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The Role of Artificial Intelligence in Sustaining the E-Commerce Ecosystem:
Alibaba vs. Tencent

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ABSTRACT

A large number of customers have used traditional e-commerce portals, where there are no assurances of product quality, display of all features, picture search, virtual chat service, product recommendation, and tracking facility. Due to these disadvantages, the customers have switched to Alibaba and Tencent products line and remain in the ecosystem. The present study drew on Quo Bias theory to investigate the customer behaviour to remain on the e-commerce platform. Twenty-eight in-depth interviews were conducted to extract the variables and propose a model based on risk theory as well as CRCB framework. An offline survey was distributed to 649 (valid) ecommerce users; valid data was assessed and analyzed using structural equation modeling (SEM). Results show CRCB was influenced by switching cost and comparative attraction. Moreover, negative (undesirable) attitudes mediate the relationship between risk perception and CRCB, which has a positive impact on undesirable WoM. The study findings help the managers and policy makers to devise a new policy and serve the customers in a better way.

KEYWORDS

AI, Alibaba, China, Ecommerce, Sustainable, Tencent

INTRODUCTION

Day by day, the global ecommerce market is blooming, and a greater number of users are using online platforms, consequently creating a shopping ecosystem involving buyers and sellers. With the help of technological breakthroughs in big data, machine learning, supercomputing, and Artificial Intelligent (AI) have become more capable and more human-like of problem solving, manipulating objects, learning, and navigating physical space (Yogesh k et al 2021). More particularly, applications of AI in different aspect have developed rapidly Don and Pee (2021). E-commerce companies are using the AI system in different prospects (Leonardo et al 2018). Data works as the main component of AI. In the modern era, data (information) is backbone of every country. According to Jack Ma,

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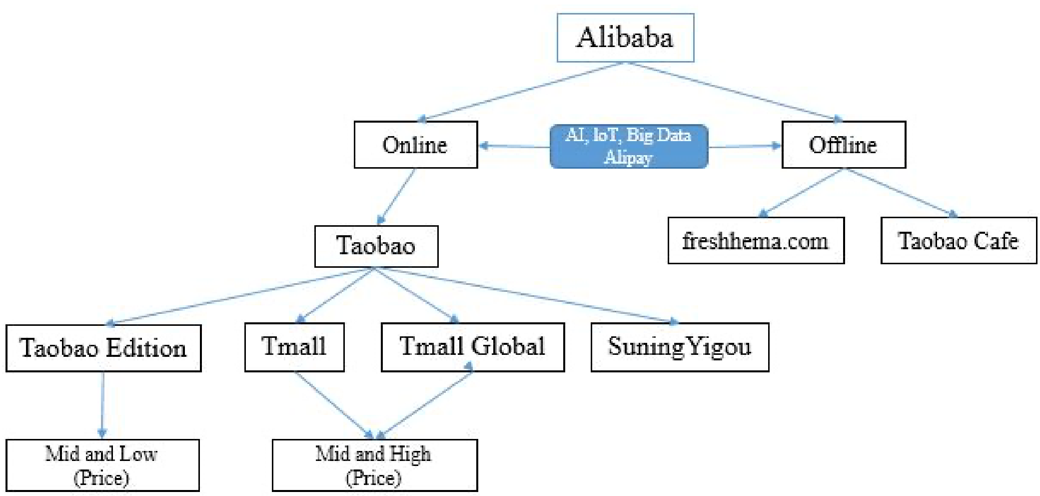
Executive Chairman of Alibaba, "Large scales computing and data are the father and mother of AI". Alibaba is working on AI "Smart Cities", where cloud-based AI will help improve traffic congestions. In the Big data, AI not only differentiates the company from its competitors, but also increases the financial and shareholder values (Hasan et al 2020).In the new digital era, the enterprises have found solutions through AI, Big data, and unmanned technologies. To attract the digital customers, mobile and e-payment system play a key role and have significant effects on customers (Emrah et al,2017).

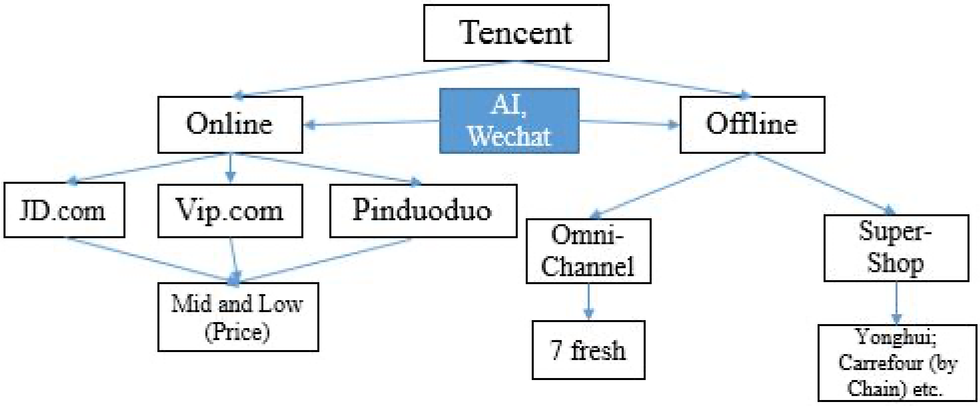
China is the one of the leading countries in the world, where the ecommerce market is larger than any other countries (China 782 million, USA 230 million, India 150 million). In prospect of Chinese market, Alibaba dominates the Chinese e-commerce market, followed by Tencent, which is an emerging challenger in the same market right now. Both companies provide good features for their own customers. Alibaba started investing the highest amount in AI, and Tencent followed the same path. Alibaba established 3,200 offline e-stores and employed Robotic system (Limited area), standing in the top position. Tencent has also achieved tremendous success in the same field and created trust in the online market. Some leading ecommerce platforms such as JD.com, VIP and Pinduoduo also joined the Tencent. According to the market evaluation, Tencent is a community-based service provider platform **(Figure 2),** and Alibaba ecommerce is a platform based on service network **(Figure 1)**. The products of both groups are an independent player of the ecosystem and are contributing to the service and economics sectors.

Figure 1. Alibaba Ecosystem



Source: Authors' explanation (Note: Alibaba Eco-system based on Major Products)

Figure 2. Tencent Ecosytem



Source: Authors' explanation (Note: Tencent Eco-system based on Major Products)

Alibaba and Tencent have been investing in the AI field, which shows a positive sign and opens a new area to sustainable e-commerce. According to China Daily (2017), Alibaba hired Amazon, which is a top AI leader, and gave a signal of competition in AI e-commerce market. Afterwards, Alibaba built Tmall Genie, which was very similar to Amazon echo. It features a voice that activates an AI Assistant and a smart home device. Also, it receives commands in mandarin. Alibaba group also brought online market innovation, which was called Ali Assistant. This Ali assistant provides customer service and process the written and spoken inquiries. According to Alibaba Group (2017), Alibaba, the Chinese ecommerce giant, is applying AI to its core e-commerce operations, redefining online shopping for millions of customers and merchants, and accelerating the process of what the company envisages to be in the future. Most of the services are available only in the Chinese mandarin language. AI assistant and product recommendation facility (by algorithms) represent another point to extend the market and to satisfy and sustain the customer needs (Niccolo Mejia ., 2018). Though Alibaba is regarded as the market leader, Tencent is an emerging challenger to Alibaba. Tencent's super app is WeChat and it has helped the company make around $450 billion USD as well as financial value. Tencent is also involved in the AI investment and has built a chat bot. It will focus on AI healthcare in the future. It has already assigned WeChat accounts to 38,000 medical hospitals and 60% appointments are accepted through online booking. JD.com is also part of the Tencent. Recently, JD.com is engaged in partnership with Siasun Robot & Automation Co Ltd, and they are working for automation tech like robots, resulting in the improvement of the warehouse system and achieving cost efficiency. From 2016 till today, JD.com has established 7 smart logistics centers and 209 warehouses using AI and fully automated systems in Gu'an China. According to CNML (2018), Tencent and JD are going to establish "the first unmanned warehouse" and AI robots will be responsible for handling and delivering the products. Tencent's another app "Pinduoduo", which is rapidly growing with nearly 61% of young generation users, falling in the age of 30s or younger (Shen. 2018). E-commerce and AI beneficiaries are mostly the young generation. AI is not only applied to e-commerce but also to all companies. These companies are the same in the field to capture the new market and take a leading position. Also, AI is not only used in the customer service sector, but also in packaging, transposition, and operations. According to Progressive Policy Institute (2017), AI has reduced the employment and achieved cost efficiency as well as cost effectiveness. On the other hand, AI in e-commerce has produced 355,000 jobs, more than it has taken (i.e., 51,000 jobs) from 2007 to 2016. According to Ksenia Striapunina (2019), the expected revenue of Chinese retailing ecommerce is $1,095.5 billion by 2023 **(Figure 3),** and Chinese ecommerce value will reach $1.8 tn by 2022, which means that Chinese ecommerce value will be double than that of the United States of America as well as 10 times more than that of Japan (Wilson, 2018).

There are more studies on online buying, selling, product rating, and online customer satisfaction, but a limited number of studies on AI in e-commerce industry. AI is considered as an important factor that sustaining the ecommerce ecology. However, there is lack of sufficient research on AI and e-commerce industry. Particularly, very few research proposed model on AI and e-commerce industry based on Chinese market. This is considered as the research gap of this study.

Based on the previous literature and gap of this study, this study specifies the objectives of this study. The primary objective is to investigate the reasons and users' experience with AI on the e-commerce platform, which escalates the customer's satisfaction and retains the buyers. The objective also extended to explain the customer reactions when they are using AI enabled Chinese e-commerce platforms, based on customer's resistance to change framework and risk theory with an empirical approach.

This research has contributed significantly to the world of both theory and practice. This study better explains customer resistance to change behavior (CRCB) by extending existing theories. Our research model has deepened our understanding of the role of AI based on the e-commerce platform. This study shows that it is likely to introduce new hypothetical theories about switching costs and rewards in order to better understand customer resistance to change behavior (CRCB). This research also contributes to literature by scrutinizing and forming the theatrical framework.

In order to accomplish the objectives of this study, both qualitative and empirical methods have been used to investigate the results. Firstly, through the qualitative approach, this study finds out the reasons why the customer left the traditional e-commerce and joined AI enabled e-commerce platforms. Secondly, this study follows empirical model. Kim and Gupta (2012) proposed a framework on customer resistance to change behavior (CRCB) based on risk theory. We employed this framework in the present study to understand the positive or negative approaches used by users when they are using AI enabled e-platforms.

In this research, we explain the customer reactions when they are using AI enabled Chinese e-commerce platforms, based on customer's resistance to change framework and risk theory with an empirical approach. Firstly, through the qualitative approach, we will find out the reasons why the customer left the traditional e-commerce and joined AI enabled e-commerce platforms. Initially, we will target Alibaba and Tencent group users, who are not stable on the specific platform. Secondly, we will test our conceptual model. Lastly, we will present the implications both in literature and practice.

LITERATURE REVIEW

AI is making headway in terms of providing value to e-commerce users. AI is the broad concept that computers, through the application of software and algorithms, can accomplish jobs in the same way that humans do. They actively influence human lifestyles in nearly every facet of daily life, and they do so through personalization (Kaplan & Haenlein, 2019; Kumar et al., 2019). Kumar et al. (Kumar et al., 2019) we define AI as a system's ability to accurately understand external data, learn from certain data, and apply certain learnings to fulfil particular targets and progress in various domains. Day by day, AI is gaining popularity in kinds of businesses operations, particularly in business administration, supply chain management, and financial management (Di Vaio, Boccia, et al., 2020). AI enters the picture as a critical revolutionary tool for personalizing and customizing items to satisfy individual needs of the customer. Satisfying customers' individual needs is also important for the current economy (Di Vaio, Palladino, et al., 2020). Besides, AI plays important roles to monitor business environment, to implement important strategies with or without minimal human intervention. By this way, AI is creating changes and modifying the economic landscape that help entrepreneurs and consumers to get the maximum benefits. Soni et al. (Soni et al., 2020) specified that AI creates new opportunities, which result in significant transformations in the entire economic systems. Soni et al. (Soni et al.,

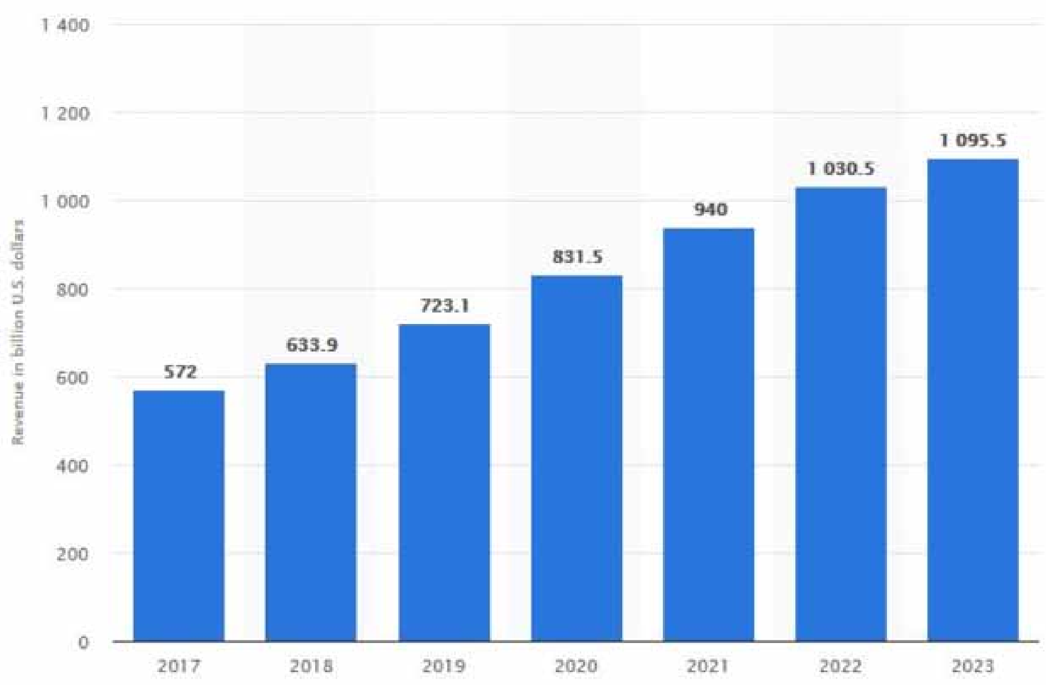
2020) also found that the significant transformation in business causes the rapid unveiling of big data patterns as well as improve product design to meet customers' preferences.

E-commerce is the main beneficiary of the increased use of artificial intelligence to improve the efficiency and quality of services. AI also helps reduce the complications of human errors. Thus, while AI can reduce employment opportunities, it brings huge benefits to organizations. Namely, AI is a significant driving force for the success and development of e-commerce. In e-commerce, AI systems enable electronic payments, network marketing, and logistics to deliver products to customers (Khrais, 2020). Di Vaio et al. [3] specified that artificial intelligence is becoming more and more important in e-commerce food companies because it can maintain sanitary conditions at the production site and ensure safe food production(Samuel &, Lemuria.,2016). It also helps to maintain high cleanliness of food production equipment.

AI assists e-commerce in capturing business trends and changing customer market needs. As a result, enhanced customer convenience leads to greater satisfaction and the balance of demand and supply processes (Khrais, 2020). When compared to humans, the automated systems acquire, examine, and appraise data at a faster rate. AI also enables e-commerce to develop new ideas on consumers' wants and keep up with changing choices and preferences. When performing some tasks in e-commerce, including forecasting demand and supply chain mechanism, human intelligence is often limited. AI revive and extents human intelligence to meet the growing e-commerce challenges (Feng, 2020; Soni et al., 2020; Xu et al., 2019).

AI can help e-commerce platforms monitor and manage customers. Through AI, a company can collect a extensive range of information that helps to evaluate customers to ensure that they are provided with high quality services. It also helps company understand influencing factors of current and prospective clients' purchasing behaviors. Through chatbots and messengers, it increases connections between e-commerce enterprises and their customers (Kumar et al., 2019; Marinchak et al., 2018). AI also help building model for rural e-commerce logistics. The AI based model increases the distribution efficiency and decreases the logistics cost (Feng, 2020). AI assistants can understand the market in a 360-degree view and provide rankings and recommendations for all competing and compared products. Also, Virtual Personal Assistant (VPA) can identify the ranking set of brands acceptable to consumers and provide recommendations that are consistent with consumers and in their best interests. In addition, VPA can eliminate the problem of irrelevant and unwanted ads (Marinchak et al., 2018). VPAs can also place online shopping orders, complete e-commerce transactions, conduct shopping and commerce inquiries, and so on. VPA typically interact conversationally with e-commerce users and adapt to consumer preferences using machine intelligence (Price & Lewis, 2017). Another application of artificial intelligence, linguistic machine translation, is already assisting clients in purchasing online products promoted in languages they do not understand. Similarly, machine translation can assist individuals who only understand their native language communicate with those who speak different languages within real time (Turban et al., 2015). AI also predict for managers about the AI-driven environment on customer management practices and branding in both developing and developed countries (Kumar et al., 2019; Xu et al., 2019;Samuel et al 2017). Even, analysing e-commerce model with decision tree—ANN provides the maximum accuracy that promotes well and fast transactions between both the parties, buyers and sellers on the platforms. Analysing e-commerce transaction through AI is also considered a powerful tool, which allows evaluate advanced credit risk system, and ultimately promote to the sustainable development of the e-commerce ecosystem (Xu et al., 2019).

Figure 3. Retail ecommerce market forecast (2017-2019)



Source: Statista by Ksenia Striapunina (2019)

The auxiliary judgment of the AI system strengthens the integration of the optimization scheme of e-commerce structure that make larger progress on the original foundation. Rational operation, one of the precepts of the digital economy and artificial intelligence system, integrates efficiency, probability, and inference to consolidate the rigor of judgment in the AI process (Xu et al., 2019). To some extent, the structure of an e-commerce website influences the development direction of the digital economy, and it is necessary to build a set of practical structure optimization driving strategies for it (Dwivedi et al., 2021; Rachinger et al., 2019). Song et al. (Song et al., 2019) suggested that AI integrated innovative optimization plan promote electronic commerce in a practical and reliable basis.

THEORETICAL BACKGROUND

1.1. Customer Struggles for Mind Change and Measurement of Quo Bias Theory

Different kinds of situations can cause customers' mind to struggle with the unique issues. These issues are being used in several digital platforms or information systems (Lee and Kim.,2019). Prior research on different types of e-commerce or digital platforms have described that the customers would like to stay on the same platform, however, due to new technological innovations, customers are switching to some other systems (Matsuoa et al., 2018; Joshi.,1991). However, many studies have shown that the customers are not willing to switch to a different platform or system (Kim and Gupta.,2012). According to Choudhury (2019) and Bowman (2019), customers are using old platforms and are being sustained because of the upgradation of technology involving user friendly AI system. It's true that there is significant growth and use of e-commerce not only in China but also in the other's markets in Asia.

The Quo Bias Theory (QBT) clearly explains information systems and customer decision-making (Samuelson and Zeckhauser.,1988). It also shows the customers' relationship with choices and product features. In addition, this theory is working on two mechanisms: loss and regret aversion. Loss mechanism suggests that psychologically, an alternative option of switching to another platform may not be better than the current option. The regret aversion mechanism indicates that after change, the customer feels regret due to fewer benefits and some uncertainties (Samuelson and Zeckhauser.,1988). This theory shows how customers can benefit from a specific platform and can be retained on that platform. This is defined as resistance behavior by QBT. Drawing on the existing theories, our research investigates the customer behavior and how to sustain the ecommerce platform, which users continue using due to new tech such as AI as well as big data, in the complex landscapes.

1.2. Perceived Risk

This research and existent literature show that perceived risk is an important variable in customer decision making process (Khedmatgozar & Shahnazi.,2018; Mendoza-Tello et al., 2019). Risk always has negative relationship with behavior. Loss or negative things are related to subjective matter and desired result (Margareta et al., 2019). According to Martin Brüne et al (2019) and Linn (2014), perceived rick has two dimensions: performance risk indicates economical factor; psychosocial risk falls in social factors. Similarly, ecommerce platforms have risk factors, which affect the end user attitudes toward different innovative facilities. In our research, interviews were conducted, and our qualitative approach helped understand the users' perceived risk when they are using different platforms. However, perceived risk factors are included in our selected research model.

1.3. WOM/eWOM

WOM and eWOM in social network help exchange the information, communicate, and provide services about the products from any place (Sicilia et at., 2016; Elvira et al.,2017; Ahrens et at.,2013). Moreover, WOM hels boost sales volumes, reputation, and perspectives (Janet., 2019). According to Anderson (1998) and Prashanth & Mahesh (2015), WOM and eWOM have a positive or negative relationship with satisfaction and dissatisfaction. Dissatisfied users spread their dissatisfaction faster than satisfied users on the Internet. Our researcher has followed negative WOM, because it's related with perceived risk and negative judgments (**Table 1**).

Table 1. AI and user Sustainability

Author	Target Point	Discussion
Philipp et at., (2017)	AI to ROI	Personalization strategies help gain 6-10% more sale for retailer by busing AI.
Consignor.,(2019)	AI and Logistics and Transportation	AI can do face/image recognition and transport plan can be fixed easily.
Thiebaut, R. (2019)	Products recommendation by AI	User can find the right products what he/she is searching. It is appreciating customer to future buy.
Macchion et al (2017)	Increasing products management	Big data have higher influence on fashion industry, especially in the ecommerce portal. It helps sustain and increase acceptability.
Thorsten Kurpjuhn(2019)	Security and Sustainability	AI can provide online and offline security in the operational sector. It helps in risk reduction.

Source: Authors' explanation

HYPOTHESIS DEVELOPMENT AND RESEARCH MODEL

Product quality is very important to e-commerce industry, especially to platform companies (Francesco., 2012). The quality of products and facilities can create a higher reputation for any e-commerce platform. Reputation is related to trust, which is linked with customer satisfaction (Javed,Sara et al 2021). High user satisfaction will increase higher reputation (Mutia et al., 2015). In China, JD.com has already made it distinguished from Taobao products because of its quality. According to Lalinthorn and Vinai (2017), perceived product quality is the judgment about having the best quality products and services, which increases the customers' overall trust and value, which is related to customer satisfaction. Previous studies have shown that satisfaction and trust are predictors of customer resistance to change (Kim and Gupta., 2012). In our interviews, we have found that dissatisfaction of most of the users from other e-commerce portals was caused by low quality and mesh products as compared to Alibaba and Tencent. Also, former users complained that other e-commerce portals don't provide digital services (e.g Live chat, image search, products recommendation etc.), and facilities (e.g. product tracking system). In our study, we changed the variables "satisfaction" and "trust" to "product quality" as the predictor of customer resistance to change in terms of AI and quality. Previous studies have covered only brands, emotions, online sharing, consumer loyalty, products reviews, and celebrity endorsements (Thomas.,2009; Andrew et al 2011; Zhuo et al., 2014; Eun-Ju and Soo.,2014; Abaid et al 2019). The QBT suggests that negative findings can influence customers' switching from one platform to another (Samuelson and Zeckhauser.,1988;Bell.,1982). On the other hand, motivated customer can continue to stay on the platform due to positive experiences with products and services in specific platform (Caviola, 2014). Therefore, we can conclude that customers having positive perceptions of product quality and services on e-commerce maintain a relationship with that specific platform. Redmond (2015), Kim &Gupta (2014), *"Social exchange theory"* and other studies suggest that trust and satisfaction can be formed when consumers' desires are satisfied. Thus, any e-commerce portal providing quality products and services can earn consumer trust and satisfaction. Therefore, we hypothesize that:

Hypothesis 1: Quality of the products is positively related to customer resistance to change behavior (CRCB)
Hypothesis 2: Quality of the products is positively related to trust and satisfaction.

1.4. Trust, Satisfaction, and Switching Cost

According to Balasubramanian, et al. (2003) and Dan et al (2009), on the ecommerce business portal, sellers must create a trustworthy environment that allows customer to have confidence in transactions, product quality, and satisfaction. Trust and Satisfaction are key elements for long-term sustainable business success (Oliver 1980, Xu et al.,(2017). According to Gautam Narula (2019), AI is creating higher satisfaction with products quality and customer overall trust, especially in the e-commerce marketplace, where the products quality and online transaction nees high privacy or security . There are a number of studies have suggested that trust plays a role in buying products and making recommendations (Kristof Stouthuysen; Ineke Teunis Evelien Reusen; Hendrik Slabbinck.,2018; Brengman and Karimov, 2012). According to Status QBT, customers who have positive a relation with specific portal or brand can maintain the relationship with the same vendor (Samuelson, Zeckhauser.,1988). Contrary to this, long-term relationship and trust in specific product, brand or portal can make the rational/unique switching costs higher than switching costs (Hitech.,2018;David.,2013).

Switching costs are the part of marketing field. Consumers switch from one brand to another in a risk perception moment (Al-Kwifi and Ahmed, 2015 ; Asimakopoulos, G. and Asimakopoulos, S. 2014, Yen, 2010). If a customer determines to change from one platform to another platform with higher perceived risks and costs, it will affect the status quo bias on the current platform (Park et al., 2017). On the other hand, due to high degree of uncertainty, customer is unable to change the platform either for attractive benefits or higher switching costs (Samuelson Zeckhauser, 1988; Farah.,2017). Losses and negative results are related to switching costs (spiritual in terms of Status quo bias). Therefore, a consumer who switch to another company tries to maintain the relationship with the current service provider and boycott to other facilities (Amjad et al.,2011; Makoto.,2018). Or, high quality service provision, assurance and less loss perception support the consumers on the present platform (lee et al., 2019). Therefore, we can hypothesize that:

Hypothesis 3: customer resistance to change behavior (CRCB) is positively related to trust and satisfaction
Hypothesis 4: Switching cost has a positive relationship with trust and satisfaction
Hypothesis 5: customer resistance to change behavior (CRCB) has a positive relationship with switching cost.

1.5. Comparative Attraction

When JD.com initially came to the market, it would offer ten times reward if a customer received low-quality products. According to Zhuo FanYang et al.,(2014) and Maria A.Halbinger.,(2018), high quality products, comparative advantages, and attractiveness play vital roles in the firm's success, especially in the ecommerce sector. Several researchers mentioned that comparative or relative attractiveness is a major factor in terms of IDT (Maria A.Halbinger.,2018; Jarunee and Napaporn.,2005). At the same time, we conceptualized "relative attraction" as "Comparative attraction". According to Kristine and Mark (2003), relative attractiveness is attraction that a customer has with the unique feature than others. Due to upgradation of technology, Chinese e-commerce market is very competitive, because consumers are very smart. They will not sustain for a long time if the platform does not have unique features and comparative attraction (Rashad and Merveen.,2014). Consumers can switch from one platform to another depending on the comparative attractiveness. Companies providing high-quality services and facilities will receive core attention of their customers, and comparative attraction is positively related with consumers' resistance to change (Kim and Gupta.,2012). Thus, we hypothesize that:

Hypothesis 6: customer resistance to change behavior (CRCB) is positively related to comparative attraction
Hypothesis 7: Switching cost is positively related to comparative attraction.

1.6. Undesirable Attitude and Perceived Risk

According to Patricea Elena Bertea (2010), *"perceived risk is considered as a major behavioral determinant. In addition, it has been found to be a barrier against e-commerce adoption"*. However, perceived risk refers to the psychological, social, and privacy risk related to attitude, behavior, and trust (Park et al 2012; Steven and Izak.,2010; Gašper et al., 2019). In this research, we considered three dimensions of perceived risk such as psychological risk, social risk, and privacy risk. Psychological risk refers to psychological negative (undesirable) effects of service provider or facilities on customers (Lee et al 2019). According to Ángel and Ignacio (2010), social risk is *"potential loss of status in one's social group as a result of adopting a product or service, and looking foolish or untrendy"*. Lastly, privacy risk refers to *"potential loss of control over personal information, such as when information about you is used without your knowledge or permission. The extreme case is where a consumer is 'spoofed', i.e. a criminal uses customer identity to perform fraudulent transactions"* (Ming-Chi Lee.,2009). In our interview we found that perceived risk exists when users use other e-commerce platforms, and consumer perceived risk is highly affected by online purchase. However, risk and negative (undesirable) attitude are related to each other (Kamalul et al.,2018). Formally, we hypothesize that:

Hypothesis 8: Negative (Undesirable) attitude is clearly related to psychological risk.
Hypothesis 9: Negative (Undesirable) attitude is positively related to social Risk).
Hypothesis 10: Negative (Undesirable) attitude is positively related to privacy risk).

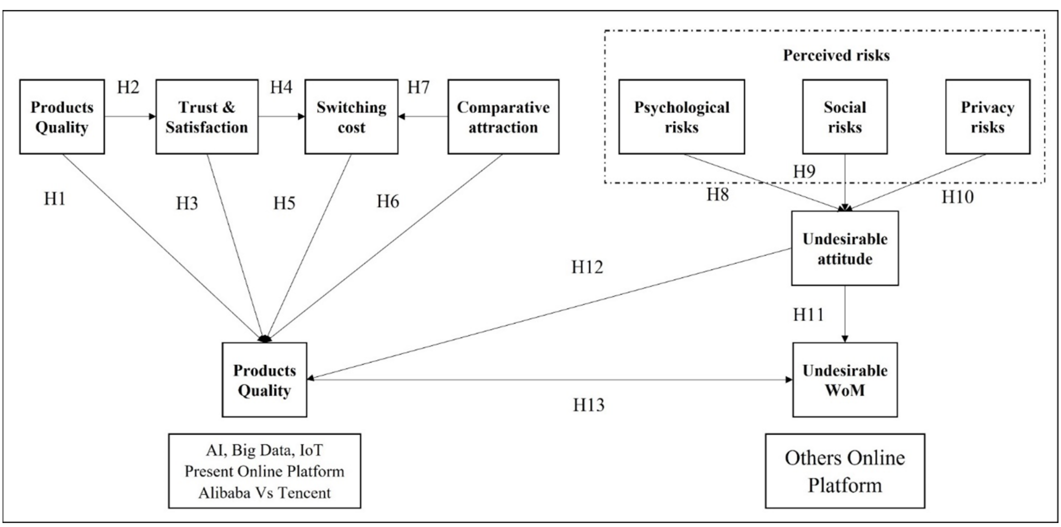
1.7. Attitude, Consumer Resistance to Change & Word of Mouth

Attitude is a kind of psychological contrast where a person shows an act from his/her own experience on any object. It can be positive or negative (Viorel and Cecilia-Roxana., 2013). According to Riadh and Melissa (2015), consumers' negative attitude also affects the consumer resistance to change and their reputation simultaneously. It also influences consumers' negative behavior (Alhulail et al, 2019). Dominique Roux (2007) contend that consumers resist change, but they use e-commerce portals. According to Chul et al (2013); Qiang eta al (2016), consumer have (diffuse/spread?) negative WoM, but they still use same or different e-commerce platform. In our research, consumers had negative experiences on other ecommerce platforms with few facilities before joining Alibaba and Tencent, where AI facilities and other services are present. According to Evie (2019) and Uptin (2017), consumers are sustaining on the same e-platform due to quality products, services, and facilities. Therefore, we hypothesize that:

Hypothesis 11: Negative word of mouth leads to negative attitude.
Hypothesis 12: customer resistance to change behavior (CRCB) is positively related to negative attitude.
Hypothesis 13: Negative word of mouth has a positive relationship with customer resistance to change behavior (CRCB).

The model framework of this study is mentioned in Figure 5 in the following section.

Figure 5. Research model



Source: Authors' illustration

METHODOLOGY

1.8. Research Setting

In modern times, information is the backbone of nations. E-commerce is also a part of the information technology. The concept of GPT (General Purpose of Technology) is not new, and it refers to different technical sectors such as industry, IT, electricity, and business. Similarly, the e-commerce market is using technology to provide goods and services. The area of present study is China. Alibaba and Tencent are leading tech industries in China. According to China National Bureau of Statistic (2016) report, China's e-commerce market growth rate was 26.2%, which generated 5.16 trillion RMB (Vishal Bali., 2018). As the marketplace expands and wealth continues to grow, as GDP increasing by 7% each year, the smaller third-tier cities have seen the fastest growth rate in online shopping adoption rates. In 2019, it expanded at a compound annual growth rate (CAGR) of 13.3 per cent from an estimated US$1.5 trillion in 2019 to US$2.6 trillion in 2023 (Thelma, 2019). Now, China's "E-commerce age" is still going on, and the companies want to be slice of the pie throughout the world. The digital economy, facilities, higher technologies, labor forces, good infrastructures, and friendly policies support the strong growth of Chinese e-commerce industry. China has become the world's largest e-commerce market and is using AI to contribute to the Chinese economy. According to Agne Blazyte (2019), *"as the digital economy takes shape, more and more people and businesses around the world are going online. The number of internet users in China reached around 804.5 million in 2018. This has driven the explosive growth of the Chinese e-commerce market, which is currently a global leader"*.

1.9. Instrument Measures

The instrument used in this study is a questionnaire that collects data from the respondents. The questionnaire was adapted according to the context of the present study, and the measures were taken from the existing literature; a three-item scale of product quality (Tamilla.M et al; 2012); a five-item scale of trust and satisfaction (Linlong Wu et al., 2016); a five-item scale of switching cost (Carter, M et al, 2009); a four-item scale of comparative attraction (Rashad and Merveen, 2014); an eight-item scale of perceived risk (Psychological, social, and privacy/security risk) (Lee et al., 2019; Ángel and Ignacio, 2010; Ming-Chi Lee, 2009); a two-item scale of undesirable WOM (Alhulail et al; 2019), a three-item scale of consumer resistance to change behavior (CRCB; Riadh and Melissa, 2015), and a four-item scale of negative (undesirable) attitude (Chul et al ; 2013; Qiang eta al., 2016; Alhulail et al, 2019).

The scale used for the measurement of the abstract variables is the 5-point Likert scale, ranging from "1=strongly disagree" to "5=strongly agree". The questionnaire is based on three sections. The first section has an open-ended question related to study description, and the second section is related to the demographic characteristics of the participants, which contains six close- ended questions. The third section is related to research constructs, which contained 34 close-ended questions. The instrument was designed in English, and later we used back-to-back translation approach and translated the questionnaire into Mandarin (Traditional Chinese language). A bilingual professor, who is expert in Digital economy; International Trade; E-commerce, and Information system field, was consulted for the Chinese version of the instrument. Items were restructured or altered to ensure comprehension, or the accuracy of the Chinese version (Vijver & Tanzer, 2004). Before handing out the survey, the face validity and content validity of the instrument was judged by doctoral candidates, who were good at both English and Chinese. The pilot test is done to further ensure the content validity (n=48), and the results show that scale of internal consistency is above the threshold level (Cronbach alpha > 0.70).

1.10. Sampling and Data Collection Procedures

In this study, we conducted an offline survey, and data was collected in a convenient means. Ten doctoral candidates were trained to distribute the survey at 4 top Chinese universities in Beijing. The questionnaire began with one open-ended question, although the study employed a critical incident method as the basis of the survey (Seckler et al., 2015). The open-ended question is *'Please think a moment about a time when you were offended using some e-commerce platforms and decided to switch or moved to Alibaba and Tencent. Try to describe your experience in a comprehensive manner as you can.'* The basic reason behind the open-ended question is to remind the customers of the past unpleasant experiences on other e-commerce platforms. It takes approximately 20 minutes to complete the questionnaire. The data was collected during the period from October 2019 to January 2020. Upon completion of the survey, participants were thanked for their kind cooperation in all stages of the survey. A total of 730 questionnaires were distributed, and 670 questionnaires were returned, out of which 649 responses were valid, representing a response rate of 88%. The remaining 21 questionnaires were discarded because they were not completed.

The use and validation of convenience sampling need to be satisfied two conditions (Seckler et al. 2015). The first condition is whether the study is exploratory in nature, and the second condition is whether the items in the questionnaire are appropriate and relevant to the respondents who answered the questions. To this point, the constructs in the present study have not been investigated in prior literature to understand the customer switching behavior on the e-commerce platform and the reason behind it, so the research is exploratory. The instrument indicators are relevant to its respondents because we selected customers who were the users of other e-commerce platforms and switched to Alibaba and Tencent (Mohsin et al., 2016). Therefore, the current study satisfies the conditions for using convenience sampling.

DATA ANALYSIS AND RESULTS

1.11. Preliminary Analysis: In-Depth Interviews

In the in-depth interviews, we collected the data from the e-commerce users. We posted a web–link of our questionnaire containing open-ended questions on WeChat groups, moments, and Weiboo (Chinese social Network), and asked them about their experiences of using online platforms. If any respondent shared his/her experience, we sent him/her a detailed interview questionnaire through WeChat and Weiboo messenger. Once we received surveyed questionnaire from the respondents, we sent (50 RMB ($6.9 Equivalent) Hongbao (traditional online giftbox that includes money) to respondents as acknowledge. The survey team asked from interviewee the structured sample questions. The example questions are as follows: 1. Why did you give up another online platform? 2. Why do you prefer Alibaba group products or Tencent communities? 3. Why do you usually change e-commerce platform? 4. Have you had any possibility to use other platforms apart from Alibaba or Tencent? We also introduced the details of Alibaba and Tencet Group products to the respondent. After nine days, we received 28 respondents including 17 Chinese, 3 Pakistani, 2 Africans, 5 Bangladeshi, and 1 from British (21 female and 7 male).

According to these interviewees, they have experienced many difficulties while using other platforms: while searching the product, most of time live chat is offline due to GST, shipment time and location are backdated (tracking issue), and there are issues related to products originality. **Table 2** shows the detail discussion of the interviews.

Table 2. Content Analysis

Interviewee Detail	Past ecommerce experience	Present ecommerce experience	Content Analysis
Feng (F),30, CN	**Yes**	Taobao. JD	I used to buy Bei Bei. Service quality isn't good. I can't communicate virtually.
Jun (F),23, CN		Tmall	I was user and brought Kindswant. Products' quality assurance problem. I can't track.
Yun (F) 23, CN		Taobao. JD	I was Xinrui Mei user (frequently). There used to be products' search problem. I can't use products' picture search option.
Ren (M) 35 CN		Tmall,JD	I was user of Magic mall, but there is product finding problem.
Run (F) 28, CN		Tmall, Taobao	Mogu Street sent fake products. There is no assurance.
Guo (F) 19, CN		Taobao. JD	Aiyong; they are not used to fast shipment and no quality.
Lee (F) 23, CN		JD	Lamabang sent me wrong products. I can't search by using picture.
Xiaw (M) 41, CN		Taobao	I was Micro shop user, but fake products are available. No instant replay virtually.
Meen (F) 31, CN		JD	Magicmall is fake apps. Now using JD.com because of fast and quality products.
Qing (F) 29, CN		Tmall	When I am using Magic mall, there is no recommendation offer but only Tmall.
Mei (F) 25, CN		Taobao	No more HQG, because they are making delay always. I always need to virtually chat for products confirmation.
Qung (M) 19, CN		Taobao. JD	I was Dang Dang Wang user, but there is neither AI assistant nor products recommendation.
Jiang (F) 23, CN		JD	I was user of Aiyong, but no option for pictures search.
Fang (F) 23 CN		Tmall	Uonvip mall was not good. Fake products are available. Delay to reply any inquiry even after sell.
Pei (F) 26, CN		Taobao	I was user of Lamabong. Products management, shipping system and time management were so bad.
Yan (F)31, CN		Taobao	Xinrui mei is FAKE apps. Most of the products are not good. Poor management and long time needed to get products.
Habib (F) 29, BD		Taobao	I was user of bikroy.com (BD). Very bad experience about products; fake products, no facility of instant chat, and seller is not available online.
Sara (F)27, PK		Taobao. JD, Tmall	I have experience of dataz.com. There is no products quality assurance. Unrelated products recommendation.
Nadia (F) 28 PK		JD	Bad experience with Homeshopping.pk and no recommendation function.
Toma (F)22, PK		Taobao. JD	I used to buy via Symbios.pk, but most of the time, there is quality problem, and there is no option for picture search.
Nazmul (M) 31, BD		JD	Bikory.com always sends fake products.
Rashad (M) 22, BD		Taobao. JD	I was user of Cellbazzer.com, but very back dated and no central management about quality.
Nazia (F) 34, BD		Taobao. JD, Tmall	Clickbd.com, most of the sellers are unprofessional. Poor quality products. There is no instant chatting option.
Selim (M) 76, BD		JD	Bikroy.com, mostly fake products.
Jakson (M) 32, UK		JD	Amazon.com is good, but some products are not good. They sent my watch 41 days later. Now JD user. It's fast and continents.
Andree (F) 54, AF		JD	I was user of Water elephant apps, but bad experience and poor-quality products. There is no refund option and no tracking system about products.
Kitla (F) 31, AF		Taobao. JD	I was used to buy via mia.com. There is no products recommendation facility.

Source: Author's explanation

1.12. Demographic Profile

Table 3 below shows the demographic profile of the participants (n=649). Female respondents are greater in number than male respondents; out of 649 participants, 412 (63.5%) were women and 237 (36.5%) were men. The age group 18-25 years had a higher representation (50.7%) than the other age groups of 26-30 years (34.4%), 41-60 years (12.5%), and 31-40 years (2.5%). The participants whose income was RMB 5,000-10,000 (US$780 to $1570) had a higher representation than other income groups RMB 5,000 (26.2%) and RMB 10,000- 20,000 (22.7%). With regards to the profession, students accounted for a major proportion (54.1%) in comparison to workers (25.4%), and others (20.5%). Respondents were also asked about the choice of e-commerce platform. Five possible options were given to them (i.e. Taobao, JD, Tmall, Vip.com, and Pingdaudau - PDD). The results indicate that majority of the respondents are users of Taobao (40.0%) and JD (20.0%), while the remaining 11.5%, 10.5%, and 8.8% of the respondents are users of Pingdaudau (PDD), Tmall, and Vip.com, respectively. In addition, participants mostly spent on e-commerce RMB 1-100 (44.8%) followed by RMB 100-500 (25.9%) and RMB 500-1000 (23.7%).

Table 3. Demographic profile of respondents (N=649)

Demographic characteristics		Frequency (n=649)	Percentage %
Gender	Male	237	36.5
	Female	412	63.5
Age	18-25	329	50.7
	26-30	223	34.4
	31-40	16	2.5
	41-60	81	12.5
Income (RMB)	5,000	170	26.2
	5,000-10,000	235	36.2
	10,000-20,000	147	22.7
	20,000-30,000	53	8.2
	30,000-50,000	44	6.8
Profession	Students	351	54.1
	Worker	165	25.4
	Others	133	20.5
E-Commerce Platform	Taobao	264	40.7
	JD	188	20.0
	TMall	68	10.5
	Vip.com	57	8.8
	Pindaudau	72	11.5
Expenditures on e-commerce (RMB)	1-100	291	44.8
	100-500	168	25.9
	500-1,000	154	23.7
	1,000-2,000	36	5.5

Source: Authors' explanation

1.13. Measurement Model

The statistical analysis was performed by using SPSS Amos Graphics version 21. We followed a two-stage procedure of Anderson and Gerbing (1988) for statistical analysis of Structural Equation Modeling (SEM). By employing this approach, we first analyzed the reliability and validity of the measurement model, and later we performed a path analysis in the structural model. The basic premise behind this approach was to preliminarily test the structural association between constructs. We first assessed the reliability and validity of latent constructs.

Estimates composite reliability by Raykov, T. (1997)

$$CR = \frac{(\sum \lambda)^2}{(\sum \lambda) + \sum Var(\varepsilon_i)} \tag{1}$$

Confirmatory factor analysis (CFA) was used to assess the reliability and validity of unobserved variables. The output generated by CFA indicates a good model fitness (χ=161.223, df =915; χ/df=1.772, RMR = 0.048, IFI=0.951, TLI=0.944, CFI= 0.950, PCFI=0.840, PNFI=0.790; RMSEA =0.044) (Hu and Bentler, 1999). The fit indices shows that unobserved variables can be perfectly measured by their items. Reliability was assessed by the scores of Cronbach alpha and composite reliability (CR). Table 4 shows that all the unobserved constructs CR scores range from 0.83 to 0.93, which is above the cut-off level of 0.70 (Hair et al., 2011) and the α scores also exceed the recommended threshold level of 0.70 (Hair et.al, 2010) ranges from 0.80 to 0.93. With regards to the convergent validity, we followed the Fornell and Larcker (1981) approach; all items should have factor loading scores greater than 0.70 and significant. **Table 4** exhibits that all items have factor loadings are above 0.70 with loadings ranging from 0.749 to 0.953 and these are all significant ($p<0.001$). The average variances extracted are above the suggested threshold of 0.50 with a value ranging from 0.50 to 0.81 (Fornell and Larcker, 1981; Hair et al., 2011) and thus supporting the convergent validity. We ensured the discriminant validity (**Table 5**) by employing two tests; the square root of average variance extracted, or diagonal value should be greater than the correlation between the constructs at the resultant rows and columns (Fornell and Larcker, 1981), and the correlation between the variables shouldn't exceed 0.85 (Kline, 2005).

Table 4. Confirmatory factor Analysis

Constructs	Items	Statements	Standardized Factor Loadings
Product Quality CR=.927, α=.927 AVE=.809 ÖAVE=.899	PrQ1	The product quality of Alibaba and Tencent group is more long-lasting than other ecommerce platforms.	.925
	PrQ2	Alibaba and Tencent offer best packaged products than other ecommerce platforms.	.816
	PrQ3	I think Alibaba and Tencent assure the product quality better than other ecommerce platforms.	.953
Trust and Satisfaction CR=.936, α=.935 AVE=.744 ÖAVE=.862	TrSa1	Alibaba and Tencent provide products assurance and advance services.	.898
	TrSa2	Alibaba and Tencent products are trusted.	.868
	TrSa3	Alibaba and Tencent groups are concerned about customers service (Online, offline).	.870
	TrSa4	Alibaba and Tencent groups invested billions to secure customer desire, so they are capable and mature.	.817
	TrSa5	Alibaba and Tencent products secure the trust and satisfaction.	.859

Table 4 continued on next page

Table 4 continued

Constructs	Items	Statements	Standardized Factor Loadings
Switching Cost CR=.937, α=.937 AVE=.749 ÖAVE=.865	SC1	I think switching from this e-Platform (Alibaba and Tencent) will take more time to some other platform.	.800
	SC2	Switching from this e-platform (Alibaba and Tencent) to last platform can make same result.	.923
	SC3	It would be trouble to switch from present (Aliabab and Tencent) to last platform.	.910
	SC4	It is very difficult to switch to present platform (Alibaba and Tencent) from last platform because of time cost mainly.	.917
	SC5	At all, if I do switch from present platform (Alibaba and Tencent) to last platform, then it would be higher loss for me.	.766
Comparative Attraction CR=.803 α=.800 AVE=.504 ÖAVE=.710	CA1	Alibaba and Tencent group products shopping would be more advantageous due to variation of the products than my last portal.	.770
	CA2	Alibaba and Tencent group products shopping would be more engaging due to use of AI facility than my last platform.	.698
	CA3	Alibaba and Tencent group products shopping would be suitable due to various options (Image search, AI, I-CHAT) than my last platform.	.647
	CA4	Overall, Alibaba and Tencent group can be best platform for ecommerce than my last platform.	.722
Psychological Perceived Risk CR=.814 α=.813 AVE=.685, ÖAVE=.828	PPR1	Last ecommerce portal will not be suitable for me (Up/Down)	.831
	PPR2	Last ecommerce portal would make psychological loss e.g., image, value.	.825
Social perceived Risk CR=.870, α=.865 AVE=.691, ÖAVE=.831	SPR1	What negative effects can occur by using last ecommerce portal than Alibaba and Tencent? (Up/down perceived social risk)	.905
	SPR2	Using other ecommerce (last used) than Alibaba and Tencent, there can be social value loss because my neighborhoods and colleagues will think that I am not valuable like them.	.823
	SPR3	About recommendation to buy anything from (last used portal) than Alibaba or Tencent group products, my neighborhoods and colleagues will think that I am very poor and classless.	.760
Perceived privacy/security risk CR=.858, α=.855 AVE=.672, ÖAVE=.819	PPSR1	What do you think about chances of privacy/security risk to use your last ecommerce platform, especially in transaction, then Alibaba and Tencent group products?	.838
	PPSR2	Sign up to other ecommerce portal (last used) can lead to losing my privacy than Alibaba and Tencent	.863
	PPSR3	If I use last local ecommerce platform, internet hacker can take the control of the account.	.749
Undesirable WoM CR=.897, α=.895 AVE=.813, ÖAVE=.901	UW1	It's impossible to recommend others to use my last ecommerce portal.	.937
	UW2	Surely, I aware the people not to use my last ecommerce portal.	.865
Consumer Resistance to Change Behavior (CRCB) CR=.923, α=.923 AVE=.811, ÖAVE=.900	CRCB1	Surely, I prefer my present ecommerce platform (Alibaba and Tencent group products).	.890
	CRCB2	I will not go back from present platform (Alibaba and Tencent) to previous ecommerce platform, even if my friends and family recommend me.	.906
	CRCB3	It would be difficult for me to change; I need to deeply think.	.888

Table 4 continued on next page

Table 4 continued

Constructs	Items	Statements	Standardized Factor Loadings
Negative (Undesirable) Attitude CR=.920, α=.920 AVE=.742, ÖAVE=.861	NA1	It is not good to use unsafe network such as my last ecommerce platform.	.834
	NA2	About last ecommerce platform, I have negative observation.	.869
	NA3	I never supported last ecommerce platform than Alibaba and Tencent.	.881
	NA4	I am not interested in last platform.	.861

Source: Authors' explanation

Table 5. Descriptive Statistics & Discriminant validity

Constructs	Mean	S.D	VIF	1	2	3	4	5	6	7	8	9	10
Product Quality	3.731	1.209	1.105	**.899**									
Trust and Satisfaction	3.930	1.079	1.137	.184**	**.862**								
Switching Cost	3.792	1.155	1.152	.234***	.217**	**.865**							
Comparative Attraction	3.991	0.748	1.401	.149**	.270**	.246**	**.710**						
Psychological Perceived Risk	4.104	0.980	1.762	-.018	.020	.034	.408**	**.828**					
Social Perceived Risk	4.065	0.943	1.690	.076	.085*	.029	.339**	.599**	**.831**				
Perceived privacy	4.065	0.951	1.076	.031	.030	.008	-.039	-.019	.160**	**.819**			
Undesirable WoM	3.812	1.203	1.253	.047	.110**	.064	.055	.045	.038	.195**	**.901**		
Consumer Resistance	3.778	1.185	1.055	.109**	.053	.135**	.019	.050	.030	.142**	.417**	**.900**	
Negative Attitude	3.971	1.029	1.005	-.019	.010	.006	.017	.007	-.024	.004	-.136**	.-047	**.861**

Note: 1= product quality. 2= trust and satisfaction, 3= switching cost, 4= comparative action, 5= psychological perceived risk, 6= social perceived risk, 7= perceived privacy, 8= undesirable WOM, 9=consumer resistance to change (CRCB), 10 = negative attitude. The bold digits in the diagonal are square root of AVE. p<0.05, **p<0.01, ***p<0.001

1.14. Structural Model

1.14.1. Measurement of Research Model Fitness

The results of the measurement model indicate good model fitness. The structural model is tested by suing SPSS Amos Graphics version 21.0. The results of structural model demonstrate goodness of fit (χ/df= 2.562 CFI = 0.960; NFI=0.98; IFI=0.961; TLI= 0.910; AGFI= 0.958; RMSEA = 0.049; SRMR = 0.045). The fit indices are in a reasonable and acceptable range (Hu & Bentler, 1999, MacCallum & Hong, 1997, Hooper et al.; (2008). Thus, these results demonstrate that the structure of research model efficiently illustrate the association between latent constructs (Hair et.al, 2011).

1.14.2. Hypotheses Testing

Structure Equation Modeling technique (SEM) with maximum likelihood estimation was employed to test the hypothesized relationships. After following first step of Anderson and Gerbing (1988) approach of statistical analysis, eventually we carried out second step; we performed path analysis by the structural model. For this, we first assessed the extent of multicollinearity in SPSS, which is an important assumption prior to testing the research model in SEM. Table 5 indicates that all predictor variables had variance inflation factor (VIF) ranging from 1.005 to 1.762. It shows that no multicollinearity issue exists among the predictor variables as they satisfy the suggested criteria (<3).

The results of hypothesized relationships are presented in Table 6. Table 6 demonstrates that the product quality has an insignificant effect on CRCB (β=-.047, t= -.943, $p < 0.001$), therefore we reject H1. Trust and satisfaction have insignificant effect on CRCB (β=0.020, t=0.499, $p < 0.001$), thus we reject H3. Switching cost has gained support as it has a positive significant effect on CRCB (β= 0.118, t= 2.852, $p < 0.001$), thus supporting H5. Comparative attraction (β=-.226, t=-7.862, $p < 0.001$) has a negative effect on CRCB. So, H6 is accepted here. Product quality positively effect trust and satisfaction (β =0.147, t=3.896, $p < 0.001$), supporting H2. Trust and satisfaction (β=0.134, t=3.451, $p < 0.001$) and comparative attraction have a significant positive impact on switching cost (β=0.183, t=4.751, $p < 0.001$), supporting H4 and H7. Perceived psychological risk and perceived social risk have a positive effect on negative (undesirable) attitude, respectively (βpsychological=0.35, t=9.712, $p < 0.001$; βsocial=.081, t=-2.014, $p < 0.001$), therefore H8 and H9 are accepted. The perceived privacy risk has insignificant effect on negative (undesirable) attitude (β=.012, t=0.308, $p < 0.001$), so H10 is rejected. Negative (undesirable) attitude has a significantly positive effect on undesirable Word-of-Mouth and CRCB (βWOM=-.117, t=-3.299, $p < 0.001$; βCRCB=.044, t=12.371, $p < 0.001$). So, we accept H11 and H12. In addition, CRCB has a positive effect on negative (undesirable) attitude (β=.412, t=-11.595, $p < 0.001$). So, we accept H13.

Table 6. Statistics of Hypotheses Testing

SL No.	Hypotheses	Estimate	*t*	Result
H1	Product Quality ® customer resistance to change behavior (CRCB)	-0.047	-0.943	Rejected
H2	Product Quality ® Trust and Satisfaction	0.147	3.896	Supported
H3	Trust and Satisfaction ® customer resistance to change behavior (CRCB)	0.020	0.499	Rejected
H4	Trust and Satisfaction ® Switching Cost	0.134	3.451	Supported
H5	Switching Cost ® customer resistance to change behavior (CRCB)	0.118	2.852	Supported
H6	Comparative Attraction ® customer resistance to change behavior (CRCB)	0.226	7.862	Supported
H7	Comparative Attraction ® Switching Cost	0.183	4.751	Supported
H8	Perceived Psychological Risk ® Negative Undesirable Attitude	0.350	9.712	Supported
H9	Perceived Social Risk ® Negative (Undesirable) attitude	0.081	2.014	Supported
H10	Perceived Privacy Risk ® Negative (Undesirable) attitude	0.012	0.308	Rejected
H11	Negative (Undesirable) attitude ® Undesirable Word-of-Mouth	0.170	3.299	Supported
H12	Negative (Undesirable) attitude ® customer resistance to change behavior (CRCB)	0.440	12.371	Supported
H13	customer resistance to change behavior (CRCB) ® Undesirable Word-of-Mouth	0.412	11.595	Supported

Source: Author's explanation

DISCUSSION AND CONCLUSION

1.15. Discussion

Switching cost and comparative attraction have positive relationships with customer resistance to change behavior (CRCB), consistent with the previous findings of Chang et al., (2013); Kim.,(2012) that switching cost and customer resistance to change behavior (CRCB) are positively related to. However, previous studies has been concluded that the effect of switching costs on CRCB is weaker than the effect of other factors. But our findings revealed that switching cost and comparative attraction have stronger relationship with customer resistance to change behavior (CRCB). Alibaba and Tencent are developing and adding feature (Facility) to increase comparative attraction in ecommerce market, where consumer/customer may sustain on the specific platform. AI tools, service, security and features significantly influence the consumer trust and loyalty (Kaabachi et al 2019).

Numerous researchers suggest that product quality, trust and satisfaction have direct relationship with customer resistance to change behavior (CRCB) (Makoto et al 2018; lee and Kim.,2019), but our study found insignificant relationship between these factors and customer resistance to change behavior (CRCB). Nevertheless, our results do not indicate that there is no relationship between product quality, trust and satisfaction, but due to customers past experience, they are affecting negative attitude. According to Dang et al (2017);Apinya et al (2019), performance expectancy, effort expectancy and facilitating conditions partially mediate the effect of social influence on switching cost and behavior. In our research, switching cost has indirect relationship with customer resistance to change behavior (CRCB), but in the case of "product quality", and "trust and satisfaction", it acts as precursor to switching cost.

Thirdly, we found that customer resistance to change behavior (CRCB) has a greater effect on negative (Undesirable) attitude towards digital/e-commerce service than switching cost and comparative attractiveness. The result shows that having negative (Undesirable) attitude towards particular service may result in customer resistance to change behavior (CRCB) and lead the consumer to undesirable word of mouth. Albeit, other factors related to cost and benefit are also vital. other fascinating implication is that it is a strong precedent to negative word of mouth (wom), along with resistance behavior.

Lastly, perceived psychological risk and perceived social risk have significant effects on negative (undesirable) attitude, and perceived privacy risk has insignificant effect on negative (undesirable) attitude. The possible reason is that users don't pay much attention to this aspect though they swap personal data against some benefits. We need to consider mostly young generation though they can handle the privacy issues in digital commerce ecosystem.

Through this research, company managers and policy makers will understand customer switching behavior and reasons for switching behavior. This research also helps managers make decision about AI enabled e-commerce feature through cost and benefit measurement. However, policy makers can implement the policy to reduce perceived rick.

1.16. Conclusion

Online-based platforms are competing fiercely in the Chinese market by fostering an omni-channel shopping ecosystem. Alibaba and Tencent is big grouped of company in China and leading tech company over the world. Alibaba started investing the highest amount in AI, and Tencent followed the same path. Alibaba established 3,200 offline e-stores and employed Robotic system (Limited area), standing in the top position. Tencent has also achieved tremendous success in the same field and created trust in the online market. Some leading ecommerce platforms such as JD.com, VIP and Pinduoduo also joined the Tencent. We conducted in-depth interviews to understand this phenomenon and built a research model based on risk theory and the customer resistance to change behavior (CRCB) framework. Even, analyzing e-commerce model with decision tree—ANN provides the maximum accuracy that promotes well and fast transactions between both the parties, buyers and sellers on the platforms. Analyzing e-commerce transaction through AI is also considered a powerful tool, which allows evaluate advanced credit risk system, and ultimately promote to the sustainable development of the e-commerce ecosystem. Structure Equation Modeling technique (SEM) with maximum likelihood estimation was employed to test the hypothesized relationships. Results suggest that switching costs and Comparative Attraction influence CRCB, while risk perceptions form Negative (Undesirable) attitude toward CRCB, which finally result in Undesirable word of mouth.

This study has some limitation too and these are also very specific. This study focuse the Chinese e-commerce platform (e.g. Alibaba and Tencent) and AI only. Therefore, only one study may be considered as limitation by some readers. The validation of this study by considering other e-commerce platforms (e.g. Amazon, e-Bay) in the context of the non-Chinese e-commerce markets is also skipped here. It would be significant of the study if an experimental analysis has been conducted to resolve possible sample bias. Meanwhile only Chinese accused participate in our study, it will be necessary to comportment research with e-commerce users in other countries in the future. We recommend the empirical analysis and comparative analysis both Chinese and other countries' e-commerce platforms. More speciafally, comparative study based on other leading e-comerce platform is highly recommended here.

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