Determining Factors of Consumer Purchase Intent in Service-Oriented B2C E-Marketplaces

An empirical study of GetEase user data and Dutch COVID-19 stringency.

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Date final version: 28th February, 2023

Bachelor Thesis International Bachelor of Economics and Business-Economics

Abstract

The shift in location of marketplaces from the physical to the digital realm demands new and updated understanding of consumer behaviour in modern e-marketplaces. This research builds on the work of Fan et al. (2013) and Koch et al. (2020) by exploring the relationship of consumer purchase intent with (a) individual demographic characteristics, (b) online behavioural patterns, (c) firm strategies, and (d) the COVID-19 pandemic. Starting with a literature review of highly cited and relevant academic papers, this study puts forth four key hypotheses, each focusing on validating the effect of one of these outlined relationships. Individual- and population-level data is then gathered from a Dutch service-oriented B2C e-marketplace and the Oxford Coronavirus Government Response Tracker. Results and analysis are generated through a combination of a random forest machine learning and a subsequent fitted logistic regression. This paper finds strong evidence for the existence of significant effects of all the outlined factors on consumer purchase intention. Thus, the null hypotheses of each of the four hypotheses can be rejected. The models formulated prove effective in generating valuable academic and business insights within the specific context in which they are applied. Having surmised key understanding regarding the variables affecting consumer purchase intent, this paper suggests that further research be conducted into the practical applications of this knowledge.

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1 Introduction

Imagine you are the proprietor of a stall at the local farmers market. Shoppers browse your wares, pick them up, turn them around, look you in the eyes, and eventually make a decision: to make the purchase, or to move on to the next stall. In this brief moment of interaction, a set of judgements is made, often implicitly. Is this item high in quality? Is the seller trustworthy? Is the price reasonable? Embedded in the answers to these questions are the fundamental variables that lead to the ultimate purchasing decision.

The relationship between consumer, product, seller, and marketplace goes back to the bazaars of early civilisations. Since then, marketplaces, sellers, consumers, and the nature of the products sold has evolved dramatically. The marketplace, which for Millennia has been characterised by a town centre or road side location, bustling stalls, haggling shoppers, and shouting salesmen, was introduced to the internet in 1982 with the Boston Computer Exchange. In 1995 the e-marketplace giants Amazon and eBay launched, both reaching one million transactions within the first two years. The town square had been moved online. Recognizing this tectonic shift from physical to digital commerce, firms started developing the picks and shovels of e-commerce. In 2000, Google launched Google AdWords. The shouting salesman was now digital. With the introduction of Amazon Prime in 2005, Square in 2009, and Apple Pay in 2014 digital shopping was becoming ever easier (Tian & Stewart, 2006). Despite this momentous shift in the very definition of the marketplace, the fundamental deciding factors that drive the ultimate purchase of one product over another, at one vendor or another, remained the same. Quality, trust and price. But, some new factors determining consumer purchase intent (CPI) did come into play. The safety and security of online payment, the use of personal information (McKnight et al., 2002), the social implications of purchasing from what had now become household brands (Koch et al., 2020), and much more, all gained heightened relevance. Consumers now have access to not just a few dozen vendors, but thousands, if not more. Being the loudest salesman in the square simply won't do it any more. With the increased competition, new ways of reaching the consumer are required, and new strategies essential.

Not only are modern marketplaces digital, these e-marketplaces also offer different products and services. Firms such as Uber, Airbnb, and Deliveroo take advantage of digitalization to provide on-demand access to existing products and experiences. The Amsterdam based startup, GetEase, takes this concept one step further, offering an e-marketplace platform for freelancers in the beauty, household, and wellness sectors to offer their services on demand and on location. Given this clear abundance of different business models it is clear that marketers and academics, alike, must expand their understanding of the new, and old, determinants of CPI. Focusing in specifically on the context of B2C service-oriented e-marketplaces such as GetEase, this search for knowledge can be condensed into the following question:

"What are individual characteristics, macro-environmental forces, and externally controllable factors that influence consumer purchase intent for on-demand lifestyle-services on electronic marketplaces?"

Before discussing the social and scientific relevance of this specific question, it is important to define some central terms. The research design of this thesis is loosely based on that of the highly cited empirical study by Fan et al. (2013), who applied research to samples of Korean and Chinese users of C2C e-marketplaces. Fan et al. (2013) treated purchase intention strictly as a measure of the extent to which an individual plans or intends to buy a product or service in the near future. Further, it is important to define externally controllable factors as those aspects of the marketing mix and strategies that a company can control. These include such factors as social media presence, pricing strategies, and the technical functionality of the e-marketplace platform.

The social and scientific relevance of this study derives from a few key aspects. First, the empirical findings of this paper provide insight into the key determinants of CPI within the context of e-marketplaces. This knowledge can be beneficial to several key parties: company decision makers, including marketing managers, but also nascent entrepreneurs, investors, and researchers. By understanding which factors have the highest impact, managers and entrepreneurs can make informed decisions about the sales channels and audiences that might yield the highest return on investment. Second, this knowledge may help nascent entrepreneurs, angel investors, and venture capitalists to assess the risks and returns associated with investments into certain verticals. Third, despite substantial academic empirical research on CPI in the context of ecommerce as a whole, there is only a limited body of peer-reviewed literature characterising these relationships specifically within the specific context of on-demand e-marketplace platforms. Fourth, this market segment, while relatively new, has experienced immense growth that was only accelerated during the COVID-19 pandemic. Research presented here builds on the work of, for example, Hesham et al. (2021) and Koch et al. (2020), and specifically addresses the need for understanding of the determinants of CPI in B2C e-marketplaces post-outbreak, instead of focusing on ecommerce as a whole or C2C e-marketplaces. In doing so, this thesis seeks to validate and update findings of pre-pandemic literature in context of the COVID-19 pandemic.

The thesis is structured as follows. A Theoretical Framework outlines the existing body of empirical and theoretical literature relevant to the topic of the thesis, covering factors ranging from perceived trust and quality, to the effects of individual demographic characteristics. This section also comprises a review of the effects of the COVID-19 pandemic. Findings from the literature review are then fused into a set of four hypotheses, which guide the research described in this thesis. The Data section presents and discusses the dataset gathered, its origins, variables, and credibility. This is followed by an overview of the Methodology applied, in which the regression method and assumptions made are highlighted. Results and Analysis are presented, along with regression tables, evaluations of each of the four hypotheses, and an interpretation of the predictive performance of the aforementioned regression models. Finally, a Discussion and Conclusion section evaluates the findings in context with previous literature, and shows potential pitfalls of this study along with recommendations for future research.

2 Theoretical Framework – a Literature Review

In this section, a theoretical framework is constructed for research on consumer purchase intent in the context of B2C e-marketplaces. CPI has a plethora of ascendants, precursors, and drivers (Park & Kim, 2008) with varying influence and relevance. A large body of academic literature exists on the subject, propelled by the shift of commerce from the physical to the digital space over the last few decades. This literature covers a range of fields, including economics, marketing, and behavioural sciences. Here, papers have been selected with a broad focus on trust and quality, and with attention to demographics. These factors are deemed to be of overwhelming importance to CPI (Shiau & Luo, 2012). Given the coincidence of the research data collection with the COVID-19 pandemic, this special condition is also incorporated into the framework.

2.1 Trust

Trust plays a key role in a consumer's decision to make a purchase. However, the term has a diversity of definitions and interpretations across disciplines and sectors. A useful general definition has been suggested by Mayer et al. (1995): “Trust is the willingness of a party to be vulnerable to the actions of another party based on the expectation that the other will perform a particular action important to the trustor, irrespective of the ability to monitor or control that other party”.

Mayer et al. (1995) have proposed that trust can be broken down into 3 principal sources: the trustee’s ability, integrity, and benevolence. Here, ability refers to the trustor's perception of the trustee's competence and skill. Integrity refers to the trustor's perception of the trustee's honesty and ethics.

Benevolence refers to the trustor's perception of the trustee's willingness to act in the trustor's best interest. Mayer et al. (1995) argued that if the trustee is perceived by the trustor to have any of these qualities, then the trustor will place a higher degree of trust in them.

McKnight et al. (2002) built on this concept, defining a purchaser's trust in a vendor's ability as 'cognitive trust' or 'rational trust', and trust in a vendor's benevolence and integrity as 'affective trust' or 'emotional trust'. The authors developed a scale to measure cognitive trust based on factors such as website design, security, privacy, and customer service. McKnight et al. (2002) also developed a scale to measure affective trust based on factors such as website reputation, vendor similarity, and communication. Although both cognitive and affective trust have significant effects, the latter was found to have a stronger impact on purchase intentions than the former. Additionally, emotional, or affective trust, appeared to often be a precursor of cognitive trust, with a positive causative effect. McKnight et al. (2002) suggested several explanations for this relationship. Firstly, they argued that emotion may lead to reason, stating that emotional trust may serve as a signal that the vendor is trustworthy from a rational perspective. Secondly, it was proposed that if the trustor experiences a sense of security and comfort when interacting with the vendor, this can reduce the consumer's perception of risk, a theory also put forward in an early study of consumer trust by Jarvenpaa et al. (2000), and backed by dozens of causal studies (e.g., Kim et al., 2008; Gefen, 2002; Shankar et al., 2002). Thirdly, McKnight et al. (2002) proposed that affective trust may lead to increased engagement with the vendor. This can provide the consumer with more information and knowledge about the website or vendor, which in turn can drive the development of cognitive trust. Several influential papers have confirmed this interpretation, including Gefen (2000), who assessed the relationship between familiarity and trust, based on a survey, finding a positive association between the two, and successively between trust and the likelihood of purchase.

In a more recent paper, Hong and Cho (2011) separated out the effects of trust in the intermediary and trust in the sellers in the marketplace. This is particularly relevant in the context of business-to-consumer e-marketplaces, where intermediaries have a central role. Using survey data from customers of a Chinese e-marketplace, Hong and Cho (2011) investigated the determinants of intermediary trustworthiness, trust in the seller community, and their respective impacts on consumer loyalty and purchase intentions. They found that trust in the intermediary is influenced by factors such as benevolence and integrity, but not by competence. This was attributed to the increasing standardization of online marketplaces. Plainly said: if many e-marketplaces have similar competence, then this won't be a deciding factor in trusting one over the other. Additionally, consumer trust in the intermediary was found to have a positive impact on trust in the sellers, and also on consumer loyalty. This, in turn, can have a significant impact on CPI. However, only a weak, and possibly indirect, relationship was found between consumer trust in the intermediary and purchase intent. Moreover, Hong and Cho (2011) found seller trust to have no significant effect on either purchase intent or customer loyalty. It can be concluded that consumers care much more about how the intermediary will treat them, than about how competent it is or how trustworthy its sellers are. Therefore, Barnes and Hinton (2007) suggested that intermediaries can best focus on establishing a trusted brand-name, playing into the “emotion over ratio” consumer mindset.

2.2 Quality

In addition to trust, quality of product and service is a key factor in a consumer’s decision to purchase. This applies not only in the physical marketplace, but also in a digital environment. Based on a review of studies of traditional service quality, Zeithaml et al. (2002) established a clear distinction between it and e-service quality. In an earlier paper, Zeithaml et al. (2000) provided the first formal definition of website service quality or e-service quality, saying "It is the quality of the interface between the customer and the website in addition to the quality of the core service itself". Zeithaml et al. (2002) proposed that e-service quality has a positive impact on factors such as customer satisfaction, trust, and loyalty, all of which are key to doing effective first-time, and repeat business. With this motivation, they established a framework for understanding e-service quality and its dimensions, building a platform for more recent research. This framework identifies five key building blocks of e-service quality: informational quality, platform design, service quality, interactivity of the service provider, and customer satisfaction. The framework further details important antecedents of e-service quality: the level of investment in technology, the level of customer support training received by employees, and the level of resources allocated to platform development and maintenance. However, Zeithaml et al. (2002) suggested that due to the dynamic nature of e-commerce, it is important to continue researching and updating the framework in accordance with the changes and advances in the field.

The later paper by Yang et al. (2004) did just that, empirically developing a scale for measuring perceived e-service quality. In addition, this study repositioned customer satisfaction from a driver of perceived quality to a second and separate dependent variable in their model. Moreover, the authors also considered a new factor, perceived platform security, in addition to the five proposed by Zeithaml et al. (2002). Working with data collected from a sample of e-commerce shoppers, Yang et al. (2004) used factor and reliability analysis to develop a validated and reliable scale for the effects of independent variables on perceived service quality and customer satisfaction. All factors were found to have a positive and significant effect on both dependent variables, with the exception of perceived security, which had a small and statistically insignificant effect on perceived service quality and customer satisfaction. No explanation was offered for this intriguing finding, but a possible cause can be found by Hong and Cho (2011), where a similar finding for the coefficient of competence on perceived trustworthiness was attributed to the increasing standardization of online marketplaces. They found responsiveness of the e-service platform to have the highest effect on both customer satisfaction and perceived quality, highlighting the importance of a solid technological foundation and consistent platform maintenance.

Fan et al. (2013) further developed the framework established by Zeithaml et al. (2000) and Yang et al. (2004). Following an established pattern, They too broke down perceived quality of e-service into four fundamental building blocks: convenience, contents, aesthetics, and interactivity. Using several statistical methods, the authors then employed a three-stage model exploring the effects of these four factors on emotional- (customer satisfaction) and behavioural-engagement. In addition, the study considered the effects of emotional and behavioural customer engagement on what Fan et al. (2013) termed relationship intention. This is, in effect, an amalgamation of CPI and net promoter score. By using survey data collected from in South Korea and China, the authors also explored how platform quality influences online shoppers' emotions and behaviours, and how these vary cross-culturally. All four components of quality, as defined by them, were found to have significant effects. However, aesthetics were found to have a significant effect only on emotional engagement, and not on the other three components. Additionally, ease of use / convenience was shown to only affect behavioural engagement. Overall, Fan et al. (2013) found that survey respondents cared most about ease of use when deciding whether to engage with a platform, and about the informational quality when deciding how they felt about it. Moreover, behavioural engagement was found to have a positive effect on emotional engagement. Fan et al. (2013) proposed that the flow experience, that is the sense of being fully absorbed in an activity, may play a role in the link between behavioural and emotional engagement. When it comes to making a decision on whether to engage in a relationship with the vendor, the paper's findings suggest emotional engagement has more significant sway than does behavioural engagement. Fan et al. (2013) posited that this is because a consumer's decision ultimately comes down to the question of how they emotionally perceive the item's value compared to its cost, rather than to how much that consumer has engaged with the product or service.

Two samples, from the South Korea and China, allowed Fan et al. (2013) to show that the effect of perceived quality on purchase intent may vary across cultures. The four components of quality were found to have less of an impact on behavioural engagement amongst Chinese consumers when compared to their Korean counterparts. Fan et al. (2013) provided several possible explanations for this finding. They argued that Chinese consumers may be more accustomed to lower quality platforms while South

Korean consumers, who are habitual online shoppers, have higher expectations in this regard. Secondly, it was proposed that the level of trust in online shopping may be different between the two cultures, with shoppers in the South Korea being more likely to trust online retailers than their Chinese counterparts.

In an earlier study, Wells et al. (2011) investigated the relationship between website quality, consumer perceptions of product quality, and purchase intentions. Here, a conceptual framework based on well-established signal theory was applied. This theory was explained by Connelly et al. (2011) as "The study of how individuals use signals to convey information about their attributes or intentions, and how these signals influence the behaviour of others." Accordingly, Wells et al. (2011) adopted a three-stage approach. The first stage followed Fan et al. (2013) in using factors such as aesthetics, responsiveness, and informational quality as precursors of quality. In agreement with other work reviewed above, Wells et al. (2011) found all four precursors to quality to have statistical significance. However, unlike Fan et al. (2013), they found that platform aesthetics were the most impactful. Having derived a model for website quality, Wells et al. (2011) then explored whether said quality can positively influence consumer perceptions of product quality. Alongside website quality, the study also incorporated the level of information asymmetry, and the perceived trustworthiness of the seller, in a model for perceived product quality. Here, information asymmetry refers to the gap in product knowledge between sellers and buyers. The model yielded several interesting findings. First, by determining the coefficient of the interaction term of website quality and information asymmetry, it is shown that the effect of website quality on consumer perceptions of product quality is stronger in consumers who have higher knowledge of the products being sold. This suggests that website quality can be a more important signal of product quality in cases where information asymmetries are reduced. Second, and aligning with studies with a focus on trust rather than quality, Wells et al. (2011) showed that the positive effect of website quality on consumer perceptions of product quality and purchase intentions is partially due to an increase in consumer trust resulting from higher website quality.

2.3 COVID-19 (Corona)

Consumers not only base their purchase decisions on micro-level factors, such as trust and quality, but also on larger macroeconomic trends and occurrences. Black swan events in particular can cascade into large shifts in consumer behaviour within very short time frames, Zwanka and Buff (2021). These come in the form of environmental disasters, economic calamities, and, of course, viral pandemics. The most recent manifestation of this, the COVID-19 pandemic, has caused a seismic shift in consumer behaviour, with high street businesses experiencing absolute lows and their online counterparts undergoing immense growth (Nanda et al., 2021). Given this context, it is key to understand whether pre-pandemic models and findings and relationships are valid in a (post-)pandemic environment.

The paper "What Have We Learned about the Effects of the COVID-19 Pandemic on Consumer Behavior?" (Hesham et al., 2021), published early in the pandemic, has served as a jump off point for subsequent studies on the subject. The study established the necessity of updated post-outbreak (start of pandemic) research on the makeup of consumer’s purchasing decisions. Hesham et al. (2021) highlighted the fact that relationships found under normal circumstances may no longer persist in pandemic conditions. Indeed, their literature review identified multiple sources citing a strong increase in online shopping due to restrictions and health concerns. This was found to be especially pronounced in categories such as groceries and household essentials. Consumer values and purchasing patterns were also found to have undergone a pivot, with greater emphasis on health and wellness, a focus on convenience and affordability, and an increased willingness to try new products and brands. Besides this, Hesham et al. (2021) surmised that as a result of the transfer to online shopping, B2C e-marketplaces became a principal channel for product discovery. With these findings, the authors constructed a multi-tier model aiming to explore the relation of the consumer’s demographics, their COVID-19 risk exposure, shopping experience, and purchase intention, with the ultimate decision to purchase. The model was tested against several large samples and surveys of consumers of healthy foods in Saudi Arabia. By first examining the effects of perceived risk and the purchasing experience on purchase intent, Hesham et al. (2021) found several interesting relationships. The risk of exposure to the COVID virus was found to have a significant positive relation with the measure of online purchase intent. This effect, however, was counteracted by the perceived risk of e-commerce, particularly with regard to the safety of personal and financial information, a relationship outlined and empirically proven also in a large pre-pandemic literature (eg., Wells et al. (2011); Fan et al. (2013); Hong and Cho (2011)). Hesham et al. (2021) attributed the perceived risk of shopping online, particularly to the safety of personal and financial information. Further, it was found that an e-platform’s purchasing experience had significant impact on consumer purchase intent, echoing much of the pre-pandemic literature outlined above, and reinforcing its validity post-outbreak. The second tier of the Hesham et al. (2021) model considered the consumer’s purchase intent and their demographic characteristics as independent variables for the ultimate purchase decision. Demographics were found to have a large effect on purchase decisions in two dimensions: age and gender. The authors found that older consumers were slower to adopt online shopping, a relationship driven in part by higher risk aversion and lack of trust in e-commerce platforms in this age group, when compared to younger consumers. In addition, females were found to be more likely to pursue online shopping during the pandemic, when compared to men. However, given that Hesham et al. (2021) drew upon Saudi Arabian data, it was noted that the context of their sampling may very well affect the wider validity of its findings, especially in an international context. Regardless, it was emphasized the importance of taking demographic characteristics into account when considering the impact of the COVID-19 pandemic on consumer behaviour.

A study of online shopping motives of generation Y and Z during the COVID-19 Pandemic (Koch et al., 2020) looked more deeply into the drivers of CPI for specific demographic groups, providing possible explanations for the findings of Hesham et al. (2021). By using structural equation modelling, the study by Koch et al. (2020) considered survey data from hundreds of German consumers. They subdivided the possible purchase motivations into three different categories: normative, utilitarian, and hedonistic. Normative determinants refer to how individuals are guided by how they think and feel, and are often driven by moral, ethical, or legal standards. This has an internal and external component. Koch et al. (2020) state that the internal component consists of close social networks, i.e., social networks of family and friends, while the external component comprises the influences that stem from external sources such as media and advertising. Utilitarian determinants refer to the perceived usefulness of the item in question. Finally, hedonistic determinants are based on an individual's desires and subjective experiences, such as pleasure, happiness, and well-being. Pre-pandemic research, as outlined above, has put a heavy emphasis on emotional drivers of CPI (e.g., Fan et al. (2013); McKnight et al. (2002)) and this was also echoed in the findings of Koch et al. (2020), with hedonistic motivations having the strongest relationship with purchase intent. Koch et al. (2020) argued that consumers were more likely to be motivated by enjoyment and pleasure during times of uncertainty. This effect was most pronounced in individuals who were practising social distancing, younger consumers, and women. Koch et al. (2020) attributed this to the fact that these groups were more likely to be affected by the pandemic. Further, they argued that both women and younger consumers were more likely to be tech-savvy and comfortable with online shopping, which may combine with higher levels of hedonic motivation. Although not a key focus of the study, Koch et al. (2020) noted that trust in online shopping was a concern for some consumers before the pandemic, but that the increased use of e-commerce during the pandemic has helped to build trust in the system, accelerating the transition to online shopping.

2.4 Hypotheses Framework

The above literature review covers academic research focused on the determinants of CPI in digital space spanning over 2 decades. It considered the core concepts of trust, quality, and the

COVID-19 pandemic, but also the demographic characteristics which drive some individuals to have higher propensity to purchase than others. Moreover, the strategies firms can employ to maximize CPI have also been highlighted. This paper distils down from the findings of the pre-existing literature a set of four key hypotheses:

1. *A significant relationship exists between demographic characteristics and CPI. (H1)*
2. *A significant relationship exists between company strategic decisions and CPI. (H2)*
3. *A significant relationship exists between previous experiences with the platform and CPI. (H3)*
4. A significant relationship exi*sts between the COVID-19 pandemic (Corona) and consumer purchase intent. (H4)*

These serve to cover all relevant effectors of CPI, and in doing so help guide research with the goal of identifying those that move the needle most in this regard.

3 Data & Methodology

In testing the four hypotheses listed above, applying the appropriate data is absolutely critical. It must cover the full spectrum of individual data at the micro-level to macro-level population statistics, and the information covered must be credible and reliable. To achieve this, a range of data-sets and sources were drawn upon to build a comprehensive sample for analysis. In this chapter, the sources used, and their background and credibility are highlighted. Following this, the resulting sample, and its variables and bias are described and explained.

3.1 Data Sources

To cover information concerning individual demographics and behaviour, and company strategy, this paper relies upon data from a Dutch B2C on-demand services e-marketplace, GetEase BV. GetEase is an open marketplace that focuses on services in the beauty, fitness, and lifestyle segments. Through an iOS and Android mobile application and a supplementary desktop web application, this platform connects service providing freelancers to consumers. The firm was founded during Q1 of 2021, and has raised substantial pre-seed and seed round funding from a combination of large European venture capital funds and angel investors. It is the first Dutch entrant of this market, and has no national competitors at the time of writing. As a source, GetEase closely reflects those selected by Hong and Cho (2011), who relied on data from similar B2C e-marketplaces.

A collection of sources concerns population-level COVID statistics. The first of these is the online platform Our World in Data (OWID). This organization provides data and research on a wide range of global issues, including health, education, and the environment. It is funded by grants from private foundations, including the Bill and Melinda Gates Foundation and the Open Philanthropy Project. The specific datasets, pulled from OWID, were generated with measurements from the Oxford Coronavirus Government Response Tracker, a project that tracks and compares the policy responses of governments around the world to the COVID-19 pandemic. Led by researchers from the Blavatnik School of Government at the University of Oxford, the project is highly credible, and its data has been widely used in academic research and policy analysis.

3.2 Sample

Through the amalgamation of the above listed data-sources, one cohesive data-set was constructed, comprising three groups of data: individual, company-level, and population wide. The data falls in one of three classes: cross-sectional, panel, and time-series data. From GetEase, both cross-sectional and panel data were collected. The former consists of user account information, such as emails, dates of birth, and addresses, from 1,031 individuals. The latter concerns both individual and firm-level variables. On the firm-level, variables range from bookings (purchases) data, to metrics detailing marketing campaigns, social media channels, and platform dynamics such as App Opens. On the individual level, analytical measures such as Time in App, and Abandoned Carts were sourced. This data spans a period of 360 days from January 31, 2021 - January 26, 2022. For this period, data per day per user is available from the first date on which they interacted with the platform. Cumulatively, this results in 49,168 individual observations. Population level data on COVID-19 was filtered to match the date range dictated by the GetEase dataset. This group contains categorical indicators of the stringency of various governmental policies and regulations. As the user sample is random by nature, no particular selection criteria were taken into account. Despite this, a degree of bias is expected due to the time window, consumer preferences, and audiences targeted by the firm's marketing. The full sample, it's variables, and its descriptive statistics are outlined in Table 1.

Table 1 *Descriptive Statistics of the Sample Variables*

Variable / Group	Observations	Mean	Std. Dev.	Min	Max
1. Individual Demographic Characteristics					
Male	49,168	0.458	0.498	0	1
Age	49,168	46.791	13.948	18	72
Friends on Platform	49,168	1.407	5.250	0	41
Amsterdam	49,168	0.808	0.397	0	1
Follower	49,168	0.455	0.498	0	1
Source					
Newsletter	49,168	0.019	0.135	0	1
LinkedIn	49,168	0.072	0.259	0	1
Other	49,168	0.909	0.288	0	1
2. Company Data					
Crash / Booking Ratio MA	49,168	0.533	0.410	0	2
Engagement / Impression Ratio MA	49,168	0.076	0.334	0	15
Influencer Impressions MA	49,168	5,980.390	6,625.120	0	18,678
Instagram Impressions MA	49,168	23.922	13.883	0	66
Total Available Discounts	49,168	58.540	129.096	0	650
3. Individual Behaviour on Platform					
Booking	49,168	0.214	0.410	0	1
Booking within 7 Days	49,168	0.023	0.151	0	1
Time in App	49,168	63.529	70.602	1	468
Drafts to Date	49,168	1.510	5.944	0	88
Bookings to Date	49,168	0.645	2.548	0	22
Drafts in Last Week	49,168	0.107	0.681	0	23
4. COVID-19 Restrictions					
Stay at Home					

	0 - No measures	49,168	0.305	0.461	0	1
	1 - Recommend not leaving house	49,168	0.683	0.465	0	1
	2 - Require not leaving house unless essential	49,168	0.011	0.106	0	1
	3 - Require not leaving house with minimal exceptions	49,168	0.000	0.000	0	0
School						
	0 - No measures	49,168	0.189	0.391	0	1
	1 - Recommend closing	49,168	0.482	0.500	0	1
	2 - Require closing (only some levels / categories)	49,168	0.086	0.280	0	1
	3 - Require closing all levels	49,168	0.243	0.429	0	1

Notes: MA in the above table refers to a Moving Average metric. This is based on a 2- week backwards looking lag, and captures the average for each of the 14 days in the 2-week time window. Besides this, the variables Source, Stay at Home, and School are categorical variables. All other variables are either binary, or continuous.

There are several variables and statistics in Table 1 that require explanation, beyond the definitions provided in Appendix Table 1. To start, the sample has four distinct variable groups: Individual Demographic Characteristics, Company Data, Individual Behaviour on Platform, and COVID-19 Restrictions. Cumulatively, a total of 19 variables are included in the sample. Critical to understanding the sample's descriptive statistics, is the firm’s marketing strategy during the time window. This focused heavily on services in the beauty segment, which caused a slight dominance of female users (54%). Further, individuals aged between 25 and 55 were targeted in online advertisements, but as GetEase is addressing consumers who are willing and able to pay a premium for the convenience of at-home services, this results in a slightly older demographic, likely to have higher levels of disposable income. It is also important to note that the firm applied burst marketing strategies during the 360-day period. This approach entails running promotions and advertisements during short periods, often less than two weeks. As a result, the variables Influencer Impressions Moving Average (MA) and Total Available Discounts are sporadically high and low, and have commensurately high standard deviations. It is important to note that a 2-week backwards-looking MA is applied for all moving average variables. Moreover, Total Available Discounts (TAD) is a cumulative sum of the value of all discounts available at a given time. Note also that during the first half of the sample period (January 2021 - July 2021), the firm was not active on Instagram, which results in a very low mean for Instagram Impressions MA. At the individual level, it is key to recognize the inherent differences in user behaviour. While some users were active on the marketplace well before the first date in the sample window, others first were observed on the platform on the very last date in the sample.

Age is shown in Table 1 as a continuous variable, but in this research it has been treated as a categorical variable with six distinct age groups. These groups are: 18-24, 25-34, 35-44, 45-54, 55-64, and 65-75. Additional descriptive statistics for each of these age groups can be found in Appendix Table 2.

Another majorly important variable to touch upon is the user location. This treated as a binary indicator of whether an individual resides at an Amsterdam postcode or not. Location data were only available for 22.227% of the total sample. 80.770% of this subset were located in Amsterdam. This paper makes the assumption that the geographic distribution of the 77.773% of users in the sample for whom no location data is available, is identical to that of the group with location data is present. The missing data points were randomly adjusted to achieve an overall 80.770% to 19.230% ratio of individuals in and outside Amsterdam. Even within Amsterdam, users were heavily clustered within higher-income neighbourhoods in and around the city centre, as illustrated in Appendix Figure 1.

3.3 Methodology

The central goal of this paper is to establish which demographic, macro, and micro factors have influenced the CPI of a young Amsterdam-based e-marketplace company. In order to tackle this question, the paper draws on a four-stage modelling approach. The stages successively incorporate variable groups, starting with Individual Demographic Characteristics, and adding Company Data, Individual Behaviour on Platform, and COVID-19 Restrictions in stages 2-4, respectively. A binary outcome variable is applied, analogous to CPI. The data is fairly complex in nature, originating from a multitude of sources, and requires appropriate estimation techniques. For this purpose, Niculescu-Mizil and Caruana (2005) have suggested multiple logistic regression. This is a generalized linear model, applied to selected dependent variable(s), the main explanatory variables, along with controls that help reduce endogeneity and limit concerns such as omitted variable bias. In each stage of the model, the logistic regression employs the same base formula:

$$logit(P(Yi = 1|Xi)) = \beta 0 + \beta 1 * Xi1 + \beta 2 * Xi2 + \ldots + \beta k * Xik + \varepsilon i$$

The logistic regression approach relies upon several assumptions to produce accurate results. Key amongst these is the assumption that the effect of the predictors on the log odds of the outcome variable is constant, meaning that the slope of the relationship between the predictors and the log odds is assumed constant. To account for this, we use a Random Forest algorithm followed by a fitted logistic regression model. This approach can capture complex non-linear relationships, account for heterogeneity, and reduce the risk of omitted variable bias. The method here is drawn from Niculescu-Mizil and Caruana (2005), who explored the determinants of consumer behaviour for online music purchases. They demonstrated that the random forest and logistic regression combination outperforms traditional linear models in terms of predictive accuracy and feature importance.

Each of the four model stages applies a logistic regression to the fitted outcome values (Yi) of the random forest machine learning model for that respective stage. In doing so, each stage explicitly seeks to answer one of the four hypotheses listed in Chapter 2 by adding a relevant set of explanatory variables to the ones included in the earlier stages. In order. Model 1, then, explores H1, Model 2 H2, Model 3 H3, and Model 4 H4.

The regression in model 1 differs significantly from the subsequent three. It serves to determine whether a base level propensity exists for individuals to place a booking based on their demographic characteristics. Here, only Variable Group 1 is used, which is strictly cross-sectional in nature. The dependent variable (Yi) of this model stage, 'Has Booking', is the binary indicator of whether the user has placed a booking. This dependant serves as an analogue for an individual overall CPI. In the following, the dependant of Model 1 is referred to as CPI. A total of six explanatory variables are included, two of which are categorical: Age and Source; three are binary: Male, Amsterdam, and Follower; and one is continuous: Friends on Platform. What is key to note here, is the categorization of the continuous variable age, a decision motivated by the likely non-linear relationship between this variable and the log odds of the outcome variable: Has Booking. As previously explained, there are a total of six age categories, normalised to the reference group age 18-24.

Next, in the subsequent three models, we introduce additional panel and time-series data from variables Groups 2, 3, and 4. These detail the time-variable company metrics, individual user behaviour, and COVID-19 responses while keeping the demographic variables constant across time. For each of these additional three models, the dependent variable (Yi) is the binary indicator of whether a booking will be placed within the next week: Has Booking within 7 Days. As in Regression 1, this metric too serves as an analogue for CPI.

The regression in model 2 focuses on the relation between company strategy and CPI. Here a total of five continuous variables from Group 2 are added: Crash to Booking Ratio MA, Total Available Discounts, Influencer Impressions MA, Instagram Impressions MA, and Engagement to Impression Ratio MA. Notable here are the backwards-looking moving average variables. Including a lag smooths the data and eliminates outliers caused by the firm's marketing strategy. It also helps account for autocorrelation of observations. In regression 3 a further four continuous variables are added from group 3: Days in App, Drafts to Date, Bookings to Date, and Drafts in Last Week. These variables serve to outline the effect of an individual's behaviour and their interaction with the platform. Finally, in Regression 4, two categorical variables pertaining to the COVID-19 pandemic are added: Stay at Home and School Closures. Each has four values, indicating the severity of the respective measures.

This study employs an out-of-sample testing technique to evaluate the effectiveness and predictive power of the four models. To do this, the sample is randomly divided into a 75% training set and a 25% testing set. The training set is used to create the models. The testing set is used to assess the models' performance in predicting outcomes that were not included in the training set. Here sensitivity, specificity, balanced accuracy, precision, recall, and F1 score are applied to assess the model performance. The trade-offs between true positive, true negative, false positive, and false negative predictions are taken into consideration by these metrics. They offer a more thorough and nuanced evaluation of the models when compared to R-squared and Pearson's chi-square test, which are unlikely to account fully for the intricacy of the data or the subtleties of the model. The chosen approach gives a more precise picture of how well the models function in practical situations. Two distinct cut-off points are set for model performance. For the predictions of Model 1, we set the cut-off at or above an odds' ratio of 0.2. For the further three models, this cut-off is set at an odds' ratio of 0.065. Model 1 differs from Models 2, 3, and 4 in that it has a time invariant dependent variable, which justifies a higher cut-off ratio. When selecting cut-offs, it is important to balance the cost of getting the prediction wrong, to the cost of getting it right. In this case, a model is constructed to determine CPI, which in a realistic use case can be applied to make decisions concerning the costs and targeting of marketing and user base re-activation efforts. In the real world use case at hand, the cost associated with a wrong prediction are low, but the benefits of identifying individuals who may have a higher CPI than others may be significant. Given this, low odd's ratio cut-offs are appropriate.

A variance inflation factor (VIF) approach is used in this study to test for multicollinearity among the independent variables. In order to satisfy the assumption that there is no multicollinearity between variables, any problematic variables were removed from the model at each stage when the VIF score was 10 or higher, which is seen as a sign of strong multicollinearity. In the following, it is assumed that no multicollinearity is present.

4 Results & Analysis

Regression findings for the four models are present and analysed in this chapter and summarised in Table 2. The evaluation of the variables impacting CPI is the study's main goal. We use the four previously highlighted hypotheses to guide the analysis of the regression results. Relevant results from the four models are brought to bear on the individual hypotheses, allowing for the discovery of bias in coefficients to an extent that would not otherwise be possible. As no single variable decides whether any one of the four hypotheses is rejected or not, we define the conditions of non-rejection as an instance in which at least one of the pertinent variables has a strong and significant impact on CPI. While the full breadth of the four models is utilized to infer relationships between the independent variables, only the coefficients of Model 4 are taken into account for the rejection and non-rejection criteria of the hypotheses.

Table 2 *Results of Fitted Logistic Regressions*

Variable / Group	Model 1	Model 2	Model 3	Model 4
Constant	-2.512	-4.721	-4.161	-6.814
1. Individual Demographic Characteristics				
Male	0.294***	-0.851***	-0.821***	-0.925***
	(0.043)	(0.111)	(0.079)	(0.08)
Age				
18-24	0	0	0	0
	(omitted)	(omitted)	(omitted)	(omitted)
25-34	1.066***	0.441**	0.416***	0.351**
	(0.071)	(0.133)	(0.112)	(0.113)

35-44	-0.001	0.264	0.315*	0.370**
	(0.082)	(0.191)	(0.133)	(0.130)
45-54	1.059***	-0.264	0.405**	0.169
	(0.068)	(0.156)	(0.125)	(0.13)
55-64	-0.202**	0.802***	0.492***	0.510***
	(0.081)	(0.164)	(0.122)	(0.102)
65-74	0.411***	-0.149	0.307*	0.310*
	(0.081)	(0.186)	(0.125)	(0.122)
Friends on Platform	0.162***	0.096***	0.059***	0.057***
	(0.004)	(0.004)	(0.045)	(0.004)
Amsterdam	0.699***	-0.338**	0.068	0.141
	(0.066)	(0.108)	(0.085)	(0.086)
Follower	1.446***	1.224***	0.706***	0.592***
	(0.212)	(0.174)	(0.089)	(0.092)
Source				
Other	0	0	0	0
	(omitted)	(omitted)	(omitted)	(omitted)
Newsletter	1.862***	1.524***	0.366*	0.610**
	(0.082)	(0.235)	(0.178)	(0.181)
LinkedIn	1.440***	0.972***	0.709***	0.693***
	(0.044)	(0.118)	(0.099)	(0.100)
2. Company Data				
Crash / Booking Ratio MA		-1.494***	-0.649***	-0.331
		(0.179)	(0.100)	(0.169)
Engagement / Impression Ratio MA		0.025	-0.085	-0.334***
		(0.050)	(0.055)	(0.076)
Influencer Impressions MA		-0.000***	-0.000	-0.000
		(0.000)	(0.000)	(0.000)
Instagram Impressions MA		-0.000	0.000**	0.000
		(0.000)	(0.000)	(0.000)
Total Available Discounts		0.000	0.000***	0.000*
		(0.000)	(0.000)	(0.000)

3. Individual Behaviour on Platform				
Time in App			-0.009***	-0.008***
			(0.001)	(0.001)
Drafts to Date			-0.005	0.009
			(0.008)	(0.007)
Bookings to Date			0.155***	0.100***
			(0.015)	(0.016)
Drafts in Last Week			0.371***	0.336***
			(0.031)	(0.030)
4. COVID-19 Restrictions				
Stay at Home				
0 - No measures				0
				(omitted)
1 - Recommend not leaving house				0.552***
				(0.120)
2 - Require not leaving house unless essential				2.416***
				(0.251)
3 - Require not leaving house with minimal exceptions				0
				(empty)
School Closures				
0 - No measures				0
				(omitted)
1 - Recommend closing				2.513***
				(0.288)
2 - Require closing (only some levels / categories)				2.193***
				(0.345)
3 - Require closing all levels				2.158***
				(0.304)
Number of Observations	49,168	49,168	49,168	49,168

Notes: The model applied above is the combination of random forest machine learning and logistic regression, previously outlined. The first column details the variables included and their parent groups, the second, third, fourth, and fifth, respect show the results of regressions 1, 2, 3, and 4. The statistics shown are coefficients, constants and robust standard errors (in parentheses). * significant at 10%; ** significant at 5%; *** significant at 1%. While not displayed above, all coefficients satisfy the assumption that no multicollinearity is present, and carry VIF scores below 10.

The constant of Model 4 is -6.814, indicating the predicted log odds of CPI when all independent variables are held at zero. This metric shows the base level CPI for females, aged between 18 and 24, who's first point of contact with the firm is unknown, when all other variables are held constant. As can be seen in Table 2, the constant experiences a consistent decrease across the four models, indicating that with each set of new variables added, more information that was previously unobserved or unmeasured is captured, leading to a better fit of the model.

4.1 Hypothesis 1

Model 4 provides strong evidence of a significant relationship between individual demographic characteristics and CPI in service-oriented B2C e-marketplaces. Five of the six relevant demographic variables show significant and strong effects on CPI. Therefore, the null hypothesis of "A significant relationship exists between demographic characteristics and CPI" is rejected.

In model 4, the coefficient of Male is -0.925, statistically significant at the 1% level. This indicates that the odds of purchase are 60.347% lower for males than they are for females. Interestingly, across the four models this variable displayed a sharp downward trend in coefficient, and in Model 1 males have 34.178% higher odds of booking, compared to females. This suggests that omitted variable bias (OVB) may have been transmitted through the variable 'Male'. The largest change of its coefficient results from the inclusion of the Group 2 variables detailing firm strategy.

The categorization of the second variable, Age, shows that the previously speculated non-linear relationship between this variable and CPI, indeed exists. As compared to the baseline group, 18 - 24, the coefficients for the groups 25 - 34 and 35 - 44 are up by 0.351 and 0.370, respectively, while the coefficients for the groups 55 - 64 and 65 - 74 are also up, by 0.510 and 0.310, respectively. Each of these is significant to at least the 10% level. However, the coefficient for the intermediate group 45 - 54 is statistically insignificant. As indicated by these numbers, individuals in the age group 55 - 64 have the highest CPI, and have 66.525% higher odds of booking than the base group. We also see significant changes here in the coefficients across the model stages. This shows that this variable, also, is generating significant OVB prior to Model 4.

Similar to the variables Age and Male, the coefficient of Friends on Platform displays signs of mediation in earlier models. Distinct rifts can be shown between Models 1 and 2, and Models 2 and 3. The final coefficient of Friends on Platform in Model 4 is 0.057, significant at the 1% level. With each additional friend using the platform, the odds of booking increase by 5.886%. The coefficient for Amsterdam proves to be the only variable relevant to H1 that is statistically insignificant. While in Models 1 and 2, this variable has significance, upon the inclusion of the variable group 3, which details individual behavioural patterns, the variable becomes insignificant. This indicates the presence of confounding variables in Group 3. Results for the binary variable Follower show that in Model 4, individuals who follow the firm's social media channels, have 80.760% higher odds of placing a booking than those who don't. This finding is statistically significant at the 1% significance level. Similarly to the changes in the constant across the model stages, Follower also shows a consistent downwards pattern, again suggesting the presence of confounding variables in groups 2, 3, and 4 that indirectly drove up the impact of being a social media follower on CPI. The final variable relevant to H1, Source, also proves significant. Each category in the variable is significant to at least the 5% level. When compared to the baseline category, Other, the coefficient of the groups Newsletter and LinkedIn are 0.610 and 0.693 higher, showing that individuals in these groups have 84.043% and 99.971% higher odds of booking, respectively. A rift between Models 2 and 3 is signalled by changes in the coefficients, showing that this variable too is a channel through which confounding variables exert influence. This effect of confounding variables is larger in the category Newsletter than in the category LinkedIn.

4.2 Hypothesis 2

Similar to H1, Model 4 also supports the second hypothesis, "A significant relationship exists between company strategic decisions and CPI". However, in this case, only two of the five explanatory variables relevant to H2 are statistically significant. Nonetheless, the null hypothesis of H3 is rejected. The variables of interest here are those in Group 2: Crash / Booking Ratio MA (CBR), Engagement / Impression Ratio MA (EIR), Influencer Impressions MA (INF), Instagram Impressions MA (IG), and Total Available Discounts (TAD).

The first of the two significant variables, EIR, has a coefficient of -0.334. This value is statistically significant at the 1% level, and implies that each unit increase in the ratio of engagement actions to impressions throughout the firm's social media pages results in a decrease of 28.395% in an individual's odds of booking. Interestingly, this variable only becomes significant in Model 4, indicating the presence of suppressor variables among the COVID metrics of Group 4. The second significant variable is TAD, which is significant at the 10% level. However, the effect of TAD on CPI is small, and when rounded to 3 decimal places, a one Euro increase in TAD only increases odds of booking by 0.047%.

4.3 Hypothesis 3

Model 4 provides strong support for the third hypothesis: “A significant relationship exists between previous experiences with the platform and CPI”. Looking at the Group 3 variables: Time in App (TIA), Drafts to Date (DTD), Bookings to Date (BTD), and Drafts in Last Week (DLW), we see that 3 out of the 4 are statistically significant at the 1% level, whereas DBD is statistically insignificant. As such, we reject the null hypothesis of H3.

The coefficient of TIA is -0.008, which corresponds to a decrease in the odds of booking by 0.797% for each day since the first use of the platform. Said plainly, the longer it has been since an individual joined the platform, the lower their intent of making a booking. On the other hand, the variable BTD displays a strong positive coefficient of 0.100 which converts to an increase in the odds of booking by 10.517%, with each additional prior booking placed by an individual. This means that the higher the count of prior bookings placed by an individual, the more likely they are to book again. This metric experiences a slight shift between Models 3 and 4. The inclusion of the Group 4 variables Stay at Home and School Closures, then, seems to solve some degree of OVB that was channelled through BTD. The coefficient of DLW is stronger still, with a value of 0.336. This means that with each additional draft booking placed by an individual within the last 7-day period, that individual’s odds of booking rises by 39.934%.

4.4 Hypothesis 4

Finally, the hypothesis, “A significant relationship exists between the COVID-19 pandemic (Corona) and consumer purchase intent”, is also strongly supported by the results of Model 4. Both of the categorical variables: Stay at Home (SAH) and School Closures (SC), and their respective categories, are significant at the 1% level. Therefore, we reject the null hypothesis of H4.

Among the coefficients of Model 4, those of SAH and SC are by far the strongest. Starting with SAH, we see that, as compared to the base category “0 - No measures”, category “1 - Recommend not leaving house” results in a 73.672% increase in the odds of booking, and category “2 - Required not leaving house unless essential” results in an even stronger 1020.097% increase. With regard to the variable SC, the relationship between stringency and CPI, looks to be non-linear. When compared to the base category “0 - No measures”, an increase in stringency to “1 - Recommend closing” results in a 1134.190% increase in the odds of placing a booking. However, further raises in the level of stringency bring smaller increases relative to the base category. “2 - Require closing (only some levels / categories)” results in an increase of 796.206%, while “3 - Require closing all levels” yields an increase of 765.381%. As such, it is clear that the COVID-19 pandemic did have a very clear, but non-linear, positive impact on CPI in the context of the firm under consideration.

4.5 Model Predictive Power

When determining the predictive power of each of the four models, it is important to note that Model 1 is not as easily comparable to the other three, than Models 2, 3, and 4 are to each other. This is because Model 1 uses cross-sectional data and all other models apply panel data. The outcome of the first model is a measure of the odds of an individual placing a booking at all, and that of the subsequent three is the measure of the odds of a booking being placed within the next 7 days. While these two outcomes are analogous in CPI, it is important to highlight the fundamental difference between them. The measures of predictive power previously outlined here are shown in further detail in Appendix Table 3.

Model 1 has a sensitivity of 0.779, meaning it correctly identifies 77.9% of individuals who have placed a booking. It does so with a precision of 0.639, meaning that 36.1% of its positive predictions are in fact false. In regard to specificity, Model 1 correctly identifies 49.9% of all true negatives. Overall, it performs decently, with a balanced accuracy score of 0.639 and a F1 score of 0.501. A balanced accuracy score above a 0.6 and a F1 score above 0.5 are widely considered acceptable, but not particularly useful. The other three models perform generally worse than Model 1. While Model 2, 3, and 4 have very similar sensitivity values of 0.969, 0.960, and 0.959 respectively, there are consistent improvements in both specificity and precision from Model 2 to 3 to 4. Despite this improvement, all three perform worse in this regard than Model 1. The balanced accuracy and F1 scores of these models also steadily increase with each set of new variables added. Despite this, their F1 scores remain at very low levels.

While all models have predictive power, Model 4 performs better than the other time varying models, with the highest metrics across the board. However, Model 1 has an advantage in identifying which users will eventually place a booking, regardless of when it happens. As such, the choice for a predictive model, either Model 1 or Model 4, depends on the context and real life application.

5 Discussion & Conclusion

5.1 Discussion

The aim of research presented in this thesis was to explore the relationships between individual demographic characteristics, firm strategic choices, individual behaviours, COVID-19 stringency, and consumer purchase intent, and to determine which individual characteristics, macro-environmental forces, and externally controllable factors influence consumer purchase intent for on-demand lifestyle-services on electronic marketplaces.

This aim has practical relevance, as understanding these factors can help both firm managers and academics, alike, in making more informed decisions with regard to who and what to focus on. By conducting a thorough literature review on the relation of CPI with trust, quality, and the COVID-19 pandemic, four hypotheses were proposed, concerning the effects of demographic characteristics, firm strategic choices, individual behaviours, and COVID-19 stringency upon CPI. Armed with data on both an individual and population level scale, we used a combination of machine learning and traditional statistical methods to draw conclusions on these four focus areas. All four were found to have a statistically significant effect on CPI in the practice of an Amsterdam-based B2C e-marketplace platform for freelancers in the beauty, household, and wellness sectors. Notably, the findings suggested that COVID-19 restrictions had the strongest impact on individual CPI.

On a more granular level, there are several factors that both the results of this study and the literature reviewed agree upon as crucially important in determining CPI. Concerning an individual's base demographics, both gender and age, were found by this research and Hesham et al. (2021) and Koch et al. (2020) to have a strong effect on CPI. These two papers showed that in B2C e-marketplaces, these relationships persisted during the COVID-19 pandemic, and in fact grew in strength. The research described in this thesis confirms this pattern, demonstrating that emotional factors have an enhanced impact on CPI during uncertain times. However, unlike Hesham et al. (2021) and Koch et al. (2020), this study found that age does not have a linear relationship with CPI. When interpreting this result, it is important to recognize the fundamental differences between the types of e-marketplaces compared. The GetEase platform offers a wide range of different services, each of which likely has an independent and distinct audience and user base. As such, a complex, compound relationship between age and CPI may manifest on a collective basis, while this relationship may be more linear in nature on a service specific level. This holds also when considering gender. Females were found to have higher propensities to make a purchase, but this will depend heavily on the context in which the study is conducted.

Several enhancements and additions are made by this thesis to previously published models. These stem mainly from the inclusion of variables detailing an individual's own, and their social network's connection to the firm and its services. Koch et al. (2020) also explore these effects, however, do so using survey data on a much higher level. As a result, there is a strong contrast between the results of this thesis and those of Koch et al. (2020). While this thesis finds a strong positive effect of both the individual's own level of social connection to the firm, and that of their social network, Koch et al. (2020) found this relationship to be insignificant. Instead, their results suggested that normative pressures such as media reports have a larger impact on consumer behaviour. A possible explanation for this contrast can be found in Fan et al. (2013). They showed that the determinants of CPI may differ across geographies. As this thesis was focused on the Netherlands, while Koch et al. (2020) worked in Germany, cultural differences may be the root cause of their contrasting findings. It is culturally plausible that German consumers place higher value on traditional news media, while Dutch consumers prefer the opinions and norms of their own social networks.

Another key finding shared by published studies and this thesis, is the connection of behavioural and cognitive interaction with the platform and CPI. Fan et al. (2013) and McKnight et al. (2002), showed how these factors can drive the extent to which consumers perceive a platform as trustworthy and its services as having quality, thus leading to increased CPI. Similarly, research presented here showed indicators of individual's past interactions with the platform to be leading positive drivers of the odds of booking. A finding supplementing research by Fan et al. (2013) and McKnight et al. (2002) was the degradation of CPI with increasing time after initial client-firm interaction.

These findings carry real-world applicable value. First, strategic decision makers, marketing managers, and firms as a whole must understand and capitalise on the immense shifts in consumer behaviour driven by black swan events like the COVID-19 pandemic. Firms which are unable to adjust to changing consumer preferences in the context of such events, will likely not be able to survive, while those firms that are able to quickly pivot and adapt to consumer preferences will thrive. Second, it is also key to consider the specific audience for each product or service at an individual rather than firm-wide level. There is no "one size fits all" approach to effective firm marketing and user re-activation strategy. Each audience will have a different and distinct channel via which sales can most effectively be generated. Third, it is important for firms to understand the crucial value of time in the equation of CPI. The earlier a consumer can be driven to purchase, the more effective and less costly this drive will be. Finally, it is also important to consider that existing customers are often those who can be activated in the most cost-effective way to place an order or booking, when compared to new customers.

5.1 Limitations and Recommendations

The work presented here, and the conclusions from this study and that of the field's existing literature, have several important limitations. First amongst these is the questionable external validity of this and many published studies. In many cases, including the research presented here, CPI is researched using a sample of consumers from just one, or at most a handful, of relevant e-marketplaces. It is in the nature of such platforms to cater to a specific vertical within the market, with specific customers whose characteristics may not accurately reflect those of the wider populace. Given this, it must be kept in mind that the results of specific studies may not translate well into the context of e-marketplaces operating within different service niches or industries altogether.

Moreover, the method, mode, and data utilised in this study leave significant space for improvement. While a total of 1,031 individuals were included in the sample, it is important to note that the same level of data was not available uniformly across the sample. For some individuals, data was only available during the later sections of the time frame, meaning that due to possible differences in marketing focus by the firm, these "newer" users may have inherent and fundamental differences to the "older" user base. Several assumptions had to be made to secure a sufficiently large sample size for the study time window in its entirety. Key amongst these was the assumption of the equal distribution of individuals in and outside Amsterdam, amongst the group for which no location data was available, compared to the group for which it was. Additionally, due to concerns about multicollinearity, several variables were excluded from modelling. While this ensured the validity of the logistic regressions, it resulted in a lack of resolution that could have been mitigated by a different methodology.

Given these limitations, several clear recommendations can be made for future research. First, the models employed here overgeneralize the context in which they are applied. In the specific case of GetEase, and similar e-marketplaces offering several distinct product or service categories, it would be prudent to take this pluriformity into account in a model for CPI. Second, while the models applied in this study do take into account the user's base level characteristics, it is key to note that these may not remain constant over time. Given this, the methodology applied may again oversimplify the true nature of CPI, and future studies considering per-user data, may benefit from applying more complex and computationally expensive methods of prediction such as random effects models, or other machine learning models. And finally, while the conclusions drawn from this paper do provide valuable insights, it would be pertinent to further explore variables that drive the needle in regard to CPI. A specific gap in knowledge exists with regard to the targeting of specific consumers. Which consumers should marketers and firms target, where, when and how? This question carries immense value for researchers and firms alike.

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7 Appendices

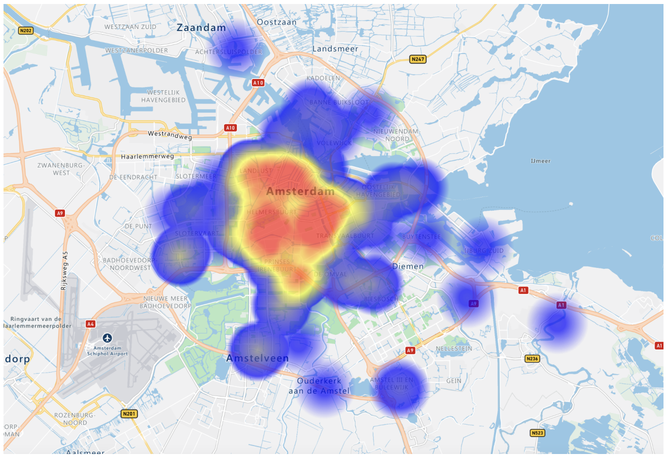
Appendix Table 1 *Variable Definitions*

Variable / Group	Definition
1. Individual Demographic Characteristics	
Male	0 if female, 1 if male.
Age	The continuous measure of age.
Friends on Platform	The firm's estimate of the count of "friends" a user has on the platform.
Amsterdam	0 if living outside of Amsterdam, 1 if living inside of Amsterdam.
Follower	0 if doesn't follow at least one of firm's social media platforms, 1 if follows at least one of firm's social media platforms.
Source	The first point of interaction between client and firm.
2. Company Data	
Crash / Booking Ratio MA	A ratio of the total count of app crashes and the total count of bookings
Engagement / Impression Ratio MA	A ratio of the total count of likes, comments, and shares and the total count of impressions on the firm's Instagram account.
Influencer Impressions MA	A count of the total estimated impressions related to specifically the firm, across social media influencers and traditional news media.
Instagram Impressions MA	A ratio of the total count of impressions on the firm's Instagram account.
Total Available Discounts	The Euro sum of the total currently available discount values.
3. Individual Behaviour on Platform	
Booking	0 if no booking ever, 1 if at least one booking ever.
Booking within 7 Days	0 if no booking within seven days, 1 if at least one booking within 7 days.
Time in App	Count of days since user first opened App or Web App.
Drafts to Date	The count of abandoned carts to date.
Bookings to Date	The count of bookings to date.
Drafts in Last Week	The count of abandoned carts within the last seven days.

4. COVID-19 Restrictions	
Stay at Home	Measure of the level of restrictions regarding staying at home.
School	Measure of the level of restrictions regarding school closures.

Appendix Table 2 *Distribution of Age and Disposable Income for Men and Women*

Variable	Frequency	Men	Women
Age			
18 - 24	37	9	28
25 - 34	248	55	193
35 - 44	209	88	121
45 - 54	190	83	107
55 - 64	219	106	113
65+	128	39	89
Total	1031	380	651



Appendix Figure 1. *Geographic distribution of users included in the study database within Amsterdam. Heatmap shows the relative density of 203 individuals for whom location data is available. Colour gradient is from blue for low relative density to reed for high* relative density.

Appendix Table 3 *Predictive Power Statistics*

Metric	Model 1	Model 2	Model 3	Model 4
Cut off	0.2	0.065	0.065	0.065
Sensitivity	0.779	0.969	0.960	0.959
Specificity (Recall)	0.499	0.149	0.283	0.331
Precision	0.504	0.103	0.144	0.161
Balanced accuracy	0.639	0.559	0.621	0.645
F1 score	0.501	0.122	0.191	0.216
Number of Observations	49,168	49,168	49,168	49,168