Towards More Convenient Services: A Text Analytics Approach to Understanding Service Inconveniences in Digital Platforms

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Abstract

In today's fast-paced world, where time is our most valuable asset, convenience is on the rise. This trend has led to a huge growth in digital on-demand services, which target convenience-oriented consumers. Using big data and text analytics, we examine the impact of service inconveniences on customer satisfaction in the context of on-demand food delivery. Building on the Model of Service Convenience and Attribution Theory, we analyze 235,147 user-generated reviews via a combination of keyword-assisted topic modelling and cumulative link model analysis. We introduce the concept of Remote support inconvenience and identify the key topics related to each inconvenience. We find that all service inconveniences negatively influence satisfaction (especially cancelled orders and remote support incidences), and the effects are exacerbated when moderated by stability or controllability attributions. These insights contribute to our theoretical understanding of service inconvenience and can help platforms identify and improve critical areas of their services.

Keywords: service inconvenience, service failure, attribution theory, on-demand services, big data analytics.

1. Introduction

From one-click ordering to 10-minute home deliveries, today's busy consumers expect convenience in every part of their service experiences. A recent study that surveyed 2,949 U.S. adults found that over 9 in 10 consumers are more likely to use a service if they find it convenient (National Retail Federation, 2020). Since the start of the COVID-19 pandemic, this tendency toward purchasing more convenient products and services has intensified even further. Due to lockdowns, online shopping and home deliveries became essential services, and their popularity skyrocketed. Consequently, many consumers continue to prefer the comfort of online purchases and home deliveries even after the end of mobility restrictions (Wang et al., 2021). As a response to these needs, on-demand service platforms (such as food delivery apps) allow customers to consume a service whenever they experience a need, anywhere and anytime (Taylor, 2018). Given the relevance of convenience from the consumers' perspective, service inconveniences can be very costly for companies. In fact, up to 97% of consumers in the aforementioned survey had backed out of a purchase because it was inconvenient to them, and 52% said that half or more of their purchases are influenced by convenience (National Retail Federation, 2020). Therefore, it is crucial to understand how consumers perceive service inconveniences and which types of inconvenience are more critical in on-demand services.

When customers face an inconvenience in a service encounter, they typically want to understand what caused the problem. Human beings are naturally inclined to look for the causes of the things that happen to them, especially in the case of negative events (Weiner, 1985). Against this backdrop, attribution theories aim to explain how individuals perceive and determine the causes of other people's actions. According to Weiner (1985), our causal attributions of negative events (such as service inconveniences) can have an impact on our emotional and cognitive responses. For instance, customers may feel more disappointed if they cannot attend a music festival because a company sold them fake tickets than if the event is cancelled because of poor weather conditions. In both cases, customers experience a service failure, which is defined as a service experience that does not fulfil the customer's expectations. Thanks to attribution theories, there have been major advances in service failure research (van Vaerenbergh et al., 2014). Nevertheless, there are at least three aspects that previous studies in this field have thus far not addressed.

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First, existing research on customer attributions of service inconveniences (a particular type of service failure) is very limited, even though research in this area is much needed. Service inconveniences can be defined in terms of the customer's time and effort that they perceive as "wasted" during a service experience (Berry et al., 2002). In a society that has gradually shifted towards more convenient products and services (Sheth, 2020), understanding how customers perceive service inconveniences is of utmost importance. This study aims to address this gap by exploring customer attributions of service inconveniences in on-demand food delivery services. To this end, the different types of inconvenience conceptualized were based on the classification proposed by Berry et al. (2002) in their Model of Service Convenience.

Second, although attribution theories have been widely applied in service research, they have been tested predominantly in an experimental setting, as opposed to analyzing consumers' feedback from their real experiences. For example, a common approach has been to ask participants how they would react in a hypothetical service encounter. Unlike traditional surveys and experiments, user reviews and ratings are not affected by "laboratory" effects, as they are posted spontaneously and voluntarily. For this reason, user-generated reviews are increasingly becoming regarded as a valuable tool to capture users' or consumers' real thoughts and generate marketing insights (Huang et al., 2021). Consequently, the current study uses text analytics to explore thousands of reviews that describe the real-life service experiences of food delivery consumers. In particular, we test the application of attribution theory in explaining the effect of inconvenience attributions on consumer satisfaction.

Third, even though several studies have analyzed how service failure attributions affect customer satisfaction, most research has focused on the failures that occur in the core service (e.g., Hess et al., 2003). The core service refers to the basic benefit that the customer receives, such as a meal in a restaurant or a haircut in a hair salon. In this research, we study the attributions of service inconveniences and their impact on satisfaction at different stages of the customer journey, including pre- and post-benefit phases. In this way, we determine which stages are more critically exposed to inconvenience attributions. These insights can help companies to identify the areas in which they need to focus their efforts to improve their services and attract convenience-oriented consumers.

Aside from addressing these three gaps in the literature, this research provides an original contribution in terms of the methodology it applies. Through a combination of keyword-assisted topic modeling and cumulative link model analysis, we measure specific constructs and analyze their effects. Our approach can be implemented to test theoretical frameworks based on user-generated content. This answers the call for the use of more advanced approaches based on text analytics to obtain theoretical insights in the field of business and marketing (Huang et al., 2021).

The main aim of the research is to analyze how service inconveniences and their attributions impact consumer satisfaction in on-demand food delivery services. More specifically, the following research questions (RQ) are investigated:

- **RQ1**: What effect does each type of service inconvenience have on consumer satisfaction?
- **RQ2**: How do causal attributions moderate the effect of each type of inconvenience on consumer satisfaction?

The structure of the paper is as follows. The literature review section explains the underlying theory, develops the hypotheses, and presents the research model proposed in the study. The third section describes the research process and methodology applied. Section four details the empirical results of the analysis. Finally, the last section discusses the results of the research, providing implications for theory and practice.

2. Literature review

2.1. Convenience and on-demand services

According to Berry et al. (2002), service convenience refers to the consumer's perceptions regarding the amount of time and effort necessary to purchase or use a service. Due to several socioeconomic developments and technological advances, there has been a constant growth in the demand for more convenient products and services. This trend has been documented for decades, but it was exacerbated by the COVID-19 pandemic lockdowns in 2020, when online shopping and home deliveries grew exponentially (Wang et al., 2021).

The increase in consumers' expectations of convenience and immediacy has driven companies to adopt on-demand service models. In contrast to scheduled services, which must be booked in advance, on-demand services allow customers to immediately satisfy their needs, anywhere and anytime (Taylor, 2018). The key characteristics of on-demand services are their high availability, responsiveness, and scalability, which can be achieved thanks to technological advances (Taylor, 2018). Some examples of this type of service include ride-hailing services (e.g., Uber) as an alternative to scheduled public transport or video streaming services (e.g., Netflix) as a replacement for cinema movies.

Another example of this phenomenon can be observed in food delivery services, which attract convenience-oriented consumers worldwide. According to McKinsey & Company, food delivery revenues have more than tripled since 2017, reaching a global market valuation worth more than $150 billion (Ahuja et al., 2021). A significant part of this growth occurred during the pandemic lockdowns of 2020. During this period, food delivery was often the only way that restaurants could continue serving their customers. As a result, many people became accustomed to the convenience of having food delivered to their doors (Sheth, 2020). Considering the sector's growth and the importance of convenience in this type of service, food delivery platforms were selected as the focus of this study.

2.2. Assessment of service convenience

Following the growing popularity of convenience-oriented services, several studies have proposed frameworks to evaluate the dimensions, antecedents, and consequences of service convenience. One of the first and most well-known conceptualizations of this construct is the Model of Service Convenience introduced by Berry et al. (2002). In their comprehensive analysis, Berry et al. presented different types of convenience based on consumers' perceptions of time and effort costs:

- *Decision convenience*: Time and effort necessary to decide whether to use a service or not, as well as to choose among competing services.
- *Access convenience*: Time and effort necessary to initiate service delivery.
- *Transaction convenience*: Time and effort necessary to conduct a transaction or payment to use or purchase a service.
- *Benefit convenience*: Time and effort necessary to experience the service's core benefit.
- *Post-benefit convenience*: Time and effort necessary to re-initiate contact with the service provider.

Building on this conceptual framework, Seiders et al. (2007) developed and validated a multidimensional scale of service convenience, which they named SERVCON. Their scale, which was tested via a survey of 705 retail customers, contained 17 items to measure each one of the five dimensions proposed by Berry et al. (2002). For instance, Access convenience was evaluated through items such as "convenient parking" or "convenient store hours". On the other hand, Lai et al. (2014) studied how SERVCON could be adapted to the context of e-shopping. By conducting a survey of 304 online shoppers, they defined a 14-item scale to assess e-commerce service convenience, EC-SERVCON (Lai et al., 2014). More recently, Vyt et al. (2022) conducted a survey of 1078 Click & Collect (C&C) consumers and presented an instrument to assess convenience in this setting. C&C represents a "hybrid" type of service encounter, where clients order products online and then collect them afterwards in a physical store. For this reason, the scale designed by Vyt et al. (2022) evaluates both traditional and digital convenience.

These studies proposed item-level variations to measure each construct of service convenience, adapting them to different sectors and contexts. However, the fundamental dimensions of the model to assess service convenience remained the same (or very similar) to those originally introduced by Berry et al. (2002).

Even though previous research has analyzed service convenience in different sectors, very little is known about how it is perceived by users of on-demand digital platform services. By the same token, existing research has evaluated customers' perceptions of service convenience based on interviews and surveys. Thus, user-generated content (such as service reviews and ratings) remains unexplored as an alternative source of consumer insights.

2.3. Attribution theory, service failure, and service inconveniences

The goal of attribution theories is to explain how humans perceive or infer the causes of other people's behaviors (Kelley & Michela, 1980). One of the most well-known attribution theories is Weiner's three-dimensional model (1985), which proposed that individuals assess the causes they perceive via the following dimensions:

- *Locus of causality*, which depends on who is perceived as responsible for the outcome.
- *Stability*, which refers to how constant over time the outcome is perceived to be.
- *Controllability*, which reflects the extent to which the outcome is regarded to be under the control of the agent causing the event.

In the context of service failure research, the attributions related to the locus dimension are not as relevant as the ones linked to stability and controllability experiences (Hess et al., 2003; van Vaerenbergh et al., 2014). The reason is that service failures are inherently caused by the service provider. Given that this study aims to analyze customers' reactions to service inconveniences caused by the provider, we will focus solely on stability and controllability attributions.

Attribution theories have been applied widely to understand how consumers evaluate the causes of service failures. Studies show that service failures (related to the service's core benefit) have a negative impact on customer satisfaction (Hess et al., 2003). Most of the existing service failure research has focused on analyzing attributions of failures related to the service's core benefit, known as outcome failures. Outcome failures occur when there is a problem related to the core benefit (e.g., a meal is served cold), whereas process failures happen when there is an issue with the service delivery (e.g., the restaurant' seats are uncomfortable). The process of service delivery consists of several phases, and each phase can be associated with different process failures, which could have distinct effects on customer satisfaction. To the best of our knowledge, existing literature does not address this issue. As a result, the effects on customer satisfaction of different types of process failures are unclear.

Building on the Model of Service Convenience, we conceptualize the different types of service inconveniences associated with each stage of the customer journey. Service inconveniences are a particular case of service failures in which the customer feels that their time and effort have been wasted (Berry et al., 2002). The research related to service inconveniences and their consequences is very scarce, but different types of service inconveniences have been linked to customer dissatisfaction. For instance, service processes that inconvenience customers through long delays may lead to them feeling unsatisfied with the service experience (Danaher & Mattsson, 1998).

When customers are dissatisfied with a particular service provider, they often react by posting a negative review and/or low rating on the provider's online platform (Nam et al., 2020). For this reason, user ratings and reviews are regarded as a useful way to capture the customer's degree of satisfaction with a product or service (Guo et al., 2017). Considering these aspects, this study uses text mining techniques to examine user reviews and analyses star ratings posted by consumers to measure their overall satisfaction with a service. In our analysis, we expect that:

H1. Service inconveniences will be negatively and significantly related to satisfaction.

Furthermore, previous research on service failures indicates that attributions of stability are negatively related to the customer's overall satisfaction (Vázquez-Casielles et al., 2007). In other words, customers seem to be less satisfied with the service provider if they feel the failure was caused by a persistent problem. In addition, stability attributions are also linked to negative word-of-mouth intentions (van Vaerenbergh et al., 2014). Thus, we posit:

H2. Stability attributions will negatively and significantly moderate the relationship between service inconveniences and satisfaction.

Regarding controllability attributions, customers are more likely to experience negative emotions (such as anger) when they perceive that the service firm could have prevented a failure (Folkes, 1984). Consequently, service failures that are perceived as controllable are negatively related to overall customer satisfaction. Moreover, when a service failure is believed to be controllable, customers express higher negative word-of-mouth intentions and higher complaint intentions (van Vaerenbergh et al., 2014). Hence, we propose the following hypothesis:

H3. Controllability attributions will negatively and significantly moderate the relationship between service inconveniences and satisfaction.

Based on the above hypotheses, our proposed conceptual model is shown in Figure 1. The model indicates how service inconveniences, stability and controllability directly or indirectly impact upon consumer satisfaction in the context of on-demand service platforms.

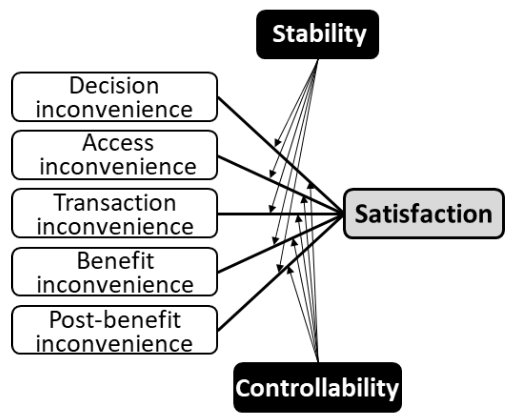

Figure 1. Conceptual model.

3. Methodology

This section describes the methodology applied in the current study, which uses topic modeling algorithms and cumulative link models to analyze user reviews and ratings from food delivery applications. First, data was collected and pre-processed. Second, exploratory data analysis was conducted. In particular, relevant keywords were identified and organized into dictionaries, which were necessary for the topic modeling analysis. Subsequently, keyword-assisted topic modeling was used to measure the constructs proposed in the research model. Finally, the impact of these constructs on consumers' star ratings was assessed through cumulative link model analysis (to test the study's hypotheses).

3.1. Data collection

The dataset used in this study was extracted from Google Play using web-scraping techniques. Based on their significance (number of installs), five leading food delivery apps were selected: Uber Eats, Grubhub, Postmates, Deliveroo, and Foodpanda. Using a Python script, a total of 469,555 reviews were collected in July 2021. The average rating was 2.6 stars (Std. Dev. 1.53; Std. Err. 0.003; Kurtosis -1.39; Skewness 0.34). In order to target reviews written in English, a country filter was applied to collect reviews from the United States (non-English reviews were removed later, during the pre-processing stage). The data that was processed did not contain any personally identifiable information.

3.2. Data pre-processing

Due to the unstructured nature of user-generated content, it is necessary to pre-process text so that it can be analyzed via text mining techniques. Among other pre-processing steps, we applied a language-detection filter to exclude non-English reviews, eliminated punctuation and common English stop words, and removed reviews shorter than 10 words. After completing the pre-processing stage, the dataset consisted of 235,147 reviews.

3.3. Exploratory data analysis

In order to conduct exploratory data analysis, WordStat 9.0 (Provalis Research, 2022) was used. WordStat is a text mining software package designed to process large quantities of unstructured data. One of WordStat's key features is its topic analysis module, which can be used to quickly obtain an overview of the most salient topics from a collection of documents. Using this functionality, the main topics in the corpus were identified, together with the most relevant keywords for each topic. To interpret and validate the topic model, we extracted the most representative reviews for each topic. As a result, we found that all the topics were negative, except for one, which was related to keywords commonly found in positive reviews (such as "like", "love", or "best"). The latter topic was excluded, given that this research focuses on service inconveniences. The last column in Table 1 (Topic's source) identifies the themes detected by WordStat.

The exploratory approach outlined is only able to detect the most frequent themes, and it does not provide a document-level topic distribution. Consequently, some of the research model's constructs could not be detected with this technique. Even though these constructs were not reflected in the most popular topics in the corpus, they could be observed when reading some of the reviews in the dataset. Hence, a more advanced technique was necessary to: (i) identify more subtle topics (related to certain constructs) and (ii) measure the importance of each construct in each review. To address these needs, keyATM (a Keyword-Assisted Topic Modeling tool) was selected to conduct a more in-depth analysis of the reviews. As its name suggests, one of the necessary inputs to run keyATM is a set of user-defined keywords that represent each one of the constructs to be measured (dictionaries).

Given that WordStat also provides unique assistance for dictionary building, it was used to gather the most representative seed words for each construct. Seed words were extracted from target reviews in the corpus, and then synonyms associated with constructs (and other related words) were added to each dictionary in WordStat's 'dictionary builder' module. As a result, 270 words were captured and included in the dictionaries. Table 1 shows the distribution of terms for each construct, along with examples. The number of words in each construct's dictionary ranged from 10 to 37.

Interestingly, a new type of service inconvenience (Remote support inconvenience) emerged when analyzing the most frequent topics. This dimension refers to the time and effort spent by consumers when they require remote assistance (e.g., via live chats, chatbots, and outsourced call centers) from the firm's customer support area. To the best of our knowledge, this construct does not appear in the original Model of Service Convenience (Berry et al., 2002) nor in any of the model's later versions. On the other hand, the following (more subtle) concepts were measured through keyATM: Payment process issues, Order cancelled, Reordering process issues, Stability and Controllability.

3.4. Construct measurement

The next step in the process was to obtain a document-level measurement of each one of the proposed constructs, which can be achieved through topic modeling. In the field of natural language processing, a topic model is a type of probabilistic model that can be used to detect latent semantic structures (topics) that occur in a text corpus (Blei, 2012). Latent Dirichlet Allocation (LDA) is one of the most well-known unsupervised topic modeling techniques (Blei, 2012). Despite its advantages and popularity, LDA has certain limitations when it comes to measuring specific concepts in a text corpus (Eshima et al., 2020). The main reason is that LDA prioritizes generalizing across more prominent themes, frequently overlooking more specific and subtle topics. This characteristic may make it difficult to appropriately measure particular concepts.

However, a new extension of LDA known as Keyword-Assisted Topic Modeling (keyATM) can overcome this limitation (Eshima et al., 2020). Being a semi-supervised approach, keyATM allows researchers to label topics by incorporating seed words of their choice before fitting the model. Empirical evidence demonstrates that providing these seed words improves the model's performance and measurement potential (Eshima et al., 2020). Through crowd-sourced validation and comparison with human coding, researchers found that keyATM outperformed LDA in several areas.

KeyATM calculates each topic's relevance in a particular document and expresses it as a percentage. A high topic weight of "Topic X" in a specific document reflects a greater likelihood that the document is related to "Topic X". In this study, the dictionaries prepared with WordStat (see Table 1) were used as an input for keyATM. Each dictionary contains seed words that represent each one of the concepts of interest. As a result, keyATM provided a document-level measure (as a percentage) of the constructs proposed in the study's research model: Stability, Controllability, and the different types of service inconvenience identified. The "Topic prevalence" column in Table 1 shows the average weight (%) of each topic in the corpus. This percentage adds up to one for each document in the dataset.

Table 1. Constructs, topics, and distribution of seed words for each construct and topic, including examples.

Construct	Construct topic	Responsible actor	No. of keywords	Example dictionary items	Topic prevalence	Topic source
Decision inconvenience	*Lack of restaurant options*	Platform	28	"restaurant", "area", "available", "choice"	14.22%	Wordstat
Access inconvenience	*Lack of app features*		17	"app", "button", "option", "feature"	14.15%	Wordstat
	Technical issues in the app		20	"bug", "error", "fix", "glitch"	5.93%	Wordstat
Transaction inconvenience	*Payment process issues*		15	"accept", "payment", "bank", "card"	4.80%	keyATM (Proposed by authors)
	Discount code issues		28	"discount", "redeem", "code", "voucher"	5.69%	Wordstat
Benefit inconvenience	*Delayed delivery*	Restaurant/ Platform	25	"hour", "minute", "wait", "delivery"	15.82%	Wordstat
	Driver interaction issues	Driver	20	"driver", "delivery", "guy", "rider"	7.67%	Wordstat
	Order cancelled	Restaurant/ Platform	10	"cancel", "refund", "arrive", "order"	4.12%	keyATM (Proposed by authors)
	Wrong order/ Missing items	Restaurant	18	"wrong", "missing", "mess", "items"	8.54%	Wordstat
Post-service inconvenience	*Reordering process issues*	Platform	16	"reorder", "previous", "replicate", "repeat"	1.02%	keyATM (Proposed by authors)
Remote support inconvenience	*Remote support issues*		19	"help", "chat", "call", "support"	10.97%	Wordstat

Stability	-	-	17	"consistent", "frequent", "multiple", "recurring"	5.01%	keyATM (Proposed by authors)
Controllability	-	-	37	"deliberate", "avoidable", "intentional", "neglect"	2.05%	keyATM (Proposed by authors)

3.5. Assessment of consumer outcomes

Based on the results obtained from keyATM, the next step was to analyze how service inconvenience (moderated by stability and controllability attributions) impacts upon consumer satisfaction for the food delivery services. To this end, the measurements of each type of service inconvenience (calculated with keyATM) are used as the independent variables in a Cumulative Link Model (CLM). In this model, stability and controllability act as moderators between service inconveniences and the dependent variable, the consumer's star rating. In this way, the model's estimates will reveal the impact of each variable on the consumer's satisfaction (reflected in the star rating). The star rating can be classified as an ordered categorical variable – a category variable with an intrinsic ordering. In this case, there are five categories (from 1 to 5 stars).

CLMs are a powerful model class when it comes to analyzing ordered categorical data such as star ratings (Agresti, 2012). Unlike other types of models, CLMs take into account the data's ordered and categorical nature, and their flexible regression framework facilitates in-depth analyses (Vargas et al., 2020). Therefore, the R package *ordinal* (Christensen & Brockhoff, 2013) was used to conduct the CLM analysis and evaluate the hypotheses proposed. Formally, a CLM is a model for an ordinal response variable Y_i that can fall in j = 1,..., J categories (where J ≥ 2). In the cases where J = 2, the CLM is equivalent to a binomial Generalized Linear Model (GLM). The response variable Y_i follows a multinomial distribution with parameter π, where π_{ij} represents the probability that the *i*th observation falls in category *j*. According to the notation proposed by Christensen & Brockhoff (2013), the cumulative probabilities can be defined as:

$$\gamma_{ij} = P(\pi_{i1} + \cdots + \pi_{ij}) \tag{1}$$

To handle data that does not follow a normal distribution, CLMs can use different link functions. For instance, the logit function (which is later identified as the optimal function for our dataset) is defined as:

$$\text{logit}(\pi) = \log[\pi/(1 - \pi)] \tag{2}$$

Cumulative logits are defined as:

$$\text{Logit}(\gamma_{ij}) = \text{logit}(\text{P}(\text{Y}_i \leq j)) = \frac{\log \text{P}(Y_i \leq \text{j})}{1 - \text{P}(Y_i \leq \text{j})} \tag{3}$$

where j = 1,…, J – 1.

A cumulative logit model (CLM with a logit link) is a regression model for cumulative logits, defined as:

$$\text{Logit}(\gamma_{ij}) = \theta_j - \boldsymbol{x}_i^T \beta \tag{4}$$

where the θ_j parameter (also known as threshold parameter) is the intercept for the *j*th cumulative logit and $\boldsymbol{x}_i$ represents a vector of predictor variables for the *i*th observation, with β as the associated set of regression parameters. Given that β is independent of *j*, its effect is equal for each one of the cumulative logits. The higher the value of $\boldsymbol{x}_i^T\beta$, the greater the probability of the response falling into the last category.

The following section explains the process of identifying the optimal CLM for our data, the details of the model selected, and the results obtained from the analysis.

4. Results

4.1. Cumulative Link Model specification

The process of model specification aims to find the simplest model with the best fit to the data. Given that there are many alternatives regarding the effects to be included in the model (or excluded from it), iterative methods are used to fit the models. In this study, a systematic model selection strategy was applied.

In particular, the "step-up" method supported by Raudenbush & Bryk (2002) was applied. Following a three-step approach, different versions of the model were tested and compared, increasing the model's complexity in every step:

- *Model 0:* In the first step, a null model with no covariates was defined as the baseline.

- *Model 1:* In the second step, the direct fixed effects were added as covariates, which capture the direct effect of each inconvenience.
- *Model 2:* In the third step, the moderating fixed effects were also added, representing the moderating effect of stability and controllability on each inconvenience.

The different models can be compared based on the likelihood ratio (LR) test. Considering two models, m_0 and m_1, where m_0 is simpler than m_1 (and nested in m_1), the LR statistic measures the evidence in the data to support m_1's additional complexity. Using the ANOVA method, we compare the models proposed via LR tests.

We find that the model that contains all the direct and moderating fixed effects (**Model 2**) presents the best fit to the data, given that it obtains the lowest fit indices (AIC and log-likelihood). Moreover, the results of the LR test show that the model's added complexity is supported by the data, with p-values significant at the 0.05 level. To identify the best link function for the data in this study, different functions were compared in terms of the fit indices of their respective models. The link functions tested were logit, probit, complementary log-log (cloglog), log-log, and cauchit. The results showed that the lowest AIC is obtained with logit as the link function. Therefore, the following cumulative logit model was fitted to the data:

$$logit\big(P(Y_i \leq j)\big) = \theta\mathrm{j} - \beta_k(\mathrm{inconvenience}_i) - \beta_k\big(\mathrm{stability}(\mathrm{inconvenience}_i)\big) - \beta_k(\mathrm{controllability}(\mathrm{inconvenience}_i) \quad (5)$$

where i = 1,..., 235,147 (for each review in the dataset); j = 1, 2 (representing the number of categories - 1); and k= 1,…, 11 (for each one of the categories within the proposed types of inconvenience, as defined in Table 1).

4.2. Updated Model of Service Convenience

This study used text mining techniques to detect the inconveniences mentioned in consumer reviews, which were classified into the categories proposed in Berry et al.'s Model of Service Convenience. However, there was one type of (in)convenience that did not fit into any of the model's categories. We named this new category 'remote support convenience'. Remarkably, this inconvenience is not related to a particular stage in the customer journey, as it can happen at any moment when the customer requires help and does not receive proper assistance. Figure 2 shows the existing and updated Model of Service Convenience, including the new dimension proposed.

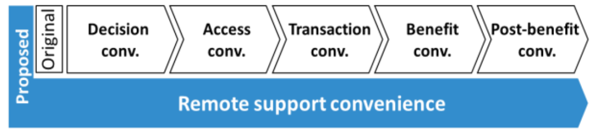

Figure 2. Extended Model of Service Convenience.

4.3. Test of hypotheses

The main research goal of this study is to analyze the effect of service inconveniences (and their attributions) on consumer satisfaction, which is measured through the user-defined star rating score. More specifically, two research questions were proposed. The first research question was related to the effect of service inconveniences on user satisfaction (RQ1). We expected that service inconveniences would be negatively and significantly related to consumer satisfaction (H1). Our second research question refers to the moderating effect of causality attributions (RQ2). In this case, we hypothesized that stability (H2) and controllability (H3) attributions would negatively and significantly moderate the relationship between service inconveniences and user satisfaction.

The results of the CLM analysis confirm H1, given that all types of service inconveniences are significantly and negatively related to user satisfaction. As observed in Figure 3, "Order cancelled" shows the greatest direct negative impact on user satisfaction (β=-2.99, p<.05), followed by "Remote support issues" (β=-2.55, p<.05) and "Delayed delivery" (β=-2.39, p<.05).

Turning to hypothesis H2, we find that the negative effects of service inconvenience on satisfaction are more harmful when moderated by stability attributions. In other words, customers are more likely to be dissatisfied if they think that the inconvenience (such as a delayed delivery) will be repeated in the future. On average, the negative effect of an inconvenience on satisfaction is almost 2.5 times stronger if customers think that it is stable (-247% compared to the direct effect on satisfaction). When perceived as stable, "Technical issues in the app" shows the most negative impact on customer satisfaction (β=-6.16, p<.05).

Regarding H3, the negative influence of service inconvenience on satisfaction is exacerbated even further when the effect is moderated by controllability attributions (as compared to stability attributions). This means that if consumers believe that a service inconvenience (such as a discount code that is not working) could have been avoided by the platform it is even more likely that they will be dissatisfied with the service. Under the moderation effects of controllability attributions, the adverse influence of an inconvenience on satisfaction is, on average, around 5.2 times stronger

(-517%) compared to its direct effect. The inconveniences linked to remote support incidences are the ones that can have the most negative effect on satisfaction if consumers perceive that they could have been prevented (β=-10.73, $p<.05$).

In conclusion, we find that: (i) all service inconveniences have a negative influence on consumer satisfaction, (ii) such negative impact intensifies when customers perceive these issues as stable (likely to repeat in the future), and (iii) the effects are even more adverse when the inconveniences are perceived as controllable (could have been avoided). Therefore, we can infer that the model supports all the hypotheses proposed.

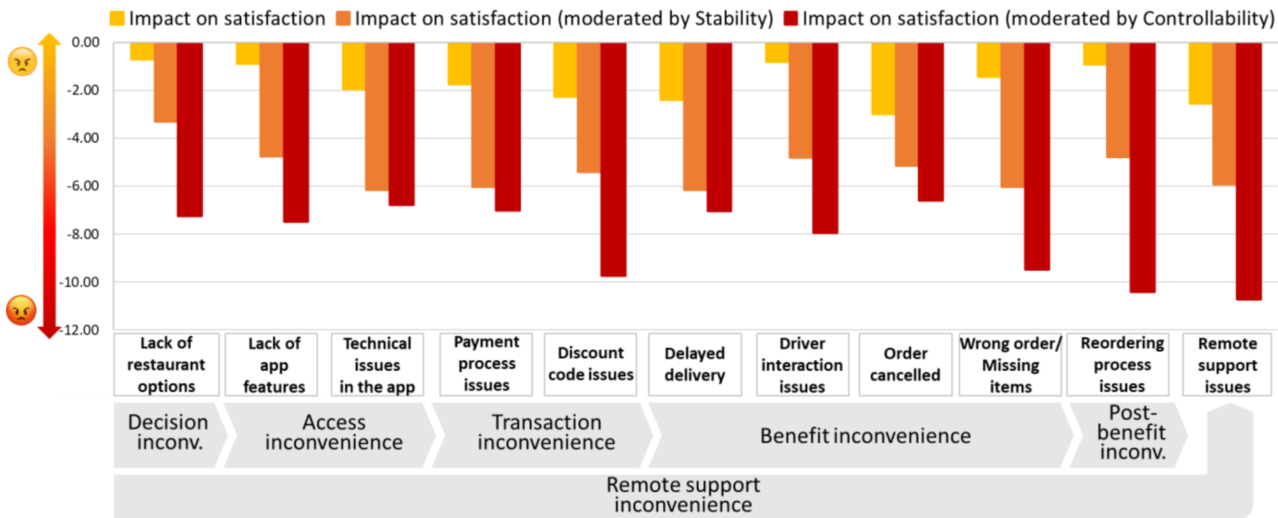

Figure 3. Impact of service inconveniences on satisfaction score (based on the CLM estimates).

5. Discussion and conclusions

As a first contribution of this study, we incorporate the time and effort spent by consumers in receiving customer support to the Model of Service Convenience. In the case of on-demand service platforms, mediating the interaction between waiting-time-sensitive customers and independent service providers can be very challenging (Taylor, 2018). To deal with these requests, platforms often use live chats, chatbots and outsourced call centers (Ostrom et al., 2021). While using these technologies allows organizations to meet the growing expectations of on-demand customers, the constant need for immediacy places enormous strain on service procedures (Ostrom et al., 2021). We believe that adding this new dimension to the model allows us to better capture the needs of digital consumers.

Second, our results indicate that when a service inconvenience is perceived as stable or controllable, its negative impact on satisfaction intensifies. Existing research had focused mainly on analyzing the attributions linked to outcome failures, which are related to the service's core benefit. By analyzing stability attributions at each stage of the customer journey, we find that the incidences related to technical issues in the app are the ones that can do the greatest harm (to customer satisfaction) when consumers believe that these are likely to repeat in the future (stable). On the other hand, the inconveniences linked to remote support incidences can have the most negative effect on satisfaction if consumers perceive that they could have been prevented (controllable).

Third, this study responds to the call for the use of unstructured data and new data analysis techniques to further advance service research (Huang et al., 2021). Although big data and machine learning-based analytics are becoming increasingly popular in marketing research, these techniques still present an enormous untapped potential. This research proposes a blueprint methodology that can be useful for scholars who wish to test theory using text analytics.

In terms of managerial implications, we encourage practitioners to take specific actions to prevent inaccurate or adverse causal attributions regarding the service's potential inconveniences. For example, they could be proactive and respond swiftly to negative customer reviews. To avoid stability attributions, the platform must ensure that consumers know that the firm wants to use their feedback to avoid similar issues in the future. To prevent controllability attributions, it is important that platform representatives clearly explain that the firm did not intentionally cause the inconveniences, aside from apologizing and offering adequate compensation.

Finally, service companies can benefit from incorporating text mining techniques to obtain consumer insights and enhance their operations. Using the methodology introduced in our study, they could analyze user-generated content and systematically identify the most critical service inconveniences experienced by their customers. These insights can help them obtain a deeper understanding of how their customers perceive their platform, as well as how they can better react to customer complaints and improve their services.

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