate partitioned pricing to the best of their abilities during late 2022 (Deese et al., 2022). Concurrently, the Consumer Financial Protection Bureau initiated an investigation on the matter (CPFB, 2022).

Previous studies have examined the effects of partitioned pricing strategies, focusing on (1) consumer behavior, (2) demand, (3) consumer preferences, (4) brand attitudes and (5) purchase intentions. These studies predominantly analyzed consumer reactions to single transaction events. Thus, there is a need to further understand partitioned pricing beyond the short-term dimension by examining its impact on brand reputation and repurchase intention (Greenleaf et al., 2015).

1.2 Problem Statement and Research Question

Considering recent probes into partitioned pricing, its pervasiveness, and the lack of principal knowledge on partitioned pricing's effect on brand reputation and repurchase intention, this paper seeks to answer the following research question: How does partitioned pricing strategies affect consumers repurchase intention and brand reputation?

2. Theoretical Background

Next, an overview of relevant theory and literature is provided to explain partitioned pricing strategies with multiple perspectives. First, theory detailing online reviews, brand reputation and repurchase intention are brought up as stand-alone entities. Second, partitioned pricing is described from two perspectives being (1) how partitioned pricing impacts customers' evaluations and (2) why partitioned pricing affects consumers' decision making. The literature is divided in two these two streams to first describe partitioned pricing as a phenomenon and what effect it has on customers. The second stream of literature is brought up to give an overview of why partitioned pricing has an impact on these evaluations. One research objective is provided after each stream of literature research objectives are provided.

2.1 Online Reviews Impact on Brand Reputation and Repurchase Intention

Previous research describes the multifaceted roles that online customer reviews have in today's digital consumer landscape. Online reviews are considered an important information source, assisting purchasing decisions in general (Zhang et al., 2014). According to an Ipsos study referred to by Gottschalk & Mafael (2022), 78% of Americans between the ages of 18 and 64 confirm that online reviews have aided them in various purchase processes. Duan, Gu and Whinston (2008) and Liu (2006) further found that consumer reliance on online reviews is part of the phenomenon electronic word-of-mouth (eWOM), defined by the Oxford Bibliography as "consumers' information sharing and exchange about a product or company via the internet, social media, and mobile communication".

Moreover, Loke & Reitter (2021) suggested that, on an aggregate level, online reviews could serve as a proxy for brand reputation. Brand reputation is defined by Ponzi et al., (2011) and Veloutsov & Moutinho (2009) as the consumers opinion of a brand that is constructed using an evaluation process based on the brand's identity, the company's promises, and the consumers holistic experience with the brand.

Furthermore, Li & Hitt (2008) and Awad & Chang (2007) concluded that online ratings of a firm exhibited significant correlation with sales. Likewise, Dellarocas, Zhang & Awad (2007) demonstrated that review valence could provide a basis for predicting future sales. Hellier et al. (2003) defines repurchase intention as "The individual's judgment about buying again a designated service from the same company, taking into account his or her current situation and likely circumstances".

2.2 Partitioned Pricings Effect on Evaluations

With regards to partitioned pricing, as established by Mortwitz et al. (1998), Kim (2006) and Lee & Han (2002), find that partitioned pricing can lead consumers to underestimate final prices. Voester et al. (2008) states that this underestimation, if noticed by consumers, can induce negative effects on brand attitude.

2.2.1 Price recall

Lee & Han (2002) undertook an experiment where participants were each asked to provide their attitude towards HiFi and computer brands after being shown an ad with the price described. Subjects were shown an ad with partitioned pricing and an ad with all-inclusive pricing. One week after providing the initial rating of their attitude towards the brand with either partitioned pricing or all-inclusive pricing, the study subjects were asked to do it again. Both for partitioned pricing and all-inclusive pricing, subjects underestimated the total costs of the products shown in the advertisements. However, the partitioned pricing advertisement had subjects underestimating the total cost by 13% and the all-inclusive price by 0.9%. Lee & Han (2002) subsequently showed the study participants the actual total price and then re-measured brand attitudes. The authors found that brand attitudes decreased with partitioned pricing and not with all-

inclusive pricing. However, the negative brand attitude effect on partitioned prices was mitigated when study participants attributed the offset of total price to their own error of recall. Thus, Lee & Han (2002) found that consumers' attitude towards brands with partitioned pricing decreases when they find out that they underestimated the total cost and that this error of recall was promoted mindfully by the seller.

2.2.2 Profits and Demand

The transition to partitioned pricing strategies is based on the possibility of raising final prices and thus increasing profits, even though customers may faultily recall prices being lower (Morwitz et al., 1998). Chen (2023) numerically showed that partitioned pricing renders higher final prices and firm profits compared to having an all-inclusive price. Firms' strategic behavior changed and even when consumers were professional and fully rational, partitioned pricing still generated higher profits (Chen, 2023).

Partitioned pricing strategies have also been found to increase demand (Xia & Monroe, 2004; Morwitz et al. 1998). Chetty et al. (2009) undertook a three-week study, analyzing the effects of including, or not including a sales tax of 7.375% in the final price for a supermarket selling personal care products. Including the sales tax in the final price (all-inclusive pricing) was found to reduce demand by on average 7.6%. Thus, Chetty et al. (2009) found that demand was stronger when partitioned pricing was used. In line with this finding, Feldman & Ruffle (2015) found that partitioned pricing, in some cases, increased consumption quantities. A laboratory shopping experiment was conducted for consumer durables where prices either included or excluded a 16% sales tax. Those subject to partitioned prices purchased 31% more goods and spent 29% more than those subject to all-inclusive prices (Feldman & Ruffle, 2015). However, Colantoni & Rojas (2015) found that a 5.5% sales tax on soft drinks used in a partitioned pricing strategy did not impact consumption. Thus, Voester et al. (2008) concluded that the exclusion of sales tax in the base price could increase demand. Yet, the authors also stated that most studies have focused on the effects of taxes, and that further studies should be done to understand other surcharges. Notably, EU member states are

required to obey the Price Indication Directive, stating that VAT shall be included in communicated consumer prices (European Justice, 2021).

2.2.3 Surcharge Characteristics

Hamilton & Srivastava (2008) found that surcharge benefit and relevancy had an impact on customers evaluation of firms having partitioned pricing. If the surcharge was considered relevant and provided benefit, it was not as likely to be evaluated negatively. However, if the surcharge was considered as non-beneficial, reactions were mostly negative. Moreover, Xia & Monroe (2004) found that evaluations were dependent on surcharge magnitude, i.e. the percentage of the final price consisting of a partitioned price component. The larger the surcharge magnitude, the larger the likelihood of negative evaluations.

Bambauer & Gierl (2008) and Lee & Han (2002), amongst others, point out that there are multiple negative effects arising from utilizing partitioned pricing. The critic stems from research indicating that partitioned pricing renders less favorable product evaluations than displaying the all-inclusive price. Burman & Biswas (2007) concluded that partitioned pricing in many cases generated negative responses, especially for customers with low need for cognition. Likewise, Bertini & Wathieu (2008) draw a similar conclusion as Burman & Biswas (2007) stating that partitioned pricing increases the focus on the partitioned pricing item, which in turn may render less favorable evaluations.

2.2.4 Research Objective 1 (RO1)

Based on the findings of Bambauer & Gierl (2008), Lee & Han (2002), Burman & Biswas (2007), Bertini & Wathieu (2008), Hamilton & Srivastava (2008) and Li & Han (2002), indicating collectively that partitioned pricing could render less favourable product reviews, connected to Loke & Reitter's (2021) finding that online reviews serve as a proxy for brand reputation on an aggregate level, research objective 1 is formulated:

RO1: Companies using partitioned prices should have less favorable product evaluations than companies without partitioned pricing, resulting in a lower brand reputation than for firms using all-inclusive pricing.

2.3 Partitioned Pricing's Effect on Judgement and Perception

From the perspective of economic theory, partitioned pricing should not have an impact on purchase decisions as decisions are, in theory, based on the all-inclusive price and not how prices are partitioned (Chen, 2023). Consequently, partitioned pricing should not impact price perceptions in a perfect market. However, multiple psychological effects impact our decision making.

2.3.1 The Anchoring Effect

The anchoring effect is a phenomenon where judgment and perception are impacted by an initial reference point. This initial reference point has a bearing on the perception and memory of the final outcome (Tversky & Kahneman, 1974). Consequently, partitioned pricing anchors the buyers' perception on the base price, instead of the all-inclusive price. This anchoring effect makes customers perceive that costs are lower with partitioned prices than with all-inclusive pricing (Kim, 2006; Lee & Han 2002; Morwitz et al. 1998). A considerable percentage, between 12.2% and 35.6% of consumers, completely disregarded the surcharge component when being asked to recall the final price (Morwitz et al., 1998). Moreover, Morwitz et al. also found that 23% of those faced with partitioned pricing even ignored the surcharge when being asked to recall the final price. Only 21.9% used actual mathematical calculation, adding the base price and surcharges. However, Bertini & Wathieu (2008) went on to state that partitioned pricing led consumers to perceive a higher total price, contrary to the general consensus highlighted above.

2.3.2 Information Saliency

Psychology research from Lynch & Srull (1982) and Hutchinson & Alba (1991) identified that consumers focused on information that is salient while Kahneman & Tversky (1979) found that consumers reduced all information they are presented with to a limited

consideration set. Consumers most often process information in the order it is presented, not integrating information across stages (Slovic, 1972; Thaler & Johnson, 1990). This research indicates that consumers might be unsuccessful when mentally combining the base price and all surcharges when being asked to recall the final price. Thus, the prevailing result is that consumers only recall the base price. Sheng et al. (2007) proposed that some consumers completely disregard surcharges to create a mental heuristic that they are receiving a favorable deal.

2.3.3 Adjustment Theory

Additionally, Kahneman & Tversky (1974) found that consumers most often used the initial piece of information presented with when making decisions. As previously stated, anchoring had an effect on the final price perception. However, adjustment theory describes that subsequent information is used to adjust the anchor, leading to price perceptions closer to reality. However, Chapman & Johnson (1999) found that consumers tended to adjust insufficiently and still underestimated the final price.

2.3.4 Complicated Surcharges and Mental Heuristics

It is cognitively demanding to calculate the base price and therefore mental heuristics are often used. When the presentation of surcharges is mentally challenging, heuristics are more often used to combine the base price and surcharges (Chetty, Looney & Kroft, 2009). For instance, Morwitz et al. (1998) put forward that having the surcharge as a percentage increased complexity, rendering more consumers ignoring the surcharge completely. Yet those employing partitioned pricing must be mindful of not spiking complexity. Having multiple surcharges, instead of one, decreased purchase intention (Xia & Monroe, 2004).

2.3.5 Prospect Theory

Prospect theory is a theory of behavioral economics stating that individuals are loss averse (Kahneman & Tversky, 1979). The aversion towards multiple losses is subjectively greater than a single loss with equivalent value to multiple losses (Thaler, 1985).

Subsequently, Voelckner et al. (2008) stated that partitioning pricing confronts consumers with multiple losses. In Voester et al.'s (2008) systematic review of partitioned pricing, the

authors drew the conclusion, with the findings of Voelckner et al. (2008) and Bertini & Wathieu (2008), that prospect theory should render negative effects on purchasing behavior when businesses apply partitioned pricing. The reason is that multiple losses are incurred and that individuals prefer fewer losses, even though they have the same monetary value.

2.3.6 Research Objective 2 (RO2)

Morwitz et al. (1998) found that a large percentage of customers completely disregarded the surcharge component when being asked to recall the final price. Moreover, the research presented by Lynch & Srull (1982), Hutchinson & Alba (1991), Kahneman & Tversky (1979), Slovic (1972) and Thaler & Johnson (1990) indicates that customers only recalled the base price of an item they purchased. Based on these findings this thesis seeks to investigate whether surcharges are experienced as unexpected. Moreover, building on the findings of Voelckner et al. (2008) and Bertinie & Wathieu (2008), indicating that partitioned pricing has a negative effect on purchasing behavior, the thesis seeks to investigate whether there is a link between the surprise effect of partitioned pricing and decreased repurchase intention. Consequently, research objective 2 is formulated:

RO2: Consumers should state that surcharges were unexpected and that this negatively influenced their perception of the brand, decreasing repurchase intention.

3. Method

This thesis qualitatively derived customer sentiments towards partitioned pricing strategies with the purpose of gaining a deeper understanding of how the utilization of these pricing strategies influences brand reputation and repurchase intention for partitioned pricing firms. According to J.A Smith (2017), textual analysis becomes an applicable way of researching a matter when the goal is to decode messages and values being embedded in textual data.

To holistically seek an answer to the research question at hand, an analysis of online customer reviews from Trustpilot, a well-established review platform, was conducted. In total, eight firms within the hotel- and ticket sales industries, two retail segments where partition pricing strategies are commonly practiced amongst firms, were used as research objects. Despite the prevalent use of partitioned pricing in these industries, some actors have contrasted the trend by keeping all-inclusive pricing strategies. To understand how the mere presence of partition pricing components influences repurchase intention and brand reputation through online review eWOM, customer attitudes towards partitioned pricing firms expressed in customer reviews were compared to the evaluations of industry peers employing all-inclusive pricing.

The gathered review samples were decoded following the methodological structure outlined by two supporting articles rooted in Grounded Theory, defined by Novel & Mitchell (2016) as “a research method concerned with the generation of theory, which is ‘grounded’ in data that has been systematically collected and analyzed. It is used to uncover such things as social relationships and behaviors of groups, known as social processes”. The development of the methodological structure in this thesis has been supported by Gioia & Corley (2013) and Nicholas et al. (2003). As described in both articles, the process of decoding textual data and constructing research relevant categories of its content is an effortful task, restricting the data quantities which can be efficiently analyzed. In the case of online reviews, this problem becomes more evident, due to the wide range of topics being discussed by customers. To support the extraction of relevant data samples used in this thesis, reviews were filtered using Generative AI.

Gartner, a technology consulting firm, defines Generative Artificial Intelligence (GAI) as “AI techniques that learn a representation of artifacts from data, and use it to generate brand-new ones”.

Keyword-lists including commonly used expressions, referring to partitioned pricing components and theoretical sub-constructs of brand reputation and repurchase intention, were compiled and provided to the GAI model. In order to avoid potential pitfalls of using GAI for filtering, two additional articles were used to support the construction of prompts compliant with the inherent capabilities of the LLM.

Subsequently, customer sentiments from partitioned pricing firms were manually derived from the filtered dataset, categorized and linked to theories stemming from previous research. This process adhered to the structure of qualitative research developed by Gioia & Corley (2013) and Nicholas et al. (2003).

The upcoming sections initially contain a justification of the articles used for methodological support, followed by a section explaining how the research structure was designed to ensure study rigor.

3.1 Methodological Justification

In order to qualitatively assess the central research objectives of this thesis, two established methodological frameworks for qualitative research were utilized. The study design was developed in accordance with Nicholas et al. (2003), which puts forward a structured approach to qualitative data analysis on web-based data types. The main focus of the article lies in the process of reducing large volumes of raw data down to a level where useful messages can be derived and purposefully analyzed and visualized. The method builds on three major steps, with the initial referred to as Elicitation. During this step, the focus of the researcher is to motivate and determine an appropriate data source suited for the purpose of the study and employ an appropriate method to collect qualitative data. During the second step, referred to as Reduction, the researchers compile a coding scheme, consisting of keywords linked to the

investigated phenomenon. Thereafter, the codes are used to categorize the observations in the data. In order to mitigate the risk of researcher biases and ensure empirical rigor, the article suggests the use of external judges to generate a list of theoretically related codes which is compared to the researchers' efforts through sub-sampling and contextual cross-checks. Throughout the coding process, the data is clustered and the researchers have to decide which parts of the data that should be examined. In the third step of the method, referred to as Visualization, Nicholas et al. (2003) suggest multiple ways of presenting the findings.

In the context of this thesis, the steps of Elicitation and Reduction described in Nicholas et al. (2003), were applied to facilitate an empirical structure in the initial steps of the research process, including the selection of industries, data gathering and coding. On the other hand, the article lacks clear guidance on how previous theories on the investigated topic effectively can be incorporated to explain findings in the data. Hence, the method used in this study was complemented by Gioia & Corley (2013). In contrast to Nicholas et al. (2003), the methodology by Gioia & Corley (2013) presents an approach where a broader range of observations, referred to as first order concepts, are grouped into broader categories, termed second order themes. According to the article, the latter are constructed on the basis of previous theories in the field of research. Finally, second order themes are grouped into overarching big picture themes, aggregate dimensions, representing the key subjects discussed in the data. In this thesis, the data structure framework by Gioia & Corley (2013), depicted in Figure X, is used to provide a visual overview of the dataset and the findings made in terms of customer reactions towards partitioned pricing and its influence on brand reputation and repurchase intention.

The combination of two guiding methodological articles is motivated through their complementing contributions to ensure study rigor in this context. The following excerpt from Gioia & Corley (2013), further highlights the encouragement by the authors to combine the methodology with other frameworks to find a methodological fit for the specific research context; “When the approach is treated as a template or cookbook, it not only constrains its innovative possibilities, but also seems to get in the way of using it to address one of its main intents: rigorously demonstrating connections between data and theory”.

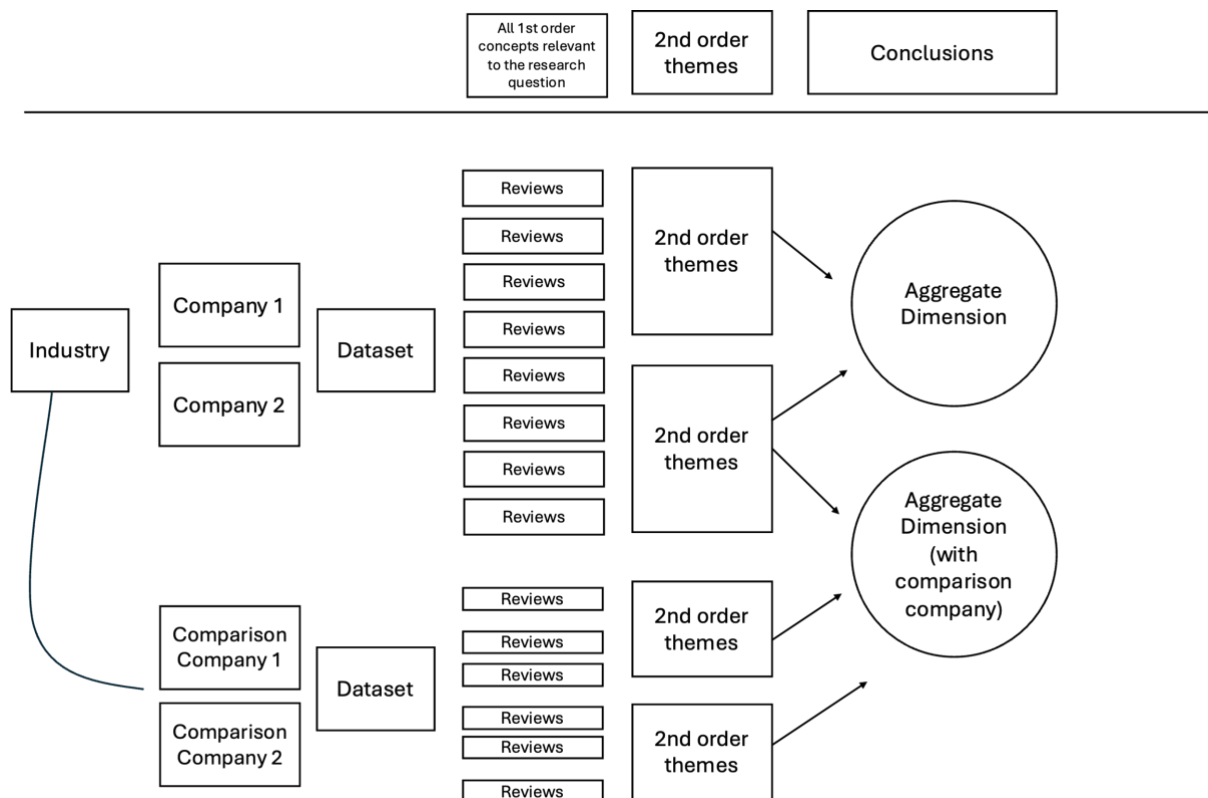


Figure 1. Visualization overview

3.2 Research Structure

3.2.1 Elicitation

The following sections motivate the selection of industries. Likewise, the pricing strategy for each firm is presented in terms of the displayed pricing component and the partitioned price.

Partitioned pricing strategies are pervasive in the hotel industry (Zhang & Tang, 2024). During 2016, hotels in the U.S. gathered an estimated \$2bn from partitioned pricing strategies in the form of mandatory resort fees, up 35% from the previous year (Young, 2016). This paper puts forward that it could be favorable to study the hotel industry as their surcharges typically are high and widespread. French and Kemmis (2023) found that 11% of the overall costs of a hotel stay comes from various fees not included in the base price and that this level of surcharge in relation to the base price is higher than for many other industries. Pairing the high level of surcharges with the omnipresence of partitioned prices within the hotel industry makes it a favorable study subject.

Marquez (2020) puts forward in his dissertation that partitioned pricing strategies are used extensively within the ticket sales industry. Upon analysis Marquez (2020) found that 4/6 (67%) of major ticket sales providers utilized partitioned prices. Thus, ticket sales companies were assessed in this thesis.

In table 1, all companies studied are listed, along with their pricing strategy.

Industry	Firm	Displayed price component	Partitioned price component(s)
Hotels	Marriott Bonvoy	Room price	Government taxes, fees & parking
	Choice Hotels	Room price	Government taxes
	Scandic	All-inclusive pricing	
	Accor	All-inclusive pricing	
Ticket Sales	Ticketmaster	Ticket price & taxes	Service fee, order processing fee & delivery fee
	Viagogo	Ticket price	Service fee, order processing fee, delivery fee & taxes
	AXS	All-inclusive pricing	
	TickPick	All-inclusive pricing	

Table 1. Pricing strategies

3.2.2 Data Gathering

Trustpilot was selected as the provider of reviewer data due to its popularity as a digital platform for consumers worldwide to share and review their experiences with retail firms. Textual reviews are provided for more than 529 000 businesses across multiple sectors (Kurt, 2023). In addition, the Trustpilot algorithm, determining the displayed review feed, prioritizes long and detailed reviews with the least variance of numerical reviewer ratings in comparison to a firm's Trustscore, the aggregate numerical rating score for a particular business (Trustpilot, 2024). Altogether, this served as quality assurance given that reviews with the highest probability of containing detailed descriptions and clear sentiments were gathered in accordance with the inherent logic of the chosen data collection method.

The task of collecting customer reviews on a high scale was undertaken using web scraping. The concept of web scraping is defined as the quest of extracting unstructured data from a HTML format and storing it into a structured file format such as CSV or JSON, using a web crawler. A web crawler is an algorithm with the ability to compose a HTTP request, targeting a website with the objective to collect resources embedded in the code (Zhao, 2017). In this study, a web-based scraping application was utilized, taking the URL codes of the targeted companies' Trustpilot pages as its input. By running a script tailored to Trustpilot's HTML structure, the web crawler efficiently managed to compile customer review data into a CSV format. Trustpilot pages for each firm were scraped in accordance with the numerical subpage order set by Trustpilot's algorithm for prioritizing review content quality. When all data had been collected, the output CSV files were manually merged twice, first by industry and secondly by pricing strategy, separating partitioning pricing firms from all-inclusive pricing firms. Throughout this process, a total of 5 570 customer reviews were collected.

Figure 2 depicts an overview of the data collection process.

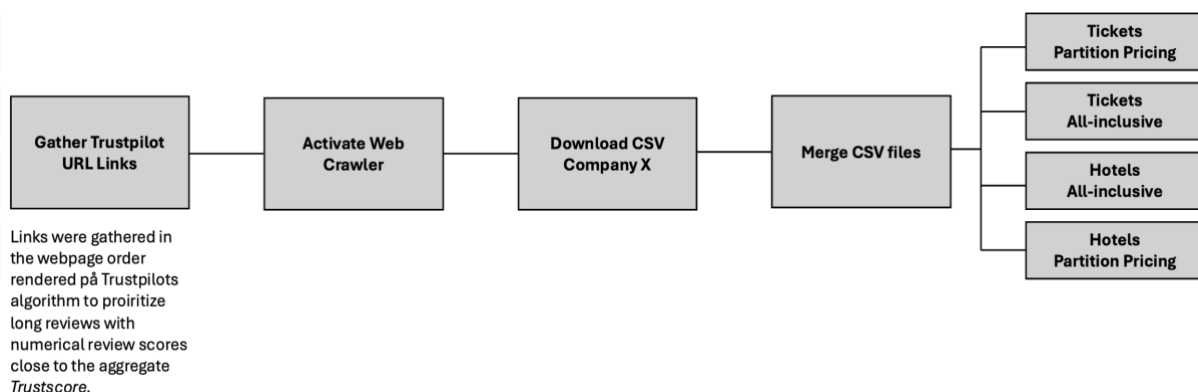


Figure 2. Data collection process

3.2.3 Reduction

Selection

Due to the unstructured nature of the collected raw data, which encompassed a wide range of subjects, reviews pertaining to the investigated topic had to be filtered. According to both Gioia & Corley (2013) and Nicholas et al. (2003), categorizing large datasets is a time consuming and effortful task which restricts the data quantities which can be efficiently analyzed. This obstacle becomes even more apparent when the focal phenomenon of the qualitative study is hidden in noisy raw data. Based on these constraints, a research team at Penn State University decided to explore how Generative AI could be utilized for qualitative research. After engaging 13 qualitative researchers in an experiment and conducting subsequent interviews, they concluded that Large Language models (LLMs), defined as “a type of artificial intelligence algorithm that uses deep-learning techniques and massively large data sets to understand, summarize, generate and predict new content” (Kerner, 2024), such as OpenAI’s ChatGPT, could serve as an efficient research tool, being employed to streamline the textual coding process. Besides enhancing coding efficiency, the adaptability and computational power of LLMs were highlighted as two of the gains, widening the array of analyzed perspectives while mitigating human biases (Zhang, 2023). On these premises, Open AI’s LLM, ChatGPT4 was utilized as a research tool in this study to undertake keyword-based filtering on the four datasets containing raw data from Trustpilot.

The filtering was operationalized by constructing two lists of keywords. The first one consisted of terms frequently used by customers in reviews when referring to the pricing strategy of the firm. The second list incorporated terms related to sub-constructs of brand reputation and repurchase intention described in four supporting articles. Since brand reputation and repurchase intention could theoretically evoke either positive or negative customer reactions by the use of partitioned pricing, the list was balanced to cover both directions of sentiments.

Brand Reputation & Repurchase Intention			
<p>Brand Reputation Definition: The consumer's opinion of a brand that is constructed using an evaluation process based on the brand's identity, the company's promises and the consumers holistic experience with the brand (Ponzi et al., 2011; Veloutsov & Moutinho, 2009).</p>	<p>Brand Reputation Constructs:</p> <p>Trustworthiness Integrity Honesty</p> <p style="text-align: right;">} Afzal et al. (2009)</p>	<p>Brand Reputation & Repurchase Intention Key Words:</p> <p>Never again Again Never return Will return Don't trust Not trust Trust Dishonest Honest Trustworthy Not Trustworthy integrity No integrity Satisfied Satisfaction Dissatisfied Fraudulent Transparent Hidden Uncertain Certain Convenient Not convenient Technical issues Positive experience Awful experience Experience Recommend Never recommend</p> <p>Not recommend Failed Succeeded Helpful Not helpful Avoid Not avoid Use again Not use again Criminal Clear Unclear Scam Reputation Judgment Identity Promise Promises Repurchase intention Repurchase Brand reputation Reputation Re-visit Value Not return Stay away Don't buy Never recommend</p>	<p>Pricing Keywords:</p> <p>Costs Cost Charges Charge Expensive Money \$ € Fee Fees Overpriced Cheap Reasonably priced Underpriced Commissions Prices Price Surcharges Surcharge Added fees Added fee Added charges Added charge Value for Money Ticket value Face Value Pricey Ripped off/Ripoff Hidden costs</p>
	<p>Repurchase Intention Constructs:</p> <p>Reputation Familiarity with vendor Satisfaction Product characteristics</p> <p style="text-align: right;">} Fang et al. (2014)</p> <p>Trust</p> <p style="text-align: right;">} Chiu et al. (2009)</p> <p>User experience Information quality Perceived value Brand equity Seller uncertainty</p> <p style="text-align: right;">} Wirapraja & Subriadi (2019)</p>		

Figure 2. Operationalization

Generative AI Data Filtering

Similar to Zhang et al. (2023), Morgan (2023) concludes that Generative AI is able to provide value in qualitative research processes. At the same time, Morgan (2023) underscores that LLM-supported research tasks shall be assigned in accordance with the inherent capabilities of the LLM, taking proactive measures to avoid potential pitfalls.

The main risk addressed by Morgan (2023) relates to the lack of model transparency when the LLM combines pre-acquired knowledge with input data provided by the user. This 'Black Box' scenario poses the risk of creating unrecognized hallucinations, i.e. nonsensical responses, which despite their incoherence might be communicated in a convincing way. This calls for controlling mechanisms employed by the authors to detect potential errors that could falsely alter the analysis.

In this study, each set of raw data was uploaded to a new environment in ChatGPT4, thereby mitigating the risks of hallucinations caused by pre-stored data. In the initial step, the model was asked to provide an overview of the columns present in the dataset to ensure that the csv-file had been successfully uploaded. Secondly, the keyword lists were handed to the LLM in two subsequent prompts, starting with the list pertaining to pricing, followed by the terms connected to brand reputation and repurchase intentions. According to Zhang et al. (2023), constructing informative prompts is a pivotal aspect when interacting with an LLM. Hence, prompts were written in accordance with the structure suggested by Zhang et al. (2023), including A) The background of the task, B) The core description of the task, C) A description on how the task shall be addressed, and C) How the output shall be presented. The filtered dataset was presented in an output csv-file, which was manually parsed by the authors to control for filtering errors. In addition, the model was asked to declare the underlying operations taken when the filtering was conducted. The detailed prompts and outputs from this process are presented in appendix 1.

Coding

When the filtered dataset had been parsed, and a few evident misclassifications had been removed, the customer reviews were decoded with the purpose of finding common concepts. In the initial open-coding phase, a coding scheme was developed during an open discussion between the authors while the filtered dataset was analyzed on a high level. Recurring concepts were noted and added to a common coding scheme before the reviews were manually categorized and grouped into broader themes connecting the observations to previous theories which could be applied to deeper understand the context of the present keywords. To ensure inter-coder agreement between the authors, sub-sampling was iteratively used to compare categorizations and improve coding coherence.

3.3 Supporting Methodological Overview

As a summary of the methodological justification section, an overview of previous research used in this thesis method is provided.

Article Name	Description	Purpose
Gioia & Corley (2013)	Presents a qualitative research framework, providing a structured approach to conduct rigorous research through the connection between decoded data categories (first order concepts), and theories from previous research (second order themes)	Used to support the visual representation of the findings, and to clarify connections between thesis findings and established theories through second order themes.
Nicholas et al. (2003)	Presents a sequential method for data preparation and decoding of web-based data through the steps of Elicitation, Reduction & Visualization.	Utilized to facilitate research structure and guide the coding process in accordance with the principles of Grounded Theory.
Zhang (2023)	GAI can be applied to expand data analysis abilities, widen perspectives and streamline the open coding process.	Increasing thesis quality and efficiency by letting GAI assist with data analysis.
Morgan (2023)	Used to mitigate errors, pitfalls and replicability issues when using GAI to analyze textual data.	Mitigating pitfalls when using GAI.

Table 2. Theoretical foundations

4. Results

Next, results from the analysis will be presented and connected to the research question and research objectives provided. First, results pertaining to reviewer ratings are presented followed by findings for ticket sales companies. Subsequently, findings from the hotel industry are showcased. Lastly, the research objectives are addressed. The findings will be exemplified using sample reviews where relevant keywords have been bolded and the contexts have been described using applicable theories from previous research. Finally, results are illustrated using the Gioia & Corley (2013) data structure model.

4.1 Ticket Sales – Partitioned Pricing

Reviews from ticket sales companies using partitioned pricing were analyzed.

Based on the filtered dataset, applying the keywords described in the method section, first order concepts were identified. Subsequently, four second order themes were constructed. These are (1) hidden fees and lack of transparency, (2) deceptive pricing strategies and value for money, (3) avoidance and warning others and (4) checkout surprises.

Hidden Fees and Lack of Transparency:

Reviewers frequently mentioned the feeling of being overcharged due to high surcharges added to the initially displayed price of the tickets. Various reviewers also expressed frustration regarding the ambiguous nature of added fees, making the firms' pricing strategies perceived as opaque.

The reviewer below expressed frustration with regards to high fees and overpriced tickets, highlighting that the fee in relation to the final price was substantial. These types of reviews were frequent.

*“It was only made clear after they had taken my money that the **face value** of my 2 x £200 bryan adams ticket was actually 2 x £65. I understand that they should charge fees etc, but why not make it open, honest and transparent before the point of purchase. I then spoke with their agents and got absolutely nowhere as they quote the ‘rules’. Had I known the exact details before clicking the buy ‘button’, i would never have purchased. (...).”*

Moreover, the review above described a lack of honesty from the ticket sales provider. Honesty is a key construct of brand reputation, and the reviewer called for openness as a way of gathering trust. The lack of transparency addressed in multiple reviews, with similar sentiment to the one above, seemed to impair the customers' holistic experience with the brand, indicating decreased brand reputation based on the interaction.

Followingly, the below review stated that he/she would not use the ticket sales provider again if he/she is charged with multiple hidden fees, indicating that partitioned pricing negatively influenced repurchase intention.

*"I really enjoyed the Jurassic World Live Tour, however the firms prices are unreasonable and will **not return** for a show if I'm being **charged multiple hidden fees** on top of a \$50 show ticket. I purchased 3 tickets at \$50 a seat and expected my total to be no more than \$200. At checkout my total was \$271. Because of the hidden fees I will not be recommending the firm to anyone in the future."*

Deceptive Pricing Strategies and Value for Money:

Reviews moreover highlighted deceptive pricing practices, such as tickets being priced much higher than advertised, questioning the value for money customers are getting. Customers felt deceived when the price displayed on the website differed from the checkout price and that firms failed to be honest.

The three below quotes illustrate common reactions to the partitioned pricing component:

*"This website **deceived me by charging higher fees than advertised** and failed to deliver the Beyoncé tickets I purchased. Avoid at all costs!"*

*"My bad experience with my last order: I paid 490 Euro for a concert. Was obviously expecting **expensive** tickets. When I received the tickets, the official **price** was 54,75! Customer chat and email of no help, they claim it is legal. Will see...**Stay away!**"*

The reviews brought up pricing aspects and subsequently indicated that others should avoid using the ticket provider. Connected to brand reputation, reviews expressed decreased trustworthiness as a result of not being honest with the pricing strategy.

Avoidance and Warning Others:

A substantial share of reviews warned others to not engage with the companies in the dataset having partitioned pricing strategies. A common finding across these reviews was that they contained an explanation concerning how the reviewers' experience was affected by fees, ending with a clear warning directed to fellow consumers. Thus, these reviews were normally longer and rich in details as they consisted of both a complaint- and warning component.

The following quotes highlight what customers have written with regards to warning others:

“DO NOT BUY TICKETS FROM THIS SITE. it's actually not worth it I am never buying tickets from here again they sent my tickets to the wrong address I got charged a bunch of fees and their customer support team is useless it's actually the biggest scam ever seriously don't buy tickets from here”

“I was cheated 1300 euros for andrea bocelli concert tickets by this website. never shop from them. i went to to concert to find out the same tickets were only 300 euros! i paid 585 euros plus a few made up charges just to scam me! they had the audacity to email me with crap like, this is for vat, this is for booking fee, this is for handling fee, bla bla bla. i know there is no bloody vat on international transactions so this was a total scam! the tickets by the organising company were on sale at the venue! for a week before! for less than one fourth the price. big cheaters!!!!!! (...)”

*“This site is **not trustworthy** at all. they say something but they do something else, this is from my own experience. whenever i buy tickets from them, they add more money to checkout so they can make their own source of income. they will even add extra charges (after buying) to send the ticket through email. I will never recommend this company to anybody at all.”*

Reviews containing a warning directed to fellow consumers expressed a feeling of decreased trustworthiness in the ticket provider, one key construct of brand reputation. On a deeper level, reviews addressed a lack of trust and low honesty by describing how the surcharge component was hidden and large in relation to the final price, tying in with the two aforementioned second order themes *Hidden Fees and Lack of Transparency* and *Deceptive Pricing Strategies and Value for Money*.

Moreover, regarding repurchase intention, reviewers explicitly stated that they would not buy tickets from the ticket provider again, connecting decreased repurchase intention with poor user experience, low information quality and seller uncertainty, all key constructs or repurchase intention.

Checkout Surprises:

Customers expressed a feeling of surprise when fees were added in the final stage of checkout. Reviewers stated that the firms in the dataset failed to be transparent with their pricing strategy. Additional costs mentioned in the reviews ranged from service charges, processing fees and delivery fees. Consequently, it is found that the surcharge component was unexpected. This is also found in the second order theme of *Hidden Fees and Lack of Transparency*.

*“(...)These tickets were **VERY pricey** so I assumed all fees were included except sales taxes. When I progressed online to payment I was shocked at the **fees** and taxes combined were another 50% of the high ticket price. If I hadn't organized a small group of friends to attend together, I would not have gone through with the purchase. And now that I have this experience, in the future I will know to watch out for the fees and I will **NOT complete a purchase if the fees are so high**.”*

4.1.1 Impact on Brand Reputation

Decreased trustworthiness and honesty were found to be a prevalent underlying subject in the reviews pertaining to ticket sales companies. However, the key construct of integrity with regards to brand reputation, was not identified in reviewers' evaluations.

Specifically, reviews highlight that their trust in the ticket sales provider decreased as a result of partitioned pricing. The common line of complaint is that reviewers expressed a feeling of being scammed and ripped off due to hidden and high fees. In turn, these aspects have a bearing on the ticket sales provider gathering worse evaluations with specific references to decreased trust. Moreover, the loss in trust does not only negatively influence brand reputation, but it also seems to indicate decreased repurchase intention as highlighted in the below review.

*The purchased tickets ended up being 3 x the standard price through this web site. **Massively ripped off**. Would **never buy through here again**. My own fault I guess for not doing thorough research. But still very unhappy. Don't trust this site, they will rip you....*

The key construct of honesty is also addressed in reviewers' evaluations. Reviewers that described the ticket sales provider as being dishonest with their pricing strategy stated that fees were hidden and that they were large in relationship to the initially advertised price. Having hidden costs seemed to decrease the perception of ticket sales company honesty, indicating that partitioned pricing negatively influenced brand reputation.

Ticket was valid and picking it up was easy. However there were a range of hidden costs which almost doubled the face value. this only became clear upon payment. I understand the need to pass on costs but would want them to be far more honest about what these were and what the actual price per ticket will be on the initial page. Over all very deceitful commercial strategy.

Consequently, a large number of reviews explicitly brought up key constructs of brand reputation in a negative manner, indicating that partitioned pricing strategies for firms within the ticket sales industry might decrease brand reputation, supporting Research Objective 1.

4.1.2 Impact on Repurchase Intention

One key aspect found in reviews was identified with regards to the connection between partitioned pricing and repurchase intention. Reviews frequently implicitly and explicitly stated not wanting to return or purchase from the company again. Specifically, customers explicitly mentioned that they never wanted to return to the ticket sales platform again due to deceptive, unreasonable and hidden fees.

The below quotes illustrate the general sentiment that repurchase intention decreased as a cause of partitioned pricing.

*"I paid more than 4 times the cost of the tickets. I made the mistake to not verify prices for the tickets on the official website. **Ripoff. Never again** will I use this site again."*

*"Total POS company. NEVER was I given a preview of total price until AFTER order. The BS charges were extreme & I would have NEVER agreed to pay them. Tried IMMEDIATELY to cancel the order & was denied by them trying to tell me that I had already agreed to what I never agreed to. Total Piece of \$H!T COMPANY. **NEVER AGAIN!!!**"*

Notably, both implicit and explicit hints to reduced repurchase intention could also be found as an underlying concept in the other second order themes above, as previously described for ticket sales companies using partitioned pricing.

Thus, it can be found that partitioned pricing within the ticket sales industry might contribute to decreased repurchase intention as the information quality, trustworthiness and perceived value was low.

However, decreased repurchase intention could not be connected to the surcharge component being described as unexpected. Consequently, Research Objective 2, further described in the end of the results section, stating that there should be a connection between fees being experienced as unexpected and reduced repurchase intention, could not be confirmed.

4.1.3 Aggregate Dimensions: Pricing and Value

As a common underlying sentiment, customers expressed significant frustration and distrust towards the firms in the dataset. Frustration and distrust are expressed within the specific context of pricing and value related complaints.

Reviews explicitly mentioned the feeling of anger, disappointment and betrayal, highlighting dishonest and deceptive pricing practices. Reviewers called for transparency and fairness in how fees are presented. Many reviews stated the desire for all costs to be clearly disclosed upfront and felt that the current policy of partitioned pricing was deceptive and decreased repurchase intention and brand reputation.

Consequently, a common underlying theme amongst all reviews (aggregate dimension) concerns pricing and value. Thus, the overarching theme that characterizes reviews for companies using partitioned pricing, within the ticket sales industry, revolves around (1) the final price being indefensibly high due to added fees in relation to the value added by the ticket sales firms, (2) that the fee structure is opaque and (3) that reviewers wrote to warn others about future usage.

4.2 Ticket Sales – All-Inclusive Pricing

Reviews from ticket sales companies using all-inclusive pricing were now analyzed and compared with the partitioned pricing dataset. In this dataset there were no complaints on non-transparent fee structures or similar topics. However, reviews from this dataset are presented to showcase the discrepancy between all-inclusive pricing- and partitioned pricing’s effect on evaluations.

Three second order themes were identified being (1) ease of purchase, (2) ticket-related issues and (3) transparency of fees. These second order themes were then concatenated to form an aggregate dimension concerning the purchasing process.

Ease of Purchase:

Customers described the purchasing process as straightforward, and that the transaction process had a positive impact on expressed satisfaction. The positive effect from ease of purchasing further strengthened the finding that average review scores were higher for companies with all-inclusive pricing compared to companies using partitioned pricing, as shown in the beginning of the results section. Examples of reviews highlighting ease of purchase can be seen below:

*“My experience was so **seamless and easy**.”*

*“Wish all of the ticketing process was as **good** as this experience was!”*

Ticket-related issues:

A central second order theme revolved around ticket-related issues. Specifically, multiple reviews brought up complaints about seating issues. Moreover, reviewers frequently complained about ticket delivery and availability. However, many reviewers also stated that customer service was very helpful.

Some example reviews are provided to highlight customer reviews concerning ticket-related issues.

*"If I could leave a 0 star I would! (...) My best friend purchased tickets for us to go see a concert that was last night being held at the Fillmore in Silver Spring, MD. He purchased these tickets a week or 2 in advance. After **fighting** with their customer service, to which will only talk to the person who **purchased** tickets and only has live chat or email no phone number, they finally email him the tickets. However, it said Fast Lane not a ticket over the QR code. When we contacted them, they said that QR code would populate our ticket when it was scanned at the venue..... what a damn joke that was!!!!"*

"WORST CUSTOMER SERVICE AND TICKET TRANSFER PROCESS EVER!

I had a friend transfer tickets to my account. While she received a confirmation email that the tickets had been sent and received by me, my account showed nothing. Called customer service each twice, each time was on hold for an hour plus and no one ever picked up. (...)"

However, multiple reviews were also thankful about customer service resolving their issues. This stands in contrast with the partitioned pricing dataset where a limited number of reviews brought up the value added by service staff.

*"trying to access transferred tickets was an absolute **nightmare**, and I accessed the live chat twice today. Khali was **AMAZING** and diagnosed my problem and corrected it in 10 minutes. I cannot **thank you enough**"*

*"Was having trouble logging into my account with phone verification but it was very easy to have a live chat to resolve my problem quickly, **thank you** to Adam S. for the help today."*

Transparency of fees:

Rather than complain about fees, reviews explicitly mentioned gratitude towards having all-inclusive pricing. Complaints found in this dataset rather revolved around the purchasing process as the overarching theme, and few complaints with regards to opaque pricing structures were made. The sentiment was different from that contained in the partitioned pricing dataset for ticket sales companies, and the transparency was generally appraised, alluding to standard practises in the industry where competitors normally use partitioned pricing.

The below quote describes how a customer experienced the purchasing process:

*"I love that there are no hidden fees and it's **easy** to use. I've gotten concert and sports tickets from the firm, and they are always official tickets. I've never had to worry about if it was a scam or fraud. I **would recommend** the firm to anyone looking for easy access to live events."*

4.3 The Hotel Industry - Partitioned Pricing

Reviews concerning pricing, fees and similar keywords were not part of the concepts and themes identified for hotel companies utilizing partitioned pricing. Reviews rather mentioned other factors pertaining to the overall hotel experience. These reviews were very context specific and lacked reactions towards partitioned pricing strategies used by the firms in the dataset. For instance, hotel reviewers were more likely to describe their experience from an overall perspective, reviewing the quality of rooms, ease of parking and other accommodation services in relation to the total price paid.

Consequently, the number of reviews expressing opinions related to partitioned pricing strategies were too few to make it constitute relevant first order themes. Thus, reviews concerning the pricing strategy could not be connected to repurchase intention for the hotel companies analyzed.

However, three other main second order themes were identified that do not link to the research question. These second order themes were (1) service quality and cost, (2) refunds and financial policies, loyalty points and rewards and (3) booking and price guarantee issues. Reviews are described to give industry specific context as a way of comparing ticket sales companies with partitioned pricing to hotel industry companies with partitioned pricing. However, reviews from the hotel companies with all-inclusive pricing are not brought up as the findings from these were inconclusive. Likewise, ticket sales companies with all-inclusive pricing did not showcase a link between pricing strategies and brand reputation and repurchase intention. Thus, no meaningful comparison can be made, and they are therefore omitted from the results section.

Service Quality and Cost:

Several reviews mentioned inadequate service, such as malfunctioning amenities and a lack of maintenance response. This led to dissatisfaction given the price paid for the hotel. For example, one review mentioned ongoing issues with a fire alarm and poor maintenance service during their stay.

*“Do not stay here! Absolutely **horrible** and **disgusting**. We arrived Friday evening 5/19 and checked in. Elevator rattled all the way up to the 6th floor. I walk into the room and there was a horrible stench of acetone or paint? Very chemical like. There were holes in the walls, stains on the floor & a weird all over stain on the balcony window. (...) there was a fire alarm going off. We tried to call down to the front desk for 10 minutes to see if it would be shut off. The phone went right to a busy tone every time before we finally **gave up**. We decided to just gather our things and check out. (...).”*

Refunds and Financial Policies, Loyalty Points and Rewards:

Customers expressed frustration over difficulties in receiving refunds. Moreover, reviews expressed being subject to unfair pricing policies. One reviewer complained about long waiting times and poor communication regarding receiving a refund check, highlighting a significant disconnect between customer service promises and actual practices.

Moreover, there were complaints about the perceived value of loyalty points. Reviews mentioned the inability to use points effectively and the overall complexity and lack of transparency in how points could be redeemed.

*“They **never helped us** get our money back from the hotel that told us they had overbooked and we had to stay at another place and **pay yet again**. Absolutely **horrible** and I do not have money to waste that way and yet you try to use them and they do not honor or help you when issues come up. **NEVER USE THEM.** (...).”*

*“(...) Their website for rewards customers, is **NO REWARD!** Set up to **scam you out of money**, make reservation following prompts to use points plus cash, at end of making reservation, it shows ALL POINTS, on their website. nothing about cash showing. called immediately..rep **refused to give refund!** told her redid reservation immediately after cancelling first one, thinking error on web, but did same thing. now card **charged** twice for 1 2 night stay!! (...).”*

Booking and Price Guarantee Issues:

Customers reported issues with overbooking and not honoring the hotels' promised rates, leading to increased costs and inconvenience. One specific review noted that their booked hotel in Nashville was overbooked and therefore failed to honor the original price when re-booking their room.

*"Do **not recommend**. They overbooked our hotel in Nashville. We didn't get a room, nor did they honor our price in finding another hotel room. **Very poor management.**"*

Thus, it is found that no second order theme, and subsequent aggregate dimension can be related to the research question with regards to the hotel industry and partitioned pricing.

These findings are confirmed when analyzing the number of reviews that contained keywords specified in figure 3 concerning fees and its impact on brand reputation and repurchase intention, in relation to the complete unfiltered dataset. 4.4% of reviews within the dataset concerning hotels utilizing partitioned pricing contained the specified keywords. In contrast, 24.3% of the dataset for ticket sales companies with partitioned pricing contained the same keywords. Consequently, it is identified that issues pertaining to partitioned pricing are not widely brought up in reviews for hotels. In contrast it seems to be a widespread topic for ticket sales companies' reviews using partitioned pricing.

4.4 Answers to Research Objectives

RO1: Companies using partitioned prices should have less favorable product evaluations than companies without partitioned pricing, resulting in a lower brand reputation than for firms using all-inclusive pricing.

Results: It was identified that reviews frequently pointed out that trustworthiness and honesty was reduced for ticket sales companies utilizing partitioned pricing.

Trustworthiness and honesty are both key constructs of brand reputation. The reviews written indicated that brand reputation decreased because of partitioned pricing strategies. Specifically, reviewers pointed out that the surcharge component was hidden and that the magnitude of it, in relationships to the initially described price, was high. These aspects made reviewers feel deceived and subject to dishonest practices.

As a comparison, there was no link between reduced brand reputation and these types of pricing strategies for ticket sales companies using all-inclusive pricing.

RO2: Consumers should state that surcharges were unexpected and that this negatively influenced their perception of the brand, decreasing repurchase intention.

Results: In the dataset containing ticket sales firms using partitioned prices, reviewers pointed out that surcharges were unexpected. Moreover, customers experienced these firms' pricing strategies as deceptive and opaque which decreased repurchase intention. However, there were not enough reviews directly expressing the linkage between the surprise effect and reduced repurchase intention to have it constitute a core finding. Thus, the thesis did not identify that surcharges were experienced as unexpected and that this directly caused reduced repurchase intention. However, in isolation the thesis found that repurchase intention generally decreased when ticket sales companies used partitioned pricing. Moreover, it was found that fees were described as surprising in isolation.

To compare, in the dataset that contained hotel firms using partitioned prices, reviewers did not mention fees or any similar aspect pertaining to partitioned pricing in

relation to brand reputation and repurchase intention. No conclusions can be made in this thesis for the hotel industry with regards to the impact of partitioned pricing.

4.5 Concepts and Themes Overview

Below is an overview of all relevant concepts identified in the filtered dataset.

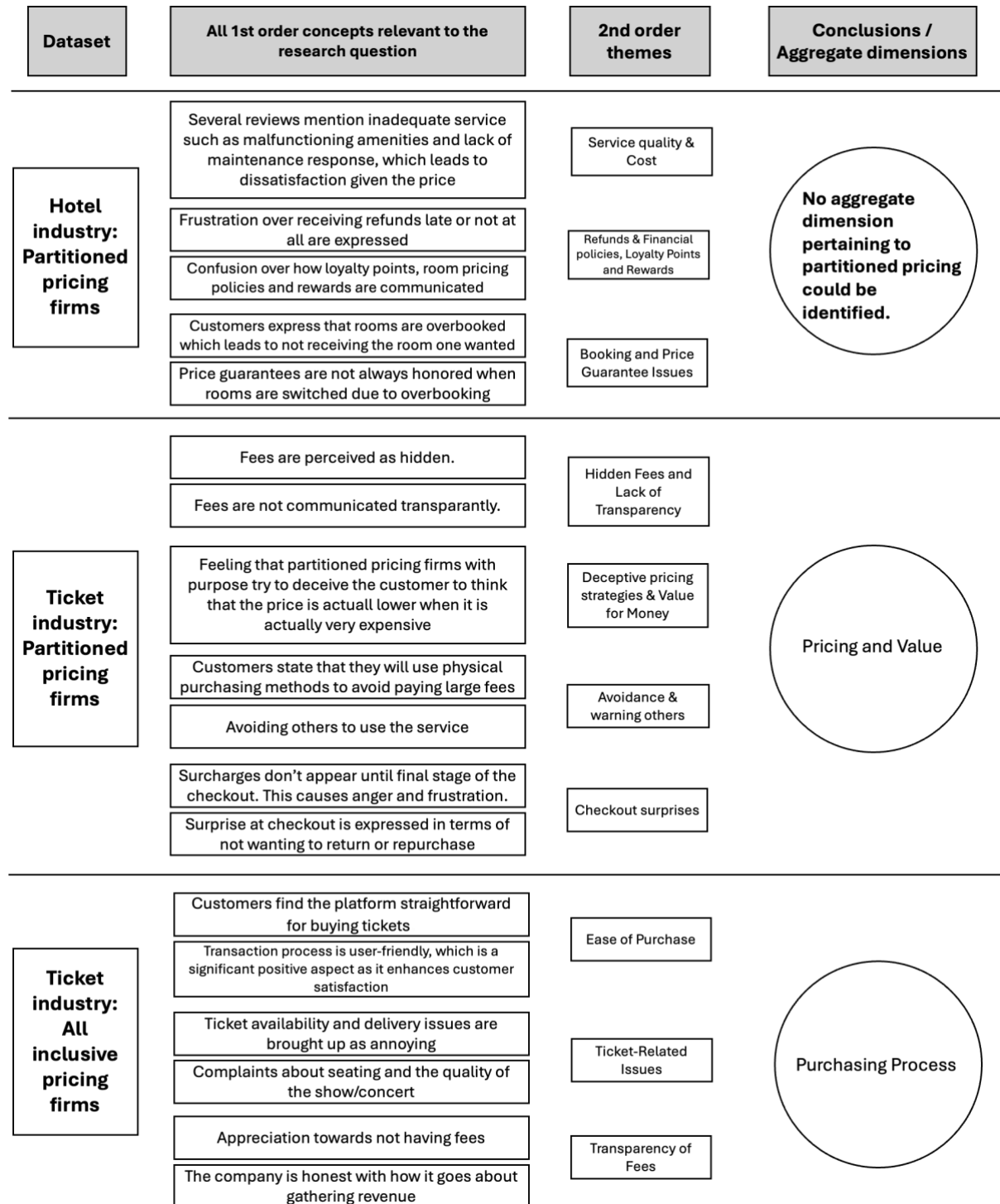


Figure 3. Theme overview

5. Discussion

The below discussion aims to address the research question: How does partitioned pricing strategies affect consumers repurchase intentions and brand reputation?

First, the study's results are discussed along with previous theoretical findings. Then, future research directions are brought up. Subsequently, a methodological discussion is held followed by research limitations and managerial implications. The discussion section ends with a general conclusion summarizing the findings of this thesis.

5.1 Theoretical Discussion

This paper found that partitioned pricing negatively influenced brand reputation for firms within the ticket sales industry employing the strategy. This finding is in line with Voester (2008), who indicates that partitioned pricing has a negative effect on brand reputation if customers notice that they underestimated the final price compared to the initially shown price. Specifically, the content in the reviews analyzed within the ticket sales industry with partitioned pricing can be connected to price underestimation. For one, customers express surprise when fees were added in the final stage of checkout. This frustration was expressed within the context of a negative feeling adhering to additional unexpected fees. However, Voester's (2008) research found that the negative effect comes only when the customer notices that they underestimated the final price. In this thesis, the concept of noticing the underestimation comes from the prevalence of negative reviews specifically containing complaints on fees. Reviewers have actively visited Trustpilot to write negative reviews about fees, indicating that they (1) notice them and (2) are angered by them. Out of the four second order concepts identified, within the ticket sales partitioned pricing dataset, two specifically contained themes concerning hidden fees as well as deceptive pricing strategies. With regards to this, customers either expressed the desire to (1) have the final costs displayed up front and/or (2) go one step further and warn others to do business with the companies in the dataset. Thus, the thesis found that customers noticed that they underestimated the final price and then went ahead to complain loudly in the post purchase evaluation phase.

This finding can be compared to the finding within the dataset that contained all-inclusive pricing for ticket sales companies, where many reviews expressed positive remarks pertaining to the transparency of fees. As established, utilizing partitioned pricing rendered negative evaluations from firms within the ticket sales industry. However, reviews for ticket sales companies using all-inclusive prices were not only neutral to the fee aspect. Rather, customers often gave praise concerning transparent pricing. This indicates a “double whammy effect” where firms using partitioned pricing got lower ratings whilst companies using all-inclusive pricing gathered increasingly positive remarks.

Moreover, customers expressed that surcharges were unexpected within the ticket sales industry dataset with partitioned pricing. This paper's findings could partially be explained and connected to the anchoring effect (Tversky & Kahneman, 1974). Customers expressed surprise when being faced with the partitioned price component, which indicated that they focused on an initial reference point, being the initially presented price net of surcharges. Moreover, Morwitz et al. (1998) showed that a substantial share of customers disregarded the surcharge component completely when being asked to recall the final price. Thus, being reminded of the surcharge component might then render a surprise reaction.

5.2 Future Research Directions

5.2.1 Repurchase Intention, Brand Reputation and Customer Lifetime Value

This study finds that repurchase intention declined when firms used partitioned pricing within the ticket sales industry.

The model built by Chen (2023), finding that profits increased when using partitioned pricing, does not, along with other studies, consider the impact of customer lifetime value. Decreased repurchase intention could decrease customer lifetime value even if short-term conversion increases. Dellorcas, Zhang & Awad (2007) have previously identified that review valence could predict future sales. Likewise, Zhang (2014) and Gottshalk & Mafael (2022) found that online reviews affected customers' purchase decisions. Thus, low

company ratings with negative review valence could decrease future sales. This thesis found that companies with partitioned pricing had lower ratings on Trustpilot. The valence of reviews for these companies were often negative, as a large number of reviews within the partitioned pricing dataset included negative opinions concerning fees. Thus, it could be theorized that utilizing partitioned pricing could decrease long-term firm profits. However, Young (2016) and Monticello (2021) found that partitioned pricing strategies are becoming more common, indicating that companies see value in utilizing it as a conversion tool.

On this point Xia & Monroe (2004) and Morwitz et al. (1998) found that partitioned pricing increased demand. However, these studies again focused on one-time conversion behavior, leaving long-term effects undiscovered. Contrary to the aforementioned, our study indicates that repurchase intention decreased for ticket sales companies when these firms used partitioned pricing, decreasing long-term demand. Along with our findings, Bertini & Wathieu (2008) found that prospect theory and the risk of incurring multiple losses should have negative effects on purchasing behavior.

Consequently, there exists a need to further understand the discrepancy between short-term and long-term effects on demand, profit and repurchase intention concerning partitioned pricing strategies. Although this thesis does not elaborate on the direct financial impacts of undertaking partition pricing practices, the increase in negative online review sentiments and ratings exhibited in this paper could potentially be mediated through eWOM and have negative profit impacts long-term. Future research could consequently investigate if potential discrepancies between long-term and short-term profits/conversion behavior arise from partitioned pricing strategies.

5.2.2 The Hotel Industry

This study found that partitioned pricing negatively influenced brand reputation and repurchase intention for companies utilizing partitioned pricing within the ticket sales industry. However, reviews did not contain complaints adhering to partitioned pricing within the hotel dataset. Morwitz et al. (1998) stated that a large number of customers

completely disregarded the partitioned price component when being asked to recall the final price. Along with this finding, it could be further studied why partitioned pricing did not come up as a central second order theme in the hotel dataset. Studies could, for example, analyze the main differences in the underlying service and products rendered between the hotel and ticket sales industries. The amount of customer touchpoints with a hotel company is greater than for a ticket sales provider, potentially making factors beyond price more important to the overall perception of a hotel company. Examples of critical touch points could be hotel breakfast, valet parking and similar. In contrast, the only touchpoint with a ticket sales company is at the point of purchase, making the sole customer impression of the firm based on transactional characteristics, where the price is central. Future research could then compare the number of touchpoints with the importance of price, having separate datasets for companies using all-inclusive pricing and partitioned pricing respectively.

5.2.3 Company Side Analysis

This thesis, along with previous studies, has predominantly focused on the effects of partitioned pricing from the perspective of customers. As partitioned pricing seems to be pervasive (Young, 2016 and Monticello, 2021), there exists a need to further understand what drives companies to use partitioned pricing, even though it seems to render negative online reviews, having an unfavourable effect on brand reputation through eWOM. One potential reason could relate to the findings of Chen (2023) indicating that partitioned pricing rendered higher profits for the firm. The goal of future research could then be to examine whether this effect persists over time, comparing the financial performance of partition pricing and all-inclusive firms.

5.2.4 Broadening Industry Selection

This thesis is limited to the hotel and ticket sales industries as partitioned pricing strategies are highly prevalent in these markets (Zhang & Tang, 2024 and Marquez, 2020). However, to broaden conclusions and mitigate potential company- and industry specific biases, a larger number of industries could be studied and compared with each other using a similar qualitative methodology as in this thesis.

5.3 Methodological Discussion

This thesis aims to provide methodological contributions to Gioia & Corley (2013) by showcasing how their qualitative research methodology can be scaled with the support of GAI. Specifically, this thesis demonstrates the application of GAI to derive textual datasets that are relevant to the focal research topic, by filtering scattered data based on theoretically relevant keywords. In turn, problems with decoding rich data can be circumvented, enabling qualitative researchers to efficiently process large volumes of textual data gathered from the web using web-scraping techniques.

As argued by Zhang (2023), capabilities of GAI as a research tool will decrease the effort exerted by qualitative researchers moving forward, paving the way for new research discoveries to be made at a greater pace and scale than before. Furthermore, the combination of web-scraped data and GAI, used in this study, exemplifies a lean set-up for examining phenomena embedded in web-based text. This approach could unlock new research frontiers which have previously been difficult to access. For instance, language barriers that may have led to research biases, favouring English-written textual data, are now eliminated, enabling higher inclusivity.

On the other hand, discussions concerning transparency and credibility of LLM output will arise along the way. The method used in this thesis mitigates the GAI “Black Box” by introducing manual cross-checking of the filtered datasets provided by the model. However, as concluded by Zhang (2023), there is a need for additional methodological GAI research exploring the use of LLMs for more analytical tasks where the “Black Box” currently hinders the acceptance of LLMs as a co-researcher.

5.4 Research Limitations

Although the incorporation of ChatGPT4 in this study is made with multiple proactive measures suggested by Morgan (2023), some limitation of LLM computational transparency remains. Since the public release of ChatGPT4, the main critique directed towards OpenAI has revolved around the "Black Box" environment in which the model operates. The lack of openness regarding the training datasets that the LLM has been subject to, alongside the inability to objectively derive if the output primarily has been influenced by pre-trained knowledge, imported datasets or the human prompts, makes the validation complex. Thus, we cannot be certain that the LLM left out a small number of reviews when filtering the dataset with definitions, constructs and key words. However, as the output data was comprehensive the materiality of this risk is low.

Moreover, with regards to the theoretical findings, the inconclusive results from the analysis of partitioned pricing companies within the hotels industry makes the overall conclusions of this paper primarily based on observations made within the ticket sales industry. Thus, this thesis findings could pose the risk of industry specific biases, and additional research would be required to draw conclusions in line with the research question on an aggregate level for multiple industries as highlighted in the future research directions section.

5.5 Managerial Implications

On a high level, this thesis found that managers should seek to avoid using partitioned pricing strategies from a brand reputation and repurchase intention perspective. If managers, however, decide to utilize partitioned pricing there are several guidelines to adhere to, even though this study found that it had negative effects on brand reputation within both industries studied, and negative effects on repurchase intention within the ticket sales industry. Previous findings from Xia & Monroe (2004) suggests that the surcharge percentage of the final price shall be minimized. Moreover, managers should be mindful that the surcharge should be considered relevant and clearly relate to a service area where customer value is provided, in order to not decrease purchase intention (Hamilton & Srivastava, 2008). Additionally, managers shall seek to minimize the number of surcharges. Increasing the number of specific surcharges decreased purchase intention (Xia & Monroe, 2004).

5.6 Conclusion

This thesis firstly identified that the use of partitioned pricing within the ticket sales industry negatively influenced brand reputation for companies within ticket sales industry. Reviewers experienced decreased trust in the ticket sales companies using partitioned pricing. Moreover, having high and hidden fees resulted in customers perceiving that the firms were dishonest, lowering brand reputation. Secondly, it was identified that repurchase intention was negatively influenced when firms within the ticket sales industry used partitioned pricing. However, the decrease in expressed repurchase intention, coming from reviews with statements containing “never again”, “will not return” or similar keywords, did not arise from surcharges being experienced as unexpected. There was not a large enough number of reviews expressing this direct link. Moreover, the effect of reduced brand reputation and repurchase intention was not found within the hotel industry. Rather, customer reviews focused on other aspects pertaining to the overall hotel experience.

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Appendix 1 - Prompts

The following prompt was used to check that the dataset had been successfully uploaded to the environment:

Prompt: “Please provide an overview of the dataset”

As a response the model provided a list of all columns present in the dataset, showcasing that the dataset was successfully loaded, and the model had received an opportunity to familiarize with the data before the interaction with the dataset was initiated. The output also displays that no personal reviewer data was fed into the model, highlighting another important aspect mentioned by Morgan (2023) in respect to LLM data privacy protection.

ChatGPT4 output:

The dataset you've provided contains online customer reviews with the following fields:

1. **name:** The name of the identity being reviewed.
2. **trust_score:** A trustworthiness score for the entity.
3. **star:** A star rating for the entity.
4. **address:** The location of the entity (e.g. United States).
5. **categories:** The type of business or service category (e.g. ticket sales).
6. **reviewer_country:** The country of the reviewer.
7. **reviewer_title:** The title of the review.
8. **reviewer_review:** The full text of the review.
9. **reviewer_rating:** The rating given by the reviewer.

The prompts used were constructed in accordance with the prompt component framework by Zhang et al. (2023).

Prompt components:

- (A) A background description of the task,
- (B) The core description of the task,
- (C) A description of how the task shall be processed,
- (D) The expected output of the task.

Prompt

[A]

Here are the theoretical definitions of “Repurchase Intentions” and “Brand Reputation”, together with a list of related constructs:

Brand Reputation Definition: "The consumers opinion of a brand that is constructed using an evaluation process based on the brand's identity, the company's promises and the consumers holistic experience with the brand."

Related constructs to Brand Reputation: Trustworthiness, Integrity, Honesty

Repurchase Intention Definition: "The individual's judgment about buying again a designated service from the same company, taking into account his or her current situation and likely circumstances"

Related constructs to Repurchase Intentions: Reputation, Familiarity with the vendor, Satisfaction, Product characteristics, Trust, User experience, Information quality, Perceived value, Brand equity, Seller uncertainty.

[B]

I would like you to filter out reviews expressing terms and phrases indicating customer repurchase intention as well as statements made having an impact on the reputation of the firm.

[C]

The filtered reviews shall contain the keywords presented in the list below. However, you are also allowed to include reviews based on their context adhering to the theoretical definitions and constructs above.

Keyword list: **See figure 3.**

[D]

Include reviews containing both upper- and lowercase variations of the keywords, and make sure to remove potential duplicates in your output. The output shall be presented in a new CSV file, ready to be downloaded.

Appendix 2 – Data Structure

The below table showcases the data structure of the dataset used, containing reviews gathered from Trustpilot for eight companies within two industries.

1. product_url : URL of the product review.
2. name : Name of the product or service.
3. number_of_reviews : Total number of reviews.
4. trust_score : Trust score of the product or service.
5. website : Website URL of the product or service.
6. star : Star rating.
7. email : contact email (left blank).
8. phone : Contact phone number (left blank).
9. address : Address of the business.
10. categories : Categories of the product or service.
11. reviewer_name : Name of the reviewer.
12. reviewer_country : Country of the reviewer.
13. reviewer_published_date : Date when the review was published.
14. reviewer_title : Title of the review.
15. reviewer_review : Text of the review.
16. reviewer_rating : Rating given by the reviewer.
17. url : URL of the review.
18. timestamp : Timestamp of the dataset entry.

Table 3. Dataset structure

Appendix 3 – Reviews

5 570 reviews were analyzed as shown in table 4 and 5.

Partitioned Pricing			All Inclusive Pricing		
Firm	Number of Reviews	Industry	Firm	Number of Reviews	Industry
Ticketmaster	762	Ticket Sales	AXS	579	Ticket Sales
Viagogo	1 435	Ticket Sales	TickPick	599	Ticket Sales
Marriott Bonvoy	674	Hotels	Scandic	397	Hotels
Choice Hotels	504	Hotels	Accor	620	Hotels
Sum	3 375	-	Sum	2 195	-

Table 4. Review count overview

Ticket Sales		Hotels	
Firm	Number of Reviews	Firm	Number of Reviews
AXS	579	Marriott Bonvoy	674
TickPick	599	Choice Hotels	504
Viagogo	1 435	Scandic	397
Ticketmaster	762	Accor	620
Sum	3 375	Sum	2 195

Table 4. Industry overview

Appendix 4 – Usage of Artificial Intelligence Tools

The below text outlines how AI has been used in this thesis and is mandatory to include according to SSE guidelines.

What AI tools have been used and how?

This thesis has used ChatGPT4 to undertake textual filtering based on keywords and constructs of reviews gathered from Trustpilot. Moreover, a minor sentiment analysis was undertaken by ChatGPT4. For further details and justification on the usage of AI tools, please see the Method section in the thesis.

Along, AI was used to check spelling and sentence building as well as to generate references.

In what ways have these tools contributed to increasing the quality of the thesis?

The AI tools, i.e. ChatGPT4, used in the thesis, has contributed by filtering text in the form of reviews. AI has allowed the study to include a larger number of reviews (5 570) than would be possible if manual textual analysis had been undertaken. Thus, AI has contributed to increase the sample size of our study and reduced the risk of human biases and shortcomings. Moreover, AI has improved language and aided with the otherwise time-consuming process of writing complete references.

What potential risks were found using AI and what measures were taken to reduce these risks?

Potential risks with using AI and the study's correctionary measures can be found in the Method section as outlined by Zhang et al. (2023) and Morgan (2023).

What are the insights gained from using AI tools in the thesis writing process?

AI was helpful by filtering reviews based on keywords and constructs to allow for scaling the number of reviews analyzed. All other data analysis was manually undertaken.