How Do Consumers Choose Offline Shops on Online Platforms? An Investigation of the Interactive Consumer Decision Processing in Diagnosis-and-Cure Markets

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Abstract

Purpose

The objectives of the present work are (1) to understand the process and consequences of the two-way communication between consumers and businesses on online-to-offline (O2O) diagnosis-and-cure services platforms and (2) to examine how consumer request-specific factors and service quote-specific factors influence consumer decisions in this interactive marketing context.

Design/methodology/approach

The study analyzed a dataset of 17,878 service requests and 57,867 price quotes obtained from an O2O platform bridging consumers and automotive repair shops. On the platform, consumers request service quotes by uploading the description of automotive damage, and multiple service providers suggest price quotes. We formulated a logit model to examine consumer decisions of responding service quotes.

Findings

This paper finds that (1) consumers receiving more severe diagnostic results are more likely to respond to the service quotes, (2) diagnostic severity and inconsistency moderate the impact of shop distances, shop sizes, and quoted prices on consumers' responses to the service quotes.

Research limitations/implications

This paper fills the gap in the literature by advancing the consumer decision processing model to address the interactive shopping experience on O2O diagnosis-and-cure services platforms. The findings are limited by the data and the research context.

Practical implications

For marketing practitioners, our empirical results imply specific positioning and targeting strategies for markets with informational and geographic barriers to expand the market scope and customer base.

Originality/value

The present work is the first to examine the consumer decision process on O2O diagnosis-and-cure services platforms. It adds value to the literature by investigating how consumers update their problem awareness through the service request-specific factors (i.e., diagnostic severity and diagnostic inconsistency) and how the request-specific factors moderate the impacts of quote-specific factors (i.e., shop distance, shop size, and quoted price) on consumers' responses to price quotes. The conceptual model and empirical findings provide substantial theoretical and practical values for e-commerce researchers and practitioners.

1. Introduction

The advances of the Internet and information technologies have enabled firms to communicate efficiently with consumers (Rust and Huang 2014). In the physical goods market, for instance, digital retailers can directly transact with customers, integrating multiple channels and streamlining the distribution process (Cao and Li 2018). Thanks to the enhanced operational efficiency, successful online retailers, such as Amazon, can offer products at lower prices (Burt and Sparks 2003). As a result, digital retailers are rapidly growing to takeover brick-and-mortar businesses, thereby substituting the mediating channels, such as local retailers. Consequently, the development of digital transactions is often understood as a competitive threat to the traditional marketplace (Reinartz, Wiegand, and Imschloss 2019). Under certain circumstances, however, firms' online and offline presences complement each other, achieving a synergistic effect (Verhoef, Kannan, and Inman 2015; Shankar et al. 2010). Evidence exists in the personal service markets, such as restaurants, taxis, and healthcare services, where service providers utilize the Internet network to improve consumers' offline experiences.

Such complementarity is the driver of online-to-offline (O2O) business models, typically operationalized as interactive websites or mobile applications (Tsai et al. 2015). O2O businesses are different from multichannel retailers offering products simultaneously through online and offline outlets (Zhang, Pauwels, and Peng 2019). Instead, they follow a two-step process where consumers' need and product information is initially communicated through the online platform, and then the product is transacted upon the offline visit (Du and Tang 2014; Xiao and Dong 2015). This interactive process differs from the passive broadcast advertising and one-way persuasive communication traditionally used by retailers (Wang 2021). Businesses understanding consumers' demands and behaviors in real-time and consumers collecting product-related information have become increasingly critical success factors in the current interactive market (Steuer 1992). For this reason, O2O platforms are especially suitable for diagnosis-and-cure services such as automotive repair and healthcare, in which critical information related to service is distributed asymmetrically between the consumers and the service providers—the experts, and the customized services are provided in-person upon consumers' visits to the physical stores.

Despite the rich literature on the emergence of interactive platforms (e.g., Xiao and Dong 2015; Chen, Wang, and Jiang 2016; Zhang, Pauwels and Peng 2019; Banerjee and Bhardwaj 2019; Roh and Park 2019), there is a limited understanding of the process and consequences of the two-way communication between consumers and businesses on O2O diagnosis-and-cure services platforms. To address this gap in the literature, we advance the classic consumer decision processing model to address the characteristics of diagnosis-and-cure services and O2O platforms. First, we specify two consumer request-specific variables, i.e., diagnostic severity and diagnostic inconsistency, to investigate the effect of the customized diagnoses provided for each service request. We further introduce three quote-specific variables, i.e., shop distance, shop size, and quoted price, and examine how diagnostic severity and inconsistency moderate their impacts on consumer decisions. Finally, we empirically tested the proposed impacts of the request- and quote-specific factors using a unique mobile-based dataset collected in the automotive repair market and found evidence supporting most of our hypotheses.

2. Theoretical Background and Hypotheses

As an emerging trend of interactive marketing, the O2O platform created an interconnected ecosystem with an online network of offline service providers and consumers (Wang 2021). Existing studies on the O2O business model have investigated various aspects, including reputation management (e.g., Xiao and Dong 2015), information quality and service quality (e.g., Chang, Hsu, and Yang 2018, Du and Tang 2014), pricing strategies (e.g., He et al. 2016; Long and Shi 2017), compensation design (Banerjee and Bhardwaj 2019), power structure (e.g., Chen, Wang, and Jiang 2016), and moral obligation (Roh and Park 2019). Previous marketing literature on open platform models has focused mainly on the effect of consumer reviews. These studies include how consumer reviews affect aggregated sales (e.g., Zhu and Zhang 2010; Berger, Sorensen and Rasmussen 2010), consumer perception and attitude (e.g., Mudambi and Schuff 2010; Pentina, Bailey and Zhang 2018; Lee, Park and Han 2008; Vermeulen and Seegers 2009), and purchase behavior (e.g., Adjei, Noble and Noble 2010). Some studies analyzed the detailed review contents (e.g., message valence, Chevalier and Mayzlin 2006; Vermeulen and Seegers 2009; Berger, Sorensen, and Rasmussen 2010; Lee, Park, and Han 2008), and others provided a more general view through meta-analyses (e.g., Floyd et al. 2014; Rosario et al. 2016; Chen and Xie 2008). However, we find a lack of attention on the O2O platform models in the context of diagnosis-and-cure services and an absence of empirical study on the determinants of consumer decisions based on industrial data.

In the following sections, we propose a consumer decision processing model specifically for O2O diagnosis-and-cure services platforms and propose hypotheses to examine the antecedents of consumers' responses to service quotes.

2.1. Consumer decision processing on O2O diagnosis-and-cure services platforms

Diagnosis-and-cure services, such as home repair and healthcare, are delivered through the two steps of seller activities: diagnosis and curing. In the diagnosis phase, service providers collect information from consumers, examine their problems, and suggest specific solutions. In the curing phase, the solutions are implemented. Throughout the process, services are customized to each consumer based on the service providers' judgment (Lee 2017). Therefore, it is common for diagnosis-and-cure services providers to use online channels for lead generation, i.e., initiation of consumer interest or inquiry of a product, rather than sales conversion (Banerjee and Bhardwaj 2019). On an interactive platform, service providers can conduct preliminary diagnoses by examining consumer-uploaded photos and literal descriptions of the issue (e.g., dents and scratches on a car) and advise repair solutions and provide cost estimations. The consumers can then decide whether to respond to the quotes and receive the repair services in offline facilities.

The main goal of the current research is to understand the consumer decision process in the interactive marketing context described above. Consumer decision processing models have long been a core theory of consumer behavior research. The traditional models analyze consumers' decision-making process following the five stages: problem recognition, information search, evaluation of alternatives, decision, and outcomes (e.g., Dewey 1910; Engel, Kollat, and Blackwell 1978; Engel, Blackwell, and Miniard 1986). More recently, research has introduced additional stages to the model (e.g., Kotler and Keller 2012's disposal stage) or discussed the psychological process for each stage of the model (e.g., Belch and Belch 2009's motivation-perception-attitude formation-integration-learning process). Also, there have been studies that contribute to the application of the model to the digital market context (e.g., Darley, Blankson Luethge 2010; Ashman, Solomon, Wolny 2015; Teo and Yeong 2003). Despite the recent development of the literature, most research has focused on the online physical goods market and adopted the five-stage model to understand online consumers. However, the existing consumer decision processing model has limitations when applied to O2O diagnosis-and-cure services platforms, where consumers rely on experts' judgment to assess the problem and constantly update the problem recognition based on customized diagnostic results received online. For instance, when the diagnostic results are severer than expected, consumers will realize that the problem they face requires more services with higher costs, which consequently affects their evaluation and decision stages. Thus, we suggest adding a stage—update of problem recognition—to the classic consumer decision process model to account for how diagnostic results from service experts help consumers update their problem recognition between information search and alternative evaluation (see Figure 1). At the problem update stage, each consumer request may receive one or multiple diagnostic quotes, based on which two key factors—diagnostic severity and diagnostic inconsistency—are perceived by consumers and affect their subsequent decision-making.

According to the online and offline shopping literature, acquisition utility is the benefits consumers perceive (e.g., service quality) and the costs they need to give up (e.g., price) when acquiring the service. On the other hand, transaction utility is the benefits consumers receive (e.g., convenient information searching) and the costs they need to bear (e.g., traveling to the store) when executing the service (Baltas et al. 2010; Chintagunta et al. 2012; Gupta and Kim 2010; Vroegrijk et al. 2013; Campo and Breugelmans 2015). In our research context, consumers receive customized quotes to update their acquisition utility based on their perception of damage severity (i.e., average quoted price). Based on the diagnoses and the quoted prices received through the platform, consumers can make inferences about the automotive damage situation unique to themselves. When consumers are provided with higher-priced quotes, their expected acquisition utility increases as they perceive higher benefits, i.e., having more serious car damage fixed (Campo and Breugelmans 2015). Therefore, we expect consumers who received more severe diagnoses to be more likely to respond to the quote providers.

***H_1*:** *On O2O diagnosis-and-cure services platforms, consumers are more likely to respond to a service quote when their customized diagnostic results are more severe.*

On the other hand, consumers may update the perception of transaction utility based on the inconsistency of quoted prices. When consumers are provided with inconsistent price quotes (i.e., high standard deviation among quoted prices), their expected transaction utility decreases due to increased search costs (Chintagunta et al. 2012; Campo and Breugelmans 2015). Under this situation, consumers may consider the

O2O platform an inefficient or unreliable channel for assessing their problems. As a result, they will be less likely to respond to service quotes received on the platform.

H2: *On O2O diagnosis-and-cure services platforms, consumers are less likely to respond to a service quote when their customized diagnostic results are more inconsistent.*

2.2. Quote-specific factors and the moderating effects of diagnostic severity and inconsistency

In this section, we discuss the three factors that are specific to each quote (shop distance, shop size, and quoted price) and investigate the moderating effects of diagnostic severity and inconsistency.

Shop distance

The development of e-commerce has deconstructed the geographic barriers in the physical goods market. However, research in marketing has documented geographic impact on consumer behaviors in the online context (e.g., Bell and Song 2007; Choi, Hui, and Bell 2010) and the importance of geographic segmentation for stores with online and offline presence (e.g., Dholakia et al. 2010; Ngwe 2017). Furthermore, since the curing phase of diagnosis-and-cure services is still primarily restricted to in-person servicing at brick-and-mortar stores, geographic distances to the store can contribute to high transaction costs (Chintagunta et al., 2012; Campo and Breugelmans, 2015) and should be one of the main factors for consumers to consider in the online diagnosis phase. Generally, a longer distance to the physical shop decreases consumers' willingness to purchase consumer goods. This phenomenon is more likely when other alternatives are available nearby (e.g., Ailawadi, Pauwels, and Steenkamp 2008; Briesch, Chintagunta, and Fox 2009).

Nevertheless, although store location matters for diagnosis-and-cure services, the use of O2O platforms may mitigate its effect by providing additional information and encouraging store visits. In other words, O2O platforms help the stores with distant locations promote themselves and initiate communication with consumers, mitigating the geographic disadvantage. In general, geographic barriers affect consumer's buying process in two aspects; 1) It requires more cost (e.g., time, effort, and money) to travel to a distant store; and 2) Long-distance obstructs the offline information flow, and thus, offline word-of-mouth and reputation are constrained within communities to a certain degree (Bala and Goyal 1998). An O2O model mitigates geographic barriers for both. First, consumers can save costs by initiating interaction with the store and receiving customized evaluations (preliminary diagnoses and price quotes) without visiting the physical location. Moreover, store information and consumer ratings and reviews are shared with consumers regardless of the distance to the store.

This mitigating effect of O2O platforms on geographic barriers is especially significant when consumers receive more severe diagnostic results through the platform. Consumers' expected acquisition utility increases as they perceive higher benefits from having more severe car damage fixed (Campo and Breugelmans 2015). The increase in acquisition utility can offset the perceived transaction costs of visiting a more distant store when consumers evaluate alternative quotes. Thus, we expect that the negative impact of shop distances weakens as the severity of diagnoses increase.

H*$_3$*: *On O2O diagnosis-and-cure services platforms, the negative effect of shop distances on consumers' probability of responding to service quotes weakens as their customized diagnostic results are more severe.*

On the other hand, when consumers face higher uncertainties of the diagnostic results, they will perceive high transaction costs, such as expected search costs, to determine the reasons for such discrepancy. Consequently, consumers may become more sensitive to additional traveling and delivery costs (Chintagunta et al. 2012). Thus, we expect the negative impact of shop distances to strengthen as diagnostic inconsistency increases.

H*$_4$*: *On O2O diagnosis-and-cure services platforms, the negative effect of shop distances on consumers' probability of responding to service quotes strengthens as their customized diagnostic results are more inconsistent.*

Shop size

Two critical dimensions determining service quality are the physical environment and people (Yarimoglu 2014). The physical environment considers designing servicescape and providing tangible evidence of service performances, such as space and layout, furnishings, equipment, and staff clothing. The people dimension accounts for interactions between customers, service providers, and other customers (Parasuraman, Zeithaml, and Berry 1985; Parasuraman, Zeithaml, and Berry 1988; Frost and Kumar 2000). Unfortunately, on O2O platforms, the physical environment and people factor cannot be directly assessed at the online diagnosis stage. Alternatively, consumers may assess the two factors based on the measures of shop sizes. For example, the legal facility area of the service shop can communicate the space of the physical environment, whereas the number of employees can communicate the availability of service personnel. Thus, a larger shop size generally improves consumers' perception of service quality when receiving diagnoses online and encourages them to contact the diagnostic quote providers on O2O platforms.

However, when the diagnostic results are severer, consumers will engage in more rigorous information searching and focus more on the process perspective of the service, i.e., reliability, problem-solving, and outcome quality (Yarimoglu 2014). Therefore, consumers' preference for larger shops may weaken as diagnostic results become more severe.

> ***H5:*** *On O2O diagnosis-and-cure services platforms, the positive effect of shop sizes on consumers' probability of responding to service quotes reduces as their customized diagnostic results are more severe.*

Prior research suggests that during initial contact, when buyers have little or no previous transaction experience with the retailer, they may base their trust on the sellers' reputation and contextual cues, such as the store size and display, the product assortment, or the seller's publicized good-will (Lewicki and Bunker 1996; Riquelme et al. 2019). When receiving inconsistent diagnoses, consumers perceive higher uncertainty on each quote and thus could rely more on the shop size as a cue to assess the service providers' trustworthiness. As a result, the positive effect of shop sizes will strengthen.

> ***H6:*** *On O2O diagnosis-and-cure services platforms, the positive effect of shop sizes on consumers' probability of responding to service quotes strengthens as their customized diagnostic results become more inconsistent.*

Quoted price

Due to the customized nature of diagnosis-and-cure services, their prices vary for each diagnostic case, and their quality is unknown a priori to consumers. Accordingly, consumers face uncertainty regarding the type of service necessary and the reasonable range of prices. Previous studies found that this information asymmetry between buyers and sellers generates high transaction costs for consumers (e.g., Anderson 1988; Wathne and Heide 2000; Read et al. 2009; Das and Rahman 2010). O2O commerce fundamentally changes the price competition in the traditional channel supply chain (Zhang, Chen, and Wu 2015). An O2O platform creates an open space for both consumers and service providers by enabling consumers' easy comparison of prices among different seller alternatives. Specifically, on O2O diagnosis-and-cure services platforms, consumers sequentially receive multiple price quotes from the providers. Under this circumstance, the previous price quotes naturally serve as the references for the ones to come. The challenge confronted by the consumers is similar to the "optimal stopping problem (Seale and Rapoport 1997)," which states that the binary decision to either stop or continue the search depends on the relative ranks of the options.

When consumers perceive severe diagnostic results based on received service quotes, they tend to be less sensitive to the quoted prices for two reasons. First, severe diagnoses increase the consumer's level of involvement, i.e., the internal state of personal relevance or importance regarding the purchase (Park and Young 1986) and thus reduce price sensitivity (Gotlieb, Schlacter, and Louis 1992). Second, higher expected acquisition benefits perceived from more severe diagnoses can compensate for the acquisition costs of quoted prices.

H7: *On O2O diagnosis-and-cure services platforms, the negative effect of quoted prices on consumers' probability of responding to service quotes weakens as their customized diagnostic results become more severe.*

The moderating effect of diagnostic inconsistency is, however, unclear. On the one hand, the literature on Agency Theory and Signaling Theory suggests that firms can provide signals to alleviate consumer perceived uncertainty on product quality (e.g., Akerlof 1970; Mishra, Heide, and Cort 1998; Kirmani and Rao 2000). Among various types, premium prices are commonly used as a revenue-risking, default-contingent signal (Kirmani and Rao 2000; Rao and Monroe 1989). On O2O platforms, consumers receiving highly inconsistent diagnoses are likely to use prices as a cue to judge the service quality due to higher perceived uncertainty, thus becoming less sensitive to quoted prices. On the other hand, when consumers face higher uncertainties of the diagnostic results, they will perceive higher transaction costs and become more sensitive to the acquisition costs of prices (Chintagunta et al. 2012). Thus, the moderating effect of diagnostic inconsistency depends on the relative strengths of these two effects.

3. Model

Since our data include a binary outcome (i.e., responded to a quote or not), we formulate the consumer decision making using a logit model (e.g., Guadagni and Little 1983; Malhotra 1984; Train 2009). Let Y_{ij} denote whether individual i responds to the jth quote she has received. We assume that the individual's response decision is driven by the latent utility u_{ij}, which has the following relationship with Y_{ij}:

$$Y_{ij} = \begin{cases} 1 \text{ if } u_{ij} > 0, \\ 0 \text{ otherwise.} \end{cases}$$

To test our hypotheses, we specify u_{ij} as:

$$
\begin{aligned}
u_{ij} = {} & \beta_0 + \beta_1 \text{DiagSeverity}_i + \beta_2 \text{DiagInconsist}_i + \beta_3 \text{ShopDistance}_{ij} \\
& + \beta_4 \text{ShopClass}_{ij} + \beta_5 \text{QuotedPrice}_{ij} + \beta_6 \text{ TimeElapsed}_{ij} + \beta_7 \text{ NoQuotes}_{ij} \\
& + \beta_8 \text{ShopDistance}_{ij} \cdot \text{DiagSeverity}_i + \beta_9 \text{ShopClass}_{ij} \cdot \text{DiagSeverity}_i \\
& + \beta_{10} \text{QuotedPrice}_{ij} \cdot \text{DiagSeverity}_i + \beta_{11} \text{ShopDistance}_{ij} \cdot \text{DiagInconsist}_i \\
& + \beta_{12} \text{ShopClass}_{ij} \cdot \text{DiagInconsist}_i + \beta_{13} \text{QuotedPrice}_{ij} \cdot \text{DiagInconsist}_i + \varepsilon_{ij}.
\end{aligned}
$$

In the equation above, DiagSeverity_i is the severity of diagnostic results to the individual's automobile, measured by the mean price of all quotes that individual i has received upon her request. DiagInconsist_i is the degree of diagnostic inconsistency measured by the standard deviation of quoted prices for individual i. ShopDistance_{ij} is the distance between the area where individual i requested service and the area where the repair shop of quote j is located. Since we expect a diminishing effect of the distance variable on consumers' response behavior, ShopDistance_{ij} is log-transformed for the model estimation. ShopClass_{ij} measures the size of the repair shop. It is a binary variable indicating whether quote j came from a "first-class" shop identified by the O2O platform. First-class shops are of larger sizes than the rest, with legal facility areas larger than one thousand square meters and three or more employees. QuotedPrice_{ij} is the price of the jth quote individual i has received (hereafter quote j). In addition, we control for two additional variables: 1. TimeElapsed_{ij}, the time between the individual's request for quotes and her reception of quote j and 2. NoPrevQuotes_{ij}, the number of quotes the individual received before quote j. We expect that consumers are less likely to respond to a slower service quote or a service quote with more competition.

With the assumption of the type I extreme value distribution for the error term ε_{ij} in the utility specifications above, the probability that individual i responds to quote j_i is given by:

$$\Pr(Y_{ij} = 1) = \frac{\exp\{u_{ij}\}}{1 + \exp\{u_{ij}\}}.$$

4. Data

The dataset for the empirical analysis is obtained from a mobile application for auto repair launched in 2013 in a developed country in Asia. The application works on both Android and iOS devices. This O2O platform bridges the communication between consumers and automotive repair shops for repair jobs ranging from minor exterior damages to heavier damages. It allows consumers to make repair requests by uploading photos and literal descriptions of the automobile damages and receive quotes from repair shops accordingly. Various types of shop information are also available to consumers on the application, such as the name, location, shop size, quoted price, customer reviews, and contact information. If consumers are interested in the quotes offered, they can contact the repair shops and make appointments through the application. Overall, there are 17,878 requests and 57,867 quotes in the data from September 1st to November 31st in 2015. Every request received at least one quote. A total of 205 repair shops provided services through the app across 125 areas in the country when the data were collected. We present descriptive statistics of the data in Table 1.

<Insert Table 1 here>

5. Results

We applied the maximum likelihood estimation method to estimate the parameters in our logit model. The estimation results are presented in Table 2. To begin with, we examine the seven main effects of $\mathrm{DiagSeverity}_i$, $\mathrm{DiagInconsist}_i$, $\mathrm{ShopDistance}_{ij}$, $\mathrm{ShopClass}_{ij}$, $\mathrm{QuotedPrice}_{ij}$, $\mathrm{TimeElapsed}_{ij}$, and $\mathrm{NoPrevQuotes}_{ij}$, respectively. The impact of $\mathrm{DiagSeverity}_i$ is positive and statistically significant ($\beta_1 = 1.631 \times 10^{-3}, p < .001$). The result suggests that more severe diagnostic results motivate consumers to respond to the quotes, supporting H1. The impact of $\mathrm{DiagInconsist}_i$ is found to be insignificant ($\beta_2 = 1.787 \times 10^{-4}, p > .4$), suggesting that the impact of diagnostic inconsistency may depend on consumer characteristics or purchase situation. For instance, when facing high diagnostic inconsistency, consumers with extroverted personalities and no prior car repair experiences may be more likely to communicate with multiple service providers while their introverted, more experienced counterparts may consider the O2O platform unreliable and switch to other channels to assess the damage further. Thus, H2 is not supported. The impact of $\mathrm{ShopDistance}_{ij}$ is negative and statistically significant ($\beta_3 = -.2062, p < .001$). The result suggests that consumers prefer service providers close by, which is consistent with the findings in the previous studies (e.g., Briesch, Chintagunta and Fox 2009). $\mathrm{ShopClass}_{ij}$ shows a positive and statistically significant impact ($\beta_4 = .1373, p < .001$), suggesting that sizable shops are more favored by consumers and confirming the positive impact of store sizes suggested by previous studies (e.g.,Yarimoglu 2014). $\mathrm{QuotedPrice}_{ij}$ was found to be negative and statistically significant ($\beta_5 = -1.583 \times 10^{-3}, p < .001$), which implies that lower prices attract consumer responses and is consistent with the findings in previous studies (e.g., Chu et al. 2010). The negative and statistically significant coefficients of

TimeElapsed_{ij} ($\beta_6 = -9.134 \times 10^{-3}, p < .001$) and NoQuotes_{ij} ($\beta_7 = -.2656, p < .001$) suggest that consumers are more likely to respond when quotes are sent promptly and when there are fewer competing quotes.

Next, we examine the moderating effect of DiagSeverity_i by interpreting the coefficient estimates of its interaction terms. First, we find a positive and statistically significant interaction between ShopDistance_{ij} and DiagSeverity_i ($\beta_8 = 9.963 \times 10^{-5}, p < .02$), indicating that consumers' sensitivity to travel distances is abated when the diagnostic results are more severe. Second, the interaction between ShopClass_{ij} and DiagSeverity_i is found to be negative and marginally significant ($\beta_9 = -1.911 \times 10^{-4}, p < .06$), suggesting that the advantage of larger shops is weakened as consumers experience more severe problems with their vehicles. Third, the interaction between QuotedPrice_{ij} and $\text{DiagSeverity}_i$was found to be negative and one-tail significant ($\beta_{10} = -2.890 \times 10^{-8}, p < .09$). In sum, our estimation results provide empirical evidence fully supporting H3 and marginally supporting H5 and H7.

Last, we examine the moderating effect of DiagnInconsist_i. First, we find the interaction between ShopDistance_{ij} and $\text{DiagInconsist}_\text{i}$ negative and statistically significant ($\beta_{11} = 1.865 \times 10^{-4}, p < .03$), suggesting that faraway shops become even less attractive when consumers perceive higher transaction costs. Second, the interaction between ShopClass_{ij} and DiagInconsist_i is found to be positive and statistically significant ($\beta_{12} = 5.150 \times 10^{-4}, p < .05$), suggesting that the advantage of larger shops is strengthened as consumers experience more inconsistent diagnoses on the O2O platform. Lastly, the positive and statistically significant interaction between QuotedPrice_{ij} and DiagInconsist_i ($\beta_{13} = 1.953 \times 10^{-7}, p < .001$) indicates that large inconsistency in diagnoses can mitigate the negative impact of quoted prices, which implies that quoted prices may serve as a quality signal in the presence of higher perceived uncertainty. Ceteris paribus, an \$8,105 $\mathrm{DiagInconsist}_i$ $(-\beta_5/\beta_{13})$ will reduce the impact of quoted prices to 0[1]. In sum, our estimation results provide empirical evidence supporting H4 and H6.

<Insert Table 2 here>

6. Discussion

This research examines how consumer request-specific and quote-specific factors influence the initiation of customer-business contact. Based on our empirical analysis, the main findings of our research are as follows: 1) On O2O diagnosis-and-cure services platforms, consumers are more likely to respond to a service quote when their customized diagnostic results are more severe. 2) The negative effect of shop distances on consumers' probability of responding to a service quote weakens as their customized diagnostic results are more severe but strengthens as their customized diagnostic results are more inconsistent. This result suggests that consumers may be willing to travel farther to increase the acquisition utility when facing more severe problems. On the other hand, the faraway shops become less attractive when consumers face high transaction costs induced by inconsistent quoted prices. 3) The positive effect of shop sizes on consumers' probability of responding to a service quote reduces as their customized diagnostic results are more severe but strengthens as their customized diagnostic results become more inconsistent. The advantage of larger shops weakens as consumers experience more

[1] Empirically, we find the maximum value of $\mathrm{DiagInconsist}_i$ to be \$6,364. Thus, in this situation, only less than one quarter of $\mathrm{QuotedPrice}_{ij}$'s impact remains due to the moderating effect of $\mathrm{DiagInconsist}_i$.

severe vehicle problems. This finding may be due to consumers' preference for specialized shops when they are rigorously searching information to solve severe problems and focusing on the process perspective of the service (i.e., reliability, problem-solving, and outcome quality; Yarimoglu 2014). However, the advantage of larger shops strengthens as consumers experience more inconsistent quotes, as consumers' primary concern becomes the uncertainty over the service providers. When receiving inconsistent diagnoses, consumers perceive higher uncertainty on each quote thus rely on the shop size as a cue to assess the service providers' trustworthiness. Previous research supports our result as they find that when buyers have little previous transaction experience with the provider, they may build trust based on the shop's reputation and contextual cues, such as the store size and display, the product assortment, or the seller's publicized good-will (Lewicki and Bunker 1996; Riquelme et al. 2019). 4) The negative effect of quoted prices on consumers' probability of responding to a service quote weakens as their customized diagnostic results become more severe and weakens as their customized diagnostic results become more inconsistent. This finding implies that quoted prices may serve as quality signals in the presence of higher perceived uncertainty due to inconsistent quotes.

7. Conclusions

7.1. Theoretical Contributions

This research advances the long-lived consumer decision processing model to address the interactive marketing process on the O2O diagnosis-and-cure services platform. Our model extends the literature by suggesting a six-stage consumer decision process: problem recognition, information search, update of problem recognition, evaluation of alternatives, decision, and outcome. We suggest that consumers first update the expected benefits and costs of the repair service based on the diagnostic severity and the transaction costs based on the diagnostic inconsistency. The updated problem recognition subsequently influences consumers' evaluation of alternative service quotes and their decisions of responding to service providers.

We empirically tested the impact of different types of consumer request-specific information (damage severity and damage inconsistency) and quote-specific information (shop distance, shop size, and quoted price) on consumer decisions, as well as the moderating effects of request-specific information, advancing the understanding of digital platforms and digital consumers. Our study shows the importance of efficient communication of information at the diagnostic stage in helping consumers initiate transactions via the O2O platforms.

7.2. Managerial Implications

Throughout the globe, O2O platforms are transforming diagnosis-and-cure services shops from brick-and-mortar to brick-and-mobile, contributing value to both consumers and service providers. For marketing practitioners, our empirical results imply positioning and targeting strategies for O2O diagnosis-and-cure businesses, which are generalizable to other markets with informational and geographic barriers. We find that consumers receiving severe diagnoses are less sensitive to shop distances, shop sizes, and quoted prices. Accordingly, we suggest the shops located in the city outskirts, smaller shops, and premium shops to specialize in severe repair jobs, such as broken axles and bent, twisted frames, or rolled-over cars. On the other hand, consumers receiving inconsistent diagnoses are more sensitive to shop distances and shop sizes but less sensitive to quoted prices. Therefore, we suggest the shops in the city outskirts and the smaller shops focus more on providing detailed, professional diagnoses than to engage with fierce price competition. That way, the shops could increase consumer's expected acquisition utility without raising perceived transaction costs. We also find that shop distances reduce the likelihood of consumers' responses to quotes in the O2O context. The finding suggests that the service providers focus more on promoting and investing (e.g., advertising and providing preliminary diagnoses) in online consumers at nearby locations. In addition, to stay competitive on an O2O platform, a diagnosis-and-cure services provider should designate personnel to manage diagnosis requests and provide timely responses to high-value prospect customers.

Furthermore, since inconsistencies in diagnoses could lower down consumers' perceived efficiency and reliability of the digital platform, the platform should also find additional methods to reduce informational barriers. Examples include platform certification to shops with high service quality and high consumer satisfaction or training artificial intelligence to conduct diagnoses based on the rich data of previous diagnostic requests, quotes, and consumer decisions. More generally, we suggest the firms with offline presence provide a customized diagnosis of each consumer's situation, location, and involvement level by taking advantage of the convenience of digital communication. Such efforts can provide consumers with more personalized and relevant experiences, yielding increased expected acquisition utility. A higher acquisition utility will help offline firms overcome informational and geographic barriers and expand their market scope and customer base.

7.3. Limitation and Future Research

Our findings are limited by the data. If available, additional data on consumers' final purchase decisions and the prices paid can further advance our understanding of the consumer decision process on O2O diagnosis-and-cure services platforms. Moreover, consumer reviews are not included in our analysis due to the limited number of reviews available from our data source. As previous studies indicate, peer reviews and word-of-mouth are the critical determinants of consumer decisions, the long-term growth of sales of services providers, and thus the success of O2O platforms (Adjei, Noble, and Noble 2010). Therefore, we call for research examining the effects of online review contents coupled with the variables investigated in this paper to study the consumer behaviors on O2O diagnosis-and-cure services platforms more comprehensively.

Our data is provided by an O2O platform exclusively operating in an Asian developed country, and the majority of the mobile app users are in the metropolitan areas. As a result, the social, economic, and industrial characteristics of the empirical research context may affect the generalizability of our findings. Moreover, since consumer's individual characteristics, including personality, stress level, and purchase situation, may influence how they interpret, process, and respond to diagnostic results and shop information, future research could contribute by studying the role of individual characteristics in their decision-making process on O2O diagnosis-and-cure services platforms based on survey or experiment data. Future researchers could also examine the consumer decision process on O2O platforms for other types of diagnosis-and-cure services, such as healthcare and home repair. It will be interesting to explore the impact of factors specific to other services and whether findings in this study still hold.

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Figure 1. Consumer Decision Processing on O2O Diagnosis-and-Cure Services Platforms

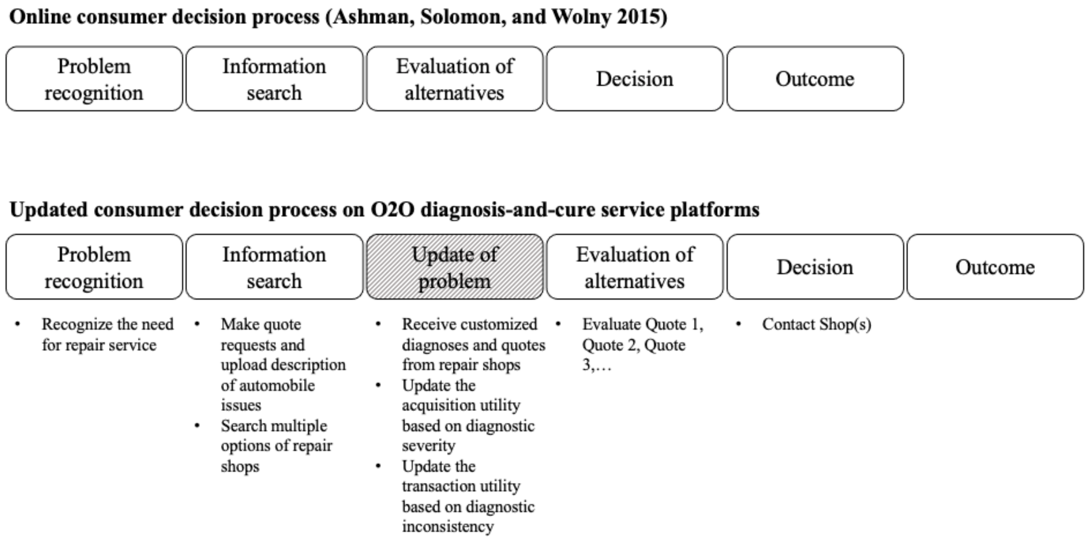

Table 1. Descriptive Statistics of Data

Variables	Mean	Median	Std. Dev.
Diagnostic severity (US $)	375.54	302.27	288.86
Diagnostic inconsistency (US $)	103.03	64.28	159.64
Distance (kilometer)	10.15	4.63	170.96
Shop Class (0 or 1)	0.47	0	0.50
Quoted price (US $)	375.54	298.18	330.05
Time taken to receive quotes (hour)	4.41	0.58	10.50
No. of previous quotes	1.78	1	1.92

Table 2. Parameter Estimates

Description	Estimate	Std. Err.	P-value
Intercept	-1.095 ***	4.108×10^{-2}	<.001
DiagSeverity	1.631×10^{-3} ***	1.479×10^{-4}	<.001
DiagInconsist	1.787×10^{-4}	2.157×10^{-4}	>.4
ShopDistance	-.2062***	1.686×10^{-2}	<.001
ShopClass	.1373***	3.990×10^{-2}	<.001
QuotedPrice	-1.583×10^{-3} ***	1.033×10^{-4}	<.001
TimeElapsed	-9.134×10^{-3} ***	1.610×10^{-3}	<.001
NoQuotes	-.2656 ***	8.892×10^{-3}	<.001
ShopDistance × DiagSeverity	9.963×10^{-5} **	4.138×10^{-5}	<.02
ShopClass × DiagSeverity	1.911×10^{-4} *	1.017×10^{-4}	<.06
QuotedPrice × DiagnSeverity	-2.890×10^{-8} *	1.812×10^{-8}	<.09
ShopDistance × DiagInconsist	-1.865×10^{-4} **	8.438×10^{-5}	<.03
ShopClass × DiagInconsist	-5.150×10^{-4}***	1.893×10^{-4}	<.01
QuotedPrice × DiagInconsist	1.953×10^{-7}***	4.128×10^{-8}	<.001

*: *p*<.10, **: *p*<.05, ***: *p*<.01.