Szent István University
Doctoral School of Management and Business Administration

An Experimental Research on the Consumer Response towards Online Personalised Pricing Strategies: A Comparative Study between Indian and Malaysian Online Consumers

Ph.D. Dissertation

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ABBREVIATIONS

AVE	Average Variance Extracted
CAGR	Compound Annual Growth Rate
CCA	Confirmatory Composite Analysis
CB SEM	Covariance based Structural Equation Modelling
E-COMMERCE	Electronic Commerce
EFA	Exploratory Factor Analysis
IBEF	India Brand Equity Foundation
OECD	Organisation for Economic Co-Operation and Development
MSME	Micro Small and Medium Enterprises
OFT	Office of Fair Trade
GDP	Gross Domestic Product
GDPR	General Data protection and regulation Act
MGA	Multi Group Analysis
PDPA	Personal Data Protection Act
PLS SEM	Partial Least Squares based Structural Equation Modelling
PPP	Purchasing Power Parity
VIF	Variance Inflation Factor
UNIDO	United Nations Industrial Development Organization

1. INTRODUCTION

Pricing is one of the four ‘P’s (product, place, promotion, price) in marketing research which plays a crucial role in determining the profitability of a seller. Employing a successful pricing strategy is pivotal to ensure sustainable revenue management in any business arena (SCHLOSSER & BOISSER, 2018; GREENSTEIN-MESSICA & ROKACH, 2018). The advent of globalisation has intensified the competition among firms, resulting in the formation of destructive price environments which are unfavourable to sellers. The contagion effect of globalisation has already become a major concern for the multinational firms (TARHAN, 2007). The problems like unanticipated transmission of crises in local economies to the global marketplace have toppled their operational plans. These issues have forced them to frame various strategic business models and pricing techniques to retain the competitive edge in today’s cut-throat business environment. Nonetheless, revenue optimisation through pricing strategies that helps retain a loyal consumer base without compromising the profitability is a highly esoteric task which many are still struggling with.

Finding the right price for a product at the right time that maximises a firm’s profitability and at the same time doesn’t hurt the consumer price perceptions is a very complicated endeavor (VICTOR et al., 2019b). It is in this regard the revenue management techniques are gaining momentum internationally. Revenue management aims at selling the right product to the right customer at the right price, time, and place ensuring the optimal usage and minimum wastage of available resources (CROSS, 1997). One of the most common and successfully practiced revenue management techniques in the Electronic Commerce segment by many multinationals including Amazon, Walmart etc. is the dynamic pricing strategy. Under dynamic pricing, the price of a product is determined in accordance with its corresponding market demand and supply in real time (HAN et al., 2018). Dynamic pricing has lately thrived as a highly effective operations research tool which has been widely used in product pricing. GÖNSCH, KLEIN, & STEINHARDT (2009) define dynamic pricing as a pricing strategy where the seller sets a non-negotiable price that changes dynamically over time.

With the advent of big data analytics, this pricing strategy has gone one step further in which price is tailor made for each individual or a group of individuals exhibiting similar characteristics such as taste, preferences, income range etc. With the availability of more and more reliable information about the willingness and ability to pay of the existing and prospective customers, the sellers are able to classify them into more refined groups (OFT, 2013). The data collected by the businesses may include some or all the information given in Table 1.

Table 1. Categories of personal data collected online

Volunteered Data	Observed Data	Inferred Data
Name	IP Address	Income
Phone Number	Operating System	Health Status
Email Address	Past Purchases	Risk Profile
Date of Birth	Website Visits	Responsiveness to Ads
Address for Delivery	Speed of click through	Consumer Loyalty
Responses to Survey	User's Location	Political Ideology
Professional Occupation	Search History	Behavioural Bias
Level of Education	"Likes" in Social Networks	Hobbies

Sources: OECD (2018), OECD (2015), EOP (2015), OFT (2013)

This highly customised pricing technique is popularly termed as personalised pricing. Personalised pricing helps the sellers squeeze consumer surplus to the maximum possible extent (Townley et al., 2017). OECD (2018, p.9) defines personalized pricing as "any practice of price discriminating final consumers based on their personal characteristics and conduct, resulting in prices being set as an increasing function of consumers' willingness to pay". With the spread of digitalization and the use of sophisticated data driven business models, the impacts inflicted by the dynamics of these new pricing strategies on consumer perceptions have already become a heated matter of discussion among academicians and policy makers. Already many ethical and privacy concerns have come up regarding the prospects of using the personalized pricing tactic in which prices are tailored based on the customer's own private information. A study conducted by Deloitte in 2018 shows that around 45% of the online consumers are concerned about sharing their data for customization of targeted advertisements offers, recommendations etc. The intention of consumers to shop online does not necessarily mean that they are willing to share their personal data. Furthermore, the study indicates that 40% of the retailers who were identified using big data analytics use the outputs to personalize prices and promotions in real time and around 12-20% of customers have had issues regarding personalized pricing (DELOITTE INSIGHTS, 2018).

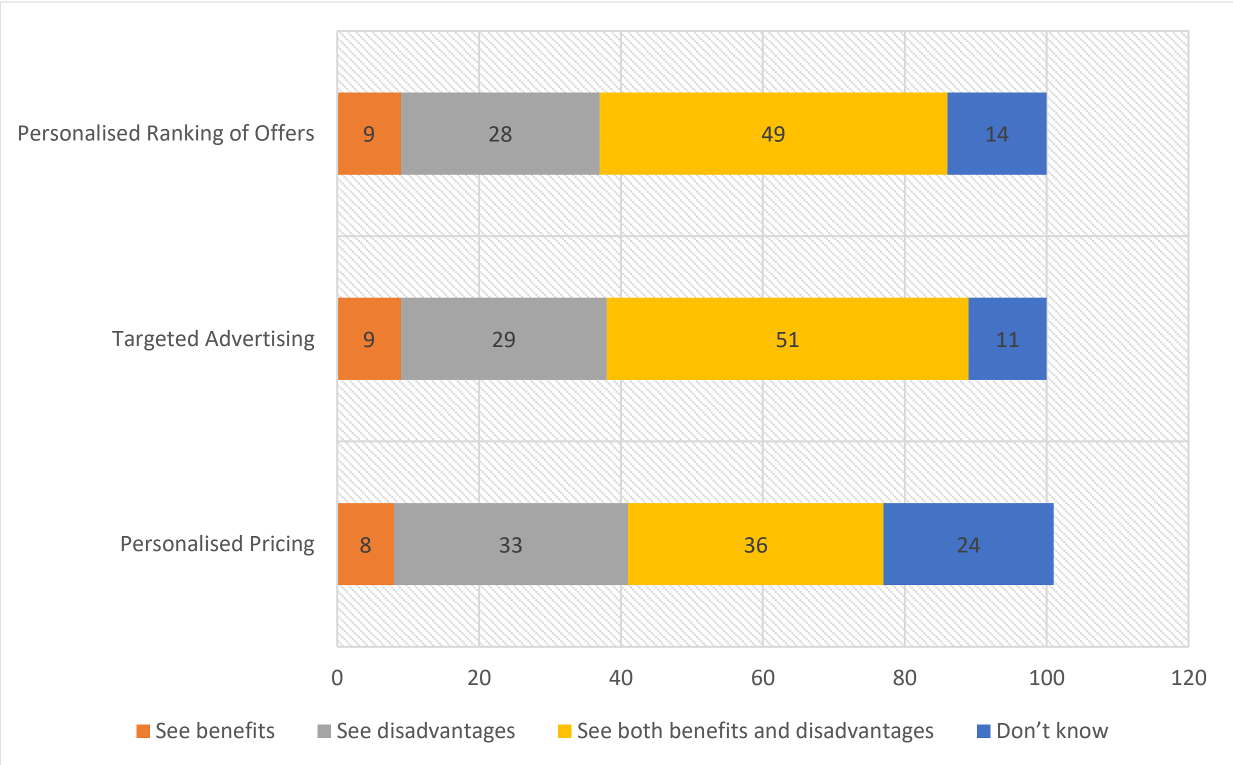
With the current pace of technological progress, although it is technically possible to estimate the willingness to pay of a consumer in real time, it is highly questionable whether the short term increase in revenue of a firm offsets the risk of losing a loyal customer base in the long run (TOWNLEY et al., 2017). In a world where data has become the new oil, individuals are cautious about sharing their personal data to third parties. Employing a hardly transparent pricing technique like personalized pricing in this context should be given much thought and research in this regard.

Given the benefits of personalised pricing to the revenue management of the firms, it is pivotal to figure out how consumers react to this novel pricing strategy at an early stage of implementation which will help the firms make adequate changes to their business tactics and execute it more effectively.

1.1. Problem Statement

The application of big data technology in the E-Commerce has enabled the sellers to have access to crucial information such as the approximate ability and willingness to pay of each consumer. This, in turn, has helped them create customised prices for each individual or for a group of individuals with similar online shopping behavioural traits. The shopping history and trends along with the personal details used for creating accounts on shopping websites are used to differentiate prices among the consumers (OECD, 2018). A study conducted by REINARTZ et al (2017) among 2000 online buyers in Germany show that the European consumers are well informed about the rapid variations in online prices. There are many options available in today's enhanced online environment to trace information regarding such price information (LAMBERTON and STEPHEN, 2016). Previous studies in the area show that the consumers do check the prices their peer group, acquaintances and other people pay for a product which they just bought (XIA et al., 2004; BOLTON, 2003; MONROE, 1973). The inherent risk which lies in here is that the consumers may apprehend that they are not being treated fairly or equally after comparing the magnitude of differences between the price they paid, and the price others had paid for the product. This discriminatory pricing technique may also evoke unanticipated reactions in at least some consumers as it affects their perceived price fairness, customer loyalty and privacy concerns (DAI, 2010; ZEITHAML et al., 1996) This could have an adverse impact on their overall purchase satisfaction which might further lead to some detrimental post purchase reactions such as spreading their negative experience by word of mouth, through online platforms as well as shunning the seller altogether and considering rivals for future purchases etc. (DAI, 2010).

It is worthwhile to mention a quote by ADAMS (1965, p.283) on equity to explain consumer's perceived attitude towards the discriminatory pricing strategies in this regard. Adams stated that "the presence of inequity will motivate the perceiver to achieve equity or to reduce inequity; and the strength of motivation to do so will vary directly with the perceived magnitude of inequity experienced". This statement could be interpreted in the light of an event happened in 2000 when Amazon attempted to practice targeted online dynamic pricing for the first time and the consumers were enraged after figuring out the discrimination in prices and filed legal complaint against the company (STREITFELD, 2000). The event reminds that the consumers do have a tendency to resort to measures which will compensate for the perceived loss due to the price differences they experience and their motivation to do so depends on the magnitude of the price difference with the reference price which the consumer perceive as fair. Some previous studies (BARBIER DE LA SERRE & LAGATHU, 2013; SCHOFIELD, 2019) show that personalized prices may be perceived as unfair by consumers. The study by REINARTZ et al (2017) depicts the reluctance among the online buyers in accepting prices which are tailored exclusively for them based on their own personal information. These results are supported by a survey conducted by European Commission in 2018 among twenty thousand consumers. Only 8% among the respondents see benefits of the personalized pricing and 36% see both advantages and disadvantages. The major results of the survey are given in Figure 1.



Note: Based on a consumer survey conducted by EU consumer programme among 21,734 respondents in 2018.

Figure 1. Consumer attitude towards personalised pricing in EU

Source: EU CONSUMER PROGRAMME (2018)

Some of the existing theoretical frameworks used in the literature to explain consumer behaviour in the E-Commerce sector are the Theory of Reasoned Action (TRA) propounded by FISHBEIN & AJZEN (1975) and its extended version, the Theory of Planned Behaviour (TPB) by AJZEN (1985). These theories basically tries to explain the desire of an individual to engage in a certain behaviour based on the information available. However, the efficacy of these theories in explaining the consumer reaction in a modern platform based economy where the prices change in real time in response to changes in inventories, individual or group preferences etc. is questionable. The reason is that these theories fail to take into account of the consumers' privacy concerns, fair price perceptions and the monetary gains and loss accruing to consumers due to fluctuations in prices. The model developed in this study tries to overcome these limitations not only by factoring in the aforementioned variables but also by using a hypothetical purchase scenario intended to familiarise the respondents with the basic notions of the pricing strategy through simulating an online purchase experience where the respondent has either a monetary gain or loss due to personalised pricing. The simulation gives the provision to distinctly assess the post purchase reactions of consumers in a positive and negative personalised pricing context. The researcher hence believes that the results of this model to be more precise and logical in a personalised context.

After reviewing the literature, a research gap was identified in the area which explicates consumer behaviour in a personalised pricing environment in the E-Commerce sector, especially in the countries like India and Malaysia with a rapidly booming E-Commerce sector. To the best of the author's knowledge, at present, there is a lack of a comprehensive model explaining consumer behaviour in a positive and negative personalised pricing context in the E-Commerce sector. Considering the dearth of studies in the research area and the novelty of the topic, this research attempts to analyse consumer reaction in a negative and positive personalised pricing environment by constructing a model melding various factors influencing consumer behaviour and test its significance using Partial least Square based Structural Equation Modeling (PLS SEM). The results of this study are expected to give new insights to the businessmen, managers, researchers and policy makers in both countries on the consumer perceptions towards this modern pricing strategy which would help them frame better business tactics, legal directives and policy framework.

1.2. Significance of the Study

The purpose of this research is to examine how online consumer behaviour changes in a personalised pricing context in the E-Commerce sector. The existing literature shows that the consumers shopping online are sensitive to the magnitude and proximity of price changes (DAI, 2010; XIA et al., 2004), and are largely concerned about sharing their personal data with the sellers (REINARTZ et al., 2017). This study primarily attempts to explain these issues using a single model.

The significance of this study is the contribution it makes to the existing literature of personalised pricing in the E-Commerce sector. Considering the absence of a model explaining consumer behaviour in an online personalised pricing context, this model after further validation and testing could be extended to expound consumer behaviour under this pricing strategy in different countries and in offline personalised pricing environments. Findings of this study along with the previous literature available in the area is expected to give insights to the businessmen and policy makers on how fair price perceptions, privacy concerns and purchase satisfaction will change in a personalized pricing context and the subsequent impact on the post purchase reactions of consumers. It is also necessary to mention the dearth of studies in the research area which connects personalized pricing with consumer behavior in general and especially in the fast-growing economies like India and Malaysia.

The online business in the developing countries in Asia offer huge business potential to the local as well as global E-commerce giants. The internet penetration in the Asian countries like India, China, Malaysia etc. are growing rapidly. India as of 2019, is the fastest growing E-Commerce market in the world, growing at a rate of 17.8% annually. The E-Commerce market in India is expected to surpass the US E-Commerce market in 2034 to become the second largest E-Commerce market in the world (IBEF, 2019). The E-Commerce market in Malaysia is also showing a rapid growth over the past few years. The contribution of E-Commerce to GDP jumped from RM 37.7 billion in 2010 to RM 85.8 billion in 2017, with a growth rate of 12.2% per year (THE STAR, 2018). The E-Commerce market in Malaysia generated a revenue of US$3,751m in 2018-19 and the Average Revenue Per User (ARPU) is estimated around US$185.06 (STATISTA, 2019).

India and Malaysia have strengthened their co-operation in the digital initiatives especially in E-Commerce since 2017. Many Indian IT firms situated in Cyberjaya, Malaysia are benefitted by the conducive business environment offered by Malaysia’s Digital Free Trade Zone (YAHAYA, 2017). Several incentives including a tax exemption up to 70-100% are offered to the Indian IT companies in Malaysia. Furthermore, Malaysia is keen to adopt India’s E-Commerce model to boost the digital initiatives in the country (ENN, 2018). Considering the cooperation between Indian and Malaysia in the E-commerce sector, and the similarity in the E-Commerce models, the online consumers in the two countries were considered as the primary sample for this study.

For the two countries with a rapidly growing online retail sector boosted by strong co-operation in digital initiatives, it is inevitable that the firms undertake a background study to figure out the perceptions and reactions of the prospective and existing consumers prior to implementing a novel pricing strategy like personalized pricing. In this regard, the results of this study would be a useful reference for the firms already practicing and those intending to practice personalised pricing technique in the Indian and Malaysian E-Commerce segment.

1.3. Objectives of the Study

1. To emphasize the significance and contribution of online business in the growth of the fast booming economies of India and Malaysia.
2. To figure out the importance of big data driven pricing strategies in the revenue management practices of E-Commerce sellers.
3. To expound how various factors influencing consumer behaviour change in an online personalised pricing context.
4. To conceptualise, test and validate a research model explicating consumer behaviour in an online personalised pricing context.

1.4. Research Questions and Hypotheses

To examine how consumers behave in a personalised pricing context, the impact of personalized pricing on various factors which influence the purchase decisions of consumers must be studied. In this research, four factors namely consumers' fair price perceptions, customer loyalty, privacy concerns, and purchase satisfaction are taken into account and how personalized pricing influences these four crucial factors is specifically studied. The subsequent changes resulting from the changes in these factors which may influence the post purchase intentions such as repurchase intentions, revenge intentions and strategic purchase intentions are examined through a partial least square based structural equation modeling (PLS SEM). The construct purchase satisfaction also plays the role of a mediator in the relationship between the independent and dependent variables. Furthermore, how customer loyalty influences the relationship between fair price perceptions and purchase satisfaction is analysed by setting customer loyalty as a moderating variable. The research questions and the hypotheses following are framed based on the previous literature available in the study area and also based on author's own previous researches.

How does the perceived price fairness of consumers in a personalized pricing context affect their post purchase reactions?

Hypothesis 1a: Fair Price Perception of consumers positively influences their repurchase intentions.

Hypothesis 1b: Fair Price Perception of consumers negatively influences their revenge intentions.

Hypothesis 1c: Fair Price Perception of consumers negatively influences their strategic purchase intentions

Hypothesis 1d: Fair Price Perceptions of consumers positively influences their satisfaction with the purchase.

Does loyalty towards the seller affect the post purchase reactions of consumers in a personalized pricing context?

Hypothesis 2a: Loyalty towards seller positively influences the repurchase intentions of the consumers.

Hypothesis 2b: Loyalty towards seller negatively influences the revenge intentions of the consumers

Hypothesis 2c: Loyalty towards seller negatively influences the strategic purchase intentions of the consumers.

Hypothesis 2d: Loyalty towards seller positively influences the consumers` satisfaction with purchase.

Do consumers have privacy concerns regarding the usage of personal data for customizing prices exclusively for them? How will the privacy concerns affect the post purchase reactions of consumers?

Hypothesis 3a: Privacy concerns negatively influences the repurchase intentions of the consumers.

Hypothesis 3b: Privacy concerns positively influences the revenge intentions of the consumers.

Hypothesis 3c: Privacy concerns positively influences the strategic purchase intentions of the consumers.

Hypothesis 3d: Privacy concerns negatively influences the consumers' satisfaction with the purchase.

Does satisfaction with purchase influence the post purchase reactions of consumers (repurchase intentions, revenge intentions and strategic purchase intentions)?

Hypothesis 4a: Customer Loyalty positively moderates the relationship between fair price perceptions and purchase satisfaction.

Hypothesis 4b: Purchase satisfaction positively influences the repurchase intentions of the consumers.

Hypothesis 4c: Purchase satisfaction negatively influences the revenge intentions of the consumers.

Hypothesis 4d: Purchase satisfaction negatively influences the strategic purchase intentions of the consumers.

The conceptual research framework to be tested in this study is given in Figure 2. The research framework illustrates the interaction between the independent variables (Faire price perceptions, Customer loyalty, Privacy concerns, Purchase Satisfaction), dependent variables (Repurchase intentions, Revenge intentions, Strategic purchase intentions), the mediating (Purchase satisfaction) and moderating variables (Customer loyalty).

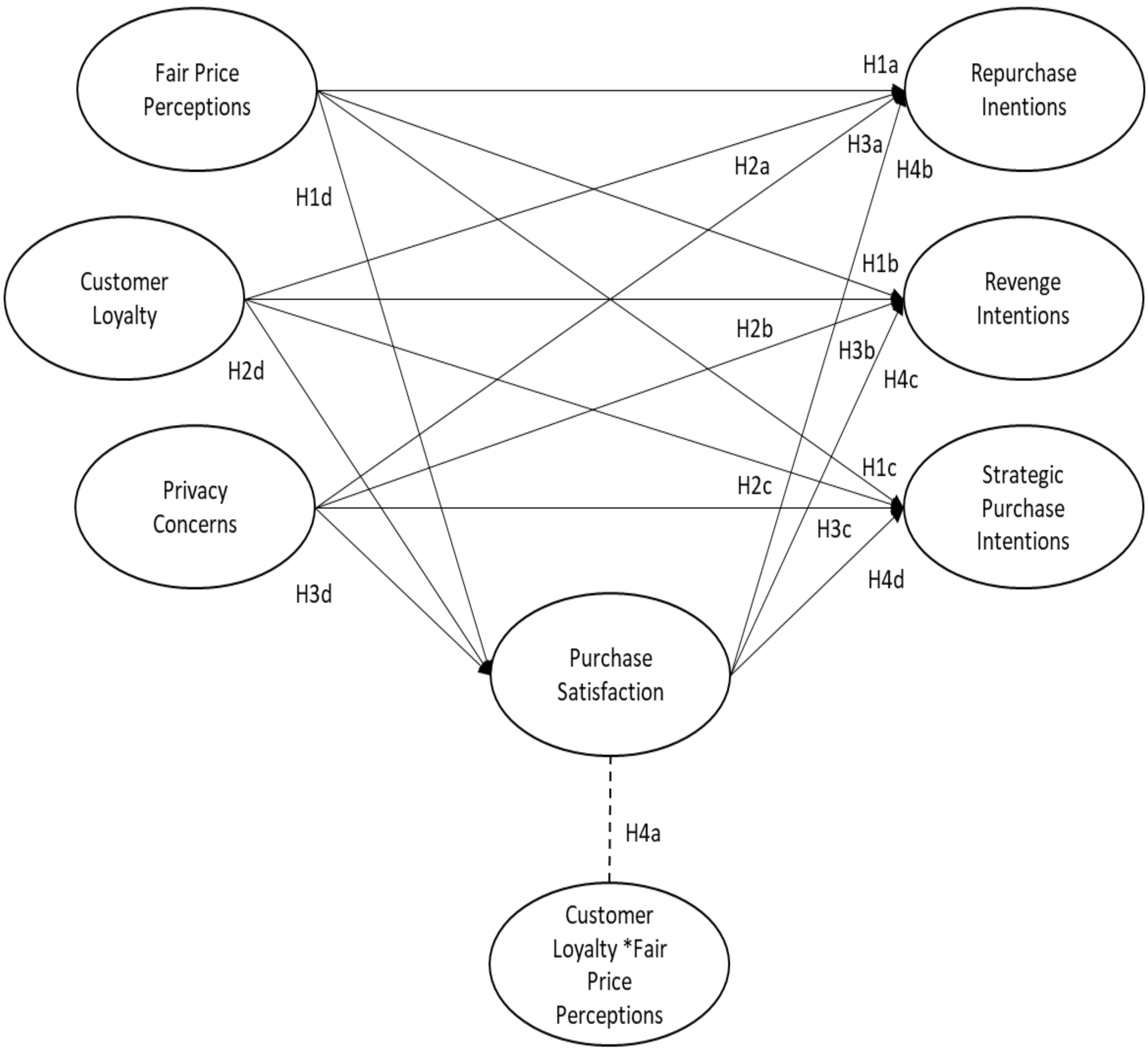


Figure 2. Research Framework

Source: Author’s own construction

2. LITERATURE REVIEW

The first part of this chapter gives an overview of the existing literature on E-Commerce, its evolution and revenue management techniques followed by a brief description of the personalised pricing and its impacts on consumers and economy. Previous studies on different aspects of personalised pricing is explained briefly to depict the literature gap in the area of consumer behaviour under personalised pricing in the E-Commerce segment. The existing legal framework in India and Malaysia on personal data protection and competition laws are also discussed. The concepts of fair price perception, privacy concerns, customer loyalty and purchase satisfaction in a personalised pricing context are further explained in the light of the existing literature.

2.1. Electronic Commerce - Definition

Electronic Commerce or more popularly, E-Commerce involves the use of internet, mobile applications and browsers to engage in business transaction. In a more formal way, it can be defined as 'digitally enabled commercial transactions between and among organisations and individuals' (LAUDON & TRAVER, 2017). There are several definitions explaining different features of E-Commerce. The definition used in this study is the one given by HOLSAPPLE & SINGH (2000, p.165) According to them,

"Electronic Commerce is an approach to achieving business goals in which technology is used to manage knowledge for purposes of enabling or facilitating the execution of activities in and across value chains as well as the making of decisions that underlie those activities."

2.1.1. Brief history of E-Commerce

The rapid advancements in the Information and Communication Technology (ICT) in the late 19^{th} century gave birth to the idea of Electronic Commerce. It is a relatively novel concept which found its place in the business arena in the early 1990s when the internet was opened up for commercial use. Although internet existed in its earliest and primitive form the 1970's, it was primarily used as a medium of Electronic Data Interchange (EDI) through which business documents were shared between companies. In the 1980's Research universities were the primary owners of computers other than big companies and few networks like BITNET and USENET were the platforms which allowed the users to send emails and share documents during those periods (MIVA, 2011). However, the concept of Electronic Commerce didn't gain much popularity until the development of the World Wide Web in the 1990s. Although many initiatives toward the realization of Electronic Commerce started in the 1960s, it was in 1991, the idea of E-Commerce became popular when the National Science Foundation removed its ban on commercial internet use. One of the main issues encountered in the infancy stage of E-Commerce was the security concerns. The Security Socket Layer (SSL), a protocol offered in Netscape 1.0, released in 1994 helped to encrypt personal information used on the web. This made secure online transactions possible and increased the trust of people using internet (HUSSUNG, 2016). The history of E-Commerce remains incomplete without citing the success story of Amazon and eBay, two companies which revolutionized the sector. Amazon in particular developed a full-fledged business model exclusively for the online retail business. The timing of their entry was perfect and is one of the reasons for the success of Amazon, an online retail firm which has attracted around 615 million customers according to a survey conducted in 2008 (DEVKATE, 2013). As pioneers, the business model set by Amazon with the customer review systems and affiliate marketing featured as an ideal model for the newcomers. eBay, which was named as Auction. Web at the time of inception had a slightly different business model from that of amazon which allowed users to bid on other people's used items. This ensured that not only tech giants and entrepreneurs, but also common people could enter into the online market and sell products. In the year 2007, there were around 220 million users and eBay was earning 52.5 billion US Dollars in auctions which show that they leveled the playing field with their business model (EBAY, 2018; HUSSUNG, 2016).

2.1.2. Milestones in the evolution of E-Commerce

A timeline of the important events in the evolution of Electronic Commerce excerpted from BIG COMMERCE (2018) is as follows.

1969 – CompuServe, the first E-Commerce Company is formed by Dr. John R. Goltz and Jeffrey Wilkins utilizing a dial up connection. This is for the first time the concept of E-Commerce is introduced to the world.

1979 – Michael Aldrid invents Electronic Shopping. He is popularly considered as the inventor of E-Commerce. This invention made the transmission of secure data through internet possible.

1982 – Boston Computer Exchange launches as one of the first E-Commerce companies.

1994 – Netscape introduces a web browser named Netscape navigator which is a user friendly browser for browsing online

1995 – Launch of Amazon and eBay which later became the global E-Commerce giants.

1998 – PayPal launches as an E-Commerce payment system to make online money transfers.

1999 – Alibaba.com launches

2004 – World E-Commerce sales is 1.3 trillion US dollars.

The unique features of E-Commerce technology as identified by LAUDON & TRAVER, (2017) are given in Table 2. These are features which make Electronic Commerce distinct from the traditional business.

Table 2. Unique Features of E-Commerce Technology

E-Commerce Technology Dimension	Significance in Business
Ubiquity	E-Commerce is available everywhere with an active internet connection - at work, at home, anywhere. (LAUDON & TRAVER, 2017) Reduces the cost of participating in the market (Business costs). Lowers the intellectual energy (mental efforts required to finish a task) necessary to complete a transaction in the market space. (SHAPIRO & VARIAN, 1999; TVERSKY & KAHNEMAN, 1981)
Global Reach	Potential to extend business across national boundaries and around the world. Entry to the global Marketspace to engage in business with millions and billions of consumers. (EVANS & WURSTER, 1997)
Universal Standards	Availability of common global technology foundations which is available to nations around the world. Lower Market Entry Costs – The only cost is to bring their products to the market. Lower Search Costs for the consumers – The efforts required to find suitable products will become considerably low and the price discovery becomes transparent, simple and accurate (BAKOS, 1997; KAMBIL, 1997)
Interactivity	Allows communication between sellers and buyers in methods like face to face experience. E.g. provisions to comment, group forums, social networking etc. (LAUDON & TRAVER, 2017)
Information Density	Availability of vast amount of quality information to all market participants The price and cost transparency existing in the E-Commerce space has increased competition among E-Commerce seller resulting in lower prices to the end buyers (SINHA, 2000)
Personalisation and Customisation	Provisions for engaging in personalized marketing and customization of products based on individual characteristics. With the advent of big data, possibilities are open to personalize prices for individual customers.
Social Technology	E-Commerce technology has become more social by involving users to make and share content with a worldwide community. The product based community forums and networks keep the sellers updated of the consumer attitudes and preferences. (LAUDON & TRAVER, 2017)

Source: LAUDON & TRAVER (2017)

Several business models evolved since the inception of Electronic Commerce in the 1960s. CHAFFEY et al (2009) classified various models of E-Commerce into the following categories;

Business to Business (B2B) – This model is perceived as the most important segment which involves transactions of goods and services between companies in the process of making economic value (CHAFFEY et al., 2009). The parties involved include manufacturers, distributors, suppliers, retailers etc. E-infrastructure which comprises necessary operating softwares, logistics arrangements serve as a virtual platform where suppliers and buyers can interact. The main purpose of B2B is to facilitate the intermediary manufacturing process for the end customers (VAITHIANATHAN, 2010).

Business to Consumer (B2C) – This model is centered around the consumers. It involves the sale of goods, services and information to consumers. Here consumers learn about various products from the online retailer websites, make the purchases, pay using electronic cash and secure payment and finally get the products delivered (VAITHIANATHAN, 2010). The main B2C markets prevalent today are the Electronic Retail (E-tail) platforms, Electronic-Banking which helps to manage personal finance using various online financial instruments. The Business to Consumer E-Commerce is mainly utilized for channel enhancement, i.e. to surpass the entry barriers and expanding already existing marketplace (LEONARD & JONES, 2014).

Business to Government and Government to Business (B2G/G2B) – This model includes of business transactions between companies and public sector. The first case involves companies taking up several activities for the public sector like a procurement contract through online systems (E.g. Online tender). In the second one, Government informing the business organization about the legal framework, rules etc. through their websites. Broadly speaking, it is a part of the Electronic Governance (CHAFFEY et al., 2009).

Consumer to Consumer (C2C) – Consumer to consumer E-Commerce allows consumers to buy and sell goods from other consumers rather than sellers through the use of technology. C2C is becoming more common in the recent period (LEONARD & JONES, 2014). Many E-commerce platforms like eBay allow consumers to sell their products to other consumers through auctions.

For this study, the researcher focuses on the pricing strategies and consumer reaction in the Business to Consumer (B2C) model.

Electronic Commerce has thrived as a modern business system which caters to the needs of merchants, organisations, consumers, government etc. through computer network and electronic infrastructure. Basically, it is buying and selling of goods and services over the internet. Adopting Electronic Commerce has helped the businesses in a wide range of areas including cutting down unnecessary expenses, increasing the speed of delivery of goods and services, improving productivity, reducing paper work and so on (YADAV, 2010). Striving to exist in a cut-throat competitive world, the companies adopt various possibilities of the Electronic Commerce in different ways to maintain a competitive edge. The online retail sector is witnessing an unprecedented wave of innovation which is mainly driven by technology. The new business models evolving day by day have a very profound effect on the global E-Commerce business and the entire value chain involved (OVUM, 2016). The worldwide E-Commerce sales was 1.33 billion US Dollars in 2014 which in 2017, touched 2.3 trillion US dollars and is projected to be around 4.88 trillion dollars by 2021 (STATISTA, 2018). Figure 3 shows the growth of worldwide E-Commerce sales over the years.

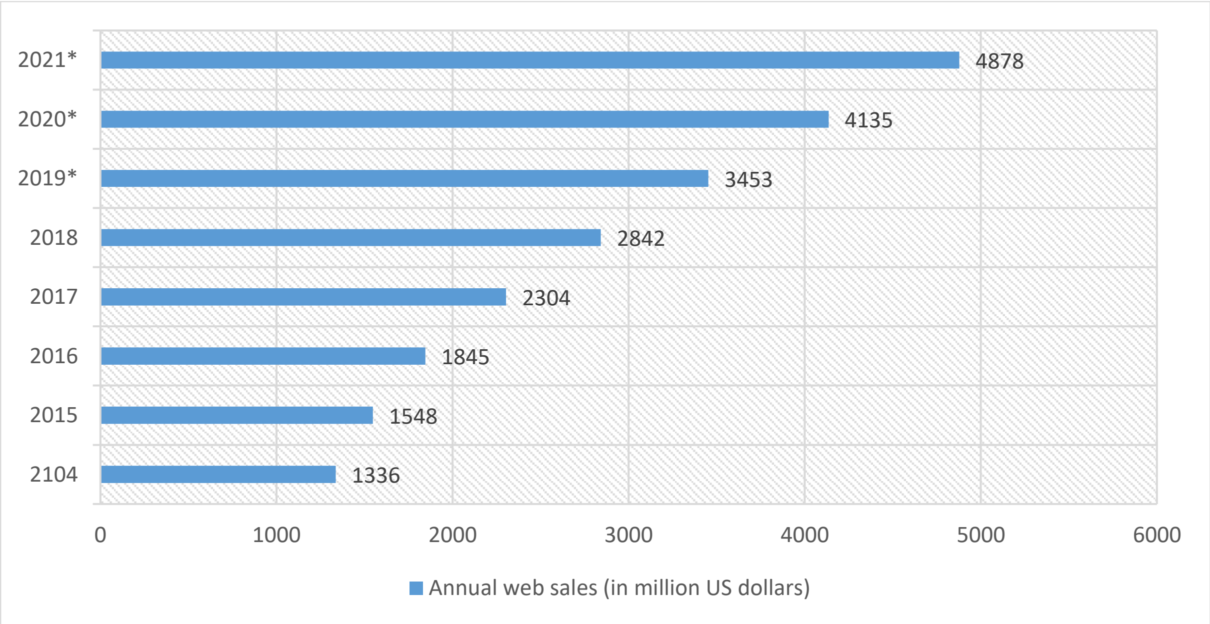


Figure 3. Worldwide retail E-commerce sales from 2014 to 2021 (in billion U.S. dollars)

Source: STATISTA (2019)

The E-Commerce sector is still evolving day by day with alterations brought forth to the existing business models and with the advent of new business models powered by sophisticated technologies and efficient revenue management systems.

2.2. An Overview of Electronic - Commerce in India and Malaysia

2.2.1. Electronic Commerce in India

India is the seventh largest country in the world covering an area of 3.3 million sq.km. The population in India as per the WORLD BANK (2017) was 1.39 billion in 2017 and is currently the most populous country in the world after China. Indian economy is the top among the fastest booming economies in the world with a growth rate of 7.3% and a total Gross Domestic Product (PPP) of 2689 billion US dollars in 2018 (STATISTA, 2019). Looking at the population structure of India, 65% of the population is aged 35 or below (WORLD BANK, 2017) and there are plenty of forecasts that this nation with an ‘emerging middle class’ of more than 500 million could potentially surpass the US economy (in PPP terms) by 2050 (PWC, 2018). The population structure and the expected rise in disposable income represents a highly motivated consumer market with plenty of opportunities to offer the world.

The recent report published by KANTAR IMRB (2018) forecasts that India’s internet users are expected to reach 627 million in 2019. The report also states that the annual growth of internet usage is 18% as of December 2018. However, the overall internet penetration is still 40%. Although this percentage is not relatively high as compared to other countries, considering the huge population and the rapid spread of internet in the rural areas owing to various national digitalization programs, this number is expected to rise in the upcoming years. The electronic commerce market in India is hailed as the fastest growing e-commerce market in the world. Revenue earned from the sector in 2017 was 39 billion US dollars which is expected to touch 120 billion dollars in 2020. Certain factors which will permit this growth are 100% FDI allowed in the business to business E-Commerce, growing young population and also the increasing internet penetration. Huge investments are already made by the E-Commerce giants like Amazon and Walmart in the country. The leading stores in the Indian e-Tail segment as in 2017 is given in figure 4.

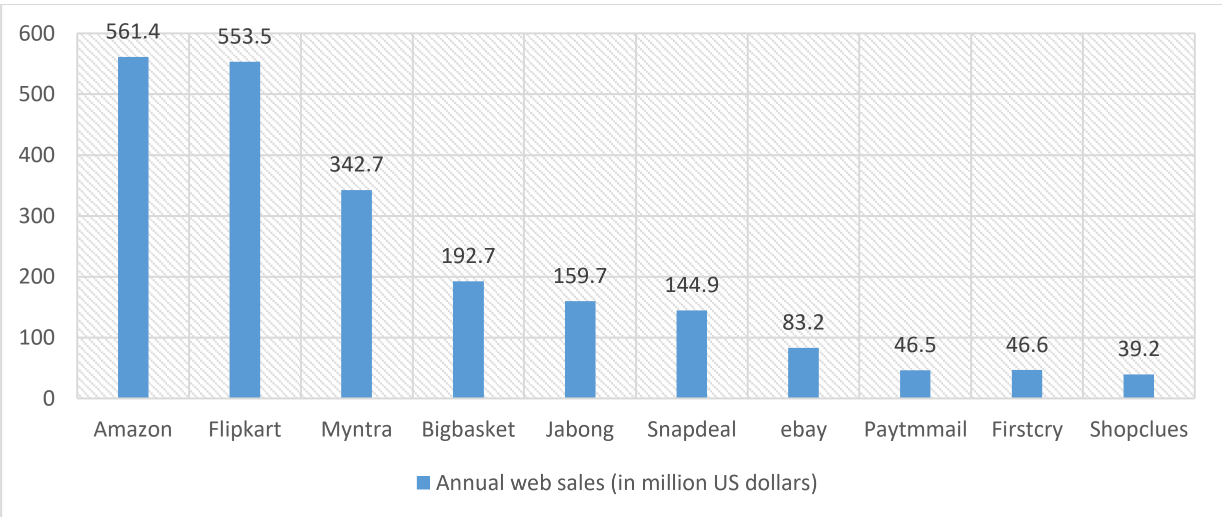


Figure 4. Leading online stores in India in 2017 ranked by net e-commerce sales (in million U.S. dollars)

Source: STATISTA (2019)

Statistics given in Figure 4 shows that Amazon.in is the leading E-Commerce seller in India with a sales volume of 561.4 million US dollars in 2017. The native E-Commerce giant Flipkart comes second in the list having done a business worth 553.5 million US dollars posing as the top competitor to the former. As per the latest report of BAIN AND COMPANY (2017), the pace of growth of Indian online retail market is higher than that of other global online markets from the period 2013 to 2017 with a Compound Annual Growth Rate (CAGR) of 53%. Furthermore, the E-Commerce sector in the country is expecting a sales volume of around 200 billion US dollars in 2026 which was only around 38.5 billion US dollars in 2017.

The number of Micro Small and Medium Enterprises in India adopting E-Commerce is increasing rapidly. The latest report of the Ministry of Micro Small and Medium Enterprises in India states that about 51 million units of MSMEs provide jobs to 117 million people in India. More than 6000 products are manufactured in the MSME sector which is about 45% of the total manufacturing and account for 40% of the total exports. UNIDO (2018) reports that those MSMEs which adopted advanced digital technologies to boost their business have seen a 27% increase in the annual revenue than the offline MSMEs. The growth has been attributed to various factors such as reduced distribution and marketing costs, reduced inventory costs, shorter time lag to the marketplace etc. Some significant statistics of the online MSMEs as reported by UNIDO (2018) are as follows;

1) MSMEs already in the E-Commerce space have seen up to 60% reduction in marketing and distribution costs.
2) MSMEs using E-Commerce have witnessed a 27% higher annual revenue growth than the offline counterparts.
3) The cost of entering the E-Commerce space is as low as 100 dollars for MSMEs.

The growth of MSME sector in India is crucial for the proposed goals of financial inclusion and employment generation. Some of the problems faced by MSMEs in the E-Commerce space such as adoption of new technology, training of staff etc are being tackled with the assistance of leading E-Commerce companies in the country. E-Commerce technology open a vast international and domestic business opportunities to the MSMEs (UNIDO, 2018).

2.2.2. Electronic Commerce in Malaysia

Malaysian E-Commerce right now is at an inflection point which implies that a rapid growth in the sector is expected in the coming years (MITI, 2018). The revenue is predicted to grow at an annual rate of 11.4%, compounded Annual Growth Rate for 2019 – 2023 with a total volume of US$5,776 m by 2023. The largest segment in the Malaysian E-Commerce market is Electronics and Media with a market volume of US$1,014m in 2019. Furthermore, the user penetration rate which is 62.5% now is anticipated to touch 65% by 2024 (STATISTA, 2019). Malaysia has prepared a National E-Commerce Strategic Roadmap with a view to double the current growth and increase the E-Commerce contribution in GDP to around RM 170 billion by 2020 (MITI, 2018). Six thrust areas were identified under this initiative are given in Table 3.

Table 3. National E-Commerce Strategic Roadmap – Malaysia

Supportive Governance Framework					
Speed up the seller acceptance of eCommerce	Augment the usage of eProcurement by businesses in the country	•Remove non-tariff barriers •Domestic e-fulfilment •Cross-border e-Commerce •offer consumers protection in e-Payments	Reallocate the prevailing incentives available to the eCommerce sellers	Provision for more strategic investments in select eCommerce seller(s)	Encourage local brands to increase cross border eCommerce transactions

Source: MITI (2018)

Furthermore, the strong online culture prevailing in the southeast Asian countries portray the potential for growth. Around 63% of the Malaysian population is aged 35 and below. The average internet use in Malaysia is clocked at 14 hours per week and 47% of the population is smartphone savvy (MITI, 2018).

A recent study by ACCENTURE (2018) shows that Malaysian Government's economic trasformation programme is intended to help develop a strong digital ecosystem in the country by 2020. The projections for 2022 is given in Table 4.

Table 4. Digital Economy Statistics – Malaysia

	Population (in million)	**Internet Penetration**	**Digital Buyer Penetration**	**Per Capita Digital Purchase**
2017	31 .6	81%	89.40%	$74
2022	33.7	87.90%	91.40%	$144.20
Change	2.10%	6.90%	2.00%	$70.20
CAGR	1.30%	3.00%	3.40%	14.30%

Source: ACCENTURE (2018)

The numbers given in Table 4 shows the ambitious plan of the Malaysian government to increase the digital per capita purchase by around $70.20 by 2022. They expect an internet penetration of around 6.9% by 2022. However, the digital buyer penetration is expected to increase only around 2% in the next three years.

Lazada.com.my is the most visited E-Commerce website with a monthly visit of 21,387,000. Other popular online retailers are Shopee, Lelong and 11 Street. The bar chart of the most visited online shopping sites in Malaysia as of first quarter of 2019 by monthly traffic is given in Figure 5.

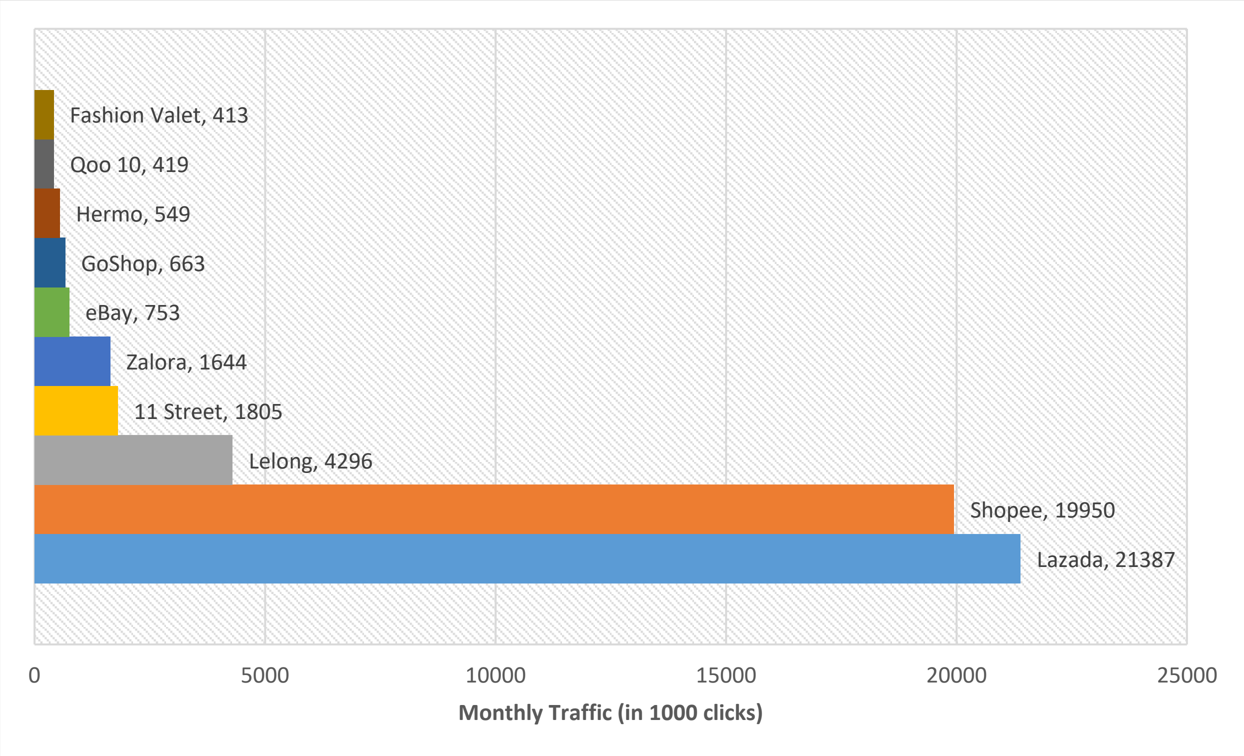


Figure 5. Highest monthly visits: Top 10 E-Commerce sellers in Malaysia

Source: Own construction based on STATISTA (2019)

Some concerns of online consumers as spotted by a survey conducted by PWC (2018) are online security issues (37% of respondents) and trust issues with the sellers (35% of respondents). However, with the advent of ultra-security measures such as 3D secure, the sellers are able to regain the trust of consumers.

2.3. Revenue Management and Pricing Strategies in E-Commerce

Revenue management can be defined as the application of analytics which are capable of predicting consumer behaviour to optimise the price, supply and inventory with an aim to maximise revenue growth. In other words, revenue management aims at selling the right product to the right customer at the right price, time and place ensuring the optimal usage and minimum wastage of available resources which in turn maximises the revenue of a firm (CROSS, 1997).

The pioneering research in the field of revenue management were carried out by ROTHSTEIN (1971, 1974) and LITTLEWOOD (1972). Their works primarily focussed on dealing with the issue of hotel and airlines overbooking. However, the revenue management practices became popular only after the work of BELOBABA (1987a; 1989b) on airline seat inventory control which was successfully applied by the American airlines. From then, many researches primarily in the airline industry came out showing the impact of revenue management on the operations of a firm (SMITH et al., 1992). In most of those original models, prices or fares were assumed to be fixed. In the 1990's, when models become too industry specific, it was required to make changes to the pricing strategies as well. In the late 1990s more concrete researches on dynamic pricing policies in a revenue management context appeared (BITRAN & MONDSCHEIN, 1997; FENG & GALLEGO, 1995, 2000). As mentioned, the airline industry lead the way in using the revenue management techniques in the forms of capacity utilisation and dynamic pricing which was later spilled over to other industries such as retailers, online retailers (GERAGHTY & JOHNSON, 1997), railways (CIANCIMINO et al., 1999), electric power supplies etc (OREN & SMITH, 1993).

Dynamic pricing has been widely applied in industries which require high initial investments, selling perishable products and a demand which is both price sensitive and stochastic. This pricing strategy find its base in the price discrimination principle in Economics.

2.3.1. Price Discrimination

TOWNLEY et al (2017, p.2) defines price discrimination as "…charging different customers or different classes of customers different prices for goods or services whose costs are the same or, conversely, charging a single price to customers for whom supply costs differ…" In simple words, it means the practice of selling the same good or service at different prices to different consumers. The logic behind the price discrimination is to set a price in accordance with the willingness to pay of a consumer rather than relating it to the cost of production (KOTLER & ARMSTRONG, 2016). In order to practice price discrimination successfully, certain conditions are to be met (VARIAN, 1989). They are as follows;

Some degree of market power **-** In order to successfully employ price discrimination, a firm should have some degree of market power. It means they should have the ability to price above the incremental costs of producing the product to discriminate prices (MCAFEE, 2008). In market structures like perfect competition, price discrimination does not exist as the buyers are well informed about the prices in the market and hence will not make the purchase from the seller who discriminate prices. They simply buy from other sellers. But Perfect competition is a highly theoretical concept and the consumers do not always have perfect information regarding the prices (FRONTIER ECONOMICS, 2018).

Ability to sort consumers - The ability to segment consumers either in terms of how much consumers are willing to pay or costs to serve the consumer. This can be done by analysing the behavioural traits exhibited by the consumers based on some observable characteristics. For example, those consumers who readily adapt to changes may be categorised as 'engaged' and those who do not as 'disengaged'. In the modern times with firms having large amounts of data, they use different analytical tools aided by big data to segment consumers.

Ability to prevent resale - The ability to prevent resale is very important requirement to employ first and third degree price discrimination. Firms should make some kind of restrictions to make it impossible or expensive to resell products (VARIAN, 1989). If the firm charges different price for different consumers, there is a chance that the ones who got products at lower prices may sell it at a higher price to others. This is also known as arbitrage.

2.3.2. Types of Price Discrimination

A.C. Pigou identified three main types of price discrimination based on the information assumed to be kept by the seller regarding the willingness to pay of the buyers (PIGOU, 1929).

a) First Degree Price Discrimination

First degree price discrimination is also known as perfect price discrimination which involves the seller setting price for each product which is equal to that consumer's maximum willingness to pay for that particular product (VARIAN, 1989). In other words, firms have perfect information about each individual consumer's willingness to pay which allow them to squeeze the whole consumer surplus. In personalised pricing where price is tailored for each individual consumer, first degree price discrimination is employed. However, perfect price discrimination is highly theoretical in nature (SHAPIRO et al., 1998).

b) Second Degree Price Discrimination

Second degree price discrimination is also known as 'Versioning' or 'menu pricing' (SHARPIRO et al., 1998) or 'nonlinear pricing' (VARIAN, 1989). Here, firm sets a menu of prices for different quantities or versions of the product. Consumers themselves choose the best option available which meets their needs. Quantity discounts are best example for second degree price discrimination.

c) Third Degree Price Discrimination

In third degree price discrimination, a certain price is assigned to a certain group of people. The seller here has imperfect information about an individual's willingness to pay and therefore set prices based on the observed characteristics or behaviour. It is also known as 'group pricing'. The group of consumers are formed based on the common characteristics such as age, geographical locations, behavioural patterns, purchase histories etc. Typical examples are student discounts and senior citizen discounts (VARIAN, 1989).

A monopolist practicing price discrimination based pricing strategies like dynamic pricing over the traditional uniform pricing has three main effects on aggregate consumer surplus (PIGOU, 1929).

I. Rent transfer effect – A monopoly seller using price discrimination has a broader variety of pricing options which aids to increase its profits (rents) at the expense of consumers.
II. (Mis) Allocation effect – In a price discriminating context, output may not be allocated efficiently. In other words, output is not essentially distributed to consumers who value it the most.
III. Output effect – Price discrimination offers a possibility for the sellers to increase output by offering products at lower prices to consumers.

The rent transfer effect and the allocation effect incline to squeeze the consumer surplus whereas the output effect increases it. Most of the price discrimination pricing strategies including dynamic pricing can be more or less categorized as third degree price discrimination (TOWNLEY et al., 2017). The impact of third-degree price discrimination on consumer surplus is thus abstruse. However, AGUIRRE et al (2010) and BERGEMANN et al (2015) state that although third degree price discrimination certainly shrinks the consumer surplus, there are instances where it could also increase.

2.4. Dynamic Pricing

Dynamic pricing is commonly referred to as the practice of changing prices based on the supply and demand responses in the market. This is not a brand new concept. As professor Paul Krugman rightly noted, dynamic pricing is just a modern version of the old practice of price discrimination (KRUGMAN, 2000). Yet, the price discrimination practiced today is different in the sense that modern technology has made dynamic pricing more commercially feasible and viable. The E-Commerce sellers are now widely employing dynamic pricing to maximize profits by charging different prices for very similar or essentially the same products or services to different customers based on various factors. (HAWS & BEARDEN, 2006). Broadly defining the concept, dynamic pricing involves the buying and selling of goods and services in markets where prices adjust freely in response to the demand and supply conditions at the individual transaction level. Although there are many auction models and 'Name Your Own Price' models which work based on the dynamic pricing principle, most retailers prefer the method which enables them to customize prices based on the willingness to pay of individuals (CARROLL & COATES, 1999).

So far, retailers were practicing price discrimination at the aggregate market-segment level. However, the current technological progress and the availability of individual level information resulted in a paradigm shift in price determination, taking this pricing strategy to a whole new level. Since the menu cost in the online retail is nominal, dynamic pricing has become a norm in the E-commerce sector as the menu cost in the internet market is minimal. The cost of changing prices in internet marketing is negligible and online sellers can easily experiment with different prices to obtain a larger profit margin (VICTOR et al., 2018a).

The first well known attempt to practice a customised online price discrimination was made by the world's largest online retailer, Amazon.com in 2000 (MILLER, 2014). Amazon experimented with dynamic pricing using their huge databases and sophisticated technological infrastructure by setting prices for each customer based on the individual implied willingness to pay. However, consumers identified that Amazon was selling the same DVD at different prices to different consumers. Many consumers filed complaints against the company and they justified their actions as a 'price test' of randomly varying prices to estimate price elasticity of demand for each item and finally had to publicly declare that they would not employ this price discrimination strategy anymore to reinstate the consumer confidence (STREITFELD, 2000). Although Amazon maintained the claim that the prices show to the consumers were completely random, many suspect that it was a targeted dynamic pricing (MILLER, 2014). Only a few evidences were found after this incidence at least for a decade where sellers engaged in targeted dynamic pricing.

However, in 2012, an Oregon based newspaper stated that the online consumers were still experiencing price discrimination in Amazon.com. The report gives an instance of one consumer who selected a set of Mahjong tiles to her online shopping cart was offered a price of 54.99$ but after some time, she recognized that the price soared to $79.99 dollars. When she dropped the item from the basket and tried adding again, it was then priced at $59.99. Wall Street Journal reported in the same year that Staples Inc.'s showed different prices to different consumers based on the geographical locations of consumers (TOWNLEY et al., 2017). The international hotel and travel bookings in US was also reported to be following a price discriminatory policy as stated in a 2015 study (ROSE & RAHMAN, 2015). A.C Pigou who first used the term price discrimination was aware of the inherent problems with this type of pricing methods. He advised that the businesses should be careful while setting price policies. He stated that;

"Since a hostile public opinion might lead to legislative intervention, [the company's] choice must not be such as to outrage the popular sense of justice." (PIGOU, 1929, p.281)

2.4.1. Advent of Big Data and Changes in Pricing Strategies

With the recent advances in technology, our understanding of data has completely changed. Today, data is reckoned as one of the most important resources in the world. Although it is a resource which is easily accessible, making the most use of this resource requires both strategical and technical expertise. Those who have the prowess to exploit this resource will gain a competitive edge over their rivals in the years to come (DELOITTE, 2016). Big data implies the huge volume of data which involves business data, data from social media platforms, data generated from machines, mobiles and GPS, data collected by government and non-government agencies, non-profit organisations etc. (US CHAMBER OF COMMERCE FOUNDATION, 2014). Big data analytics is reckoned as a disruptive technology which makes the existing technology obsolete, plummeting the value of investment made on the established ones (DANEELS, 2004). The services provided by professionals ranging from advertising to diagnosis are now substituted by the data-driven innovative applications (WANG et al, 2016). As a result, organisations are keen to invest more in developing big data infrastructures and skilled personnel (WAMBA et al., 2015). A data-driven eco system can optimise a wide range of operations in a firm like improving value chain, building better customer relationships, efficient use of available resources etc. Firms, in this era of cut throat competition are striving to maximise their profitability by executing day to day operations very rationally and utlising the available labour force in the most efficient and economic way (KOPISHYNSKA et.al., 2016; VICTOR & FEKETE-FARKAS, 2018).

Multinational companies like Amazon, Starbucks, Netflix, TMobiles etc. have already started unlocking the vast potential of the data generated within their companies. A study conducted by IDG in 2016 reports that about 78% of the large companies who have already embarked on leveraging the potential of big data agree that the tactical use of data analytics has changed the way they conducted the businesses. (IDG, 2016). The data-driven economy in Australia added approximately 67 billion dollars in new value to the Australian economy in 2013 alone. This is about 4.4% of the country's total GDP (STONE & WANG 2014). Many cities like Manchester, Amsterdam, Chicago, Barcelona etc are making use of big data to improve transportation networks, digital public services with a view to support better town planning and local area development. (OJO et al., 2015). In central and eastern Europe region, the revenue generated from big data analytics was nearly 2.73 billion dollars in the end of 2016 which also shows an increase of 8.9% than the previous year (IDG, 2016).

Insights from big data transforms the way organisations perceive business impediments and aids them to make informed and efficient decisions based on objective data. Unlike the previous times, companies now have access to different kinds of customer related data which are collected from a wide range of sources including websites, mobile apps, soical medias, blogs etc. This enormous amount of data undergoes a sound analysis which finds imperceptible patterns, trends and correlations which are too minute to be identified and are being transformed into meaningful insights. Once the companies have started making valuable insights from the data generated, they can modify their business plans and strategies in line with what data portray as the real customer needs. Efficient logistics and inventory management depend on the accuracy of sales forecasts (VICTOR & FEKETE-FARKAS, 2018). This is where big data plays a pivotal role. The precise sales and demand forecasting using big data helps to reduce inventories and manage logistics movement in a very efficient way (KOT et al., 2011). Many companies have already initiated using insights from big data analytics for a people centric decision making. For instance, Sense-T, a real time data analytics company has synthesized the data on water, weather, crops, farm equipment etc in order to aid the farmers in the area to make efficient crop harvesting and to assist the government in improving water catchment systems and finally to help the consumers identify where the food is sourced from (STONE & WANG, 2014; VICTOR & FEKETE-FARKAS, 2018).

Big data has a wide range of applications in online retail markets (COMPETITION MARKET AUTHORITY, 2018). According to Profitero, the online retail giant, Amazon is making around 2.5 million price changes on a daily basis to optimise their profit earnings. This is how businesses make use of the potential of big data towards their end (PROFITERO, 2013).

Latest reports state that they have been earning profits for 11 quarters successively since 2015 (JASON, 2018). Big data driven algorithimic pricing is gaining popularity in the modern times. It is not just E-Commerce giants like Amazon and Walmart are using pricing algorithms, smaller online retailers are also following the suit (CHEN et al., 2016; LE & LIAW, 2017). The study found out after analyzing 30000 Amazon’s third party sellers and price history of 1641 best-selling third party products, around five hundred sellers were using big data driven pricing strategies. Furthermore, these retailers got more feedbacks and managed to sell more products than the non-algorithmic sellers. The research also reported that some sellers were changing prices from 10 to sometimes more than 100 times a day which left them with the conclusion that pricing algorithms are used to compete with the price changes of their rivals (CHEN et al., 2016). The COMPETITION MARKET AUTHORITY (2018) also concurs the use of algorithmic pricing by large Amazon third party sellers which are developed by professional algorithm suppliers.

2.5. Personalised Pricing

The fourth industrial revolution, rapid advancement of the internet of things and the digital technologies have enabled the sellers to know more about the choices and preferences of consumers. With the availability of public and private data such as location, gender, age, search history, sensitivity to price offers etc firms are now able to estimate the approximate willingness to pay of consumers and engage in a more polished form of price discrimination such as personalised pricing. In personalised pricing, prices are tailored for each individual customer or for a bunch of customers who display similar online charactersitic traits. Through this pricing strategy, the sellers squeeze a major share of the consumer surplus which in turn maximise their profits (GEHRIG et al., 2012).

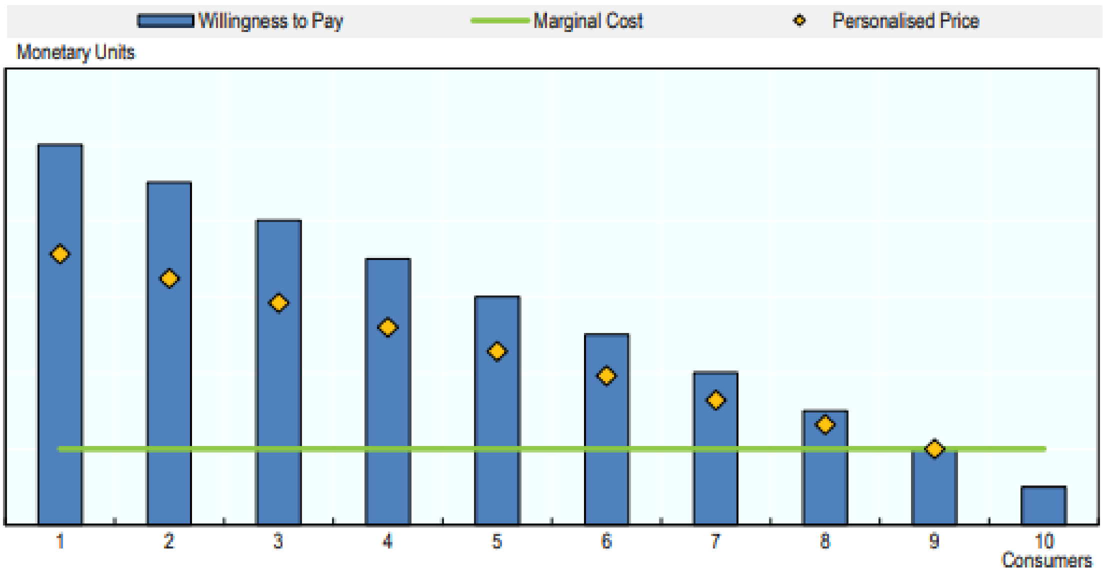
The Office of Fair Trade UK defines personalised pricing as "…the practice where businesses may use information that is observed, volunteered, inferred, or collected about individuals' conduct or characteristics, to set different prices to different consumers (whether on an individual or group basis), based on what the business thinks they are willing to pay." (OFT, 2013, p.2).

Sellers in the traditional markets and bazaars are not unfamiliar with this pricing technique. Haggling is a very common practice in many of the bazaars and agricultural markets. Sellers in these markets are mostly able to figure out the willingness of consumers to pay for a product, which helps the sellers tailor prices for each customer. For the online retailers, the information about the personal details of their customers remained ambiguous until the dawn of big data analytics. Big data has made it possible to collect information and to know more about the details of the actual and future customers without having met them personally. The firms now have the possibilities to make changes in prices more rapidly and offer personalised targeted advertisements for individual online consumers, as well as customize prices for each customer on the basis of their income, spending habits, past purchases, online reviews, social media engagements etc. (VICTOR et al., 2019a). This practice is often ascribed to the practice of first degree price discrimination or "perfect price discrimination" in which the sellers are able to squeeze the total consumer surplus (ARMSTRONG, 2006). Nevertheless, the idea of first degree price discrimination is highly theoretical in nature which requires perfect information about the income, taste, preferences, choices, etc. of the existing and potential consumers.

From an economic standpoint, there are some hindrances which check the prevalence of first degree price discrimination (EDWARDS, 2006). First of all, the firms are required to have perfect monopoly to have perfect control over the price. Perfect monopoly is a highly theoretical concept which are rarely encountered in the real world (VARIAN, 1989). Secondly, even a perfect monopolist will have to set the prices below the equilibrium level at times to attract customers. Finally, perfect information about the consumer behaviour is a 'wild dream' of every seller which they often don't get. Hence, the possibility of first degree price discrimination or perfect price discrimination is near to impossible from an economic standpoint (SALOP & STIGLITZ, 1977).

In reality, only a proportion of the total willingness to pay of consumers are grabbed by the sellers. Furthermore, firms do group consumers who exhibit similar traits and tailor prices for each group instead of customizing prices for each individual customer. This is an example for third degree price discrimination (TOWNLEY et al., 2017).

Figure 6 illustrates personalised pricing as a function of the willingness to pay of the consumer. As mentioned, the seller does not charge price equal to the total ability to pay of a consumer due to several reasons.



Note: In a personalized pricing context, the price charged changes in accordance with the estimation of the willingness to pay of a consumer.

Figure 6. Illustration of Personalised Pricing

Source: OECD (2018)

Although the terms dynamic pricing and personalized pricing are usually used interchangeably, they are distinct and have different meanings. The main difference is that while personalized pricing involves setting prices for individuals on the basis of their personal characteristics, dynamic pricing implies altering prices (often in real time) in accordance with the changes in demand and supply. Dynamic pricing does not entail a discrimination based on consumers' observed characteristics. This in a way allude that dynamic pricing poses fewer concerns with regard to discrimination and facilitates the price mechanisms to function efficiently as compared to personalized pricing (OECD, 2018).

2.5.1. Empirical and Anecdotal Evidences of Personalised Pricing

The concerns regarding personalized pricing became sound only in the past few years. This perhaps is due to a variety of reasons. The European Commission states that firms might have already embarked on personalized pricing but executing in a non transparent way, being dreaded of adverse consumer reactions. Moreover, detecting personalized pricing is not an easy task. "technical possibilities for online personalisation have become much more advanced and hard to capture/measure" (EU CONSUMER PROGRAMME, 2018, p.43).

Empirical evidences for the existence of personalised pricing in digital markets was examined by HANNAK et al (2014). The study investigated 300 real world user accounts and cookies to detect personalized pricing in 16 popular Electronic Commerce websites. The results show that 9 out of 16 websites use some sort of personalization. Furthermore, the EU CONSUMER PROGRAMME (2018) survey shows that 12 to 20% of the consumers reported bad experiences related to personalized pricing.

The study by MIKIANS et al (2013) reported a number of online firms in various sectors including hotels, travel agencies, clothing and apparels, online retailers etc. who offered personalized deals to customers based on various attribute of the customers. IORDANOU et al (2017) found out that some online sellers made price discriminations based on geographical locations and type of browser used. The study shows that the online prices offered to people in different countries are highly dispersed and the dispersion within countries are comparatively lower due to legal reasons.

2.5.2. Personalised Pricing vs Uniform Pricing

As mentioned earlier, personalized pricing does not always necessarily happen at the individual consumer level due to the lack of perfect information. The firms might instead go for customizing prices for groups of people who represent similar characteristics (TOWNLEY et al., 2017). However, for the purpose of illustration, personalized pricing is set as a linear function of the willingness to pay of consumers. The graphical illustration of the uniform pricing and personalized pricing is given in Figure 7.

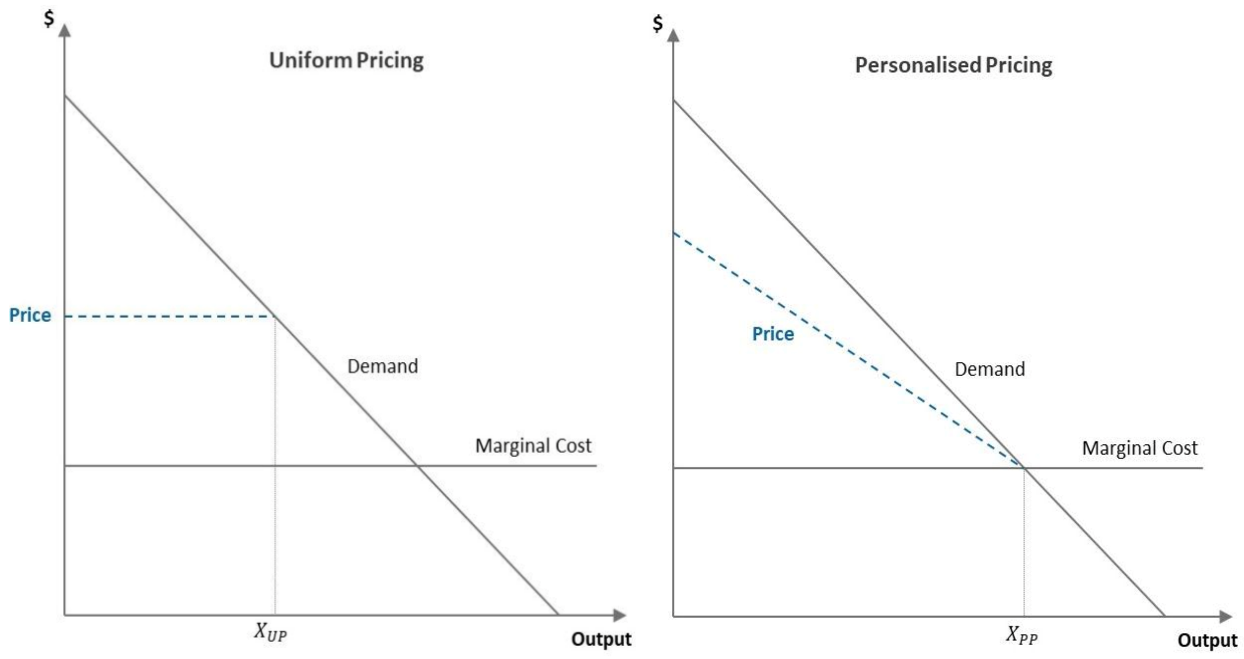


Figure 7. Illustration of uniform pricing and personalized pricing

Source: Personalised Pricing in the Digital Era, OECD REPORT (2018, p.18)

Under uniform pricing or fixed pricing strategy, each consumer pays literally the same price for each product sold. The personalized pricing on the other hand works as a linear function of the willingness to pay identified of the consumer based on their observed behaviour and preferences. Under personalized pricing the price charged depends on his/her willingness to pay.

2.5.3. Personalised Pricing and the Economic Paradigms

Very few previous works available in the field of personalized pricing as it is a relatively novel research area. The existing literature along with major economic theories are analysed to examine the economic effects of personalized pricing.

Theoretically, personalized pricing has the capability to improve allocative efficiency in an economy. The total social welfare which is a sum of producer surplus and consumer surplus (VARIAN, 1985) increases with the personalization of prices. To be more precise, firms set low prices for poor consumers who otherwise cannot afford the product and at the same time maintain their profitability by charging high prices to the rich customers for the same product which ultimately increases both consumer and producer surpluses. This result is concurred by the study of INDEREST & SHAFFER (2009) which state that price discriminatory strategies improves allocative efficiency in an economy. However, the conventional price discrimination strategies may not necessarily increase the total social welfare due to lack of accurate information (SCHWARTZ, 1990).

The highly sophisticated nature of personalized pricing makes it a hardly transparent pricing technique. This might make the consumer reaction highly complex due to higher search costs and the dilemma of the consumer to defer purchase and wait for price markdowns to make the purchase. Nevertheless, the information asymmetry gives an upper hand to the sellers and the consumers eventually lose a considerable share of consumer surplus due to the increased search costs (OFT, 2013).

Studies have shown that the conventional price discrimination strategies do have both positive (GRENNAN, 2015; NEVO & WOLFRAM, 2002) and harmful effects (SHILLER, 2013; CUDDEFORD-JONES, 2013) on the distributional outcomes in an economy. Personalised pricing will cause a redistribution of consumer surplus from consumers who are relatively price elastic to those who have inelastic demands. Over and above, depending upon the accuracy of information on the consumer preferences and choices, the producers also squeeze a proportionate portion of consumer surplus resulting in the transfer of surplus from one economic agent to another i.e. consumers to producers (TOWNLEY et al., 2017). Hence the potential impacts of personalized pricing on distributional outcomes in an economy also depends on the accuracy of information collected by the firms.

2.5.4. Personalised pricing and its impact on consumers

The accuracy of data on consumer preferences and choices is the most critical factor which enables personalised price discrimination in digital markets.

One of the important questions to be addressed while employing personalised pricing is to figure out how consumer reactions change when sellers have accurate and detailed information regarding consumer likings and preferences. A relevant model in this regard is that of ESTEVES (2014). The model assumes that all suppliers in the market have sources to obtain private information on consumer preferences. The accuracy of the information collected may vary though. At one end, they have completely useless information and on the other end, the firm has accurate and perfectly usable information. The results portray that the more accurate the information collected is, higher are the prospects to earn profits at the expense of consumers. But the competition between the firms also get intense in this situation. Due to extreme competition, aggregate consumer surplus increases and the situation becomes favourable to the consumers.

Similar results are shown in the studies of SHY & STENBACKA (2015), COLOMBO (2015), LIU & SERFES (2004). These studies share a common finding that whether consumers get benefited when sellers have accurate knowledge of consumers' likings and willingness to pay mainly depends on the extent of the data induced competition among the sellers. However, there are models which depicts scenarios where information dampens competition among sellers (LIU & SHUAI, 2013).

Many dynamic models are available in the Economic literature which discusses the actions of seller with increasing information about consumers. The model developed by FUDENBERG & TIROLE (2000) presumes that the seller has no knowledge about the buyers in the first phase of sales. The sellers observe and categorise their buyers based on their reactions. The buyers who made the purchase reveal their brand preferences and the buyers who didn't make any purchase were assumed to have very low willingness to pay for any other brands. In the second phase three price options are offered; a specific price for the customers who made the purchase, an attractive price for the customers who didn't make the purchase and another price for consumers who bought from the rivals. The results show that competition gets strong and consumers are benefited rather than in a uniform pricing.

MATSUMURA & MATSUSHIMA (2015) shows a model with two firms (duopoly) where the firms using personalised pricing, take part in actions which bring down the marginal cost. However, when the ex-ante costs difference between the firms are considerably big, the small firm in the model would not use personalised pricing although the fixed cost is close to zero. The rationale behind this move is that the large firm might engage in more cost cutting activities which would ultimately be harmful to the small firm.

However, there are studies which give opposite results. CHEN & ZHANG (2009) show that sellers with more accurate information will be able to rule out the presence of highly price sensitive consumers which help them to have a control on price cutting and handle the competition. This will hurt the consumers in aggregate.

2.5.5. Personalised Pricing – Legal Framework in India and Malaysia

The existing legal framework is reviewed to examine whether there are sufficient laws to safeguard consumer's interest in a personalised pricing environment. The legal frameworks available in India and Malaysia to protect the welfare of consumers are discussed here.

Competition law is an important legal framework set to protect consumer welfare. MOTTA (2004, p.31) specifies competition policy as "the set of policies and laws which ensure that competition in the marketplace is not restricted in a way that is detrimental to society". Some general concerns in this regard are raising prices, reducing output, quality deterioration, depriving consumer choices etc. Although competition laws differ from country to country, certain notions prevail in all competition law frameworks (SINGH, 2011).

The competition Act of 2002, Section 4 states the provisions relating to the Abuse of Dominance. According to the COMPETITION COMMISSION OF INDIA (2002, p.12) "Dominance is not considered bad per se but its abuse is. Abuse is stated to occur when an enterprise or a group of enterprises uses its dominant position in the relevant market in an exclusionary or/ and an exploitative manner." The act gives a list of activities which are considered as abusive by the dominant firms. It prohibits practices which have adverse effects on the healthy competitive practices in India and regulates unfair conduct by the dominant firms. Section 4(2) clauses (a) to (e) of the Act specifies the abusive activities.

1. Imposing unfair or discriminatory conditions directly or indirectly while buying and selling of goods or services
2. Engaging in unfair or discriminatory price practices (including predatory pricing) in purchase or sale of goods or services.
3. Impeding production of goods or provisions of services in the market
4. Restricting technical or scientific advancements relating to goods or services to the disadvantage of consumers.
5. Using dominant stance in one relevant market to enter into, or protect other relevant market.

The Malaysian Parliament passed the Competition Act 2010 in May 2010. The competition legislation in Malaysia was prepared in line with the legislations in Singapore and the UK.

A general overview of the Competition Act with special regard to the protection of the interests of the consumers in the country are as follows.

1. The Act prohibits all forms of anti-competitive agreement which may prevent, restrict or distort competition within the country.
2. Any practices of abuse by enterprises who have dominant positions in any markets in the country

The Anti-Competitive Agreement of COMPETITION COMMISSION ACT (2010) Section 4(1) & 4(2) prohibits

1. The fixing of prices or other trading requirements directly or indirectly.
2. Sharing of non price information like standards and technology which hinder competition
3. An agreement which restricts the potential of enterprises to set new standards or to sell novel products or may obstruct the new entrants to the market.

On 27 July 2018, India issued a draft bill on comprehensive data protection law. The bill to be named as "Personal Data Protection Act, 2018" was brought in a few weeks later following European Union's "General Data Protection Regulation" which took effect on 25 May. Many of the data protection regulations were adopted and modified from the existing EU data processing regulations and US style data privacy laws 2018 (DETERMANN & GUPTA, 2018). Certain provisions like Section 5(1) restricts personal data collection without explicit consent of the individual and also it further mandates that the data shall be processed for specific, clear and lawful purposes only (PDP BILL, 2018). An important regulation concerning companies which are using consumer data is that they are required to keep physical copy of the data collected. This is termed as 'data localisation'. This will require the firms to set up cloud pods operating from India (JHA, 2019). The Act also provides provisions like *"right to be forgotten"* which allows the consumers to back out from disclosing their personal data*, "privacy by design"* which mandates the new tech systems to incorporate privacy protection as a priority along with other services it is supposed to provide etc which are adopted directly from the EU GDPR (DETERMANN & GUPTA, 2018). Although the Act encompasses a wide range of data protection and privacy issues, the high discretionary powers of the state in collecting personal data and the ambiguities in certain terms like "appropriate mechanisms" for obtaining consent from the consumers for collecting personal data must be further worked out and clarified. These ambiguities otherwise in case of an issue in the future will not be in favour of the stakeholders CHAKRABORTY & CHOWDHURY (2019).

The Malaysian Personal Data Protection Act (PDPA) passed on 2nd June 2010 was the first comprehensive data protection regulation passed by the Malaysian Government. The Act was enforced on 15th November 2013 (LAWS OF MALAYSIA, 2016). This act is applicable to any person or entity who uses and processes or has the authority to process 'personal data' for the commercial purposes. Mainly the stakeholders are required to adhere to 7 general data regulation principles. The crux of the principles are as follows. The Act requires that personal data can be collected and processed with the permission of the subject. The users of data must not employ it for any purpose other than the ones stated at the time of data collection. The subjects must be informed of the type of data being collected, its uses, and other choices available to them. Protection of personal data from any kinds of misuse, unauthorised access etc has to be ensured by the data users. The data collected must not be kept after the fulfillment of the original purpose of use. Access must be given to the subjects to correct incomplete or inaccurate data (LAWS OF MALAYSIA, 2016; CHEAH, 2018). The implementation of PDPAs provisions is entrusted to a Personal Data Protection Commissioner who will be advised by a Personal Data Protection Advisory Committee. Fines for violation of the clauses in Personal Data Protection Act range from RM 100,000 to RM 500,000 and if convicted, the offenders may also be subjected to 1-3 years of imprisonment (DLA PIPER, 2019). Malaysia is planning to make amendments to its data protection laws. European Union's General Data Protection Regulation (GDPR) will be taken into consideration to bring in changes in the current business practices by making the personal data regulations more effective (AUSTIN, 2019).

The legal framework currently prevailing in India and Malaysia do not ban the usage of data based algorithmic pricing like personalised pricing unless it breaches the provisions of the legislations discussed above.

Table 5 summarises the previous works in the area of personalised pricing. Most of the previous studies focus on the legal issues, economic efficiency and consumer welfare in a personalised pricing context.

Table 5: Summary of previous literature relevant to personalised pricing

Research Paper	Key Area Addressed	Authors	Important Findings
Personalized pricing in the digital era	Competition, Legal Issues, Economic Efficiency	SCHOFIELD, 2019	The article studies how Competition and Markets Authority (CMA) will address the personalised pricing strategy which may create problems in the competition in digital markets. Study suggests that personalised pricing may cause problems in a market where there is limited competition and lack of awareness among buyers about the strategy.
Competitive Personalized Pricing	Consumer Privacy Concerns, Duopoly Competition	CHEN et al., 2018	The study considers a duopoly model where firms personalise prices for a targeted group of consumers. The findings show that active consumers will benefit at the cost of passive consumers. Active identity management by a group of consumers can undermine the efforts of firms to discriminate prices which will cause harm to the firms.

The Value of Personalized Pricing	Cost of Pricing	ELMACHTOUB et al., 2018	The paper analyses the viability and feasibility of the application of personalised pricing compared to that of other pricing strategies in terms of flexibility and accuracy. The results states that firms will have to make huge investments in the form of technological attributes, data scientists and other infrastructural facilities required to personalise consumer profiles at more refined levels.
Price Differentiation and Dispersion in Retailing	Economic Efficiency, Pricing Concerns, Consumer Attitudes	REINARTZ et al., 2017	The study sheds light on how differentiation of prices may be used to attain consensus between the interests of firms and consumers. The results show that price differentiation can improve welfare when firms frame prices in a customer oriented manner and when fair competitive policies are effective.
Pricing with Cookies: Behavior-Based Price Discrimination and Spatial Competition	Information Asymmetry, Market Equilibrium, Welfare of Firms	CHOE et al., 2017	The paper assumes a dynamic competition model between two firms. Results show that the presence of information asymmetry leads to two asymmetric equilibria and one firm choose price in an aggressive manner. The pricing strategy of firms hurt each other in each phase and both end up in a worse off situation as compared to when they use simple non price disrimination strategies.
Big Data and Personalised Price Discrimination in EU Competition Law	Legal Issues, Economic Efficiency, Consumer Welfare	TOWNLEY et al., 2017	The paper discusses if Algorithmic Consumer Price Discrimination (ACPD) is unlawful under the EU competition law. The findings of the study show that online retailers can have a better understanding of consumer behavior compared to that of the normal retailers, online consumers face a higher risk of exploitation which make them think that they are being treated in an unfair manner. The paper also portray that some consumers may get benefitted due the ACPD driven competition among sellers. The study concludes with ta note that although consumers may be benefitted from this strategy, it will ultimately be advantageous to the powerful online retailers.

Personalized pricing and price fairness	Transperancy in pricing	RICHARDS et al., 2016	The study states that transparency in personalised pricing can make the strategy look mare fair to the consumers. If consumers are also included in the price setting process, inequity aversion can be atleast partially reversed.
A note on fairness and personalised pricing	Price setting, Consumer welfare	VULKAN & SHEM-TOV, 2015	The study is based on an experiment where the researchers allow the consumers to take up the roles of sellers who have access to consumer data including their willingness to pay. The results show that the consumers (as sellers) charged fixed percentage (64%) of the total willingness to pay of each consumer which led to fair but uneven prices.
What do we worry about when we worry about price discrimination ? The law and ethics of using personal information for pricing	Legal Issues, Consumer welfare	MILLER, 2014	The paper analyses different discrimination based pricing practices and its impact on consumers. The findings show that with more and more practicing price discrimination based pricing strategies, the consumers may get benefitted. Some consumers may have to bear high costs and others may get products at very cheap rates. The paper also emphasises that the consumers will have to take up the costs of lost privacy and information security. The consumer outrage resulting from the unfair treatment by sellers will question the long term reign of any exploitative price discrimination practice.

Source: Own construction based on literature

2.6. Theoretical Background

This section gives an overview of the economic theories related to the behaviour of consumers in a personalized pricing environment. Theories from both behavioural economics and microeconomics that are related to the research area are discussed here.

2.6.1. Choice under uncertainty through the lens of behavioural economics

The emergence of behavioural Economics as a new branch of Economics began with the failure of the traditional assumption of rationality as held by many economic theories. Eminent Economists like Becker (1978) supported the rational choice theory in which he states that human beings have steady preferences and always aim at increasing their level of satisfaction. However, KAHNEMAN & TVERSKY (1979) propounded the prospect theory, which is in contrast to the rational choice theory, explains that human decisions may not be always optimal. Daniel

Kahneman and Amos Tversky in their work “Prospect Theory: An analysis of decision under risk” published in 1979 criticised the expected utility theory which was then generally accepted as a normative model of rational choice. They argued that the individual responses would be different if choices are outlined as a gain or loss. The theory outlines that individuals do not like losses which are more than gains that are equivalent. Hence they would try taking risks in order to avoid a perceived loss (KAHNEMAN & TVERSKY, 1979). The concept of `bounded rationality` which appeared in the works of Herbert Simon also implied the significance of psychologically informed economics. This theory primarily explained that our minds should be interpreted by taking into account of the surroundings in which they developed. Due to the limitations in the computational capacities and the information available to us, the decisions taken by our minds can be sub-optimal (SIMON, 1982). Perosnalised pricing in online purhcase situations limit the consumer’s ability to perceive the real situation and to make optimal choices. With the limited information available, the consumers are more likely to make sub optimal choices and might end up paying a higher price for a product than others.

2.6.2. Information Asymmetry and Search Costs in the E-Commerce Markets

As noted by Herbert A Simon, the availability of information is a major factor which influences human decisions. It is in this regard, the works of George Akerlof on ’Information Assymetry’ becomes significant. Information asymmetry occurs when one entity engaged in a transaction has better or superior information than the other. In a usual purchase scenario, the seller knows more than the buyers although the other way around is also possible (AKERLOF, 1978). The presence of information asymmetry may lead the buyers to take sub-optimal decisions which can cause market inefficiencies. The presence of information asymmetry is very high in online markets as compared to that in brick and mortar markets. The advent of modern pricing strategies in which price changes minute by minute based on the most recent information has made it difficult for the online buyers to make an informed decision while buying a product.

However, the advancements in information and technology has benefited the consumers as well. With the different tools available online, buyers are now able to get more information about the goods and trade partners which in turn reduces the information asymmetry between the two and strengthens the market position of buyers. Nevertheless, the buyers are required to spend time, energy and costs in order to acquire information to narrow down the information asymmetry. This is commonly known as search costs. According to the search cost theory, consumers will continue searching for a product which is comparatively better until the marginal costs of searching becomes higher than the marginal benefits (BAKOS, 1997). These costs are commonly categorised into external costs and internal costs. External costs are the monetary loss, time lost in search etc which cannot be controlled by the consumer (SMITH et al., 1999). Internal costs are associated with the theory of bounded rationality which involves the mental capacity and ability of the consumer to carry out the search. This also depends on the knowledge, understanding and talent of the consumers. PEREIRA (2005) inferred that the arrival of internet has reduced the search costs to a some extent especially in the E-Commerce arena as consumers are able to easily compare the prices of products. Again this varies from people to people based on their willingness to engage in searching for better alternatives. Regular consumers are mostly fine with `satisficing` rather than the optimisation of choices. Satisficing is seeking a satisfactory result rather than the best results. In simple words, it is a sequential search process where the consumers automatically stops the search once they reach a threshold at which they seem to be happy with the results (SIMON, 1956).

However, those who are willing to engage in further and more intensive search process are identified as ’strategic consumers’ in this research. They use different tools available online such as online reviews, price tracking extensions, price comparing softwares etc to monitor the prices of products. This will narrow down the information asymmetry which arise due to the application of novel pricing strategies such as personalised pricing and dynamic pricing and aid them to make better informed decisions.

A normal consumer`s inability to choose an alternative seller who offers cheap prices doesn’t mean that the consumer is satisfied or want continue purchasing from the existing seller. This simply implies that the consumer is unaware of the cheaper price choices available due to some reasons. Offering higher prices to these kind of consumers is exploiting their ignorance which is not desirable. A major reason for this might be the inability of the sellers to identify and segment vulnerable groups. However, in cases where consumers are able to acquire at their highest willingness to pay, they tend to compare the prices with their reference points and undermine the efficiency improvement. Hence distributive justice through personalised pricing is rather difficult to obtain as we look through the lens of behavioural economics (TOWNLEY et al., 2017).

2.6.3. Impact of Personalised Pricing on Consumers’ Justice Perceptions

Many concerns regarding consumer’s fairness perceptions and trust in personalised pricing environment are being recently discussed in the academic literature. An important concern is that these issues are difficult to be handled as they do not directly come under the purview of law and policy making. Furthermore, approaching practical cases from the viewpoint of fairness is rather a subjective process.

John Rawls in his celebrated work, 'Justice as Fairness: A Restatement' portrays his perspective on justice in social systems and theories. "Justice is the first virtue of social institutions, as truth is of systems of thought. A theory however elegant and economical must be rejected or revised if it is untrue; likewise, laws and institutions no matter how efficient and well-arranged must be reformed or abolished if they are unjust" (RAWLS, 2001, p.3).

While addressing fairness issues, justice comes as an important reference point (RAWLS, 1991). Aristotle also defined a fundamental principle of justice 2000 years ago that "equals should be treated equally". The highly subjective nature of the issue makes it difficult to say whether it is a justiciable practice to discriminate people based on their personal and observed characteristics. BREST (1985) in this regard points to the fundamental problem that ideal of equality does not provide an axiom of legitimate difference. Furthermore, the perception of fairness and unfairness is a highly personal subject which changes from person to person depending upon personal beliefs, social norms etc. It is also not easy to point out at what point a price becomes unfair to a person (XIA et al., 2004). Nevertheless, studies have pointed out that personalising prices is perceived generally as an unfair practice by consumers (GARBARINO & LEE, 2003; ODLYZKO, 2004; EU CONSUMER PROGRAMME, 2018).

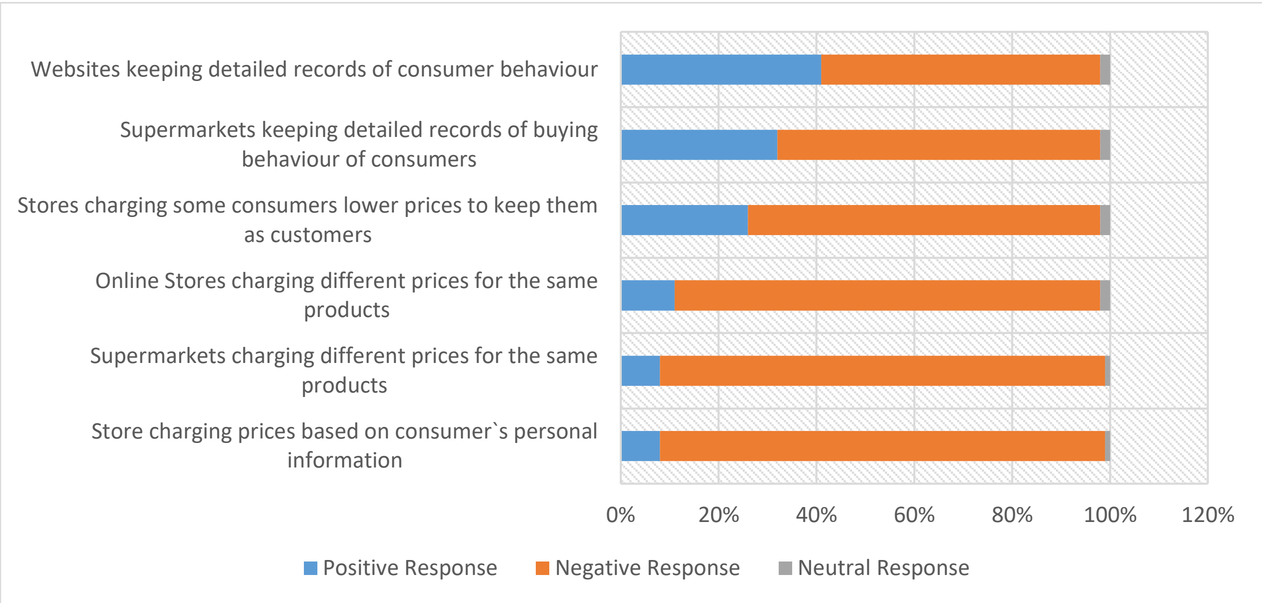


Figure 8. Consumer Attitudes towards personalised pricing in US

Source: TUROW et al (2005), OECD (2018)

Figure 8 shows the results of a survey conducted in US by TUROW et al., (2005) among 1500 households in 2005 also showed an antagonistic response from 91% of the respondents that they do not want stores to personalise prices exclusively for them. Only 11% of the respondents were in favour of online stores charging different prices to different people. However, 50% of the respondents were in favour of stores using their personal information to improve the services offered.

2.7. Fair Price Perceptions

The concept of fair price was always a besetting question to the economists and philosophers for centuries. Dating back to AD 301, the Roman Emperor Diocletian punished the merchants who violated the societal concept of 'just' price (*justum pretium*, the right price) with death sentence (BAKER, 2010). Although the concept of 'just' price evolved over the centuries, still a big question which remains is that 'who gets to decide what is just or fair?'. There is a great debate going on this subject among the philosophers over the past centuries (NEUHAUS, 1992). Friedrich August von Hayek on the question of what constitutes a 'just' price makes the following statement in his book 'The Road to Serfdom' published in 1944. " Have we not all some idea of what is a "just price" or a "fair wage"? Can we not rely on the strong sense of fairness of the people? And even if we do not now agree fully on what is just or fair in a particular case, would popular ideas not soon consolidate into more definite standards if people were given an opportunity to see their ideals realized?… What standards we have are derived from the competitive regime we have known and would necessarily disappear soon after the disappearance of competition. What we mean by a just price, or a fair wage is either the customary price or wage, the return which past experience has made people expect, or the price or wage that would exist if there were no monopolistic exploitation" (HAYEK, 1944, p.140).

XIA et al (2004) explains fair price perception as the consumer's assessment of a product's price to decide whether it is sensible and justifiable. Buyers decide the basket of products to buy which maximises their purchase satisfaction based on the prices and utility derived from different comparable products (MONROE, 1973). As a buyer becomes more price conscious, his/her price perceptions changes and the choice of the buyer becomes largely based on the price rather than other attributes of the products (GABOR & GRANGER, 1961). The concept of fair price is largely a subjective notion which is shaped by individual perceptions and social norms and varies from person to person. With changes in perceptions and norms, the fairness perception also evolve over time. Hence a price perceived as unfair today may be perceived fair as time goes by (MAXWELL, 1995).

Fair price perception of a consumer is formed through several reference points such as competitor prices, past prices, cost of manufacturing etc (MONROE, 1973). Empirical studies have shown that if the consumers are not satisfied with the prices offered by a seller, they may show a negative behaviour such as a tendency to avoid the seller in future purchases, taking revenge in the form of spreading negative news about the seller etc (XIA et al., 2004). By offering a price which a consumer perceives as fair will have a positive effect on his purchase satisfaction and repurchase intentions (OLIVER & SWAN, 1989a, b; CAMPBELL, 1999; CAMPBELL, 2007). The figure 9 shows how fair price perceptions are formed and the probable actions which a consumer might resort to in case the price charged by the seller is perceived as unfair.

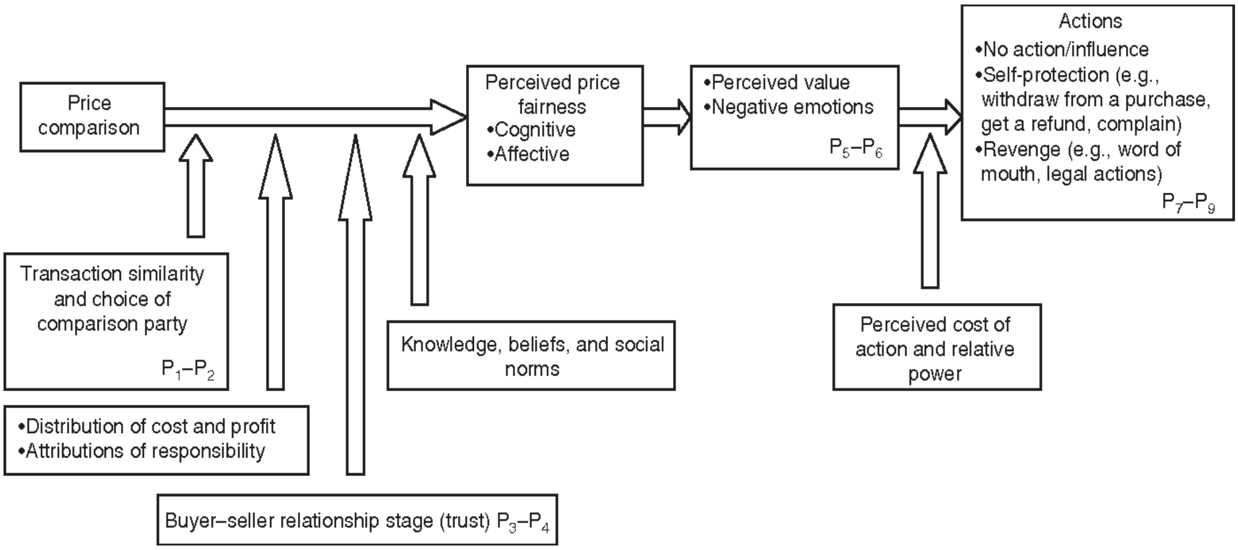


Figure 9. Perceived Price Fairness – Conceptual Framework

Source: XIA et al (2004 p.2)

Some theoretical background can also be attributed to the question 'how fair prices perceptions are formed?'. Based on Helson's Adaptation level theory (HELSON, 1964), many researches have proven that an important determinant of price perception is the price 'last paid'. It serves as the buyer's notion of 'fair price' in relation to the current or actual price level. The consumers consider the last price paid for a particular product as a reference point and the price perceptions are formed based on the current price level (MONROE, 1973). According to the assimilation contrast theory, the noticeable high and low prices offered to a consumer influence his price perceptions. This high and low price along with the reference price may either enhance the perceived value of a product which consumer considers as a bargain or diminish the perceived value which he deems as too expensive.

BOLTON (2003) explains that consumer's understanding of prices, profits and cost of production are some factors which form price perceptions. However, people do not have precise information about these factors. Price differences for them are the fairest when attributed to quality differences. According to AUSTIN et al., (1980) most of the fairness perceptions and judgments of people are based on comparison. People have a tendency to check the activities of other people who belong to same class/group (WOOD & BANDURA, 1989). Thus, they perceive a price as unfair if it is higher than what their reference group actually paid.

One of the factors which moderates the price perceptions of consumer is the customer loyalty. The loyal customers would not see a minor price change as a reason to abstain from future purchases (XIA et al., 2004; MARTIN et al., 2009). However, a price fluctuation of high magnitude will be treated as same by the loyal and non-loyal customers.

2.7.1. Price Sensitivity and Online Consumers

Price sensitivity in simple terms is described an individual consumer's response or reaction towards the changes in price levels. Price sensitivity differs from person to person. Each customer has a range of acceptable prices and the limits of price range is highly personal. Price sensitivity means the extent to which individuals apprehend and react to the variations in prices (MONROE, 1973). The price competition among online sellers is very intense. Each seller offers attractive and customised recommendations to the customers to grab a large portion of the market. There are many works related to different pricing tactics employed in the online markets and buyers' reactions to these tactics (MONROE, 1990; NAGLE & HOLDEN, 1987). However, most these works deal with the response of the market as a whole, price elasticity of demand for products etc. Price sensitivity studies on individual level are scarce due to various factors such as cost, time etc. (GATIGNON, 1984; KANETKAR et al., 1992). The use of big data analytics has empowered the sellers to probe details including price sensitivity on individual levels and customise prices and offers exclusively for them or for groups with similar traits (OECD, 2018).

Based on the price elasticity of products, other commonly used pricing techniques are the penetration price and skimming price strategies. The price of a newly launched product is determined based on several factors like cost of production, competition, customer value etc. The sellers choose penetration pricing strategy to maximize their share of market by charging a very low price. Penetration price is commonly adopted when there is tough competition in the market and when the demand for the product is price elastic (HULTINK et al., 1997; MARN et al., 2004). On the other hand, sellers adopt a skimming price strategy when they face no or little competition and when the demand is price inelastic. Studies have shown that penetration pricing tends to lower the reference price perceived by consumers and this can have a major impact on the sales in the initial stages. However, for the sellers, it is not feasible to keep the consumers reference price perceptions low as in the long run they will have less power in setting prices. On the other hand, skimming price strategies may lead to higher reference price perceptions in the beginning and eventually it falls (LOWE & BARNES, 2012). The perceived reference price point plays a crucial role in the formation of fair price perception of consumers (MONROE, 1973). Therefore, how firms set prices and what pricing strategy they adopt influence consumers' purchase decisions and ultimately the overall sales.

This research intends to examine how changes in fair price perceptions of consumers in a personalised pricing context influence their post purchase reactions.

2.8. Purchase Satisfaction

Customer centricity is the new norm for success in the modern times. Firms which fail to adapt to the changing customer needs have no future. One of the significant factors which determines the repurchase intentions of a consumer is the perceived purchase satisfaction. Purchase satisfaction is described by CRONIN et al (2000) as the degree of positive feelings a consumer gains from a shopping experience and portrays his/her assessment of the overall purchase experience. The purchase satisfaction a consumer gain from a purchase experience in the offline and online environment are different (CAO & LI, 2015; ANSARI et al., 2008). The whole buying experience online is much effortless as compared to that of buying offline. The online consumers are provided with an opportunity to shop at any time of the day, month or year and the products are just a few clicks away from being delivered to the consumer.

With the digital payments method gaining momentum along with the cash on delivery option available to those who do not prefer digital payments, online sellers offer ultimate shopping convenience to the customers. The online purchase process is simply divided into three major stages by KALAKOTA & WHINSTON (1996). Pre-purchase activity is considered as the first stage which consists of surfing the web for products. The second stage involved the selection of the product and payment and the last step where the product is being delivered to the consumer. This looks much simpler as compared to the five, six stages involved in the traditional or offline purchases. The computer plays an intermediary role in the transaction and the web environment impacts the overall customer satisfaction in an online purchase.

The modern world is witnessing a rapid change in the customer behaviour and expectations. With the advent of industry 4.0, they anticipate the sellers to deliver cutting edge features on shopping websites and state of the art services at cheaper prices. The sellers on the other hand, are trying to adapt to these changes as fast as possible to satisfy their customers and to maintain a competitive edge in cut-throat market situation. One of the main hurdles in this regard is that the customer perception which motivates them to engage in a purchase process is not linear. HERNANDEZ et al (2010) states that the perceptions which persuade consumers to shop online for the first time are not identical to those which motivate the repurchase behaviour. The factors change as a consumer's perception evolves from the past experience. Hence it is pivotal to figure out and characterise the online consumer behaviour with precision. It will also help the sellers to identify the needs of the consumers and satisfy them in a better way.

Previous researchers suggest that satisfaction with a purchase improves the confidence of buyers in a seller (BANSAL & TAYLOR, 1999; CRONIN et al., 2000; RUCCI, et al., 1998; SIAU & SHEN, 2003). YI (1990) in his paper named 'Critical review of customer satisfaction' states that satisfaction with a purchase has an impact on the repurchase intentions of consumers as well as their post-purchase reactions and attitudes. An experimental study conducted by OZER & GULTEKIN (2015) takes purchase satisfaction as a mediating variable to assess the distinction between the pre and post purchase moods of consumers. Their results show that post-purchase attitude and satisfaction of customers are positively influenced by the pre-purchase mood of the consumers.

2.9. Customer Loyalty

The literature portrays customer loyalty as a multi-dimensional concept which involves both attitudinal and behavioural elements. The term customer loyalty is often defined in two broad ways. In the first one, customer loyalty is described as an attitude where various feelings make an affinity or attachment towards a product, service or an organisation. The degree of these feelings show the extent to which a customer is loyal to the aforementioned (JACOBY & KYNER, 1973). The second set of definitions is more of behavioural where loyalty implies repurchase intentions, improved relationship with the seller and recommending the product, seller, service or organisation to others etc. (YI, 1990).

There are plenty of researches asserting the relationship between customer loyalty and purchase satisfaction (PATTERSON & SPRENG, 1997; COLGATE & STEWART, 1998; HOCUTT, 1998). These studies show that consumers are satisfied when the sellers are able to cater to their level of expectations which in turn makes them loyal to the sellers. At the same time, when consumers are not satisfied, their loyalty towards the seller falls (OLIVIA et al., 1992). Making the customers happy and satisfied will help in building a loyal customer base (BOLTON, 1998; YANG & PETERSON, 2004).

HALLOWELL (1996) through an empirical research showed that the purchase satisfaction - loyalty relationship is two way rather than one way.

Customer Satisfaction ⟷ **Customer Loyalty** ⟷ **Profitability**

Firms do take measures to retain a loyal customer base as it is a major determinant of the repurchase intentions of consumers which in turn is critical in increasing the profitability. (HALLOWELL, 1996; OLIVER, 1997; SILVESTRO & CROSS, 2000). Studies show that the expectations of the loyal customers would be higher than that of the non-loyal customers (HUPPERTZ et al., 1978; HEILMAN et al., 2000). Fairness perceptions of consumers is considered as an antecedent to trust and loyalty (MORGAN & HUNT, 1994).

Based on the previous literature, this research investigates how loyalty towards the seller influences a consumers' post purchase reactions. Along with this, the role of customer loyalty in moderating the relationship between fair price perceptions and purchase satisfaction is also examined. Loyal customers are generally insensitive to price changes to a great extent while non-loyal customers show high sensitivity to price fluctuations. Nevertheless, this largely depends on the degree of price volatility (MARTIN et al., 2009). MARTIN et al (2009) states that the various reasons which motivate the sellers to increase prices have a significant effect on the consumer's fairness perceptions. Furthermore, a high price increase may affect the fairness perceptions as well as their overall purchase satisfaction.

2.10. Personalised Pricing and Privacy Concerns

The business strategies employed in E-Commerce segment have seen many changes over the past few decades. With the advancements in IoT and data analytics, even the minute digital footprints left by individuals on the web space are helping firms know more about their existing and prospective customers (ASHWORTH & FREE, 2006). The pricing techniques such as dynamic pricing and personalised pricing in which the sellers use the consumer's private information for product recommendations and tailoring prices are mostly data driven. The consumers are coaxed to share data in many ways by the sellers through accepting cookies, creating accounts etc. (MAURY & KLEINER, 2002). The generation of data, collection, analysis and its commercial use has become inevitable for the growth of digital economy. These data are used by firms and governmental agencies to analyse human behaviour, interests, desires etc to frame better strategies and policies which ultimately promote growth and well-being of people. However, with the proliferation in the collection and use of data, people are increasingly becoming aware of their privacy and what they share on online public spaces.

The concept of information privacy was defined long ago by WESTIN (1967) as the capacity of an individual to manage the conditions under which his/her personal data is gathered and utilized. According to CHO et al (2010) and ZHOU & LI (2014), privacy concerns means an individual's understanding of the risks and the probable adverse consequences resulting from sharing personal information. Studies have shown that individuals who are more concerned about privacy are engaged in privacy-protective behaviours such as deleting browser cookies, untagging photos, using VPNs etc (DIENLIN & TREPTE, 2015). However, researches also show that consumers are willing to swap their personal information for smaller rewards (KOKOLAKIS, 2017, ACQUISTI & GROSS, 2006). This particular behaviour of individuals is termed by researchers as "Privacy Paradox" (BROWN, 2004; NORBERG et al., 2007) which shows the contradiction between the attitude of people towards the disclosure of personal information and their real conduct (KOKOLAKIS, 2017). This term stems from the idea that despite being highly concerned about privacy, individuals are willing to exchange their personal information for perceived benefits.

The study by CARRASCAL et al (2013) portrays a situation where the respondents traded their browsing history for just about 7 Euros. This paradoxical behaviour has got profound implications in the E-Tail segment. The consumers might be ready to share their personal information based on their loyalty and trust on the seller. On the other side, studies and surveys show that consumers exhibit many concerns regarding the gathering and usage of their private personal information (TRUSTe, 2014; PEW RESEARCH CENTER, 2014). The consumers are really worried about the transparency issues in the collection and usage of their personal data by the companies and have concerns regarding the potential advantages and disadvantages of the same (PALMER, 2005). There are also studies which show that privacy concerns and privacy-management behaviour are interrelated (WU et al., 2012). The online buyers having privacy concerns have been found engaged in activities such as removing personal information or supplying false information (SON & KIM, 2008), deleting cookies after browsing and not disclosing personal details (SPIEKERMANN et al., 2010).

An online consumer who is highly privacy conscious may have a tendency to believe that not every condition is satisfied while making an online purchase compared to an offline purchase situation. Thus, privacy concerns have an adverse impact on the consumer's perceived control over E-Commerce use (PAVLOU & FYGENSON, 2006). The studies of FORTES & RITA (2016), EASTLICK et al (2006), VAN SLYKE et al (2006), and VENKATESH et al (2002) infer that concerns about privacy may have undesirable impacts on the attributes like trust on the seller, perceived usefulness of Electronic Commerce, perceived risk of using E-Commerce etc. GAO et al (2015) using a SEM analysis, found out that the privacy and security concerns of individuals can affect the overall satisfaction from an online purchase and may have an adverse impact on their repurchase intentions.

Based on the findings from the previous literature and the results of the discussion with the experts in the field, the relationship between privacy concerns and purchase satisfaction, repurchase intentions, reprisal intentions and strategic purchase intentions in a personalised pricing scenario are examined in this research. A new construct comprising information particularly relevant to a personalised pricing context was developed and validated in a previous study and is used in this research (VICTOR et al., 2018a).

2.11. Revenge Intentions

BECHWATI & MORRIN (2007, p.144) define the consumer intentions for revenge *as* "the retaliatory feelings that consumers feel towards a firm, such as the desire to exert some harm on the firm, typically following an extremely negative purchase experience." Previous studies have shown that the consumers may seek retaliatory measures after having negative experiences with a seller (GREGORIE et al., 2010; DE CAMPOS RIBEIRO et al., 2018; WEN HAI et al., 2018). There are several forms through which the consumers may express their revenge intentions against a seller or a brand. Broadly, they can be divided as direct revenge where the consumers take revenge at the shops or at the point of sale. The second type is indirect and more common where the revenge happens mostly outside the premises of the company, e.g. on internet. The direct revenge intentions can be controlled by recruiting more personnel to protect the properties and investing in other security measures. But the indirect revenge intentions are hard to be controlled and may make serious harm to the company's reputation through the uncontrolled spread of the negative news on internet (KRISHNAMURTHY & KUCUK, 2009).

According to NYER (1999), the consumers who are dissatisfied have a higher tendency to complain and this behaviour may be viewed as a channel to express their frustration, exploring options for redressal and seeking revenge against the seller. The consumers have the opinion that the sellers deserve punishments for the harm they cause to the consumers in form of high price fluctuations, providing unsatisfactory services etc. (GREGORIE et al., 2010). In the online context, the revenge intentions involve spreading negative word of mouth online through social media, product review sections etc. The online platforms offer more anonymity, convenience and reach. The negative product reviews mostly involve warning other customers about the experience a consumer had had with a seller which may motivate prospective buyers to abstain from buying the product. The study by ZHANG et al (2018) shows that these revenge intentions contribute to the online co-destruction of value of the company.

In this research, how do price fluctuations of high magnitude, privacy concerns of the consumers, deteriorating customer loyalty and purchase satisfaction in a personalised pricing context provoke revenge intentions in online consumers is explored. The construct revenge intentions was taken from the studies of ZEITHAML et al (1996) and DAI (2010) and was tested in a previous work published by the researcher (VICTOR et al., 2018a) for ensuring validity and consistency with the scale used for the model.

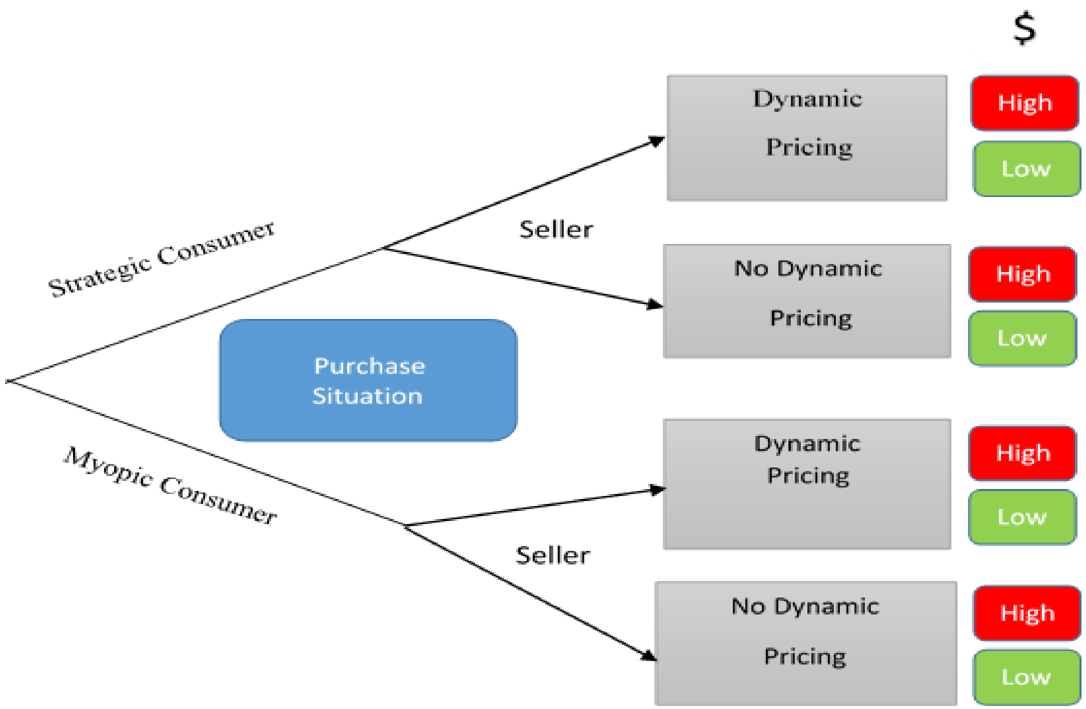
2.12. Strategic Purchase Intentions

The outspread of Information and Communication Technology (ICT) has been advantageous to the consumers as well. Nowadays consumers are well aware of the different pricing techniques employed by the firms. The term "Strategic Consumer" is often used in the literature these days to outline a rational forward-looking consumer who is capable of making inter temporal purchase decisions to maximise own utility (PAPANASTASIOU & SAVVA, 2016). In simple words, strategic consumers make the decisions to buy a product or not based on all the information available and might delay the purchase if it doesn't maximise their utility. Revenue optimisation in a market with a high number of strategic consumers can be a big problem for the firms and have been acknowledged by many previous studies (AVIV & PAZGAL, 2008; BESBES & LOBEL, 2015; LIU & VAN RYZIN, 2008) Although the employment of sophisticated pricing techniques like dynamic pricing strategy was expected to neutralize the effect of the consumers making strategic decisions, with consumers having access to the price history of products sold online, they tend to make even better purchase decisions which hurt the profitability of sellers.

The existence of strategic consumers in the market can cause many problems to the operational decisions of firms. The crucial decisions such as product launches and their timings, the amount of inventories and stocks to be kept etc may get adversely affected if the consumers exhibit a strategic purchase behaviour (AVIV & PAZGAL, 2008; LIU & VAN RYZIN, 2008). Therefore it is pivotal that the firms have an understanding of the reasons why consumers engage in strategic purchases where they track prices and wait for price markdowns. This can help firms make better business tactics to reinforce their competitive edge and retain a loyal customer base. HAWTHORNE & STANLEY (2008) stated how knowledge and action are interrelated.

The relationship between knowledge and action is supported by reasoning and therefore the concept of knowledge is twined with the logical reasoning behind an action. This is further supported by BANDURA (1980), asserting that the response patterns of individuals are formed on the basis of the knowledge and awareness of a person. In an online purchase context, it is highly likely that the consumers who are aware of the pricing strategy will take advantage of it. An example which can be given in this regard is the consumers waiting for the price markdowns to book flight tickets. This happens quite a lot in the airline industry (KANNAN, 2001). This behaviour could be seen in the online marketplace in the near future as consumers are slowly getting acquainted with the pricing strategies of the E-Commerce sellers. This has been made possible with the advent of web-based extensions and applications which allow consumers to monitor and track the current and past variations in prices (VICTOR et al., 2018b).

There are studies showing that the sellers may engage in a personalised dynamic pricing rather than employing dynamic pricing alone. With the widespread usage of IoT and big data analytics, it is easier for the sellers to estimate the inventories as well as customer traits and combine them to frame a pricing strategy which is more effective and profitable. (KRAMER et al., 2018; AYDIN & ZIYA, 2009). This means that the sellers may set prices as bait to make the consumers buy products. They may try different combinations of prices until the consumer buys the product. This will make the prices fluctuate but within a particular limit. Although these are all hypothetical statements as and we have limited real world evidences, we cannot reject the possibilities for these improvised forms of pricing strategies becoming widespread in the near future keeping the rapid progress of IoT and big data technologies in mind. How dynamic pricing may impact the revenue of sellers and producers in the presence of myopic and strategic consumers is illustrated using a game tree in Figure 10.



BUYER	SELLER	PRODUCER
No Action	No Gain	Lose
Gain	Small Gain	Gain
No Action	No Gain	Lose
Gain	Small Gain	Gain
Lose	Large Gain	Gain
Gain	Small Gain	Gain
Lose	Large Gain	Gain
Gain	Small Gain	Gain

Figure 10. Dynamic pricing and returns to the buyer, seller and producer

Source: Author's Own Construction

The application of the illustration above may be extended to the case of personalised dynamic pricing as well.

In the context of platform economies, clear distinction is made between a seller and a producer. Producer is the one who manufactures a product or render a service and the seller is the entity that connects producers with the buyers. Best examples for sellers in E-Commerce are Amazon, Alibaba, eBay etc.

The game tree given in figure 10 assumes that a strategic consumer who tracks prices, will not purchase (no action) from a Seller if the price is high (higher than perceived value), be it in dynamic pricing or non dynamic pricing situations. Producer's goal is to push the product through seller. Dynamic pricing does not directly benefit producer, because each unit sold to buyer through a seller earns the same margin for producer. Dynamic pricing typically benefits seller, not producer. Hence producer only wants products to be sold (out of shelve). The fringe benefits earned from employing discriminatory pricing strategies such as dynamic pricing and personalised pricing accrue to the sellers rather than the producers. The strategic consumers win in a price discriminatory situation as they track prices and wait for the price markdown to make the purchase. However, myopic consumers fail to track the changes in prices and may end up paying exorbitant prices. Hence, the strategic consumers gain with discriminatory pricing and myopic consumers loses.

This construct is added to the model to capture the behavioural intentions of the online consumers to exhibit a strategic purchase behaviour which could act as a protection against the discriminatory pricing strategies such as dynamic and personalised pricing.

In summary, there are many factors influencing the online consumers in making the decision to make a purchase or not. It would be theoretically far from possible to frame a compendious framework encompassing the impact of all the aforementioned factors. Hence, this research particularly examines the impact of personally customised differential price changes of high magnitude on consumer's fair price perceptions, perceived privacy risks and customer satisfaction and how this impacts the post purchase reactions among existing and prospective consumers.

3. MATERIALS AND METHODS

This chapter gives a detailed account of the materials and methods used to conduct this research. The chapter begins with the description of the questionnaire development, sampling method and size followed by a table consisting of the measurement items used in the questionnaire and a description of the research tool used.

Figure 11 shows the procedure used in the questionnaire design, development, and analysis.

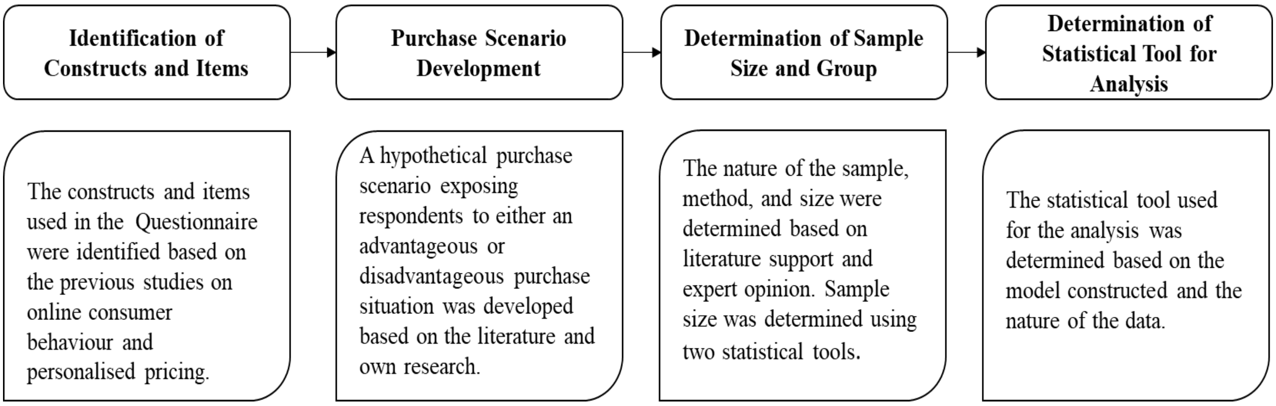


Figure 11. Procedure followed in the development of questionnaire and analysis

Source: Author's own construction

3.1. Questionnaire Design and Development

The final draft of the questionnaire consisted of four sections. The first section comprised a 5 point Likert scale based questions eliciting consumer loyalty towards the E-Commerce seller given in the questionnaire. The second section involved a hypothetical purchase scenario and the third with a 5 point Likert scale questions which were to be answered by the respondents based on the scenario they read. The fourth section consisted of a set of questions asking the basic demographic details of the respondents.

The key part of the questionnaire is the purchase scenario given in the second section. A hypothetical purchase scenario was formulated based on the studies of MARTINS (1995) and DAI (2010) which exposed the respondent to either a positive or negative purchase situation where they experience a major price difference compared to the prices others paid for the same product which they had just bought. MARTINS (1995) states that the buyers tend to compare the price they paid for a product with similar income groups or peer groups which they consider as reference points and any discrepancies found in the prices will have an adverse impact on the fair price perceptions of the former. Based on this finding, the purchase scenarios formulated consisted of a situation in which the consumers were exposed to major price differences and were then asked to rate their reactions on a 5 point Likert scale based questions. Amazon.in was chosen as the E-Commerce seller for the questionnaires distributed in India and Lazada.com.my was the seller for those questionnaires distributed in Malaysia.

The basic framework for the scenario was adopted from DAI (2010) which was modified to fit the needs of this study. The key idea of personalised pricing was briefly explained in the purchase scenario to help the respondents acquaint with the basic notion of personalised pricing. Familiarisation of the concept was considered important as it was assumed that majority of the respondents were not aware of this pricing strategy due to its novelty. Based on the definition given by OECD (2018) on personalised pricing, the privacy concerns which may arise while employing this pricing strategy were also subtly mentioned. The purchase scenario developed was basically modified into two situations. The first situation comprised of a positive hypothetical purchase context where the respondents have monetary benefits from the price fluctuations. In the second purchase situation, the respondents were put in a disadvantageous position in which they experience monetary lose due to price fluctuations. The negative hypothetical purchase scenario used in the Indian negative questionnaire is given as a sample in Figure 12.

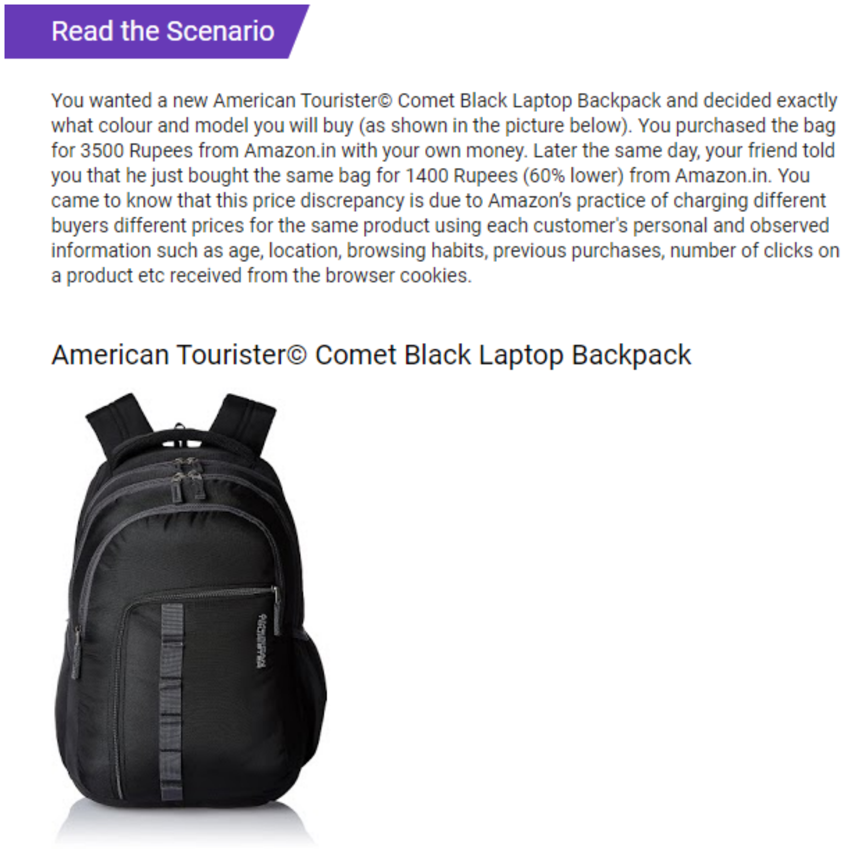
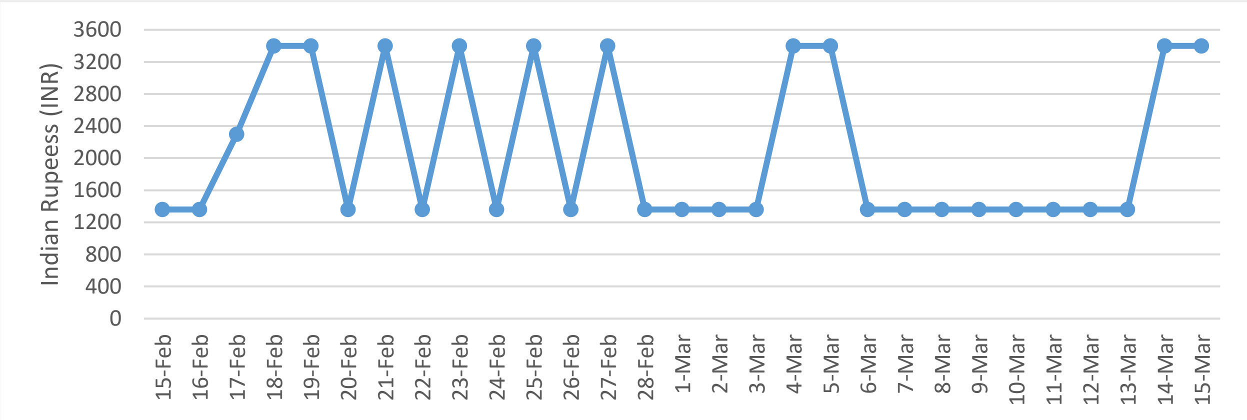


Figure 12. Hypothetical Purchase Scenario

Source: Own construction based on DAI (2010)

For the Malaysian questionnaires, Lazada.com.my, one of the leading E-Commerce retailers was chosen as the seller based on local interests and the currency used in the scenario was the Malaysian Ringgit (RM). For the Indian purchase scenarios, Amazon.in was chosen as the online seller based on the interests of the local respondents and the currency used in the scenario was the Indian Rupees (INR). The general questionnaire along with all four purchase scenarios used in the positive and negative questionnaires are attached as Appendix 14,15 16 and 17.

The product used in the purchase scenario and the price differences given in the study were determined based on the actual observation made by the researcher for a previous study related to this field. The real price variation and the descriptive statistics of the price variations of the product used in amazon.in for one month from 15th February 2017 to 15th March 2017 was observed and the details are given in Figure 13 and Table 6.



Note: 1 Rupees (INR) = 0.014 USD

Figure 13. Real price variation of the product used in the hypothetical Purchase Scenarios

Source: Adapted from VICTOR & BHASKAR (2017)

The range of price fluctuation is between Rs.1360 to Rs. 3400 which is around 60% price difference. The findings of the study indicated that the consumers are unhappy with the magnitude of price difference (VICTOR & BHASKAR, 2017).

Table 6. Price Variation of the product – Descriptive Statistics

Range of Variation	Mean	Coefficient of Variation	Standard Deviation
Rs. 1360 – Rs. 3400	2096	43.39%	978.261

Note: 1 Rs (INR) = 0.014 USD

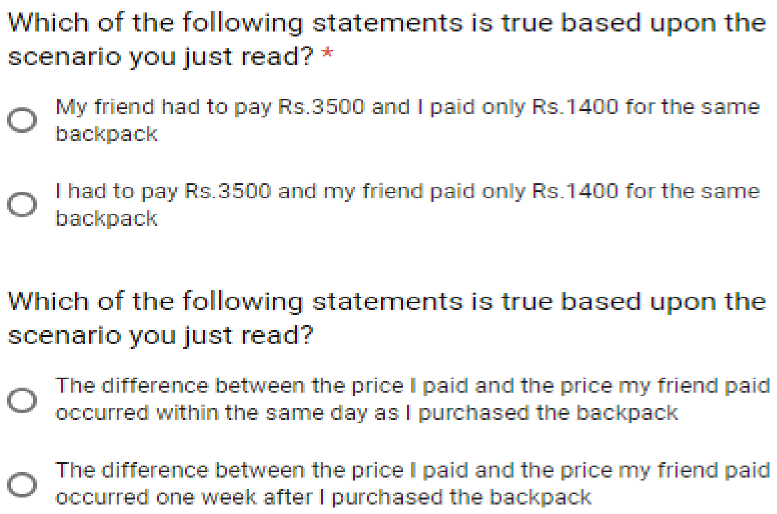
Source: (VICTOR & BHASKAR, 2017)

Two questionnaires comprising either positive or negative purchase scenario were prepared and distributed randomly to two different set of sample population in India and Malaysia. Fair price perceptions, privacy concerns, and customer loyalty were taken as the independent variables and repurchase intentions, strategic purchase intentions and reprisal intentions constituted the dependent variables. Purchase satisfaction was taken as the mediator variable in the relationship between the independent and dependent variables.

The items measuring customer loyalty were given in the beginning of the questionnaire followed by the purchase scenario. This was done intentionally to obtain the real and unbiased attitude of consumers towards the seller which were not influenced by the negative or positive purchase scenario given in the questionnaire.

3.1.1. Manipulation Check

Two manipulation check items were included at the end of each purchase scenario to ensure that the respondents read through the scenarios thoroughly. These items were placed to get a preliminary evaluation of the respondents' understanding of the purchase scenarios. Manipulation checks were one of the criteria for finalising the data used for analysis. The manipulation check items used for the Indian negative hypothetical purchase scenario is given in figure 14.


Which of the following statements is true based upon the scenario you just read? *

- My friend had to pay Rs.3500 and I paid only Rs.1400 for the same backpack
- I had to pay Rs.3500 and my friend paid only Rs.1400 for the same backpack

Which of the following statements is true based upon the scenario you just read?

- The difference between the price I paid and the price my friend paid occurred within the same day as I purchased the backpack
- The difference between the price I paid and the price my friend paid occurred one week after I purchased the backpack

Figure 14. Manipulation Check Items

Source: Author's Own Construction

3.1.2. Measurement Items

The scales used in the conceptual model include both which were adopted from relevant literature and the ones which were developed by the researcher. The constructs developed by the researcher were tested in previously published research papers in the study area (VICTOR et al., 2018a; VICTOR et al., 2019b). The scales and respective items used in this research are given below in Table 7. As mentioned in the questionnaire development section, Amazon.in was given as the online seller in the questionnaires distributed in India and Lazada.com.my for the questionnaires distributed in Malaysia.

Table 7. Items Used in the Questionnaire

Constructs		Items	Sources
Customer Loyalty	CL1	I prefer buying products from Amazon.in. (Lazada.com.my)	MCMULLAN & GILMORE (2003)
	CL2	Amazon.in (Lazada.com.my) is a retailer that interests me.	
	CL3	I would recommend Amazon.com (Lazada.com.my) to others	
	CL4	I feel it is safer to buy products from Amazon.in (Lazada.com.my).	
	CL5	I frequently purchase products from Amazon.in (Lazada.com.my).	
	CL6	I would encourage others to use Amazon.in (Lazada.com.my).	
	CL7	I would consider Amazon.in (Lazada.com.my) as first choice when buying products online	
Fair Price Perception	FPP1	The price I paid was fair	DARKE & DAHL (2003)
	FPP2	The price I paid was justified.	
	FPP3	The price I paid was honest.	
	FPP4	The price I paid was equitable	
	FPP5	The price I paid was a rip off	
Purchase Satisfaction	PS1	I am satisfied with the price I paid	MARTIN-CONSUEGRA et al. (2007); WANG & HEAD (2007); RAI et al (2002); SPRENG et al (1996)
	PS2	My choice was wise.	
	PS3	I am satisfied with my purchase decision.	
	PS4	I think I selected the right retailer.	
	PS5	I am happy with my purchase decision.	
	PS6	I feel badly about my purchase decision.	
	PS7	I am satisfied with the purchasing process through Amazon.in.	
	PS8	Overall, I am satisfied with the purchase experience.	
	PS9	Overall, I am pleased with my purchase experience.	
Privacy Concerns	PC1	I am not interested in sharing my personal information to get personalised prices	VICTOR et al (2018a)
	PC2	I am not interested in sharing my personal information to get personalised product recommendations	
	PC3	I fear that my personal information used for online purchases may attract the attention of cyber criminals	
	PC4	I would be happy if there is an option to not share my personal information with the seller	
	PC5	I fear that my personal information about payment method may be stolen	

Revenge Intentions	RI1	I will say negative things about Amazon.in's (Lazada.com.my) pricing policy to other people.	ZEITHAML et al (1996); DAI, 2010
	RI2	I will complain to other customers about Amazon.in's (Lazada.com.my) pricing policy.	
	RI3	I will complain to governmental agencies about Amazon.in's (Lazada.com.my) pricing policy.	
	RI4	I will complain about Amazon.in's (Lazada.com.my) pricing policy through online social networking channels	
	RI5	I will switch to Amazon.in's (Lazada.com.my) competitor after my experience with their pricing policy.	
	RI6	I will stop buying products from Amazon.in (Lazada.com.my).	
Repurchase Intentions	RP1	I will continue to buy products from Amazon.in (Lazada.com.my) regardless of their pricing policy.	ZEITHAML et al (1996)
	RP2	I will continue to buy products from Amazon.in (Lazada.com.my) if I need the product in the future.	
	RP3	I will buy more products from Amazon.in (Lazada.com.my) in the next few years regardless of their pricing policy.	
	RP4	I will continue to buy products from Amazon.in (Lazada.com.my) even if the prices are somewhat higher than those of Amazon.in's (Lazada.com.my) competitors.	
Strategic Purchase Intentions	SPI1	Having witnessed my friend's situation, I will track the price of the products before future purchases to avoid paying higher prices	VICTOR et al (2018a)
	SPI2	I will consider the changing prices as an opportunity to buy products at lower prices	
	SPI3	I will use some software applications or browser extensions to track the changes in the price of the product	
	SPI4	I will motivate my friends & family to track the prices to avoid paying higher prices	

Source: Author's own construction based on previous studies in the area.

3.2. Sampling Method, Size and Distribution of Questionnaire

The questionnaires were distributed mainly among the internet savvy millennial population in India and Malaysia. Majority of the respondents in both countries were in the age group of 20 – 40. The millennials were targeted as the primary group of respondents on the basis of the Malaysian E-commerce consumers survey, 2018 and the Report of the Indian Brand Equity Foundation, 2017. According to the Malaysian E-Commerce Report, young consumers aged between 20 – 40 made more online purchases than other age groups (MCMC, 2018). In the case of Indian consumers, around 75% of the internet users in the country belong to the age group of 15 – 34 (IBEF, 2017).

A judgemental sampling technique was employed to determine the sample population as it was presumed that the respondents had got prior online shopping experience. This precondition of previous online shopping experience was presumed considering the difficulties to familiarise the respondents with the basic concepts of online shopping and to avoid anomalies caused by the ignorance of respondents in the area of online shopping. This was one of the reasons for adopting the purposive sampling technique. Both google forms and paper questionnaires were used to collect the data. The questionnaires were mainly distributed among the people who frequently purchased online in the Indian states of Kerala and Tamil Nadu and the Malaysian states of Malacca and Cyberjaya. As the target population identified was millenials based on the IBEF (2017) and MCMC (2018) report, the majority of the questionnaires were distributed among the internet savvy university students in the above mentioned states in both countries. The feasibility and reliability of using university students as samples in researches especially in the areas of web usability and online shopping has been demonstrated by many studies (GEFEN, 2002; KUO et al., 2009; ZHANG et al., 2011; NATHAN, 2015). With personalised pricing tactic expected to be adopted by online sellers in the near future, the attitude and reactions of the student community who are the potential customers of E-Commerce market matters a lot. Nonetheless, questionnaire distribution was not limited to the student community, the online consumers belonging to other age groups visiting Lulu mall and Alleppey Beach in the state of Kerala, domestic tourists in Malacca city in Malaysia were also approached with paper questionnaires.

One of the shortcomings with regard to data collection which could be addressed in future studies is the non representative nature of the sample population. The responses were mainly collected from two states in both countries which may not fully represent the general characteristics of the entire population under study. Furthermore, a limitation regarding the questionnaire is the high probability for the presence of common method bias in the case of two constructs namely ‘revenge intentions’ and ‘repurchase intentions’. These limitations should be taken into consideration in future researches to be conducted in this area of study.

HAIR et al (2011) gives the criteria to determine the sample size for PLS SEM. According to them, the size of minimum sample should be equal to or larger than the following;

1. Ten times the largest number of formative items used to estimate a construct or
2. Ten times the largest number of structural paths pointed at a certain latent construct used in the structural model.

This study uses only constructs which are reflective in nature. So the first rule is not applicable here. The sample size estimated for the study was 720; 180 for each questionnaire which satisfies the sample adequacy requirements for PLS SEM set by the “10 times rule”. (HAIR et al., 2011) The highest number of links in the conceptual model framed in this study is 8. So, the sample size chosen is more than adequate for testing the model. The samples obtained for each purchase scenario is given in Table 8.

Table 8. Sample Size Obtained for the Negative and Positive Purchase Scenarios for Both Countries

Indian Positive Purchase Scenario	Indian Negative Purchase Scenario	Malaysian Positive Purchase Scenario	Malaysian Negative Purchase Scenario
192	184	194	181

Source: Author's own work

For each scenario,180 responses were included in the analysis after ensuring the absence of extreme outliers in the data. Furthermore, the minimum sample size for the study was confirmed using WarpPLS 6.0. The software takes into account of the minimum significant path value and allows the user to set the required power level and significance level before calculating the required sample size. The protocols used to analyse the minimum sample size was determined based on the studies of KOCK & HADAYA (2018) which suggests the use of either an Inverse Square Root method or Gamma-Exponential method. The level of significance was set as 0.05 and the power level required was given as 0.800. Based on the analysis of the first set of data collected, the minimum absolute significant path coefficient in the model was automatically set by the software as 0.197.

The results based on the criteria above is given in Figure 15. The Inverse square Root method suggests the use of a minimum of 159-160 samples to attain 0.80 power level. On the other hand, Gamma Exponential method suggests using a minimum sample size of 145-146 to attain the required power level of 0.80.

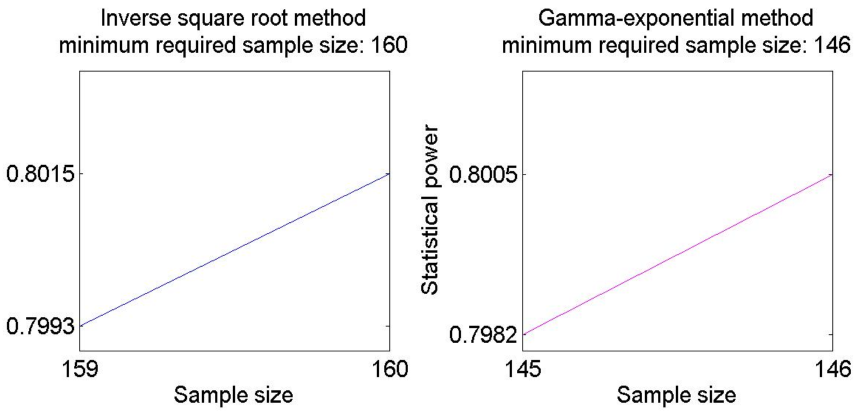


Figure 15. Sample Size determination based on Inverse Square Root method and Gamma-Exponential method

Source: Author's own work using WarpPLS

The sample size of 180 used to analyse each purchase scenario is higher than the sample size requirements stipulated by the 10 times rule method, Inverse Square method and Gamma-Exponential method.

3.3. Data Analysis

Both descriptive and inferential statistical methods were used to analyse the primary data collected. SmartPLS 3.0 was used to do partial least square based structural equation modeling to test the hypotheses formulated and answer the research questions. Exploratory Factor Analysis (EFA) and other descriptive statistics were performed using R Studio. The ANOVA and Wilcoxon Rank Sum test (Mann Whitney Test) were performed using STATA 13.

3.3.1. Partial Least Square Based Structural Equation Modeling (PLS SEM)

Partial Least Squares based Structural Equation Modelling (PLS SEM) is used to analyse the proposed research framework. Structural Equation Modelling is a multivariate statistical procedure used to simultaneously examine relationships among variables in the cases where the variables under study are complex, hypothetical or are difficult to observe directly (WILLIAMS, VANDENBERG, & EDWARDS, 2009). SEM is a very popular statistical technique used in behavioural sciences. In the recent times, it has been widely used in social sciences and business studies too. SEM comes as a combination of factor analysis, regression and path analysis.

SEM is usually distinguished into two. Co-Variance based SEM (CB SEM) and Variance based SEM (PLS SEM). Both are two different approaches to the same problem. CB-SEM uses the Maximum Likelihood (ML) method as the estimation procedure and aim at "minimising the difference between the observed and estimated covariance matrix" (HAIR et al., 2011a, p.139). On the other hand, PLS-SEM, employs the Ordinary Least Squares (OLS) method which is commonly used in regression procedures to explain the variance of the latent constructs by "minimising the error terms and maximising the R2 values of the independent and dependent variables that are (target) endogenous constructs'' (HAIR et al., 2014, p.14).

PLS SEM has relatively less assumptions and restrictions compared to that of CB SEM. When it comes to the size of data, CB-SEM demands bigger sample sizes than PLS-SEM for robust output and normal distribution of the data is very important as CB-SEM employs the maximum likelihood approach. On the other hand, PLS SEM gives robust output even with smaller sample sizes and does not require the normality of data which is very hard to adhere to in the cases of behavioural researches. Furthermore, CB SEM requires apriori theoretical background to back the model formulated. If the model framed lacks theoretical backing and is at the infant stage of testing and theory development, CB-SEM would not be the right choice (ASTRACHAN et al., 2014).

This research is one of the pioneering works analysing the impact of personalised pricing on consumer behaviour. The work aims at predicting the endogenous variables rather than confirming an existing theory. Furthermore, the sample size chosen for each purchase scenario is 180. PLS SEM gives robust results when the sample size is small. Hence, PLS SEM is considered as the appropriate method to test the research model framed.

3.3.2. Formative and Reflective Measurements

Structural Equation Modeling (SEM) requires the appropriate specification of the measurement models. Misspecification errors may occur if the researcher is paying little attention to the directional relationship between the constructs and measures (CHIN, 1998). Measures are also known as scale items, items which can be categorised as ones that are influenced by the latent variables (reflective) or those influence the latent variables (formative) (FREEZE & RASCHKE, 2007).

There are fundamental differences between the formative and reflective measurement constructs.

In the case of formative constructs, the items form the construct. It means the variations in the items measured is reflected on the construct, nevertheless, the variation in the constructs do not cause any change in the items. Formative measurements are termed as ‘causal’ indicators and is popularly known as combination variable or composite variable (MACCALLUM et al., 1993). A common example cited as a reference for formative constructs is socio economic Status which is measured by education, income, occupational status, prestige etc. A positive change in income would increase the socio-economic status even without any changes in the other items. Therefore, a simultaneous change in all indicators is not required in the case of a formative constructs (BOLLEN & LENNOX, 1991). As shown in figure 16, the arrows of the items are pointing towards the construct. The causal effect is flowing from the indicators or items as measured by x1, x2, x3, x4 to the composite variable or the construct. This indicates that the construct is derived by the measurement items.

Precaution should be taken while dropping an item form a formative construct as it is similar to erasing a part of the construct and is not recommended once an item is verified as a part of the construct (BOLLEN & LENNOX, 1991).

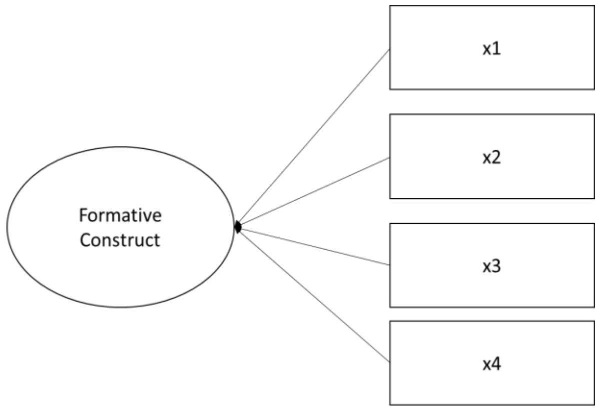


Figure 16. Formative Construct – Graphical Representation

Source: Author's own construction based on Freeze & Raschke (2007)

Reflective constructs in simple words can be explained as items that are reflected because of the construct. The changes in the indicators of a reflective construct are caused by the variations in the construct itself. Unlike formative constructs, variations in the items measured does not cause any variations in construct (FREEZE & RASCHKE, 2007).

An example of a reflective construct is 'perceived ease of use'. It could be defined as the extent to which a person thinks that a particular system would require less efforts. This construct is measured by six reflective items or indicators. The items are; easy to learn, controllable, lucid and understandable, easy to become skillful, flexible and easy to use (DAVIS et al., 1989) . Considering this example, an increase in the perceived ease of use will be marked by an increase in all these items measured. This also implies that there exists a high level of correlation between the items in a reflective construct. Hence dropping an item will not change the conceptual meaning of the construct as in a formative construct due to the interchangeable nature of the items (JARVIS et al., 2003).

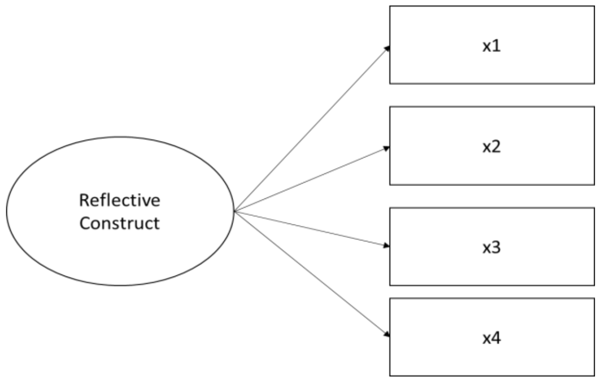


Figure 17. Reflective Construct – Graphical Representation

Source: Author's own construction based on Freeze & Raschke (2007)

As figure 17 shows, the arrows are pointing towards the measures, unlike the formative constructs. Here the causal effect is transferred from the construct to the measures (x1, x2, x3, x4) which means that the items or measures are derived from the construct.

The items used to measure the constructs (factors) in this research as given in Table 8 are reflective in nature. The conceptual research framework with the inner and outer models proposed for the study is given below in Figure 18. The inner model in SEM is the part which shows the relationships among the different latent variables in the model. The outer model, on the other hand, shows the relationships among the latent variables in the model and their respective indicators.

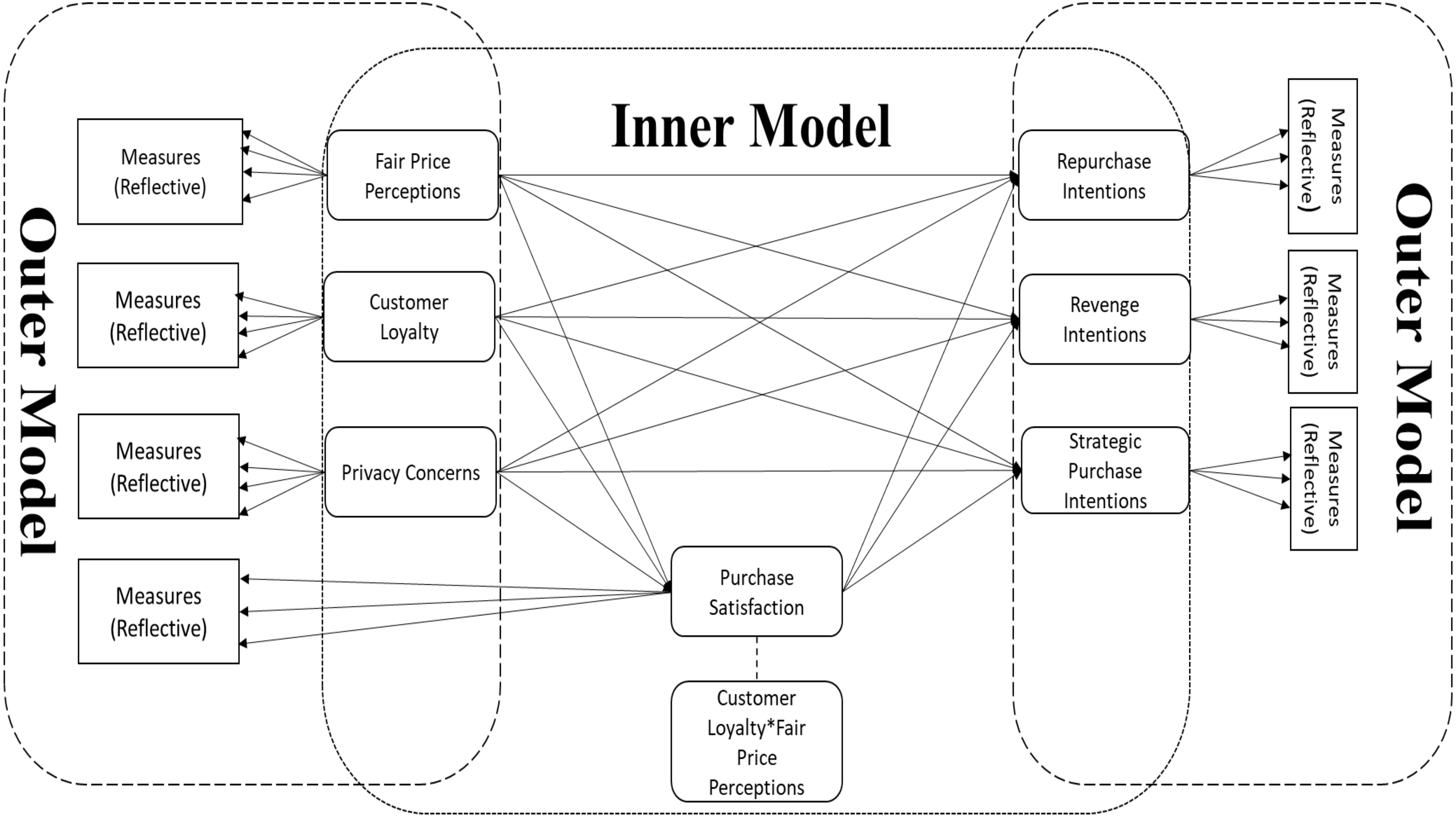


Figure 18. The Inner and Outer Model of the Research Framework

Source: Author's Own Construction

3.4. Research Procedure – Flow Chart

The steps followed in the procedure for conducting PLS SEM is depicted in figure 19. The steps followed are based on the methods followed in the seminal paper ʼA Primer on Partial Least Squares Structural Equation Modeling' by HAIR et al (2014) which is considered as one of the standard papers on the methodology used for PLS SEM.

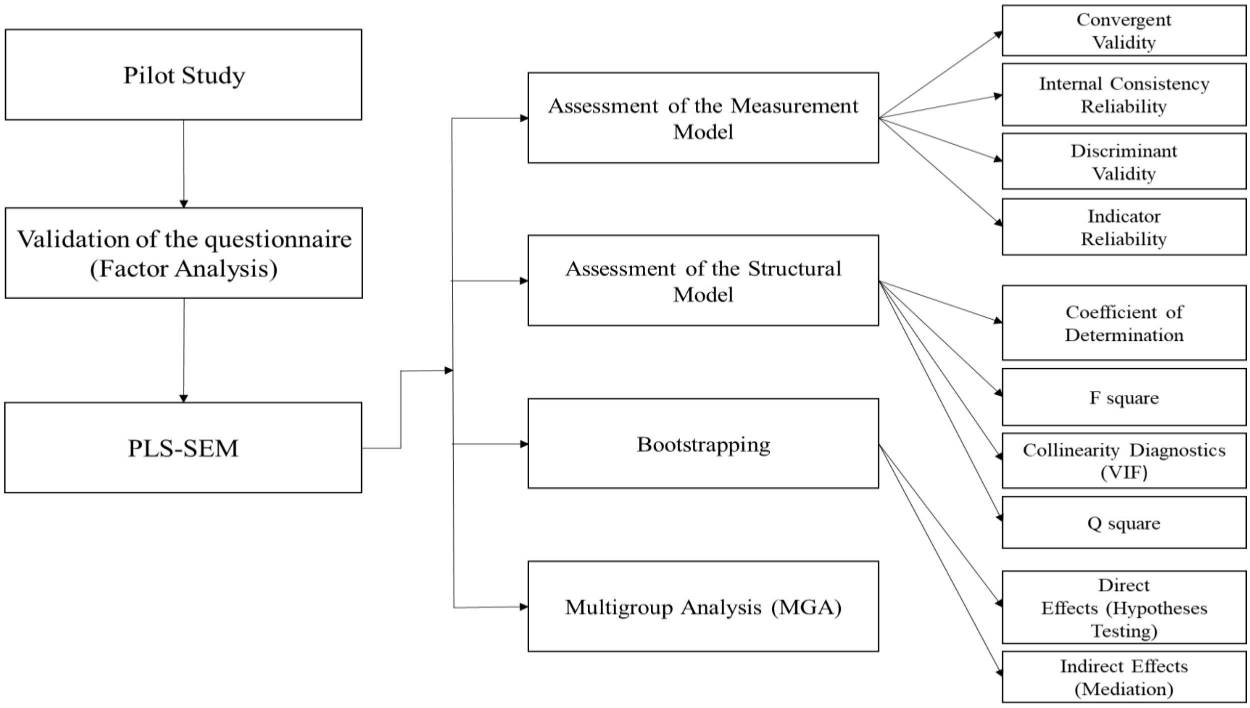


Figure 19. Procedures followed in PLS SEM

Source: Author's own construction

3.5. Pilot Study

A pilot study was conducted to ensure that the information in the purchase scenarios were conveyed clearly to the respondents. The clarity of wording of the Likert Scale questions was also thoroughly checked with the results of the pilot study. Further, the questionnaire was validated using an exploratory factor analysis (EFA) and using a confirmatory composite analysis (CCA)

3.5.1. Validation of the Questionnaire

Face validity, construct validity and construct validity criteria were used to validate the questionnaire. Face validity was ensured through seeking advice from the subject experts on the suitability of the measurement items and the hypothetical purchase scenario used in the questionnaire. A detailed evaluation of the questionnaire was done by prof. Maria Fekete-Farkas, head of Microeconomics Department, Szent Istvan University and Dr. Robert Jeyakumar Nathan, Head of the Marketing Department, Multimedia University, Malaysia. The suggestions of the experts in the field were taken into consideration and final version of the questionnaire was prepared based on their comments and suggestions. The construct validity and criterion validity of the constructs under study were already established through literature support. Nevertheless, an exploratory factor analysis was conducted to bolster the construct validity. RStudio 1.2.1335 was used to do the factor analysis. A sample size of 180 was used to perform the Exploratory Factor Analysis. The PLS SEM method uses a Confirmatory composite Analysis (CCA) which is commonly used in PLS SEM as an alternative to Confirmatory Factor Analysis (CFA). This method offers a number of advantages over the regular CFA (HAIR et al., 2018). The results of the CCA for each model separately is attached as appendix 6, 8, 10 & 12. The results are in line with the requirements of the methodology used.

Seven factors were extracted with Principal Component method using Varimax rotation. Kaiser-Meyer-Olkin (KMO) factor adequacy test was conducted to test the factor adequacy. The factors customer loyalty (CL), fair price perception (FPP), purchase satisfaction (PS), privacy concerns (PC), revenge intentions (RI), repurchase intentions (RP) strategic purchase intentions (SPI) showed a sampling adequacy of 0.84 as reported in Table 9. KAISER (1974) states that a KMO value of 0.5 is the minimum value required to confirm factor adequacy. Values in the range of 0.80-0.89 is considered as meritorious. Hence the factor adequacy of this research is confirmed.

Table 9. KMO Factor Adequacy Test

Kaiser-Meyer-Olkin factor adequacy															
Call: KMO(r = x)															
Overall MSA = 0.84															
MSA for each item =															
CL1	CL2	CL3	CL4	CL5	CL6	CL7	FP1	FP2	FP3	FP4	FP5	PS1	PS2	PS3	
0.83	0.86	0.87	0.90	0.91	0.84	0.81	0.93	0.89	0.89	0.48	0.62	0.92	0.92	0.90	
PS4	PS6	PS5	PS7	PS8	PC1	PC2	PC3	PC4	PC5	RI1	RI2	RP1	RI3	RP2	
0.93	0.93	0.76	0.90	0.88	0.52	0.57	0.70	0.68	0.63	0.69	0.72	0.83	0.83	0.90	R
P3	RP4	RI4	RI5	RI6	SPB1	SPB2	SPB4								
0.86	0.85	0.74	0.72	0.82	0.83	0.70	0.69								

Source: Author's own work based on Rstudio Results

The results of the Bartlett`s test of sphericity given in Table 10 Shows that the chi square value o f 4007.928 is significant at o.oo1%. The p value here is 0.00 hence it is confirmed that the correla tion matrix of the research constructs is not an identity matrix.

Table 10. Bartlett's Sphericity Test

Bartlett's Test of Sphericity	
Chi Square	4007.928
p.value	0.00
df	703

Source: Author's own work based on RStudio Results

After meeting the KMO factor adequacy and Bartlett`s test of sphericity criteria, an exploratory factor analysis was conducted with varimax rotation. Table 11 shows the results of the Factor analysis.

Table 11. Preliminary Results of Factor Analysis

Item Names	Items	Factor1	Factor2	Factor3	Factor4	Factor5	Factor6	Factor7
Customer Loyalty (CL)	CL1		0.806					
	CL2		0.748					
	CL3		0.817					
	CL4		0.733					
	CL5		0.699					
	CL6		0.806					
	CL7		0.747					
Fair Price Perception (FPP)	FP1							0.844
	FP2							0.811
	FP3							0.668
	FP4							**0.206**
	FP5							**0.311**
Purchase Satisfaction(PS)	PS1	0.796						
	PS2	0.889						
	PS3	0.746						
	PS4	0.874						
	PS6	0.718						
	PS5	**-0.397**						
	PS7	0.778						
	PS8	0.729						
Privacy Concerns (PC)	PC1					0.538		
	PC2					0.568		
	PC3					0.738		
	PC4					0.622		
	PC5					0.709		
Revenge Intentions (RI)	RI1			0.829				
	RI2			0.841				
	RI3			0.604				
	RI4			0.551				
	RI5			0.590				
	RI6			**0.372**				
Repurchase Intentions (RI)	RP1				0.578			
	RP2				0.621			
	RP3				0.780			
	RP4				0.567			
Strategic Purchase Intentions (SPI)	SPB1						0.626	
	SPB2						0.574	
	SPB3						0.832	
	SPB4						0.608	

	Factor1	Factor2	Factor3	Factor4	Factor5	Factor6	Factor7
SS loadings	7.163	4.641	2.639	2.191	2.012	1.920	1.716
Proportion Var	0.188	0.122	0.069	0.058	0.053	0.051	0.045
Cumulative Var	0.188	0.311	0.380	0.438	0.491	0.541	0.586

Source: Author's own work based on RStudio Results

The cut off value was set as 0.50 to remove items after factor analysis based on MOOI & SARSTEDT (2010). All items except FPP4, FPP5, PS5 and RI6 (shown in boldface in Table 11) had values above 0.50. The cumulative variance with all items included was 0.586.

The items with low loadings were removed and factor analysis was conducted again. The results of the analysis conducted with factor loadings above 0.50 is given in Table 12.

Table 12. Factor Analysis Results After Elimination of Items with Low Factor Loadings

Item Names	Items	Factor1	Factor2	Factor3	Factor4	Factor5	Factor6	Factor7
Customer Loyalty (CL)	CL1		0.815					
	CL2		0.744					
	CL3		0.811					
	CL4		0.735					
	CL5		0.699					
	CL6		0.819					
	CL7		0.746					
Fair Price Perception (FPP)	FP1							0.858
	FP2							0.823
	FP3							0.678
Purchase Satisfaction (PS)	PS1	0.802						
	PS2	0.887						
	PS3	0.750						
	PS4	0.863						
	PS6	0.710						
	PS7	0.771						
	PS8	0.737						
Privacy Concerns (PC)	PC1					0.544		
	PC2					0.599		
	PC3					0.716		
	PC4					0.418		
	PC5					0.686		
Revenge Intentions (RI)	RI1			0.797				
	RI2			0.861				
	RI3			0.617				
	RI4			0.581				
	RI5			0.554				
Repurchase Intentions (RI)	RP1				0.584			
	RP2				0.622			
	RP3				0.773			
	RP4				0.575			
Strategic Purchase Intentions (SPI)	SPB1						0.599	
	SPB2						0.876	
	SPB3						0.557	
	SPB4						0.619	

	Factor1	Factor2	Factor3	Factor4	Factor5	Factor6	Factor7
SS loadings	6.994	4.596	2.381	2.155	2.069	1.939	0.908
Proportion Var	0.200	0.131	0.068	0.062	0.059	0.055	0.026
Cumulative Var	0.200	0.331	0.399	0.461	0.520	0.575	0.601

Source: Author's own work based on RStudio Results

The results of the second analysis show that all items except PC4 had loadings above 0.50 as shown in Table 12. GUADAGNOLI & VELICER (1988) states that scores above 0.40 are considered stable in exploratory factor analysis, since PC4 was the only item with loading below 0.50, it was retained based on this less stringent criterion. KMO factor adequacy test value improved to 0.85 and the Bartlett`s test for sphericity showed a chi square value of 3679.423 with p value less of 0.00 and degree of freedom of 595. The cumulative variance of the total model has now increased from 0.586 to 0.601. Based on these results, the final data for the PLS SEM analysis was prepared.

4. RESULTS AND DISCUSSION

4.1. Demographic Profile of the Respondents

This section gives a detailed overview of the nature of the data used in the study. The demographic characteristics of the respondents from Malaysia and India are given in the following tables and charts. As discussed in the previous chapter, the sample size used for analysing both positive and negative purchase scenarios of Malaysia was 360 and that for India was 360. So, a total of 720 samples were used in the analysis. For better tabular depiction and visual appeal of the results, certain acronyms are used in the table headings. They are, **Mal_Neg** - Malaysian Negative Purchase Scenario, **Mal_Pos** – Malaysian Positive Purchase Scenario, **Ind_Neg** – Indian Negative Purchase Scenario and **Ind_Pos** – Indian Positive Purchase Scenario.

Table 13. Gender of the Respondents

Gender	Frequency					
	Mal_Neg	Mal_Pos	Percentage	Ind_Neg	Ind_Pos	Percentage
Female	97	109	57.22%	91	106	54.72%
Male	83	71	42.77%	89	74	45.27%
Total	180	180	100%	180	180	100%

Source: Author's own work based on Rstudio Results

The results given in Table 13 show that majority of the respondents under study in both countries were females. Out of the 720 respondents participated, 403 were females, which is around 55.97% and the male participants constituted 44.02% of the total respondents i.e. 317. The number of female respondents participated in the study in Malaysia were 206 and the number of males were 154. In the case of Indian respondents, the number of male participants were 197 and the number of females were 163.

Table 14. Age Group of the Respondents

Age	Frequency					
	Mal_Neg	Mal_Pos	Percentage	Ind_Neg	Ind_Pos	Percentage
15 – 25	119	95	59.44%	101	108	58.05%
26 – 35	49	63	31.11%	56	35	25.27%
36 – 45	6	12	5%	20	27	13.05%
46 – 55	2	7	2.5%	3	8	3.05%
56 and above	4	3	1.94%	0	2	0.55%
Total	180	180	100	180	180	100

Source: Author's own work based on Rstudio Results

As per the results given in Table 14, majority of the respondents in Malaysia (59.44%) and India (58.05%) belonged to the age group of 15 -25. The age group of 26 – 35 constituted the second highest category with 31.11% in Malaysia and 25.27% in India. The number of respondents belonging to the age bracket of 36-45 in Malaysia (5%) was much lesser than that in India (13.05%). However, the percentage of respondents belonging to the age groups of 46-55 and 56 and above are comparatively lesser than the other age brackets in both countries, i.e. 4.44% in Malaysia and 3.1% in India.

Table 15. Monthly Family Income of Malaysian Respondents

Monthly Family income	**Frequency**		
	Mal_Neg	Mal_Pos	Percentage
Below RM2000	38	30	18.88%
RM2001 - RM4000	62	53	31.94%
RM4001 - RM6000	48	57	29.44%
RM6001 - RM8000	26	36	17.22%
RM8001 and above	6	4	2.77%
Total	180	180	100

Note: 1 RM = 0.24 USD
Source: Author’s own work based on RStudio Results

Table 15 gives the results of the monthly income received by the Malaysian respondents under study. The results show that around 31.94% of the total respondents earn a monthly income of RM2001 – RM4000. 29.44% of the total respondents were earning an income of RM4001 – RM6000 and 17.22% were earning RM6001 – RM8000. The percentage of respondents earning RM10001 and above was 2.77 and 18.88% of the respondents were earning below RM2000. According to the Department of Statistics, Malaysia, median and mean monthly income in 2016 was RM5,228 and RM6,958 respectively (DOSM, 2016).

Table 16. Monthly Family Income of the Indian respondents

Monthly Family income	**Frequency**		
	Ind_Neg	Ind_Pos	Percentage
Below Rs.10,000	3	5	2.22%
Rs.10,000 – Rs. 25,000	49	46	26.38%
Rs. 26,000 – Rs. 50,000	70	83	42.50%
Rs. 50,000 – Rs. 75,000	35	34	19.16%
Rs. 75,000 and above	23	12	9.72%
Total	180	180	100%

Note: 1 Rs = 0.014 USD
Source: Author’s own work based on RStudio Results

Table 16 shows the results of the monthly income received by the Indian respondents. From the results, it could be seen that majority of the respondents (42.5%) were earning a monthly income of Rs.26,000 – Rs.50,000. Around 26.38% were earning a monthly income of Rs. 10,000 – Rs. 25,000. Around 19.16% of the total respondents belonged to the income group of Rs.50,000-Rs.75,000 and 9.72% were earning a monthly income above Rs.75,000. Percentage of respondents earning a monthly income below Rs.10,000 was 2.2.

Table 17. Educational Qualification of the Respondents

Educational Qualification	Frequency					
	Mal_Neg	Mal_Pos	Percentage	Ind_Neg	Ind_Pos	Percentage
High School	2	0	0.55%	1	1	0.55%
Bachelors Degree	102	87	52.5%	118	95	59.16%
Masters Degree	57	73	36.11%	56	68	34.44%
PhD	19	20	10.83%	15	26	11.38%
Total	180	180	100%	180	180	100%

Source: Author's own work based on RStudio Results

Statistics on educational qualification of the respondents as given in Table 17 show that majority of the respondents in Malaysia (52.5%) and India (59.16%) had bachelors degree. Around 36.11% of the Malaysian respondents and 34.44% of the Indian respondents were holding a masters degree. 10.83% of the total respondents in Malaysia had a PhD degree and the percentage of Indian respondents with a PhD degree was 11.38%. The respondents with a high school certificate was 0.55% in both countries, i.e. 2 respondents each.

4.2. Assessment of the Selected Constructs

4.2.1. Assessment of the Antecedent Construct – Customer Loyalty

The construct 'Customer Loyalty' was set as an antecedent factor to assess the influence of the loyalty towards the seller on the post purchase reactions. As explained in the methodology section, the items to measure customer loyalty were given in the first part of questionnaire i.e. before the respondents were exposed to the hypothetical purchase scenarios. Customer Loyalty influences the price perceptions of the consumers which has a direct effect on their overall purchase satisfaction. Literature on customer loyalty shows that the loyal customers do tolerate price hikes to some extent. Hence, the efficacy of the antecedent construct in creating the necessary stimulation to assess its impact on post purchase reactions for both Malaysian and Indian purchase scenarios is analysed visually here.

Stacked charts, one of the best tools available to visualise Likert scale based questionnaires are used to depict the consumer responses. The zero percentage at the centre shows neutral responses and to the right, the rate of responses with ‘agree’ and ‘strongly agree’ is shown in positive percentages and to the left, the rate of ‘disagree’ and ‘strongly disagree’ is shown in negative percentages.

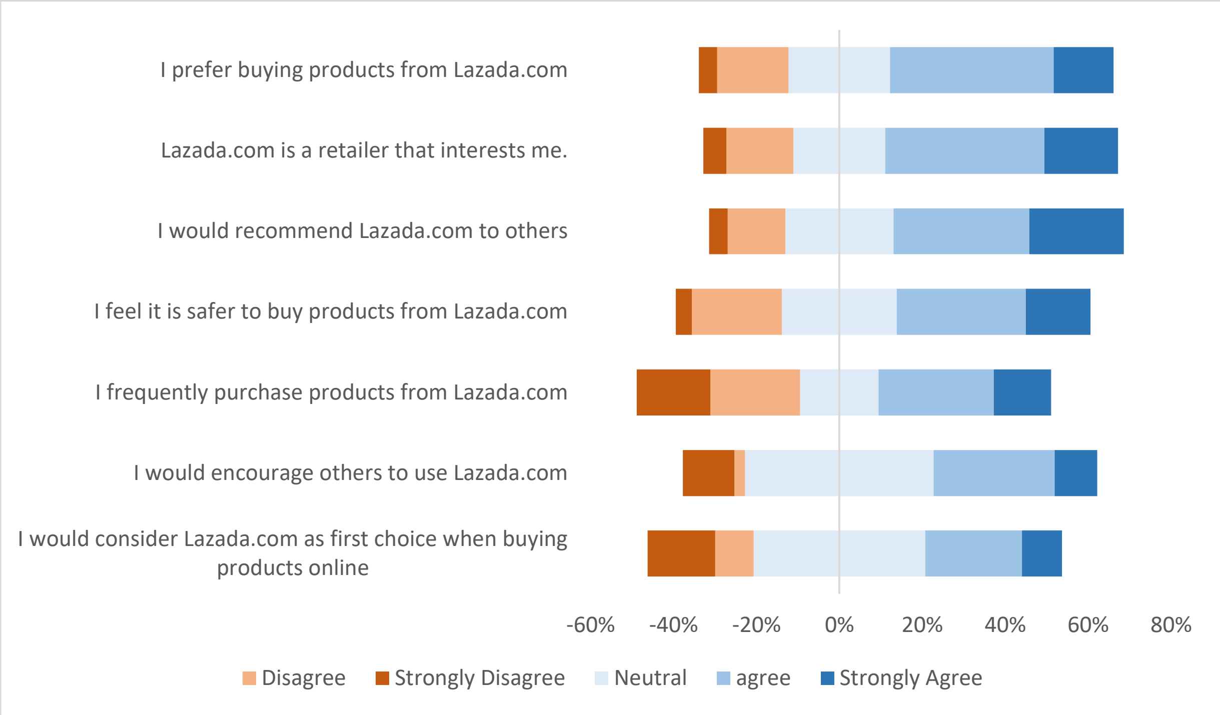


Figure 20. Customer Loyalty – Malaysian Purchase Scenarios

Source: Author’s own work

Most of the Malaysian respondents agree that Lazada is a retailer that interests them, and they prefer buying products from Lazada, one of the largest online retailers in the country. Majority of the respondents also agree that they would recommend the services of Lazada to others implying that the existing buyers are satisfied with them. Regarding the safety concerns of using Lazada, there is a slight increase in the number of neutral responses and the disagree responses. When it comes to the frequency of purchases from Lazada, there is a considerable increase in the rate of responses in the disagree and strongly disagree sections. One of the reasons might be the less pervasiveness of the E-Commerce markets in some parts of the country. Although majority of the respondents agreed that they would encourage others to use Lazada, there is an increase in the neutral responses implying that they wouldn’t be interested in forcing others to use Lazada. Using Lazada as a first choice is also a 50-50 question with increased rate of neutral responses. Considering the cut-throat competition in the E-Commerce market all over the world and in the fast developing digital ecosystem in countries like Malaysia, Lazada has done a decent job in building a loyal customer base according to the results shown in figure 20.

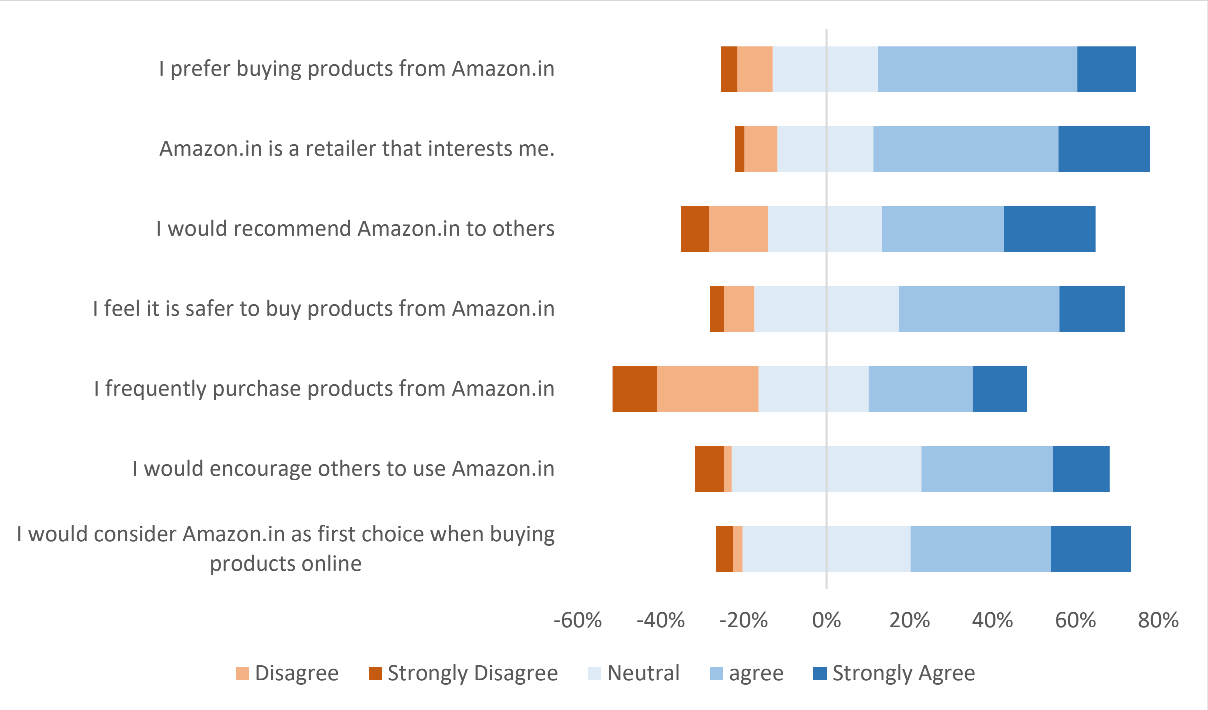


Figure 21. Customer Loyalty – Indian Purchase Scenarios

Source: Author's own work

For the Indian purchase scenarios, Amazon seems to have made a considerable influence in the Indian E-Tail segment. Most of the respondents agree that Amazon is preferred to other online retailers in India. Unlike the Malaysian case, most of the Indian respondents believe that Amazon offers a safe and secure platform for online purchases. The number of respondents who think that Amazon is safe is higher than that of the Malaysian respondents who opined that Lazada is safe. Similar to the Malaysian situation, the frequency of purchase from Amazon is lesser in India. Two of the most prominent reasons might be the less pervasiveness of digital shopping in the remotest parts of India and the tough competition faced by Amazon in the Indian E-Commerce market. Regarding the recommendation of the seller, most of the respondents agreed that they would recommend and encourage others to use the services of Amazon. Furthermore, the number of respondents who agreed that they would consider Amazon as their first choice in online purchases is very high. This implies that the Indian respondents are very loyal to Amazon.

By assessing the responses of the respondents as depicted in figure 20 and figure 21, the loyalty of the respondents to the E-Commerce vendors given in the purchase scenarios in both countries are confirmed as reasonably good enough for the analysis.

4.2.2. Privacy Concerns of the Respondents

The privacy concerns of the respondents in a personalised pricing context were also examined in detail. Personalised pricing uses the observed and inferred data about a consumer which includes personal information to tailor prices for each individual or a group of individuals with similar traits. One of the major sources of data collection is through website cookies (OECD, 2018). It is required to figure out how cautious are the consumers in sharing their personal data with a third party to better understand their attitude.

The hypothetical purchase scenarios developed in the questionnaires imparted information regarding how personal information is being collected and used by the online retailers to customise prices. The concerns of the respondents regarding their online privacy and personal data sharing were then elicited through a construct developed for this purpose. The construct named 'privacy concerns' was developed by the researcher and was validated and used in a previously published work (VICTOR et al., 2018a). The items used in the construct with their respective responses for the Malaysian and Indian purchase scenarios are given in figure 22 and figure 23.

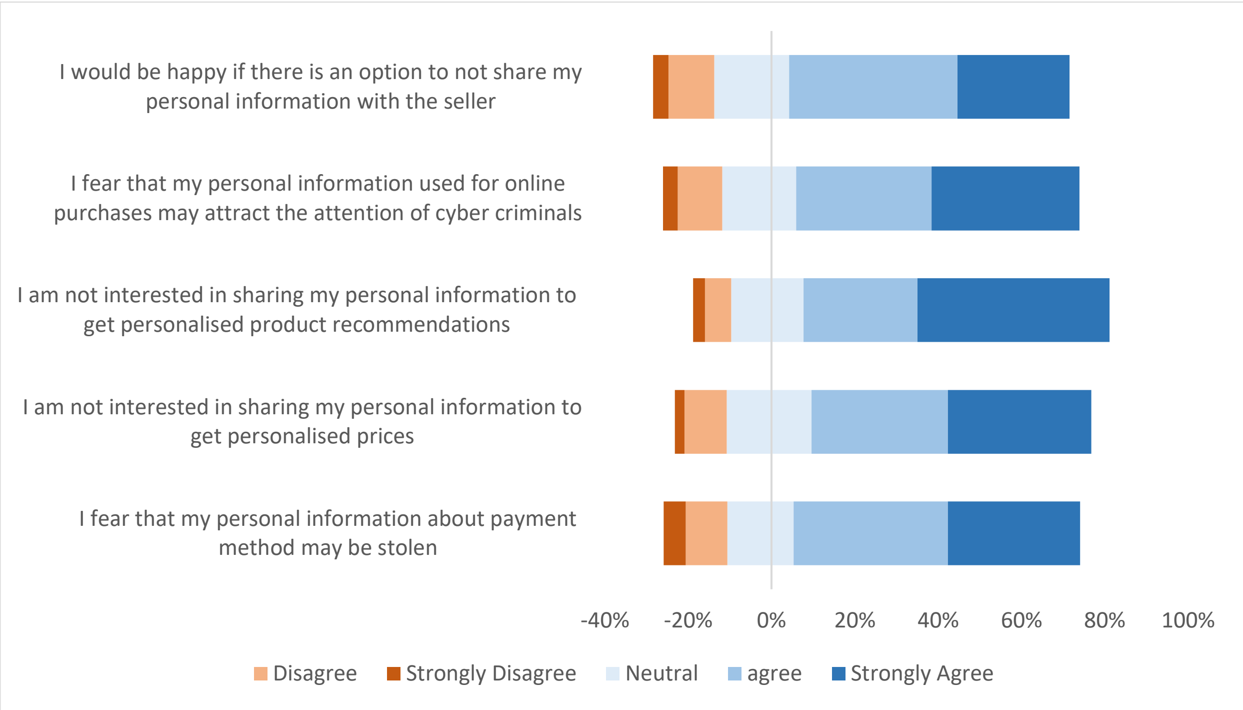


Figure 22. Privacy Concerns - Malaysian Purchase Scenarios

Source: Author's own work

Majority of the Malaysian respondents agree that they would be happy if the online retailer is providing an option to voluntarily exclude themselves from the data sharing with the seller. However, around 30 percent of the respondents either disagree or take a neutral position regarding the option for exclusion. Data sharing for personalised product recommendation is also not desirable for most of the Malaysian respondents implying that they might be irritated by the recommendations they get every now and then after visiting online shopping websites. Surprisingly, the number of respondents who disagree that they don't need personalised prices are lesser than that of the respondents who disagree the need for personalised product recommendations. This portrays the mindset of some Malaysian respondents who believe that personalised pricing can be beneficial to them. Regarding the safety of the payment methods and attack of cyber criminals in a data sharing environment, majority of the Malaysian respondents agree that they fear that such a thing can happen due to the disclosure of personal data.

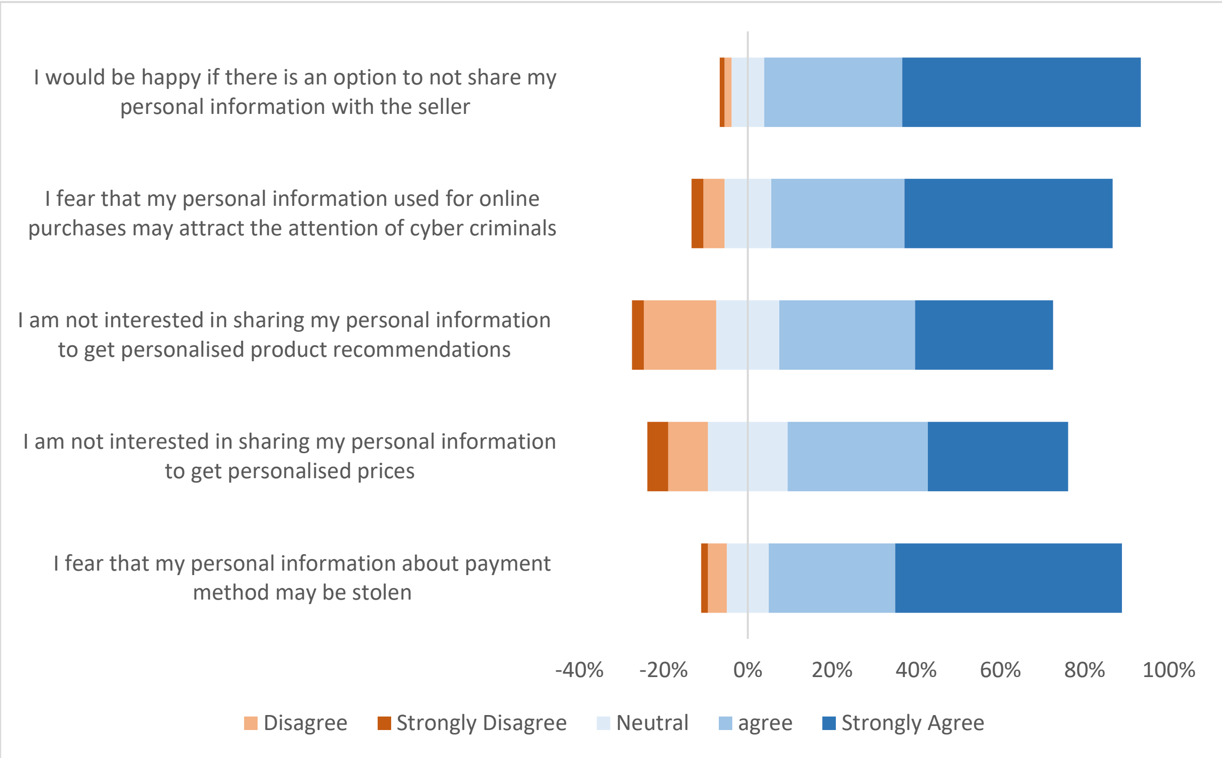


Figure 23. Privacy Concerns - Indian Purchase Scenarios

Source: Author's own work

For more than 90 percent of the Indian respondents, a choice given to not share their personal information with the seller would make them happier. Compared to the Malaysian respondents, the rate of Indian respondents who agree that they do not want to share personal information for personalised product recommendations and is lesser implying that some of the Indian consumers find personalised product recommendations as useful. More than half of the respondents also agreed that they don't want to share personal information for personalised prices. Regarding the safety of the payment methods and attack of cyber criminals in a data sharing environment, the percentage of Indian respondents have concerns are higher than the former. One of the reasons might be the increasing number of cybercrimes in India. Another interesting observation regarding some of the Indian respondents is that although they acknowledge the benefits accruing from sharing personal data with the sellers, they still require the choice not to share their data.

By assessing figure 22 and figure 23, it could be seen that the privacy concerns of both Malaysian and Indian respondents are more or less similar. However, the Indian Respondents are more sensitive than the Malaysian respondents when it comes to the safety concerns while using online platforms for shopping in a data sharing environment. Interestingly, relatively higher number of Indian respondents have also shown interest in sharing their personal information for personalised prices and product recommendations than the Malaysian respondents. Overall, the results show that majority of the respondents under study have serious privacy concerns in a data sharing personalised pricing context.

4.3. Assessment of the Gender wise Differences Using Wilcoxon Rank Sum Test (Mann Whitney Test)

In order to test for gender wise differences among the respondents in their attitude towards the variables under study, a Wilcoxon rank sum test (Mann Whitney test) was done. The results for the Malaysian purchase scenarios are given in Table 18.

Table 18. Wilcoxon Rank Sum Test Results for the Malaysian Purchase Scenarios

	Malaysia Positive				**Malaysia Negative**			
	Rank Sum		Z statistic	Sig	Mean		Z Statistic	Sig
Constructs	**Male**	**Female**			**Male**	**Female**		
Customer Loyalty	6553	9737	-1.179	0.2385	5929	5852	0.846	0.3978
Fair Price Perceptions	6115.5	10174.5	0.114	0.9092	6045.5	5735.5	0.419	0.6751
Privacy Concerns	6327.5	9962.5	-0.512	0.6087	6586.5	5194.5	-1.565	0.1177
Purchase Satisfaction	5953.5	10336.5	0.593	0.5531	6191	5590	-0.113	0.9097
Repurchase Intentions	6687	9603	-1.583	0.1135	6219.5	5561.5	-0.218	0.8272
Revenge Intentions	6302	9988	-0.441	0.6596	5892	5889	0.988	0.3231
Strategic Purchase Intentions	5630	10660	1.560	0.1187	6469.5	5311.5	-1.137	0.2555

Source: Author’s own work based on Stata results

The null hypothesis for the Wilcoxon Rank Sum test is that there is no significant difference in the attitude of male and female respondents towards the variables under study. Since the significance values for the Z statistic are above 0.05 for all variables, the null hypothesis cannot be rejected in both purchase scenarios, hence it can be concluded that there is no significant difference between the attitude of the Malaysian male and female respondents towards the variables under study.

The results of the Wilcoxon test conducted to assess the gender wise difference in the attitude of Indian respondents are reported in Table. 19.

Table 19. Wilcoxon Rank Sum Test Results for the Indian Purchase Scenarios

	India Positive				**India Negative**			
Constructs	Rank Sum		Z statistic	Sig	Rank Sum		Z statistic	Sig
	Male	**Female**			**Male**	**Female**		
Customer Loyalty	5961.5	10148.5	1.002	0.3161	7058.5	9051.5	-1.170	0.2422
Fair Price Perceptions	6353	9757	-0.157	0.3517	9450	8674	-2.280	**0.0226**
Privacy Concerns	5694.5	10415.5	1.797	0.0723	6640	9470	0.059	0.9531
Purchase Satisfaction	6052	10058	0.735	0.1104	7236	8874	-1.689	0.0912
Repurchase Intentions	7007	9103	-2.107	**0.0351**	7844	8266	-3.487	**0.0005**
Revenge Intentions	6848.5	9261.5	-1.634	0.428	6891.5	9218.5	-0.683	0.4946
Strategic Purchase Intentions	6205.5	9904.5	0.281	0.512	7063	9047	-1.186	0.2355

Source: Author's own work based on Stata results

The results reported in Table 19 shows that there is a statistically significant difference between the Indian male and female respondents in both purchase scenarios in their attitude towards repurchase intentions. Based on the results, the female respondents seem to have higher repurchase intentions in the Indian negative and positive purchase scenarios as compared to the male respondents. The fair price perception of female respondents is also higher in the Indian negative purchase scenario as compared to their male counterparts.

4.4. Assessment of the Differences among Income Groups Using One Way ANOVA

A one-way Analysis of Variance (ANOVA) Test was conducted for the negative and positive purchase scenarios separately to test for any differences among the attitude of the respondents belonging to different income groups. ANOVA is commonly used for dealing with three or more independent, unrelated groups. For analyzing two groups such as gender, a t test is typically used.

For the Malaysian purchase scenarios, the respondents belonged to five income slabs starting from below 2000 Malaysian Ringgits to above 8000 Malaysian Ringgits.

Table 20. ANOVA Test Results for the Malaysian Purchase Scenarios

	Malaysian Positive Purchase Scenario				**Malaysian Negative Purchase Scenario**			
Constructs	Mean Square		F	Sig	Mean Square		F	Sig
	Between Groups	Within Groups			Between Groups	Within Groups		
Customer Loyalty	.970	.903	1.07	0.3706	.970	.903	0.82	0.5136
Fair Price Perceptions	.3729	.7505	0.50	0.7381	1.917	.979	1.96	0.1040
Privacy Concerns	1.491	.1868	7.99	**0.0000**	.543	.708	0.77	0.5488
Purchase Satisfaction	.6733	.4283	1.57	0.1838	1.19	.521	2.30	0.0616
Repurchase Intentions	.0785	.3870	0.20	0.9364	1.10	.430	2.58	**0.0400**
Revenge Intentions	.4853	.4559	1.06	0.3757	1.00	.438	2.29	0.0627
Strategic Purchase Intentions	.52041	.5794	0.90	0.4663	.178	.734	0.24	0.9137

Source: Author's own work based on Stata results

The ANOVA test results for the Malaysian positive purchase scenario reported in Table 20 show that there is a statistically significant difference in the privacy concerns of respondents belonging to different income groups. For the Malaysian negative purchase scenario, a statistically significant difference was found for the repurchase intentions.

A Tukey post hoc test and a pairwise comparisons of means were carried out to identify the groups that have different means. Only the significant results are reported in the post hoc tests shown in Table 21 and Table 22.

Table 21. Pairwise Comparisons of Means for the Malaysian Purchase Scenarios

Scenario	Constructs	Mean				
		Below RM 2000	RM 2001 -4000	RM 4001-6000	RM 6001 - 8000	Above RM 8001
Malaysia Positive	Privacy Concerns	3.26	3.32	3.41	3.67	3.88
Malaysia Negative	Repurchase Intentions	3.10	2.78	3.05	3.50	3.09

Note: 1 RM = 0.24 USD
Source: Author’s own work based on Stata results

Table 22. Tukey Post Hoc Test for the Malaysian Purchase Scenarios

Scenario	Income Group	Contrast	Std. Err.	Tukey	
				t	p value
Malaysia Positive	RM6001 - RM8000 vs RM2001 - RM4000	.352	.082	4.29	**0.000**
Malaysia Negative	RM6001 - RM8000 vs Below RM2000	-.309	.288	-2.77	**0.049**

Note: 1 RM = 0.24 USD
Source: Author’s own work based on Stata results

The results of the Tukey post hoc test reported in Table 22 show that there is a statistically significant difference between the means of the respondents belonging to the income group RM6001 - RM8000 and RM2001 - RM4000 for the Malaysian positive purchase scenario. From the Pairwise comparisons of means table, it could seen that the income group RM6001 -8000 has a higher mean score (3.41) as compared to the mean of the income group RM 2001 – 4000 (3.32). This result indicates that the income group RM 6001 – RM 8000 has higher privacy concerns as compared to the income group RM 2001 - RM 4000.

For the Malaysian negative purchase scenario, a statistically significant differ difference of means is seen between the income group RM 6001 – RM 8000 and Below RM 2000. The pairwise comparisons of means show that the mean score is higher for the income group RM 6001 – 8000 (3.50) as compared to the income group Below RM 2000 (3.10). The result portrays that the income group RM 6001 – 8000 has a higher repurchase intentions as compared to the income group Below RM 2000 in a personalised pricing context.

The ANOVA test results for the Indian positive and negative purchase scenarios are reported in Table 23. The Indian respondents belonged to five income slabs starting from Below Rs. 10,000 to Above Rs. 75, 000.

Table 23. ANOVA Results for the Indian Purchase Scenarios

Constructs	India Positive				India negative			
	Mean Square		F	Sig	Mean Square		F	Sig
	Between Groups	Within Groups			Between Groups	Within Groups		
Customer Loyalty	1.19	.712	1.68	0.1567	.244	.7689	0.32	0.8657
Fair Price Perceptions	3.22	.618	5.21	**0.0005**	3.554	.7016	5.07	**0.0007**
Privacy Concerns	1.68	.897	1.87	0.1173	.3216	.5839	0.55	0.6987
Purchase Satisfaction	1.287	.496	2.59	**0.0384**	1.336	.770	1.73	0.1445
Repurchase Intentions	.889	.434	2.05	0.0897	.020	.332	0.06	0.9930
Revenge Intentions	.446	.515	0.87	0.4853	.309	.517	0.60	0.6641
Strategic Purchase Intentions	2.68	.678	3.95	**0.0043**	.0965	.669	0.14	0.9653

Source: Author's own work based on Stata results

For the Indian positive purchase scenario, a statistically significant difference was seen for three factors namely fair price perceptions, purchase satisfaction and strategic purchase intentions among the various income groups. For the Indian negative purchase scenario, a statistically significant difference was seen for the factor fair price perceptions. As ANOVA test does not give information about the exact groups for which the means are different, a Tukey post hoc test and a pairwise comparisons of means were conducted to identify the groups that differ. Only the significant results are reported in the post hoc tests shown in Table 24 and Table 25.

Table 24. Pairwise Comparisons of Means for the Indian Purchase Scenarios

Scenario	Constructs	Mean				
		Below Rs. 10,000	Rs. 10,000 – 25,000	Rs. 26,000 - 50,000	Rs. 51, 000 - 75,000	Above Rs. 75,000
Indian Positive	Fair Price Perceptions	2.40	3.05	2.71	2.24	2.55
	Purchase Satisfaction	2.20	2.95	2.74	2.48	2.76
	Strategic Purchase Intentions	3.58	3.81	3.72	3.63	3.17
Indian Negative	Fair Price Perceptions	2.40	3.05	2.71	2.24	2.55

Note: 1 Rs = 0.014 USD
Source: Author's own work based on Stata results

Table 25. Tukey Post Hoc Test for the Indian Purchase Scenarios

Scenario	Income Group	Contrast	Std. Err.	Tukey	
				t	p value
India Positive	Rs. 26,000 – 50,000 vs Rs. 10,000 – 25,000	-.4490309	.1445629	-3.11	**0.019**
	Rs. 51, 000 – Rs. 75, 000 vs Rs. 10,000 – 25,000	-.4776564	.1655436	3.07	**0.021**
	Above Rs. 75,000 vs Rs. 10,000 – 25,000	-.6426334	.2272284	3.40	**0.007**
India Negative	Rs. 51, 000 - 75,000 vs Rs. 10,000 – 25,000	-.8141667	.1861879	-4.37	**0.000**

Note: 1 Rs = 0.014 USD

Source: Author’s own work based on Stata results

The Tukey test results for the Indian positive purchase scenario indicate that there is a difference between the means of the income group Rs. 26,000 – 50,000 and Rs. 10,000 – 25,000 in their attitude towards fair price perceptions. From the pairwise mean comparison table, it could be ascertained that the fair price perceptions of the income group Rs. 10,000 – 25,000 is higher than that of the other group, 26,000 – 50,000 as the mean score of the former (3.05) is higher than that of the latter (2.71). The purchase satisfaction mean score for the income group Rs. 51, 000 – Rs. 75, 000 differed from that of Rs. 10,000 – 25,000. From the pairwise mean comparison table, it can be seen that the income group Rs. 10,000 – 25,000 with a mean score of 2.95 has higher purchase satisfaction as compared to the income group Rs. 51,000 – Rs. 75, 000 for which the mean score is 2.48. A statistically significant difference was observed between the means of the income group Above Rs. 75,000 and Rs. 10,000 – 25,000 in their attitude towards strategic purchase intentions. As per the results in the pairwise mean comparison table results, the income group Rs. 10,000 – 25,000 with a mean score of 3.81 has higher strategic purchase intentions as compared to the income group Above Rs. 75,000 with a mean score of 3.17.

For the Indian negative purchase scenario, a significant difference in the mean scores was observed between the income groups Rs. 51, 000 - 75,000 and Rs. 10,000 – 25,000 in their attitude towards fair price perceptions. From the pairwise mean comparison table, it could be seen that the fair price perceptions of the income group Rs. 10,000 – 25,000 with a mean score of 3.05 is higher than that of the other income group Rs. 51, 000 - 75,000 having a mean score of 2.24.

4.5. Item Statistics

The item statistics for both positive and negative purchase scenarios of the two countries were estimated using SmartPLS 3.0. Measures of central tendency including mean and median as well as measures of variability such as standard deviation, kurtosis, and skewness were checked to ensure that the data used for analysis was good enough. Normal univariate distribution of a dataset can be proved if the skewness and kurtosis values of a dataset fall within the range of +/-2 (GEORGE & MALLERY, 2010). Nevertheless, one of the main benefits of using PLS SEM is that it doesn't require normal distribution of the data being analysed. The item statistics were however thoroughly checked to ensure that there are no extreme values in the data analysed. The presence of extreme outliers is not desirable in exploratory studies. The results of the mean, median, standard deviation, excess kurtosis and skewness of the independent variables for negative and positive purchase scenarios for both countries are attached as appendix 2, 3, 4 and 5.

The mean, median, standard deviation, skewness and excess kurtosis for all the items under study for both countries were within the suggested threshold limits, hence it was ensured that there were no extreme outliers in the data under study.

After ruling out the presence of extreme outliers in the dataset, the validity of the measurement and structural models were then tested.

4.6. Assessment of the Measurement Models

The measurement model refers to the outer model that relates the latent variable to its indicators. It is required to assess the measurement model for convergent validity, internal consistency and reliability and discriminant validity prior to testing the structural model HAIR et al (2014). The convergent validity is assessed using Average Variance Extracted. Cronbach's Alpha and Composite Reliability are used to assess the internal consistency reliability. For assessing the discriminant validity, Fornell - Larcker criterion was used. Indicator reliability was confirmed by assessing the outer loadings. The convergent and discriminant validity results for both the Indian and Malaysian purchase are given in the following sub chapters.

4.6.1. Convergent Validity and Internal Consistency Reliability

Convergent validity in simple words can be explained as the degree of confidence of a researcher that a characteristic trait is well estimated by the relevant indicators. AVE estimates the level of variance measured by a construct as compared to the level of variance captured due to measurement error (CAMPBELL & FISKE, 1959). For testing convergent validity of the reflective models, the appropriate method is to examine Average Variance Extracted (AVE) of each construct. The Average Variance Extracted (AVE) displays the average communality for the latent constructs in a given reflective model. The square root of AVEs can be used to assess the discriminant validity. The AVE values should be equal to or greater than 0.50 to be considered as having adequate convergent validity (CHIN, 1998). It implies that the items should be able to explain at least 50% of the total variance of the respective factor.

For ensuring adequate internal consistency reliability, the Composite reliability (CR) values should be above 0.70. Nevertheless, CR values above 0.95 are undesirable in researches. The problem with CR values above 0.95 is that it alludes the presence of unnecessary items in a construct. As redundant items have the capacity to make an adverse impact on the content validity and error term correlations, it is suggested to identify and reduce the number of redundant items (Hair et al., 2017). Composite reliability measure is considered as less biased as compared to Cronbach Alpha measures. Cronbach's Alpha is also used to test if the items belonging to the latent variables show adequate convergent validity and hence exhibit internal consistency and reliability. Conventionally, a Cronbach Alpha value above 0.70 is considered acceptable (HAIR et al., 2014).

The Rho_A used in PLS SEM models is one of the important measures of reliability. It gives an estimate for the squared correlation of the construct score with the score that is unknown or the true construct score. The minimum score to be attained for Rho_A is 0.7 (DIJKSTRA & HENSELER, 2015).

Table 26. Results of the Measurement Model Assessment – Indian Purchase Scenarios

Constructs	Cronbach's Alpha		Rho_A		Composite Reliability		Average Variance Extracted (AVE)	
	Ind_Neg	Ind_Pos	Ind_Neg	Ind_Pos	Ind_Neg	Ind_Pos	Ind_Neg	Ind_Pos
Customer Loyalty	0.912	0.916	0.915	0.921	0.930	0.933	0.655	0.665
Fair Price Perception	0.807	0.861	0.818	0.866	0.886	0.915	0.721	0.782
Privacy Concerns	0.803	0.737	0.823	0.791	0.859	0.807	0.55	0.552
Purchase Satisfaction	0.929	0.940	0.932	0.942	0.944	0.931	0.707	0.736
Revenge Intentions	0.774	0.839	0.868	0.847	0.853	0.893	0.609	0.677
Repurchase Intentions	0.827	0.790	0.862	0.843	0.877	0.854	0.589	0.544
Strategic Purchase Intentions	0.753	0.725	0.787	0.752	0.843	0.829	0.577	0.552

Source: Author's own work based on SmartPLS results

Table 26 gives the results of the assessment of the measurement model. The Composite Reliability values range within 0.829 – 0.931 for the positive Indian purchase scenario and 0.843 – 0.944 for the negative Indian purchase scenario. Although the Composite Reliability values for the constructs customer loyalty and purchase satisfaction are above 0.90, they are not higher than the recommended critical threshold of 0.95 and did not seem to have any significant adverse influence on the overall content validity or error term correlations. Hence the factors were retained without changes.

The Cronbach's Alpha and Rho_A for all constructs in both purchase scenarios are higher than 0.70 implying that the items are internally consistent. The Average Variance Extracted (AVE) for all constructs is also higher than 0.50 as specified by CHIN (1998). Hence the convergent validity and internal consistency reliability of the measurement model for Indian negative and positive purchase scenarios is confirmed. The results of the assessment of the measurement model for the Malaysian purchase scenarios are given in Table 27.

Table 27. Results of the Measurement Model Assessment – Malaysian Purchase Scenarios

Constructs	Cronbach's Alpha		Rho_A		Composite Reliability		Average Variance Extracted	
	Mal_Neg	Mal_Pos	Mal_Neg	Mal_Pos	Mal_Neg	Mal_Pos	Mal_Neg	Mal_Pos
Customer Loyalty	0.909	0.929	0.911	0.932	0.928	0.942	0.650	0.701
Fair Price Perception	0.887	0.875	0.888	0.885	0.930	0.923	0.815	0.799
Privacy Concerns	0.755	0.817	0.826	0.835	0.831	0.871	0.501	0.576
Purchase Satisfaction	0.930	0.928	0.931	0.934	0.944	0.942	0.705	0.699
Revenge Intentions	0.836	0.841	0.840	0.906	0.891	0.892	0.672	0.680
Repurchase Intentions	0.798	0.825	0.853	0.859	0.853	0.877	0.542	0.591
Strategic Purchase Intentions	0.862	0.822	0.873	0.878	0.906	0.880	0.707	0.649

Source: Author's own work based on SmartPLS results

The results in Table 27 shows that the composite reliability values range between 0.831 – 0.944 for the Malaysian negative purchase scenario and 0.871 – 0.942 for the Malaysian positive purchase scenario. Similar to Indian purchase scenarios, the composite reliability values for the constructs customer loyalty and purchase satisfaction are higher than 0.90. However, they were retained as the values are below the critical threshold of 0.95.

The Cronbach's Alpha and Rho_A for all the constructs in both purchase scenarios meet the minimum requirement of having values equal to or above 0.70. The Average Variance Extracted (AVE) for all constructs is higher than 0.50. Hence the convergent validity, as well as internal consistency reliability of the measurement model for both Malaysian purchase scenarios, is confirmed.

4.6.2. Discriminant Validity

The aim of the discriminant validity assessment is to confirm that a reflective construct under study is related to its own indicators when compared to the other constructs. Discriminant validity is ensured when the constructs are not highly related to each other or in other words, are not highly correlated.

The Fornell - Larcker Criterion is used to assess discriminant validity of the measurement models used in this study. The FORNELL - LARCKER (1981) criterion states that a construct`s Average Variance Extracted (AVE) should be greater than its squared correlation with the other constructs used in the model. The results of the discriminant validity test for each model separately are given in Table 28, 29, 30 and 31.

Table 28. Discriminant Validity – Indian Negative Purchase Scenario

	CL*FPP	CL	FPP	PC	PS	RP	RI	SPI
CL*FPP	**1.000**							
CL	0.048	**0.815**						
FPP	0.095	0.124	**0.884**					
PC	-0.048	0.103	-0.165	**0.684**				
PS	0.263	0.276	0.786	-0.156	**0.858**			
RP	0.253	0.420	0.414	-0.094	0.597	**0.823**		
RI	-0.207	-0.137	-0.297	0.306	-0.311	-0.251	**0.738**	
SPI	-0.132	-0.116	-0.177	0.319	-0.275	-0.045	0.315	**0.743**

Source: Author's own work based on SmartPLS results

The Square root of AVE is given diagonally in Table 28 and the correlation with the other variables are given below the diagonal values. In order to ensure discriminant validity, the values given diagonally i.e. the AVE values should be higher than that of the correlation values which appear below them.

As per this criterion, the measurement model for Indian negative purchase scenario shows adequate discriminant validity as the values given diagonally are higher than those given below them.

Table 29. Discriminant Validity – Indian Positive Purchase Scenario

	CL*FPP	CL	FPP	PC	PS	RP	RI	SPI
CL*FPP	**1.000**							
CL	-0.215	**0.816**						
FPP	-0.249	0.536	**0.867**					
PC	-0.164	0.123	0.230	**0.738**				
PS	-0.273	0.611	0.781	0.154	**0.850**			
RP	-0.077	0.502	0.296	-0.103	0.436	**0.829**		
RI	-0.079	-0.019	0.058	0.318	-0.080	-0.022	**0.754**	
SPI	-0.067	0.235	0.250	0.287	0.332	0.274	0.245	**0.754**

Source: Author's own work based on SmartPLS results

The AVE values given diagonally for the Indian positive purchase scenario given in Table 29 are higher than the correlation values that appear below them, hence the discriminant validity of the Indian positive purchase scenario is ensured. The results given in Table 30 and 31 show that the both Indian purchase scenarios meet adequate discriminant validity as per the Fornell – Larcker criterion.

Table 30. Discriminant Validity – Malaysian Negative Purchase Scenario

	CL*FPP	CL	FPP	PC	PS	RP	RI	SPI
CL*FPP	**1.000**							
CL	0.126	**0.806**						
FPP	0.147	0.336	**0.903**					
PC	0.027	0.038	-0.124	**0.708**				
PS	0.193	0.391	0.742	-0.133	**0.840**			
RP	0.175	0.605	0.479	-0.071	0.607	**0.820**		
RI	0.244	0.185	0.068	0.219	0.160	0.200	**0.736**	
SPI	-0.109	0.103	-0.250	0.258	-0.119	-0.047	0.113	**0.841**

Source: Author's own work based on SmartPLS results

The correlation values in Table 30 is lesser than the respective AVE values given diagonally in boldface. Hence, the discriminant validity of the Malaysian negative purchase scenario is confirmed.

Table 31. Discriminant Validity – Malaysian Positive Purchase Scenario

	CL*FPP	CL	FPP	PC	PS	RP	RI	SPI
CL*FPP	**1.000**							
CL	0.027	**0.837**						
FPP	0.154	0.108	**0.894**					
PC	0.096	-0.047	0.146	**0.759**				
PS	-0.103	0.378	0.593	0.098	**0.836**			
RP	-0.046	0.462	0.230	-0.109	0.386	**0.824**		
RI	0.081	0.041	-0.155	0.301	-0.160	-0.184	**0.769**	
SPI	-0.051	0.139	0.098	0.362	0.274	0.129	0.194	**0.805**

Source: Author's own work based on SmartPLS results

The AVE values of the constructs given diagonally in Table 31 is higher than the correlation values that appear below them. Hence it is confirmed that the measurement model for Malaysian positive purchase scenario show adequate discriminant validity.

4.6.3. Indicator Reliability

The outer loadings of the items were assessed to ensure the indicator reliability. PLS SEM uses Confirmatory Composite Analysis (CCA) to obtain the outer loadings. HULLAND (1999) suggests the minimum required outer loading to be 0.70 or above for each item. However, HAIR et al (2014) states that the items with loadings in the range of 0.40 to 0.70 may be deleted only if removing them would have a positive impact on the composite reliability and Average Variance Extracted (AVE). Items with loadings below 0.40 should be necessarily deleted. The outer loadings for both Indian and Malaysian purchase scenarios along with the models showing path coefficients and R square values are attached as Appendix 6, 7, 8, 9, 10, 11, 12 & 13. The results show that the outer loadings for Indian and Malaysian purchase scenarios meet the prescribed requirements.

By ensuring adequate convergent validity, internal consistency and reliability, and discriminant validity through the established assessment techniques, the overall quality of the measurement models for the positive and negative purchase scenarios of both countries was reckoned as sufficient. The researcher then proceeded with the assessment of the structural models

4.7. Assessment of the Structural Models

The assessment of the structural models were done using a five step method as suggested by HAIR et al (2014) that consists of the assessment of the coefficient of determination (R^2), F Square Values (effect size), Q^2 (predictive relevance) and Variation Inflation Values (VIF) that check for collinearity issues and path coefficients.

4.7.1. Coefficient of Determination (R^2)

The R^2 or the coefficient of determination is the measure of the combined effect size of the exogenous variables on the endogenous variables. CHIN (1998) has described the R^2 values above 0.67 as substantial, 0.33 as moderate and 0.15 as weak. However, it is commonly believed that a \`high\` R Square is very relative to subjects which means that a lower R square in a particular field might be considered higher in another field (GARSON, 2016).

The adjusted R^2 penalises for the increased number of the independent variables or the complexity of the model and the sample size (HENSELER, 2017). Hence it is advisable to check the adjusted R^2 while comparing models.

Table 32. R Square Values

Constructs	R Square				Adjusted R Square			
	Ind_ Neg	Ind_ Pos	Mal_ Neg	Mal_ Pos	Ind_ Neg	Ind_ Pos	Mal_ Neg	Mal_ Pos
Purchase Satisfaction	0.681	0.667	0.582	0.493	0.674	0.659	0.570	0.482
Repurchase Intentions	0.409	0.318	0.529	0.284	0.396	0.302	0.516	0.267
Revenge Intentions	0.183	0.136	0.102	0.154	0.164	0.116	0.078	0.135
Strategic Purchase Intentions	0.175	0.172	0.153	0.205	0.156	0.153	0.130	0.187

Source: Author's own work based on SmartPLS results

The results given in Table 32 show that the R Square values for the construct Purchase Satisfaction in Indian purchase scenarios are 0.686 and 0.667. This means that the independent variables are able to explain more than 50% of the total variation in Purchase Satisfaction. In the case of Malaysian purchase scenarios, the values are 0.582 and 0.493 which also show a moderate effect. The R Square values for the construct Repurchase Intentions in Indian purchase scenarios are 0.40 and 0.31 and that of Malaysian purchase scenarios are 0.52 and 0.28. These show a moderate and weak effect respectively. The construct revenge Intentions has R Square values equal to or below 0.15 for all models except the Indian negative purchase scenario.

Since this research is one of the pioneering works in the field of personalised pricing and consumer reactions, these results are important reference for future works in the area. The construct Strategic Purchase intentions has R Square values above 0.15 implying a weak effect. The adjusted R Square values after penalising for the model complexity and sample size are also given for better understanding of the results.

4.7.2. F^2 Values

Cohen's f^2 showing the effect size for each path model is calculated by taking into account of the change in R^2 when a particular construct is removed from the model. The f^2 effect size is calculated using the equation: F^2 = (R2 original – R2 omitted)/(1- R2 original).

COHEN (1988) describes f^2 values of .02 as a small effect size, .15 as medium effect size and .35 as high effect size. The f^2 values for the Indian purchase scenarios are given in Table 33 and for the Malaysian purchase scenarios in Table 34.

Table 33. F Square Values – Indian Purchase Scenarios

	Purchase Satisfaction		**Repurchase Intentions**		**Revenge Intentions**		**Strategic Purchase Intentions**	
	Ind_Neg	Ind_Pos	Ind_Neg	Ind_Pos	Ind_Neg	Ind_Pos	Ind_Neg	Ind_Pos
CL*FPP	**0.105**	0.018						
CL	**0.10**	**0.137**	**0.118**	**0.19**	0.014	0.002	0.007	0.001
FPP	**1.645**	**0.714**	0.004	0.01	0.008	0.002	0.006	0.007
PC	0.006	0.002	0.004	**0.04**	**0.087**	**0.075**	**0.103**	**0.067**
PS			**0.204**	**0.023**	0.007	**0.026**	**0.037**	**0.05**

Source: Author’s own work based on SmartPLS results

The results given in Table 33 shows the F^2 values and the effect sizes. As per Cohen`s classification, the effect size of the fair price perception on purchase satisfaction in both negative and positive purchase scenarios are more than 0.35, implying a high effect. The effect size of purchase satisfaction on repurchase intentions is medium in Indian negative purchase scenario.

Customer loyalty has a medium effect on the repurchase intentions in both negative and positive purchase scenarios. The effect of purchase satisfaction and privacy concerns on strategic purchase intentions is small. The values which are given without boldface imply no or little effect on the dependent variable.

Table 34. F Square Values – Malaysian Purchase Scenarios

	Purchase Satisfaction		**Repurchase Intentions**		**Revenge Intentions**		**Strategic Purchase Intentions**	
	Mal_Neg	Mal_Pos	Mal_Neg	Mal_Pos	Mal_Neg	Mal_Pos	Mal_Neg	Mal_Pos
CL*FPP	0.013	**0.081**						
CL	**0.052**	**0.202**	**0.336**	**0.157**	0.015	0.018	0.004	**0.029**
FPP	**0.921**	**0.635**	0.000	0.006	0.006	0.010	0.015	**0.071**
PC	0.008	0.004	0.002	**0.021**	**0.057**	**0.134**	**0.154**	**0.056**
PS			**0.159**	**0.034**	**0.024**	**0.020**	**0.061**	0.007

Source: Author’s own work based on SmartPLS results

The F^2 values for the Malaysian purchase scenarios are given in Table 34. Similar to the Indian purchase scenarios, the fair price perceptions have a high effect on the purchase satisfaction. Customer Loyalty has a high effect on the repurchase intentions for both negative and positive purchase scenarios. The effect of purchase satisfaction on repurchase intentions is medium in the case of negative purchase scenario and small in positive purchase scenario.

Very similar to the Indian scenarios, the purchase satisfaction, and privacy concerns have only small effect on the revenge intentions in both purchase scenarios. The effect of privacy concerns on strategic purchase intentions is medium in negative purchase scenario and small in the positive purchase scenario. The values which are without boldface imply no or little effect.

4.7.3. Collinearity Diagnostics

Collinearity exists when there is a high level of correlation between two or more independent variables. Two or more independent variables are said to be collinear if they are measuring the same underlying factor. These definitions are most commonly referred to in the multiple regression models.

Collinearity can cause problems such as high standard errors, making significance tests unreliable etc. while conducting OLS regression (GARSON, 2016). A common assertion in PLS SEM analysis is that a Variance Inflation Factor (VIF) coefficient above 5.0 indicate the presence of multicollinearity (HAIR et al., 2014).

Table 35 shows the inner VIF values for the Indian purchase scenarios and Table 36 for the Malaysian purchase scenarios.

Table 35. Inner VIF Values for Indian Purchase Scenarios

	Purchase Satisfaction		**Repurchase Intentions**		**Revenge Intentions**		**Strategic Purchase Intetnions**	
	Ind_Neg	Ind_Pos	Ind_Neg	Ind_Pos	Ind_Neg	Ind_Pos	Ind_Neg	Ind_Pos
CL*FPP	1.031	1.030						
CL	1.142	1.016	1.199	1.202	1.199	1.202	1.199	1.202
FPP	1.167	1.056	2.242	1.596	2.242	1.596	2.242	1.596
PC	1.025	1.032	1.030	1.028	1.030	1.028	1.030	1.028
PS			2.359	1.826	2.359	1.826	2.359	1.826

Source: Author’s own work based on SmartPLS results

The inner VIF coefficients for the Indian positive and negative purchase scenarios as given in Table 35 are well below the threshold value of 5. The outer VIF coefficients i.e. the VIF coefficient for each indicator in both purchase scenarios were also assessed and the range is between 1.338 – 3.598 for positive purchase scenario and 1.213 – 3.824 for the negative purchase scenario. Hence the presence of multicollinearity from the Indian structural models is ruled out.

Table 36. Inner VIF Values for Malaysian Purchase Scenarios

	Purchase Satisfaction		Repurchase Intentions		Revenge Intentions		Strategic Purchase Intetnions	
	Ind_Neg	Ind_Pos	Ind_Neg	Ind_Pos	Ind_Neg	Ind_Pos	Ind_Neg	Ind_Pos
CL*FPP	1.031	1.030						
CL	1.142	1.016	1.199	1.202	1.199	1.202	1.199	1.202
FPP	1.167	1.056	2.242	1.596	2.242	1.596	2.242	1.596
PC	1.025	1.032	1.030	1.028	1.030	1.028	1.030	1.028
PS			2.359	1.826	2.359	1.826	2.359	1.826

Source: Author's own work based on SmartPLS results

The inner VIF coefficients given in Table 36 show that the values are well below the recommended threshold. Furthermore, the VIF coefficient for each indicator was also assessed and they range between 1.364 – 4.148 for the negative purchase scenario and 1.650 – 3.598 for the positive purchase scenario. Therefore the chances of multicollinearity is ruled out from the Malaysian structural models.

4.7.4. Q^2 Values

The Stone-Gleisser Q^2 value shows the predictive power of the exogenous variables over the endogenous variables by using a technique named blindfolding. A Q^2 value above 0 is normally considered as acceptable implying that the variable has predictive relevance (HAIR et al., 2017). The predictive relevance for the Indian purchase scenario is reported in Table 37 and the Malaysian purchase scenario in Table 38.

Table 37. Predictive relevance (Q^2) for the Indian Purchase Scenarios

	SSO		SSE		Q^2 (=1-SSE/SSO)	
	Ind_Neg	Ind_Pos	Ind_Neg	Ind_Pos	Ind_Neg	Ind_Pos
CL*FPP	179.000	179.000	179.000	179.000		
CL	1,253.00	1,253.00	1,253.00	1,253.00		
FPP	537.000	537.000	537.000	537.000		
PC	895.000	895.000	895.000	895.000		
PS	1,253.000	1,253.000	674.069	699.386	0.462	0.442
RP	716.000	716.000	533.623	575.590	0.255	0.196
RI	895.000	895.000	827.210	847.058	0.076	0.054
SPI	716.000	716.000	658.608	660.936	0.080	0.077

Source: Author's own work based on SmartPLS results

The values reported in Table 37 show that both the positive and negative purchase scenarios have valid predictive relevance scores. The construct purchase satisfaction has the highest predictive relevance with 0.462 and 0.442. The repurchase intentions comes with the second highest values with 0.255 and 0.196. The Q^2 values for revenge intentions and strategic purchase intentions are also higher the 0 implying that they also have valid predictive relevance but much lesser than the other two constructs.

Table 38. Predictive relevance (Q^2) for the Malaysian Purchase Scenarios

	SSO		SSE		Q^2 (=1-SSE/SSO)	
	Ind_Neg	Ind_Pos	Ind_Neg	Ind_Pos	Ind_Neg	Ind_Pos
CL*FPP	153.000	180.000	153.000	180.000		
CL	1,071.000	1,260.000	1,071.000	1,260.000		
FPP	459.000	540.000	459.000	540.000		
PC	765.000	900.000	765.000	900.000		
PS	1,071.000	1,260.000	666.998	863.365	0.377	0.315
RP	612.000	720.000	417.507	601.963	0.318	0.164
RI	765.000	900.000	738.816	832.604	0.034	0.075
SPI	612.000	720.000	554.393	643.007	0.094	0.107

Source: Author's own work based on SmartPLS results

Table 38 shows the results for the Malaysian purchase scenarios. As in the case of Indian purchase scenarios, the construct purchase satisfaction has a higher predictive relevance in both purchase contexts. The construct repurchase intentions has a higher predictive relevance in the Malaysian negative purchase scenario as compared to the positive purchase scenario. The constructs revenge intentions and strategic purchase intentions also have valid predictive relevance score but with score much lesser than the other two constructs.

After ensuring that the quality of the measurement and structural model for the positive and negative purchase scenarios for India and Malaysia meet the standard requirements, the researcher proceeded with the hypotheses testing using the bootstrapping technique.

4.8. Hypotheses Testing and Bootstrapping Test Results

Bootstrapping is a non-parametric method which uses resampling techniques to estimate the significance of PLS coefficients. Since PLS SEM does not require the assumption that the data under study follows normal distribution, parametric tests are not applied to test the significance of the path coefficients, loadings etc. Bootstrapping basically is a non-parametric technique which works based on the assumption that the sample distribution gives the exact information about the population under study where it draws huge number of subsamples by substituting the original sample and estimate the model parameters for each resample. Subsamples are formed by haphazardly choosing numbers from the original dataset. These resamples are then used for testing the path model formulated. Usually, this process is continued until 5000 random samples are created (HENSELER, 2017). The significance of the path coefficients can be estimated using the t statistics as well as p values using the bootstrapping method. The hypotheses formulated for the study are the various paths given in the research model. Therefore, by testing the significance of each path coefficient, the associated hypothesis may be accepted or rejected.

Table 39. Bootstrapping Results for the Indian Negative Purchase Scenario

H#	Path	Original Sample (O)	Sample Mean (M)	Standard Deviation (STDEV)	T Statistics (|O/STDEV|)	P Values
H1a	FPP -> RP	-0.049	-0.044	0.1	0.489	0.625
H1b	FPP -> RI	-0.135	-0.157	0.146	0.924	0.356
H1c	FPP -> SPI	0.11	0.106	0.118	0.939	0.348
H1d	FPP -> PS	0.741	0.747	0.037	20.159	**0.000**
H2a	CL -> RP	0.302	0.304	0.069	4.352	**0.000**
H2b	CL -> RI	-0.132	-0.128	0.093	1.423	0.155
H2c	CL -> SPI	-0.044	-0.041	0.078	0.567	0.571
H2d	CL -> PS	0.171	0.166	0.049	3.46	**0.001**
H3a	PC -> RP	-0.066	-0.069	0.056	1.187	0.235
H3b	PC -> RI	0.259	0.261	0.082	3.174	**0.002**
H3c	PC -> SPI	0.313	0.324	0.076	4.119	**0.000**
H3d	PC -> PS	-0.053	-0.052	0.043	1.226	0.22
H4a	CL*FPP-> PS	0.154	0.144	0.05	3.071	**0.002**
H4b	PS -> RP	0.518	0.511	0.097	5.32	**0.000**
H4c	PS -> RI	-0.145	-0.127	0.137	1.063	0.288
H4d	PS -> SPI	-0.309	-0.308	0.109	2.845	**0.004**

Source: Author's own work based on SmartPLS results

The bootstrapping results reported in Table 39 shows that the influence of fair price perceptions on repurchase intentions (β = -0.0.049, $p > 0.05$), reprisal intentions (β = -0.135, $p > 0.05$) and strategic purchase intentions (β = 0.110, $p > 0.05$) are not significant. So the hypotheses H1a, H1b and H1c are not accepted. The fair price perception of the consumers has a very strong positive relationship (β = 0.741, $p < 0.001$) with purchase satisfaction. Hence the hypothesis H1d is accepted. The construct customer loyalty has a significant positive influence on the purchase satisfaction (β = 0.171, $p < 0.01$) and repurchase intentions (β = 0.302, $p < 0.001$) and hence the hypotheses H2d and H2b are accepted. However, the influence of customer loyalty on revenge intentions (β = -0.132, $p > 0.05$) and strategic purchase intentions (β = -0.132, $p > 0.05$) are not significant as per the results and the hypotheses H2a and H2c stand rejected. The construct privacy concerns also doesn't have a significant influence on purchase satisfaction (β = -0.053, $p > 0.05$) and repurchase intentions (β = -0.066, $p > 0.05$) and we reject hypotheses H3d and H3b. Privacy concerns shows a positive and significant relationship with revenge intentions (β = 0.259, $p < 0.01$)

and strategic purchase intentions (β = 0.313, $p < 0.01$). Hence, we accept hypotheses H3c and H3a. The customer loyalty plays the role of a positive moderator in the relationship between the fair price perception of consumers and purchase satisfaction (β = 0.154, $p < 0.01$). The results also show that purchase satisfaction is negatively correlated with strategic purchase intentions implying that an increase in purchase satisfaction will bring down the intentions of consumers to display a strategic purchase behaviour (β = -0.145, $p < 0.01$). However, the relationship between purchase satisfaction and reprisal intentions although depict a negative correlation is not significant (β = -0.309, $p < 0.01$). There is a strong positive relationship between purchase satisfaction and repurchase intentions (β = 0.518, $p < 0.01$). So, we accept hypotheses H4a, H4b, H4d and reject H4c. The structural model for Indian negative purchase scenario with the bootstrapping results and t statistics is given in figure 24.

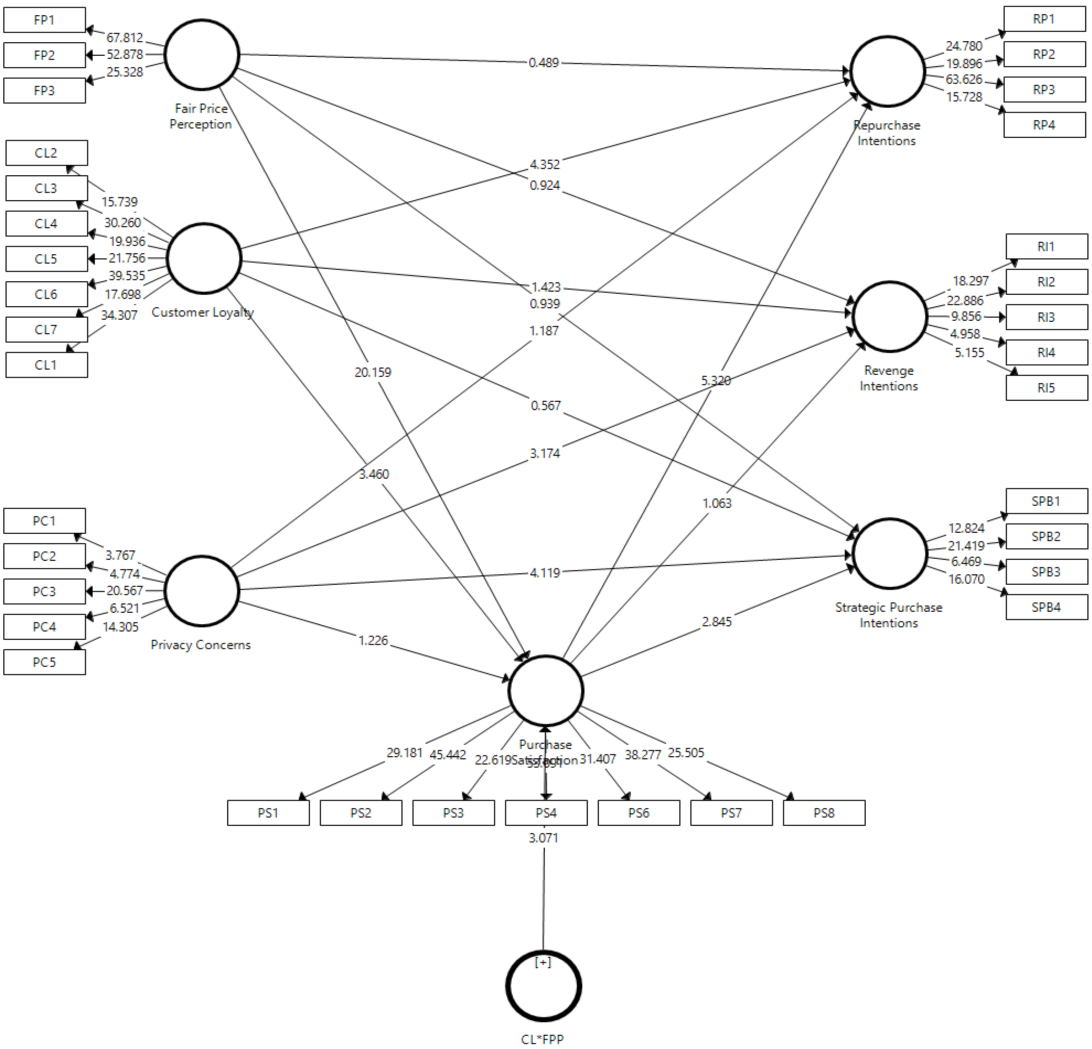


Figure 24. Bootstrapping Results for the Indian Negative Purchase Scenario with 5000 iterations

Source: Author`s Own Work using SmartPLS

Table 40. Bootstrapping Results for the Indian Positive Purchase Scenario

H#	Path	Original Sample (O)	Sample Mean (M)	Standard Deviation (STDEV)	T Statistics (|O/STDEV|)	P Values
H1a	FPP -> RP	-0.125	-0.122	0.104	1.20	0.230
H1b	FPP -> RI	0.218	0.223	0.12	1.81	0.070
H1c	FPP -> SPI	-0.103	-0.11	0.117	0.873	0.383
H1d	FPP -> PS	0.632	0.631	0.044	14.296	**0.000**
H2a	CL -> RP	0.396	0.398	0.081	4.877	**0.000**
H2b	CL -> RI	0.013	0.014	0.135	0.098	0.922
H2c	CL -> SPI	0.05	0.046	0.095	0.521	0.603
H2d	CL -> PS	0.263	0.265	0.047	5.541	**0.000**
H3a	PC -> RP	-0.172	-0.175	0.063	2.742	**0.006**
H3b	PC -> RI	0.313	0.318	0.075	4.189	**0.000**
H3c	PC -> SPI	0.252	0.259	0.075	3.369	**0.001**
H3d	PC -> PS	-0.035	-0.03	0.048	0.729	0.466
H4a	CL*FPP-> PS	-0.047	-0.049	0.031	1.527	0.127
H4b	PS -> RP	0.318	0.315	0.113	2.814	**0.005**
H4c	PS -> RI	-0.306	-0.315	0.136	2.244	**0.025**
H4d	PS -> SPI	0.343	0.358	0.128	2.677	**0.007**

Source: Author's own work based on SmartPLS results

The results reported in Table 40 shows that the construct fair price perception has a strong influence on purchase satisfaction ($\beta = 0.632$, $p < 0.01$) and similar to the Indian negative purchase scenario, the construct doesn't have a significant influence on the constructs repurchase intentions ($\beta = -0.125$, $p > 0.05$), reprisal intentions ($\beta = 0.218$, $p > 0.05$) and strategic purchase intentions ($\beta = -0.103$, $p > 0.05$). Hence the hypothesis H1d is accepted and the hypotheses H1b, H1c and H1a are rejected. Customer loyalty has a positive and significant influence on purchase satisfaction ($\beta = 0.263$, $p < 0.01$) and repurchase intentions ($\beta = 0.396$, $p < 0.01$). The influence of customer loyalty on revenge intentions ($\beta = 0.013$, $p > 0.05$) and strategic purchase intentions ($\beta = 0.050$, $p > 0.05$) are also not significant. So, the hypotheses H2d and H2b are accepted and H2a and H2c are rejected. The construct privacy concerns has a negative influence on repurchase intentions ($\beta = -0.172$, $p < 0.05$) implying that a highly privacy conscious consumer might not be interested in making further purchases from a seller who uses personal information for customising prices. The relationship between privacy concerns and reprisal intentions is positive and significant ($\beta = 0.313$, $p < 0.01$). Privacy concerns can also increase the intentions to display a strategic purchase behaviour as they have a positive and significant relationship ($\beta = 0.252$, $p < 0.01$). However, the relationship between privacy concerns and purchase satisfaction is not significant for the Indian positive purchase scenario (β = -0.035, p > 0.05). Hence, we accept hypotheses H3a, H3b and H3c and reject H3d. The construct Customer Loyalty's role as a moderator in the relationship between fair price perception and purchase satisfaction is not significant for the Indian positive purchase scenario (β = -0.47, p > 0.05). The construct purchase satisfaction has a negative and significant relationship with reprisal intentions of the consumers (β = -0.306, p < 0.05) and a significant positive relationship with repurchase intentions (β = 0.318, p < 0.05). Furthermore, purchase satisfaction is positively related to the construct strategic purchase intentions (β = 0.343, p < 0.05). So we reject hypothesis H4a and accept H4b, H4c, H4d.

The structural model for the Indian positive purchase scenario with the bootstrapping result and t statistics is given in figure 25.

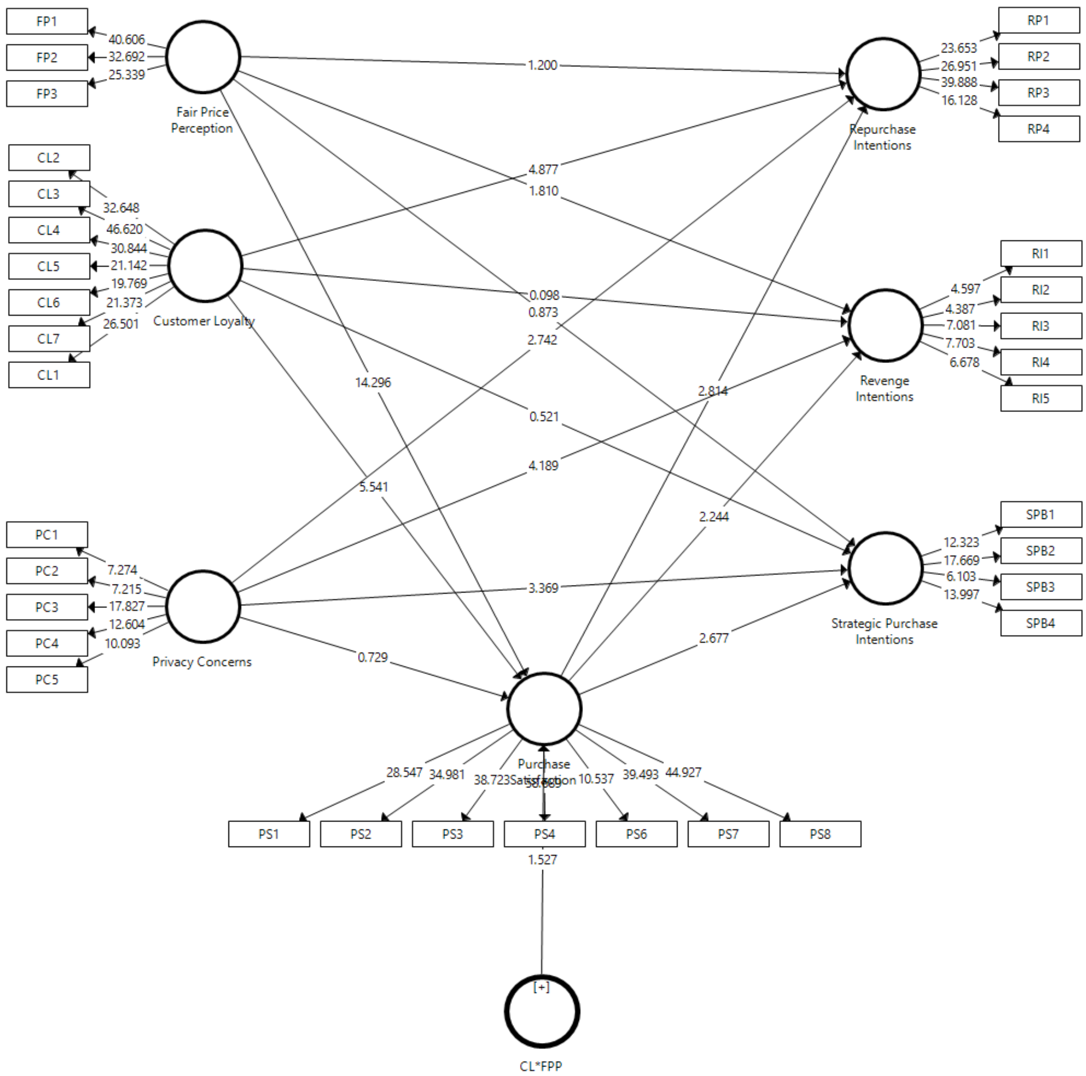


Figure 25. Bootstrapping Results for the Indian Positive Purchase Scenario with 5000 Iterations

Source: Author's Own Work using SmartPLS

Table 41. Bootstrapping Results for the Malaysian Negative Purchase Scenario

H#	Path	Original Sample (O)	Sample Mean (M)	Standard Deviation (STDEV)	T Statistics (|O/STDEV|)	P Values
H1a	FPP -> RP	0.017	0.014	0.108	0.161	0.872
H1b	FPP -> RI	-0.113	-0.118	0.173	0.649	0.516
H1c	FPP -> SPI	-0.367	-0.371	0.129	2.835	**0.005**
H1d	FPP -> PS	0.671	0.673	0.05	13.544	**0.000**
H2a	CL -> RP	0.436	0.434	0.07	6.184	**0.000**
H2b	CL -> RI	0.127	0.121	0.126	1.002	0.316
H2c	CL -> SPI	0.172	0.18	0.09	1.909	0.056
H2d	CL -> PS	0.158	0.156	0.06	2.654	**0.008**
H3a	PC -> RP	-0.03	-0.03	0.055	0.538	0.591
H3b	PC -> RI	0.23	0.231	0.113	2.04	**0.041**
H3c	PC -> SPI	0.222	0.233	0.106	2.084	**0.037**
H3d	PC -> PS	-0.058	-0.053	0.05	1.16	0.246
H4a	CL*FPP-> PS	0.065	0.065	0.042	1.543	0.123
H4b	PS -> RP	0.42	0.426	0.107	3.908	**0.000**
H4c	PS -> RI	0.225	0.227	0.144	1.556	0.120
H4d	PS -> SPI	0.116	0.125	0.107	1.083	0.279

Source: Author's own work based on SmartPLS results

The bootstrapping results for the Malaysian positive purchase scenario as given in Table 41 shows that the construct Fair price perception does not have a significant influence on repurchase intentions ($\beta = 0.017$, $p > 0.05$) and revenge intentions ($\beta = 0.516$, $p > 0.05$) and the hypotheses H1a, H1b are rejected. Another important finding is that the fair price perceptions has a significant negative influence on the strategic purchase intentions of consumers ($\beta = -0.367$, $p < 0.01$). The construct fair price perception has a positive and direct influence on purchase satisfaction as in Indian positive and negative purchase scenarios ($\beta = 0.671$, $p < 0.01$). Hence the hypotheses H1c and H1d are accepted. Customer loyalty has a positive influence on purchase satisfaction ($\beta = 0.158$, $p < 0.05$) and repurchase intentions ($\beta = 0.436$, $p < 0.01$) and so, we accept hypotheses H2a and H2d. However, customer loyalty does not have a significant influence on purchase satisfaction ($\beta = 0.127$, $p > 0.05$) and strategic purchase intentions ($\beta = 0.172$, $p > 0.05$). Hence the hypotheses H2b and H2c stand rejected. The relationship between privacy concerns and repurchase intentions is not significant ($\beta = -0.03$, $p > 0.05$). There is a significant positive relationship between privacy concerns and reprisal intentions ($\beta = 0.23$, $p < 0.05$), implying that as privacy concerns increase the reprisal intentions of consumers also increase. Privacy concerns also does not have a significant influence on the purchase satisfaction of the consumers ($\beta = -0.058$, $p > 0.05$). So the hypotheses H3a, H3d are rejected and the hypotheses H3b and H3c are accepted. Customer loyalty does not have a significant influence on the relationship between fair price perception and purchase satisfaction (β = 0.065, $p > 0.05$). The influence of purchase satisfaction on the repurchase intentions is significant and positive (β = 0.23, $p < 0.05$). However, it does not have a statistically significant influence on reprisal intentions (β = 0.225, $p > 0.05$) and strategic purchase intentions (β = 0.116, $p > 0.05$). So the hypotheses H4a, H4c H4d stand rejected and H4b is accepted.

The structural model for the Malaysian negative purchase scenario with the bootstrapping result and t statistics is given in figure 26.

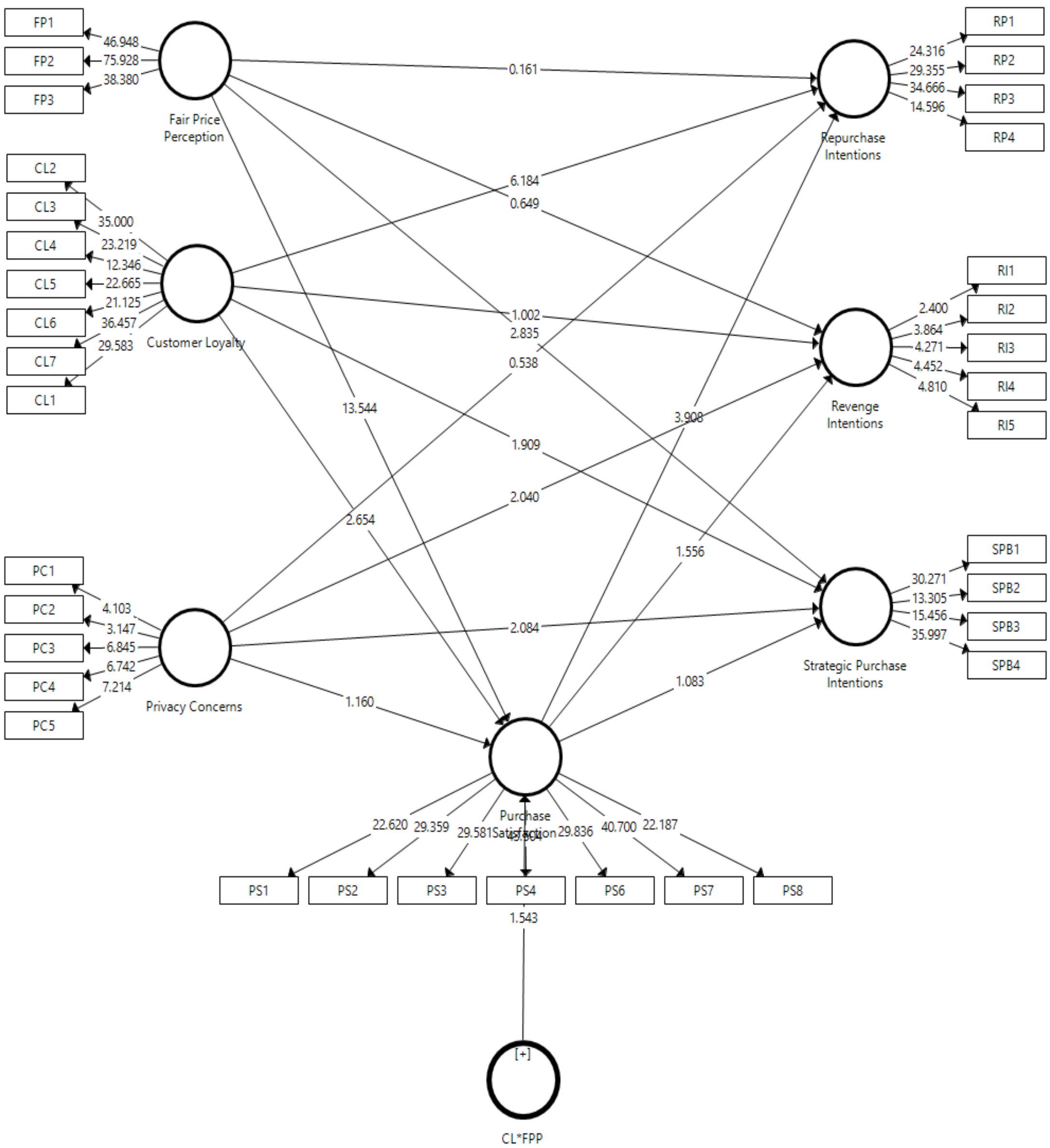


Figure 26. Bootstrapping Results for the Malaysian Positive Purchase Scenario with 5000 Iterations

Source: Author's Own Work using SmartPLS

Table 42: Bootstrapping Results for the Malaysian Positive Purchase Scenario

H#	Path	Original Sample (O)	Sample Mean (M)	Standard Deviation (STDEV)	T Statistics (|O/STDEV|)	p values
H1a	FPP -> RP	0.084	0.088	0.088	0.949	0.343
H1b	FPP -> RI	-0.115	-0.119	0.091	1.252	0.211
H1c	FPP -> SPI	-0.136	-0.135	0.076	1.806	0.071
H1d	FPP -> PS	0.583	0.585	0.056	10.444	**0.000**
H2a	CL -> RP	0.368	0.373	0.074	4.94	**0.000**
H2b	CL -> RI	0.136	0.138	0.086	1.592	0.112
H2c	CL -> SPI	0.058	0.06	0.093	0.621	0.535
H2d	CL -> PS	0.322	0.321	0.064	5.041	**0.000**
H3a	PC -> RP	-0.124	-0.125	0.083	1.501	0.133
H3b	PC -> RI	0.341	0.35	0.079	4.349	**0.000**
H3c	PC -> SPI	0.355	0.359	0.095	3.741	**0.000**
H3d	PC -> PS	0.048	0.045	0.077	0.626	0.531
H4a	CL*FPP-> PS	-0.179	-0.177	0.063	2.829	**0.005**
H4b	PS -> RP	0.210	0.201	0.098	2.146	**0.032**
H4c	PS -> RI	-0.177	-0.175	0.104	1.699	0.089
H4d	PS -> SPI	0.298	0.304	0.085	3.518	**0.000**

Source: Author’s own work based on SmartPLS results

The results reported in Table 42 show that the construct fair price perceptions does not have a statistically significant relationship with revenge intentions (β = -0.115, $p > 0.05$) repurchase intentions (β = 0.084, $p > 0.05$) and strategic purchase intentions (β = -0.136, $p > 0.05$). So, the hypotheses H1a, H1b, H1c are rejected. Fair price perception has a very high positive significant relationship with purchase satisfaction (β = 0.583, $p < 0.01$), hence hypothesis H1d is accepted. Customer Loyalty does not have a significant relationship with revenge intentions (β = 0.136, p > 0.05) and strategic purchase intentions (β = 0.058, $p > 0.05$). So, the hypotheses H2c and H2d are not supported. However, there is a significant positive relationship existing between customer loyalty and purchase satisfaction (β = 0.322, $p < 0.01$) and also between customer loyalty repurchase intentions (β = 0.368, $p < 0.01$), hence the hypotheses H2a and H2d are supported. The relationship between privacy concerns and purchase satisfaction is not significant (β = 0.048, p > 0.05). Privacy concerns also has a non-significant relationship with repurchase intentions (β = -0.124, $p > 0.05$). So, the hypotheses H3d and H3b are rejected. The relationship between privacy concerns and revenge intentions is positive and significant (β = 0.341, $p < 0.01$). A significant and positive relationship also exists between privacy concerns and strategic purchase intentions (β = 0.355, $p < 0.01$) and hence we accept H3c and H3d. The construct customer loyalty does play the role of a negative moderator in the relationship between Fair Price Perception and Purchase

Satisfaction (β = 0.436, p < 0.01). The construct purchase satisfaction has a positive and significant relationship with repurchase intentions (β = 0.210, p < 0.05) and strategic purchase intentions (β = 0.298, p < 0.01). Purchase satisfaction has a non-significant relationship with revenge intentions (β = 0.298, p > 0.05). Hence the hypotheses H4a, H4b and H4d are accepted and H4c is rejected.

The structural model for the Malaysian negative purchase scenario with the bootstrapping result and t statistics is given in figure 27.

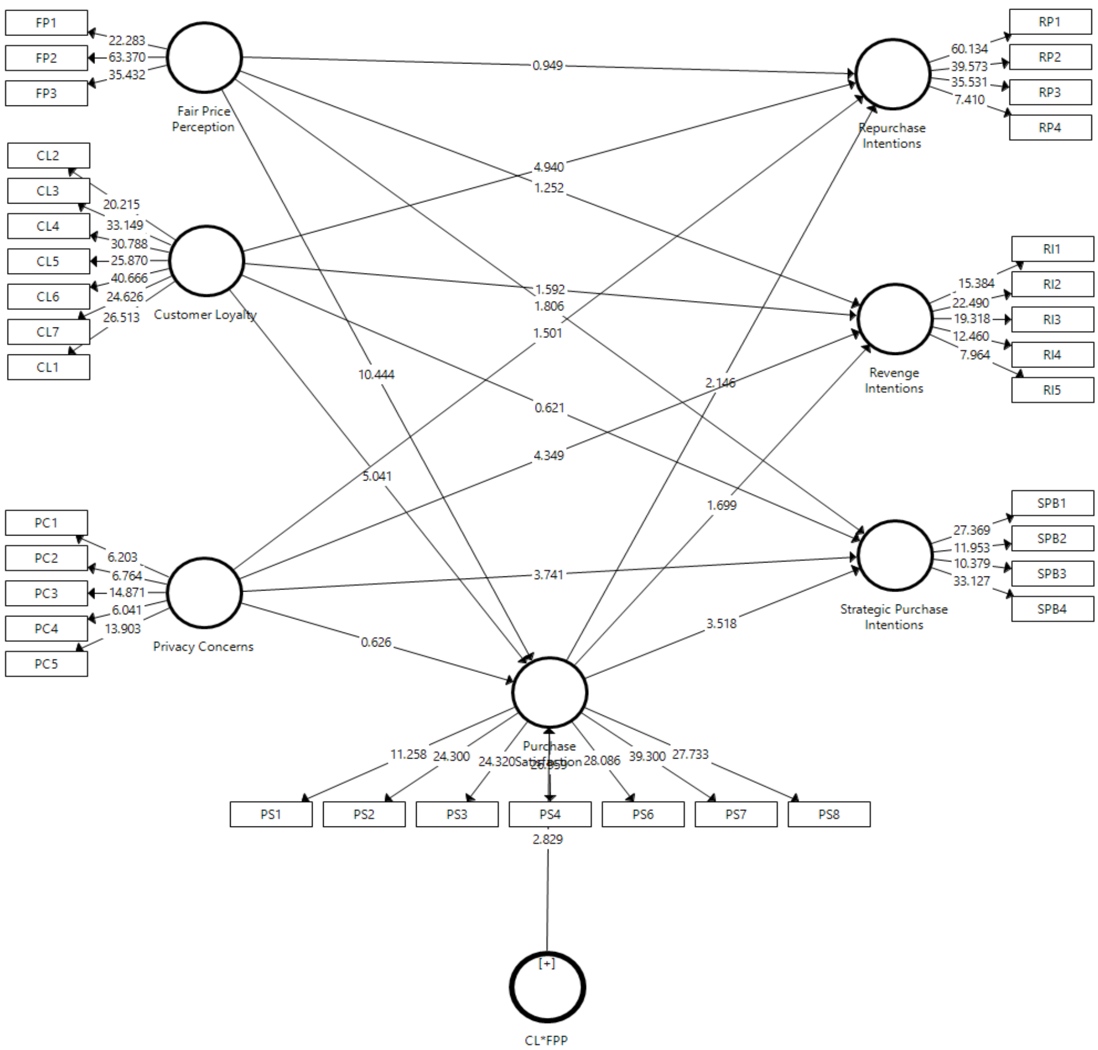


Figure 27. Bootstrapping Results for the Malaysian Positive Purchase Scenario with 5000 Iterations

Source: Author’s Own Work using SmartPLS

The summary of the hypotheses test results for the positive and negative purchase scenarios for India and Malaysia is given in Table 43.

Table 43. Summary of the Hypotheses Test results for the Indian and Malaysian Purchase Scenarios

Hypotheses		Ind_Neg	Mal_Neg	Ind_Pos	Mal_Pos
Hypothesis 1a	Fair Price Perception of consumer positively influences the repurchase intentions	Not Supported	Not Supported	Not Supported	Not Supported
Hypothesis 1b	Fair Price Perception of consumers negatively influences the revenge intentions.	Not Supported	Not Supported	Not Supported	Not Supported
Hypothesis 1c	Fair Price Perception of consumer negatively influences the strategic purchase intentions.	Not Supported	**Supported**	Not Supported	Not Supported
Hypothesis 1d	Fair Price Perceptions of consumers positively influences the satisfaction with the purchase.	**Supported**	**Supported**	**Supported**	**Supported**
Hypothesis 2a	Loyalty towards seller positively influences the repurchase intentions of the consumers.	**Supported**	**Supported**	**Supported**	**Supported**
Hypothesis 2b	Loyalty towards seller negatively influences the revenge intentions of the consumers	Not Supported	Not Supported	Not Supported	Not Supported
Hypothesis 2c	Loyalty towards seller negatively influences the strategic purchase intentions of the consumers.	Not Supported	Not Supported	Not Supported	Not Supported
Hypothesis 2d	Loyalty towards seller positively influences the consumers` satisfaction with purchase.	**Supported**	**Supported**	**Supported**	**Supported**
Hypothesis 3a	Privacy concerns negatively influences the repurchase intentions of the consumers.	Not Supported	Not Supported	**Supported**	Not Supported
Hypothesis 3b	Privacy concerns positively influences the revenge intentions of the consumers.	**Supported**	**Supported**	**Supported**	**Supported**
Hypothesis 3c	Privacy concerns positively influences the strategic purchase intentions of the consumers.	**Supported**	**Supported**	**Supported**	**Supported**
Hypothesis 3d	Privacy concerns negatively influences the consumers' satisfaction with the purchase.	Not Supported	Not Supported	Not Supported	Not Supported
Hypothesis 4a	Customer Loyalty psotively moderates the relationship between fair price perceptions and purchase satisfaction.	**Supported**	Not Supported	Not Supported	Not Supported
Hypothesis 4b	Purchase satisfaction positively influences the repurchase intentions of the consumers.	**Supported**	**Supported**	**Supported**	**Supported**
Hypothesis 4c	Purchase satisfaction negatively influences the revenge intentions of the consumers.	Not Supported	Not Supported	**Supported**	Not Supported
Hypothesis 4d	Purchase satisfaction negatively influences the strategic purchase intentions of the consumers.	**Supported**	Not Supported	Not Supported	Not Supported

Source: Author's own construction

4.9. Multi-Group Analysis

The Multi Group Analysis (MGA) is conducted to check if there is any significant difference between the groups under study (HENSELER et al., 2009). For this purpose, the data for the Indian and Malaysian positive purchase scenario was combined as the first group and the data for the Malaysian and Indian negative purchase scenario was combined as the second group. The groups were tested to identify any significant differences in the path coefficients. The significance of path differences can be checked using three methods namely, Constrained Latent Growth Test, Satterthwaite Test and Pooled Standard Error Test. For this study, the results of the Constrained Latent Growth Test are reported.

Table 43. Multigroup Analysis – Indian and Malaysian Respondents

	Path Coefficients- GROUP_country (Negative Purchase Scenarios)			**Path Coefficients - GROUP_country (Positive Purchase Scenarios)**		
	Ind_Neg	**Mal_Neg**	**p value**	**Ind_Pos**	**Mal_Pos**	**p value**
CL*FPP-> PS	0.182	-0.003	**0.012**	0.095	-0.171	0.492
CL -> PS	0.171	0.181	0.145	0.275	0.317	**0.001**
CL -> RP	0.332	0.422	0.168	0.375	0.395	0.070
CL -> RI	-0.191	-0.004	**0.020**	-0.069	0.070	0.193
CL -> SPI	-0.196	0.208	**0.044**	0.070	0.063	0.101
FPP -> PS	0.718	0.680	0.286	0.677	0.516	**0.001**
FPP -> RP	-0.055	0.070	0.238	0.140	0.136	0.096
FPP -> RI	-0.191	-0.049	**0.006**	0.153	-0.173	**0.043**
FPP -> SPI	-0.016	-0.340	0.201	-0.017	-0.012	**0.044**
PC -> PS	0.003	-0.028	0.324	0.011	0.141	0.318
PC -> RP	-0.074	-0.045	0.298	-0.166	-0.164	0.311
PC -> RI	0.204	0.268	0.385	0.153	0.355	0.177
PC -> SPI	0.216	0.256	0.232	0.208	0.279	0.266
PS -> RP	0.433	0.372	0.399	0.366	0.144	0.163
PS -> RI	-0.126	0.228	**0.001**	-0.192	-0.107	0.291
PS -> SPI	-0.328	-0.129	**0.048**	0.260	0.290	0.238

Source: Author's own work based on WarpPLS results

The Multigroup analysis results as reported in Table 43 shows that there is a statistically significant difference between the Malaysian and Indian respondents for many paths. For the negative purchase scenario, it could be seen that customer loyalty is a positive moderator in the relationship between fair price perceptions and purchase satisfaction in the Indian purchase scenario but for the Malaysian purchase scenario, it is negative, and the coefficient size is too small. The relationship between customer loyalty and revenge intentions is negative and significant however, again for the Malaysian purchase scenario, the coefficient size is too small. The relationship between customer loyalty and strategic purchase intentions is negative for the Indian purchase scenario but positive in the Malaysian purchase scenario. There is a negative relationship between fair price perceptions and strategic purchase intentions in the Indian purchase scenario and the Malaysian purchase scenario. However, the coefficient size is small in the Malaysian purchase scenario as compared to the Indian scenario. For the relationship between purchase satisfaction and revenge intentions, the Malaysian purchase scenario shows a positive relationship and Indian purchase scenario shows a negative relationship. The relationship between purchase satisfaction and strategic purchase intentions is negative and significant for both purchase scenarios.

The results of the multigroup analysis for the negative purchase scenarios hint that the loyalty of the Malaysian respondents to the seller is considerably lower than that of the Indian respondents which does explain the reasons for the Malaysian respondents' higher intentions to display a strategic purchase behaviour and revenge intentions despite the high purchase satisfaction levels. The results also explain that the Malaysian respondents are more vulnerable in a negative purchase situation than the Indian respondents.

In the positive purchase scenario, the relationship between customer loyalty and purchase satisfaction is positive and significant. The relationship between fair price perceptions and purchase satisfaction is also significant in the positive purchase scenarios for both countries. For the relationship between fair price perceptions and revenge intentions, surprisingly the Indian purchase scenario shows a positive relationship and the same is negative for the Malaysian purchase scenario. The relationship between fair price perceptions and strategic purchase intentions is negative in both purchase scenarios.

The results for the positive purchase scenarios show that both Indian and Malaysian respondents exhibit similar behaviour except for the relationship between fair price perceptions and revenge intentions. For the Indian respondents, the relationship between fair price perceptions and revenge intentions is positive implying that rather than changes in prices, there is something else which considerably influences the revenge intentions of the Indian consumers.

4.10. Mediation Analysis

Bootstrapping process in SmartPLS estimate the bootstrapped path coefficients and indirect effects. Indirect effect is used to show the mediation effects. When a third variable interferes in the relationship between an independent and dependent variable, a mediation effect is said to exist

(HADI, et al., 2016). It is important to check for the mediation effects separately in each purchase scenario as purchase satisfaction is a taken as a mediator construct, mediating the relationship between the dependent and independent variables. The mediation effect will throw light on any indirect relationship between the independent and dependent variables as mediated by purchase satisfaction.

The results of the Mediation effects for Indian purchase scenarios are given in Table 44.

Table 44. Indirect Effects – Indian Purchase Scenarios

Path	**Original Sample (O)**		**T Statistics (|O/STDEV|)**		**p value**	
	Ind_Neg	Ind_Pos	Ind_Neg	Ind_Pos	Ind_Neg	Ind_Pos
CL*FPP ->PS -> RP	0.091	-0.015	2.681	1.293	**0.007**	0.196
CL -> PS -> RP	0.104	0.064	3.028	2.017	**0.002**	**0.044**
FPP -> PS -> RP	0.428	0.148	5.442	2.058	**0.000**	**0.040**
PC -> PS -> RI	-0.025	-0.007	0.997	0.490	0.319	0.624
CL*FPP -> PS -> RI	-0.021	0.015	0.827	1.066	0.408	0.286
CL -> PS -> RI	-0.024	-0.066	0.831	1.488	0.406	0.137
FPP-> PS -> RI	-0.097	-0.153	0.886	1.540	0.376	0.124
PC ->PS-> RI	0.006	0.007	0.550	0.439	0.582	0.661
CL*FPP -> PS-> SPI	-0.047	-0.021	1.880	1.317	0.060	0.188
CL -> PS -> SPI	-0.054	0.091	2.059	2.125	**0.040**	**0.034**
FPP -> PS -> SPI	-0.221	0.211	2.509	2.382	**0.012**	**0.017**
PC -> PS -> SPI	0.013	-0.010	0.878	0.457	0.380	0.648

Source: Author's own work based on SmartPLS results

The mediation effects reported in Table 44 for Indian purchase scenarios show that the construct customer loyalty which plays the role of moderator in the relationship between fair price perception and purchase satisfaction has a positive indirect effect on the repurchase intentions. However, the beta value is considerably small ($\beta = 0.091, p < 0.05$). The construct customer loyalty has an indirect effect on repurchase intentions in both positive ($\beta = 0.104, p < 0.05$) and negative purchase scenarios ($\beta = 0.064, p < 0.05$). The Beta value for the positive purchase scenario is comparatively smaller than the negative purchase scenario. Fair price perception has a positive mediation effect on the repurchase intentions in both positive ($\beta = 0.428, p < 0.05$) and negative purchase scenarios ($\beta = 0.148, p < 0.05$). Customer loyalty has a negative mediation effect on the strategic purchase intentions in the Indian negative purchase scenario ($\beta = -0.054, p < 0.05$) and a positive mediation effect on strategic purchase intentions in the positive purchase scenario ($\beta = 0.091, p < 0.05$). The construct fair price perceptions also has a negative mediation effect on the strategic purchase intentions in the negative purchase scenario (β = -0.221, $p < 0.05$) and a positive mediation effect on the strategic purchase intentions in the positive purchase scenario (β = 0.211, $p < 0.05$). Other specific indirect effects given in the table are not statistically significant.

Table 45. Indirect Effects – Malaysian Purchase Scenarios

Path	**Original Sample (O)**		**T Statistics (|O/STDEV|)**		**p value**	
	Mal_Neg	Mal_Pos	Mal_Neg	Mal_Pos	Mal_Neg	Mal_Pos
CL*FPP ->PS -> RP	0.018	-0.038	1.046	1.598	0.295	0.110
CL -> PS -> RP	0.065	0.068	2.144	1.984	**0.032**	**0.047**
FPP -> PS -> RP	0.259	0.122	2.956	2.081	**0.003**	**0.037**
PC -> PS -> RI	-0.012	0.010	0.536	0.565	0.592	0.572
CL*FPP -> PS -> RI	0.012	0.032	0.817	1.399	0.414	0.162
CL -> PS -> RI	0.042	-0.057	1.393	1.564	0.164	0.118
FPP-> PS -> RI	0.168	-0.103	1.691	1.622	0.091	0.105
PC ->PS-> RI	-0.008	-0.009	0.461	0.531	0.645	0.596
CL*FPP -> PS-> SPI	0.010	-0.053	0.883	2.021	0.377	**0.043**
CL -> PS -> SPI	0.036	0.096	1.605	2.703	0.109	**0.007**
FPP -> PS -> SPI	-0.142	0.174	1.742	3.299	0.082	**0.001**
PC -> PS -> SPI	-0.006	0.014	0.462	0.588	0.644	0.557

Source: Author's own work based on SmartPLS results

The mediation results as given in Table 45 shows similar results to Indian purchase scenarios where the relationship between customer loyalty and repurchase intentions were mediated by purchase satisfaction in the Malaysian negative (β = 0.065, $p < 0.05$) and positive (β = 0.068, $p < 0.05$) purchase scenario. However, the size of the coefficient is small in both scenarios. Purchase satisfaction also mediates the relationship between fair price perceptions and repurchase intentions in negative (β = 0.259, $p < 0.05$) and positive (β = 0.122, $p < 0.05$). The indirect effect of customer loyalty which moderates the relationship between fair price perception and purchase satisfaction on strategic purchase intentions is significant in Malaysian positive purchase scenario (β = 0.010, $p < 0.05$). The relationship between customer loyalty and strategic purchase intentions is positively mediated by purchase satisfaction (β = 0.036, $p < 0.05$) in the Malaysian positive purchase scenario. There is a negative mediation effect in the relationship between fair price perception and strategic purchase intention (β = -0.142, $p < 0.05$) in the Malaysian positive purchase scenario. Other indirect effects given are not significant.

4.11. Overall Model Fit Assessment

The most popular model fit criteria used in the PLS based SEM analysis are the Standardised Root Mean Square Residual (SRMR) and the Normalised Fit Index (NFI) (HENSELER, 2017). SRMR shows the approximate fit of the model formulated by calculating the difference between the observed correlation matrix and model-based correlation matrix. This implies that a lower SRMR value shows a better fit. Conventionally, a value below 0.08 is considered as a good fit (HU & BENTLER, 1998). However, in case of PLS SEM, more flexible cutoff of up to 0.10 can be considered as acceptable model fit (HENSELER et al., 2015). For the Normalised Fit Index (NFI), values above 0.90 is considered as acceptable (BENTLER AND BONETT, 1980). The other two measures; d_ULS (the Squared Euclidean Distance) and d_G (the geodesic distance) are two different methods to estimate the discrepancy between estimated model and the saturated model. HENSELER & SARSTEDT (2013) states that the use of PLS based Goodness of Fit (GoF) such as 'Tenenhaus GoF' does not give proper information about the goodness of model fit. Hence the use of it is not recommended if the purpose of a research is to test or compare models.

Table 46. Assessing Overall Model Fit for Indian and Malaysian Purchase Scenarios

	Estimated Model			
	Ind_Neg	**Ind_Pos**	**Mal_Neg**	**Mal_Pos**
SRMR	0.077	0.082	0.084	0.08
d_ULS	4.727	4.192	4.429	4.016
d_G	1.165	1.436	1.3	1.326
Chi-Square	1,112.09	1,353.51	1,104.94	1,258.76
NFI	0.936	0.899	0.908	0.923

Source: Author's own work based on SmartPLS results

The model assessment results as given in Table 46 shows that all four model satisfy the SRMR requirement as suggested by HENSELER et al (2013). Indian negative purchase scenario and Malaysian positive purchase scenario satisfy the 0.08 cut off requirement as given by HU & BENTLER (1998). All four models further satisfy the Normalised Fit Index (NFI) criterion as well. Hence, the overall model fit of all four models are confirmed.

4.12. Discussion of the Findings

The study examined how personalised pricing influences the fair price perceptions, privacy concerns, purchase satisfaction and the ensuing impact on the post purchase reactions such as repurchase intentions, revenge intentions and strategic purchase intentions. The mediating role of purchase satisfaction in the relationship between the independent constructs (fair price perceptions, customer loyalty and privacy concerns) and the dependent constructs (repurchase intentions, revenge intentions and strategic purchase intentions) was also investigated. Furthermore, the role of customer loyalty in moderating the relationship between fair price perceptions and purchase satisfaction was examined explicitly. The positive and negative hypothetical purchase scenarios developed for the study based on a previous research (DAI, 2010) helped the respondents figure out the basics of personalised pricing tactics. The model developed was tested with the responses collected for the positive and negative purchase scenarios from India and Malaysia. After confirming the validity requirements of all four models separately, bootstrapping was applied to test the structural models and the hypotheses formulated.

From the results in general, it could be seen that the fair price perceptions of the consumers have a very strong positive influence on the purchase satisfaction in the negative and positive purchase scenarios for the respondents in both India and Malaysia. This finding corroborates with the results of the previous studies which show that perceived price fairness has a positive association with customer's overall purchase satisfaction (FORNELL, 1992; CRONIN, 2000; MARTIN-CONSUEGRA et al., 2007). The relationship between fair price perceptions and repurchase intentions is fully mediated by purchase satisfaction in both purchase scenarios for the two countries. The results showed a strong positive mediation effect. However, the direct relationship between the two constructs is insignificant in both purchase scenarios. This finding implies that although fair price perceptions has a strong influence on repurchase intentions, many other factors such as brand image, availability of different varieties of products, the customer service rendered by the store etc. may also have an impact on the repurchase intentions. Since these are factors which improve the overall purchase satisfaction of a customer, focusing on improving price perceptions without managing the aforementioned factors may seem to be less likely to increase the repurchase intentions of consumers.

An interesting result from the study is that the relationship between fair price perceptions and revenge intentions was not significant in both purchase scenarios for the two countries. There was no mediation effect of purchase satisfaction in the relationship between the two as well. This conjecture may perhaps pertain to the fact that the respondents are already used to the extremely fluctuating pricing situations such as in airline booking, hotel room booking etc. They might be of the view that volatile prices are very common in today's world, hence there is no need to express their negative emotions towards the seller. The fair price perceptions of the consumers do not have a significant influence on the strategic purchase intentions in all scenarios except for the Malaysian negative purchase scenario where there is a negative relationship between the two. The mediation results show that there is a significant negative mediation effect in the Indian negative purchase and a positive mediation effect in the Indian positive and Malaysian positive purchase scenarios. These findings portray that when the respondents in the negative purchase scenarios were hurt by the fluctuation in prices of high magnitude, the respondents in the positive purchase scenarios considered it as an opportunity to purchase products at lower prices. These results are in line with the findings of a previous study conducted by the author in Poland (VICTOR et al., 2019b).

The construct customer loyalty was set as an antecedent factor to distinctly see its impact on the post purchase reactions. Customer loyalty has a positive influence on the repurchase intentions in both purchase scenarios for two countries. This result is supported by many other studies in the field (DIXON et al., 2005; POWERS & VALENTINE, 2008; CURTIS et al., 2011) showing that customer loyalty has a positive relationship with the repurchase intentions. The loyalty towards the seller didn't have a significant relationship with both revenge intentions and strategic purchase intentions. However, in Indian negative purchase scenario, purchase satisfaction plays the role of a weak negative mediator in the relationship between customer loyalty and strategic purchase intentions and a weak positive mediator role in the Indian positive purchase scenario. This result depicts the attitude of the respondents where they use the situation for their advantage in the positive purchase scenario and also express their concerns that offering a fair price would reduce the strategic purchase intentions in a negative purchase scenario. The Malaysian negative purchase scenario however, shows an interesting result that purchase satisfaction plays a weak positive moderator role in the relationship between customer loyalty and strategic purchase intentions. These results could be related to the findings of SUH & YI (2012) reporting that even a loyal and satisfied customer is susceptible to other situational factors such as offers by the competitors, better prices etc. Customer Loyalty has a significant positive relationship with the purchase satisfaction in both purchase scenarios for the two countries. Purchase satisfaction also mediates the relationship between customer loyalty and repurchase intentions in both purchase scenarios for the two countries under study. This result is in line with the findings of OLIVER (1999) and JULANDER et al (2003) stating that loyal customers are typically the most satisfied ones. This research also confirms that loyal customers are satisfied with the seller and display higher repurchase intentions.

Privacy concerns was included in the scale to capture the respondent's fears and concerns about data sharing in a personalised pricing environment. Except for the Indian positive purchase scenario, privacy concerns did not have a significant influence on the repurchase intentions of the consumers. It is very interesting to notice that privacy concerns has a significant positive relationship with the revenge intentions and strategic purchase intentions in both purchase scenarios for the two countries. The stacked chart analysis also showed the increased concerns of the respondents in both countries regarding the sharing of their personal data with the sellers. This imply that as privacy concerns of the customers increase, they will resort to revenge intentions which include spreading negative news against the seller, shunning the seller altogether, buying from the competitors etc. The studies by FORTES & RITA (2016) and EASTLICK et al (2006) also show that as privacy concerns increases, the consumer trust on the seller decreases which may lead to the display of retaliatory acts like buying from the competitors. The positive relationship between privacy concerns and strategic purchase intentions in both purchase scenarios for the two countries explain the attitude of the respondents that they are likely to trade off privacy concerns to some extent for cheaper price offers. Privacy concerns does not have a significant relationship with the purchase satisfaction of consumers in both scenarios and there is no significant mediation effect as well. This finding implies that privacy concerns as such is less likely to have an impact on the purchase satisfaction. This result is in contrast with the study by GAO et al (2015) which states that privacy concerns has a direct influence on purchase satisfaction. It could be thus assumed that in a personalised pricing context, privacy concerns is less likely to have a direct influence on the purchase satisfaction of consumers.

Customer loyalty plays a significant moderator role in the relationship between fair price perceptions and purchase satisfaction in the Indian negative and Malaysian positive purchase scenarios. For the other two purchase scenarios, the effect is insignificant. For the Indian negative purchase scenario, there is a positive moderation effect implying that as fair price perception increases coupled with a high level of customer loyalty, the purchase satisfaction of the consumer increases. In the case of Malaysian negative purchase scenario, customer loyalty is a pull moderator, having a negative impact on the purchase satisfaction. It means, as fair price perception increases, the purchase satisfaction decreases due to the moderation effect of customer loyalty. One of the reasons for this result is the attitude of respondents towards the seller. If customers have a negative attitude towards the seller, it can have an adverse impact on the relationship between the fair price perceptions and purchase satisfaction.

Purchase satisfaction of the respondents do have a positive and significant effect on the repurchase intentions in both negative and positive purchase scenarios. As discussed earlier, overall purchase satisfaction of the consumers increases the repurchase intentions. Regarding the relationship between purchase satisfaction and revenge intentions, except for Indian positive scenario, all other paths are insignificant. The Indian positive purchase scenario had also shown the increased privacy concerns of the respondents compared to the other purchase scenarios. The result implies that the respondents who were exposed to this purchase scenario are more sensitive than the other three groups of respondents. Except for the Malaysian negative purchase scenario, the relationship between purchase satisfaction and the strategic purchase intentions is significant. For the Malaysian and Indian positive purchase scenarios, there exists a positive relationship between the two variables and for the Indian negative purchase scenario, the relationship is negative. The results clearly make sense by explaining the attitude of consumers in both positive scenarios, that the consumers are likely to take advantage of the pricing strategy to buy products at cheaper prices. However, the consumers in the negative purchase scenario thinks that as purchase satisfaction improves, they are less likely to indulge in a price tracking and strategic purchase behaviour. These results corroborate with the previous studies conducted among the millennials in India and Poland (VICTOR et al., 2018b; VICTOR et al., 2019b).

The gender wise differences in the attitude towards the variables under study were examined using Wilcoxon Rank Sum test and the results showed that there was no significant difference for the Malaysian respondents in both purchase scenarios. For the Indian respondents, there was a significant difference in the fair price perceptions and repurchase intentions in Indian negative purchase scenario and repurchase intentions in the Indian positive purchase scenario. For assessing the differences among the income groups, a one-way ANOVA was used. The ANOVA test along with the post hoc test results showed that the respondents with higher income have higher privacy concerns as well as repurchase intentions as compared to the groups with lower income in Malaysia. For the Indian respondents, the strategic purchase intentions, purchase satisfaction and fair price perceptions of the low income group is higher than that of the high income group.

The Multigroup Analysis (MGA) between the two countries showed that the Malaysian respondents and the Indian respondents reacted quite differently in the negative purchase scenario. The results imply that the Malaysian respondents were less loyal to the seller in the negative purchase scenario. They displayed a higher strategic purchase intentions and revenge intentions notwithstanding the high level of purchase satisfaction. This result hints that the Malaysian respondents as compared to the Indian respondents seems to be more vulnerable in a negative purchase scenario and tend to take protective measures like tracking prices and engaging in reprisal activities against the seller. A plausible explanation is that the Indian respondents have higher resistance towards price volatility due to their incessant exposure to the price variations of high magnitude and proximity in the E-Commerce segment (VICTOR & BHASKAR, 2017). For the positive purchase scenarios, the respondents showed more or less similar behaviour except in the case where the Indian respondents showed a positive relationship between fair price perceptions and revenge intentions. One of the reasons for this result is that there are other factors that may induce revenge intentions in Indian consumers even when the price seems fair enough to them.

4.13. New Scientific Results

Based on the results and discussion, the new scientific results drawn from this research are as follows.

1. The study reveals that in data sharing environments like personalised pricing, the consumers are concerned about sharing their personal data with the sellers. Higher the privacy concerns, more the chances are that the consumers may turn against the seller and exhibit reprisal intentions which involve spreading negative word of mouth, switching to competitors, shunning the seller, and displaying strategic purchase behaviour.

2. Another distinctive result observed from the study is the full mediation effect of purchase satisfaction in the relationship between fair price perception and repurchase intentions of the consumers. The direct relationship between fair price perceptions and repurchase intentions is not significant in both negative and positive purchase scenarios alluding that purchase satisfaction fully mediates the relationship between fair price perceptions and repurchase intentions.

3. One of the novel results brought forth by this study is the tendency of the consumers who are aware of the prospects of personalised pricing to exhibit strategic purchase behaviour. The result implies that the consumers may track the prices of products and wait for the price markdowns before making purchases online.

4. A major contribution of the research to the existing literature is the inclusion and validation of two new constructs namely ‘strategic purchase intentions’ and ‘privacy concerns’. These constructs may be included in future studies using scales which measure consumer attitude and reactions in a discriminatory pricing context.

The novel results obtained from this study contribute to the existing stock of knowledge in the emerging field of consumer behaviour under online personalised pricing.

In both positive and negative purchase scenarios for the two countries, privacy concerns of the respondents have a negative relationship with the revenge intentions. The result implies that the consumers, regardless of the purchase experience they had are concerned about their privacy. The result can be related to the existing literature which explains the growing consumer privacy concerns in digital environments. The mediation effect of the purchase satisfaction in the relationship between fair price perceptions and repurchase intentions was observed in both positive and negative purchase scenarios for the two countries. This result is intriguing in the sense that unlike previous studies in the field which mainly emphasize the significance of offering a fair price to increase repurchase intentions, this study highlights the need to improve factors influencing purchase satisfaction which furthers repurchase intentions.

The intentions of consumers to display a strategic purchase behaviour was observed in the relationship between privacy concerns and strategic purchase intentions. Furthermore, the mediation results showed that purchase satisfaction mediated the relationship between fair price perceptions and strategic purchase intentions in negative and positive purchase scenarios for two countries. The novelty observed here is in the positive purchase scenarios, where purchase satisfaction played a positive mediator role indicating the tendency of consumers to take advantage by tracking prices regardless of the level of purchase satisfaction obtained. This result contributes to the emerging study area of the price tracking behaviour of consumers which has wide implications to the day to day operational strategies of manufacturers and sellers. Finally, the inclusion and validation of two new constructs namely privacy concerns and strategic purchase intentions help in analyzing two different dimensions involved in online buying under a discriminatory pricing strategy.

5. CONCLUSION AND RECOMMENDATIONS

5.1. Conclusion

This research has attempted to explicate the behaviour of the Indian and Malaysian online consumers under a personalised price setting in the E-Commerce sector. Based on the literature review, it was construed that the fair price perceptions, privacy concerns and customer loyalty play a significant role in influencing the post purchase intentions of consumers in the E-Commerce sector. The research framework was a synthesized model with post purchase intentions i.e. repurchase intentions, revenge intentions and strategic purchase intentions taken as dependent variables and fair price perceptions, privacy concerns, customer loyalty, purchase satisfaction taken as independent variables. The descriptive statistics showing the characteristics of respondents from both countries indicate that the number of female respondents is slightly higher than the male respondents in both countries. Majority of the respondents in both countries had got high educational qualifications and mostly belonged to the middle-income category.

Partial Least Square based structural equation modeling was used to test the significance of the relationship between the dependent and independent variables. According to the literature, fair price perceptions is pivotal in determining purchase satisfaction and the repurchase intentions of the consumers. This study also draws similar results that the fair price perceptions of consumers have a positive influence on the purchase satisfaction and extends the application of the results to a personalised pricing environment. However, the direct influence of the fair price perceptions on the repurchase intentions is not significant in both purchase scenarios for the two countries but fully mediated by purchase satisfaction implying that the sellers should give care to improving the overall purchase satisfaction of the consumers along with offering them fair prices to increase the repurchase intentions in a personalised price setting.

The results also indicate that the consumers are worried about private data sharing for personalised prices and recommendations. If the privacy concerns of the consumers are not addressed properly, the consumers may display strategic purchase intentions and reprisal intentions which involves spreading negative word of mouth, switching to competitors, shunning the seller etc. Furthermore, loyal customers are more likely to be tolerant to price variations as compared to the non-loyal customers in an online personalised pricing context. The study also found out that the consumers who are aware of the fluctuations in prices are highly likely to display a strategic purchase behaviour implying that they would track prices and wait for price markdown before making the purchase. This tendency may hurt the fringe benefits earned by the sellers who employ discriminatory pricing tactics like personalised pricing. Most of the findings in the study are consistent with the previous literature available and related theories in the field.

The results obtained from this study mainly pertain to the online consumers in India and Malaysia (particularly to the online consumers in the region under study) or the consumers in other countries or states with similar characteristics. More studies in different parts of the world are required to be conducted to verify the research model and to generalize the results and findings.

5.2. Recommendations

Based on the findings of this research certain recommendations are provided for future researches in the area as well as to the online retailers to streamline their business considering the shift in consumer behaviour in a personalised price setting in the E-Commerce sector. Although the prospects of personalised pricing sound appealing to the online sellers, the consumers' reactions portray that they are not as happy as the sellers. One of the biggest worries of consumers is the privacy concerns. Keeping aside all the possibilities and benefits, the idea of using one's own private information for individualized price customization is not desirable to many of the consumers.

Based on the results, offering better prices without improving the purchase satisfaction of the consumers is less likely to materially affect the repurchase intentions. In a personalised price setting, although fair price perceptions has an influence on the repurchase intentions, the sellers should consider other factors which improve the purchase satisfaction of the consumers such as brand image or web store image, quality of the services provided, substitutes available etc. to positively influence the repurchase intentions of the consumers.

Retaining a loyal customer base is one of the crucial strategies to be followed in a personalised price setting as the results showed that the loyal customers tend to show higher repurchase intentions and increased purchase satisfaction regardless of the positive or negative purchase scenarios. Furthermore, customer loyalty played a positive moderator role in the relationship between fair price perceptions and purchase satisfaction in Indian negative purchase scenario. Hence it could be assumed that the loyal customers may not react adversely to fair to moderate level of price fluctuations (presumed on the basis of the magnitude of fluctuation given in the purchase scenarios). Based on this finding, the sellers may use moderate level fluctuation in prices while tailoring prices for the loyal customers to maximise profitability.

The sellers should take the price tracking behaviour of the consumers into consideration and make the spectrum of variation as small as possible such that the search cost and time delays involved in price tracking are higher and outweigh the normal purchases without price tracking. This will ensure a regular marginal revenue to the sellers rather than occasional windfall gains which has a higher risk of losing the loyal customer base. The tendency among consumers to track prices of the products sold online is increasing. These consumers who regularly track prices of products using various applications and browser extensions will have information regarding the magnitude and proximity of price variations. They are most likely to wait for price markdowns to make the purchases. As per the results, the low income consumers have a higher tendency to display a strategic purchase behaviour.

The sellers must take necessary measures to make their pricing practices as transparent as possible to win the trust of consumers as the findings show that majority of the respondents would be happy if there is a choice to opt themselves out from sharing data for price customization. As privacy concerns increases, there are higher chances that they might indulge in reprisal activities. The privacy concerns of the Indian respondents seemed to be higher than that of the Malaysian respondents. So, the online retailers in India must give special attention to address this issue.

5.3. Research Limitations and Future Research Directions

One of the research limitations which merits further exploration in this study area is the non representative nature of the sample data collected. As explained in the data collection method, the sample was collected from a few states in both countries and thus may not fully represent the general characteristics of the population under study. Furthermore, it is highly likely that the constructs namely ‘repurchase intentions’ and ‘revenge intentions’ may have the issue of common method bias which may be addressed in future researches. It is also highly recommended that in future researches, other significant variables such as ‘trust’ which might influence consumer behaviour in an online purchase context may be included in the model. Further studies with appropriate purchase scenarios should be developed and applied to verify and extend the results of this study to an offline personalised pricing context. The research model and scale used in the study should be applied in other countries so as to test the reliability of the instrument as well as to generalize the results. Furthermore, region specific studies, based on the theory of legal origin would help in understanding the operation of personalised pricing under different legal frameworks and the consumer behavioural changes observed in such regions. The hypothetical purchase scenarios used in the study may be improved by adding details which may make the consumers more aware of personalised pricing and help elicit a better and accurate response.

6. SUMMARY

Personalised pricing is a discriminatory pricing strategy mainly impelled by the recent advancements in the IoT and big data analytics. It is one of the most sophisticated and customised pricing techniques identified to be used in the business for revenue management. With the consumers becoming increasingly aware of the novel business tactics, how their behaviour changes under a pricing strategy which is largely based on private data sharing for customised prices and recommendations is worth exploring and was the motivation for this research. This study has attempted to disentangle the complex pattern of relationship among different variables which affect online consumer responses and sheds light on the behavioural shift among the consumers under a personalised price setting in the E-Commerce sector in India and Malaysia.

Previous researches in the study area were explored thoroughly to identify the research gap and the research model was formulated based on the literature review and researcher's own previous works. Primary data for the research was collected from India and Malaysia through both online and paper questionnaires. A total of 751 responses were received and based on the requirement of the study, 720 responses i.e. 360 from each country were finalized for the analysis. The questionnaire consisted of a hypothetical purchase scenario which puts the respondent in either an advantageous or a disadvantageous situation due to the fluctuation in prices driven by personalised pricing. The respondents in both countries answered the questionnaires with one of the purchase scenarios and the responses were compared and tested for significance.

Partial Least Square based Structural Equation Modelling (PLS SEM) was used for analyzing the research model. Although the scale used in this research was already tested and validated, an Exploratory Factor Analysis (EFA) was carried out prior to conducting the PLS SEM analysis for reconfirming the validity. ANOVA and Wilcoxon Rank Sum test were used to test the gender differences and differences among income groups in their attitude towards the variables under study. The hypotheses formulated were tested against the two purchase scenarios for both countries using the bootstrapping method.

The results show that fair price perception of consumers is positively correlated with the overall purchase satisfaction in a personalised pricing context. Purchase satisfaction fully mediates the relationship between fair price perceptions and repurchase intentions in both purchase scenarios for the two countries. The study has identified that the consumers in both India and Malaysia are concerned about sharing their data with the sellers. The Indian consumers seemed to be more sensitive than the Malaysian consumers when it comes to data sharing. The results show that higher privacy concerns induce consumers to engage in reprisal activities which may hurt the profitability of the sellers. The finding is significant in both purchase scenarios for two countries. The construct ‘strategic purchase intentions’ was introduced to assess the consumers intentions to engage in a price tracking behaviour. The construct developed by the researcher himself has yielded very interesting insights. In positive purchase scenarios, customers do have the tendency to take advantage of the fluctuating prices by keep tracking them and making the purchase when the price falls. In negative purchase scenarios, they express the desire to get better price offers from the sellers. Privacy concerns also showed a positive association with the strategic purchase intentions in both scenarios for the two countries.

Purchase satisfaction does have a positive association with the repurchase intentions of the consumers in both purchase scenarios. There is a negative association between strategic purchase intentions and purchase satisfaction in Indian negative purchase scenario and positive association in the Indian positive and the Malaysian positive purchase scenarios implying that regardless of the satisfaction with purchase, consumers want to take advantage of the price volatility in positive purchase scenarios. The Multigroup Analysis conducted to test the differences between the two groups of respondents showed that the Malaysian respondents, as compared to the Indian respondents are easily hurt by the price changes in a negative purchase scenario and are more inclined to resort to engage in reprisal and price tracking activities. Both Malaysian and Indian respondents exhibited similar traits in the positive purchase scenario except for the relationship between fair price perceptions and revenge intentions where Indian consumers showed a positive association signifying that other factors may influence the revenge intentions even when consumers are offered a fair price.

Considering the novelty of the field of study, this research is one of the pioneering works which may be used as a reference for future works by academicians and researchers. More importantly, the findings of this study may give useful insights to the e-tailers around the world who are planning to adopt the personalised pricing strategy for revenue management.

7. APPENDICES

APPENDIX (1) References

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Appendix (2). Item Statistics for Customer Loyalty, Fair Price Perceptions, Privacy Concerns and Purchase Satisfaction – Indian Purchase Scenarios

Items	Mean		Median		Standard Deviation		Excess Kurtosis		Skewness	
	Ind_Neg	Ind_Pos	Ind_Neg	Ind_Pos	Ind_Neg	Ind_Pos	Ind_Neg	Ind_Pos	Ind_Neg	Ind_Pos
CL1	3.77	3.59	4	4	0.971	0.939	0.279	-0.412	-0.748	-0.342
CL2	3.59	3.53	4	4	0.98	0.957	0.423	-0.759	-0.762	0.065
CL3	3.81	3.61	4	4	0.98	1.023	0.46	-0.269	-0.764	-0.338
CL4	3.62	3.65	4	4	0.951	0.964	0.051	-0.783	-0.505	-0.365
CL5	3.05	2.97	3	3	1.191	1.097	-0.87	0.590	0.003	0.774
CL6	3.55	3.45	4	4	0.958	0.95	0.23	-0.099	-0.474	-0.466
CL7	3.45	3.34	4	3	1.201	1.254	-0.74	-0.436	-0.372	-0.286
FP1	2.47	3.63	2	4	1.224	0.948	-1.10	-0.123	0.259	-0.403
FP2	2.58	3.39	3	4	1.181	0.951	-0.88	-0.229	0.178	-0.554
FP3	2.85	3.43	3	4	1.172	0.968	-0.88	0.753	-0.107	-0.856
PS1	2.67	3.19	3	4	1.181	1.02	-0.96	0.768	0.218	-0.961
PS2	2.69	3.73	3	4	1.286	1.021	-1.18	-0.052	0.067	-0.549
PS3	2.61	3.82	2	4	1.227	0.964	-0.88	0.514	0.321	-0.795
PS4	2.64	3.91	3	4	1.316	1.00	-1.17	-0.307	0.220	0.786
PS6	2.88	3.68	3	4	1.223	0.992	-0.98	0.034	-0.036	-0.590
PS7	2.77	3.86	3	4	1.172	0.92	-1.05	0.025	0.043	-0.577
PS8	2.68	2.16	3	4	1.271	1.124	-1.08	-0.060	0.174	-0.364
PC1	3.76	3.59	4	4	1.128	0.96	-0.15	-0.335	-0.755	0.768
PC2	3.72	3.72	4	4	1.048	0.944	-0.22	-0.730	-0.601	-0.532
PC3	3.81	3.59	4	4	1.113	0.912	-0.29	-0.251	-0.690	0.835
PC4	4.08	3.70	4	4	1.047	1.271	0.30	0.456	-1.000	-1.178
PC5	3.89	3.56	4	5	1.056	1.24	-0.12	-0.345	-0.747	-0.807

Appendix (3). Item Statistics for Customer Loyalty, Fair Price Perceptions, Privacy Concerns and Purchase Satisfaction – Malaysian Purchase Scenarios

Items	Mean		Median		Standard Deviation		Excess Kurtosis		Skewness	
	Mal_Neg	Mal_Pos	Mal-_Neg	Mal_Pos	Mal_Neg	Mal_Pos	Mal_Neg	Mal_Pos	Mal_Neg	Mal_Pos
CL1	3.38	3.42	3	4	1.011	1.07	-0.23	-0.55	-0.43	-0.41
CL2	3.37	3.46	3	4	1.028	1.12	-0.49	-0.57	-0.32	0.47
CL3	3.44	3.55	4	4	1.06	1.17	-0.53	-0.57	-0.33	-0.43
CL4	3.41	3.32	4	3	0.95	1.09	0.02	-0.57	-0.46	-0.07
CL5	2.86	2.93	3	3	1.226	1.32	-0.88	-0.83	0.02	0.33
CL6	3.25	3.41	3	4	1.088	1.01	-0.45	-1.21	-0.36	-0.17
CL7	3.02	3.10	3	3	1.185	1.20	-0.89	-0.46	0.03	-0.51
FP1	2.66	3.38	3	4	1.172	1.13	0.72	-0.90	0.30	-0.51
FP2	2.86	3.46	3	4	1.071	1.10	-0.55	-0.42	0.00	0.55
FP3	2.86	3.28	3	3	1.104	0.93	-0.67	-0.09	0.17	-0.34
PS1	2.89	3.91	3	4	1.193	1.18	-1.01	-0.44	0.10	-0.93
PS2	2.62	4.03	3	4	1.095	0.98	-0.79	1.81	0.13	-0.76
PS3	2.84	3.80	3	4	1.161	0.92	0.69	0.40	0.00	-0.62
PS4	2.94	3.98	3	4	1.193	0.97	-0.9	1.42	0.14	-1.06
PS6	3.09	2.44	3	4	1.111	0.98	-0.94	-0.40	0.16	0.89
PS7	3.11	3.58	3	4	1.131	0.92	0.62	0.35	-0.13	-1.15
PS8	3.07	3.85	3	4	1.172	0.97	0.78	1.09	-0.21	-0.73
PC1	3.61	3.78	4	4	1.079	1.14	-0.96	0.37	-0.23	-0.79
PC2	3.51	3.80	4	4	1.067	1.16	-0.72	-0.41	-0.16	0.58
PC3	3.87	3.75	4	5	1.005	1.00	-0.78	1.45	-0.25	-1.36
PC4	3.98	4.42	4	5	0.967	0.79	-0.96	3.34	-0.28	-1.64
PC5	3.94	4.30	4	3	1.034	0.93	0.13	1.81	-0.72	-1.45

Appendix (4). Item statistics for Reprisal intentions, Repurchase Intentions and Strategic Purchase Intentions – Indian Purchase Scenarios

Items	Mean		Median		Standard Deviation		Excess Kurtosis		Skewness	
	Ind_Neg	Ind_Pos	Ind_Neg	Ind_Pos	Ind_Neg	Ind_Pos	Ind_Neg	Ind_Pos	Ind_Neg	Ind_Pos
RI1	2.73	3.75	3	2	1.181	1.236	-0.89	-0.901	0.17	0.113
RI2	2.82	4.11	3	2	1.135	1.107	-0.83	-0.876	0.21	0.068
RI3	2.94	3.70	3	3	1.13	1.258	-0.78	-0.676	-0.23	-0.147
RI4	2.50	2.37	2	4	1.07	1.105	-0.22	-0.433	0.44	0.346
RI5	3.33	2.42	3	3	1.098	1.194	-0.46	-0.454	-0.31	-0.325
RP1	2.97	3.09	3	2	1.173	1.082	-0.85	-0.690	-0.16	-0.121
RP2	2.47	2.21	2	4	1.201	1.008	-0.83	-0.784	0.44	0.381
RP3	2.67	3.45	3	3	1.068	1.1	-0.54	-0.575	0.19	0.213
RP4	3.27	2.96	3	2	1.147	1.106	-0.71	-0.585	-0.21	-0.260
SPB1	3.86	2.30	4	4	1.136	1.077	-0.03	-0.686	-0.83	0.236
SPB2	3.84	2.42	4	4	1.03	1.101	0.13	0.070	-0.76	-0.777
SPB3	3.21	3.08	3	3	1.196	1.135	-0.93	0.110	-0.10	-0.711
SPB4	3.92	2.35	4	4	1.009	1.076	0.20	-0.741	-0.80	0.248

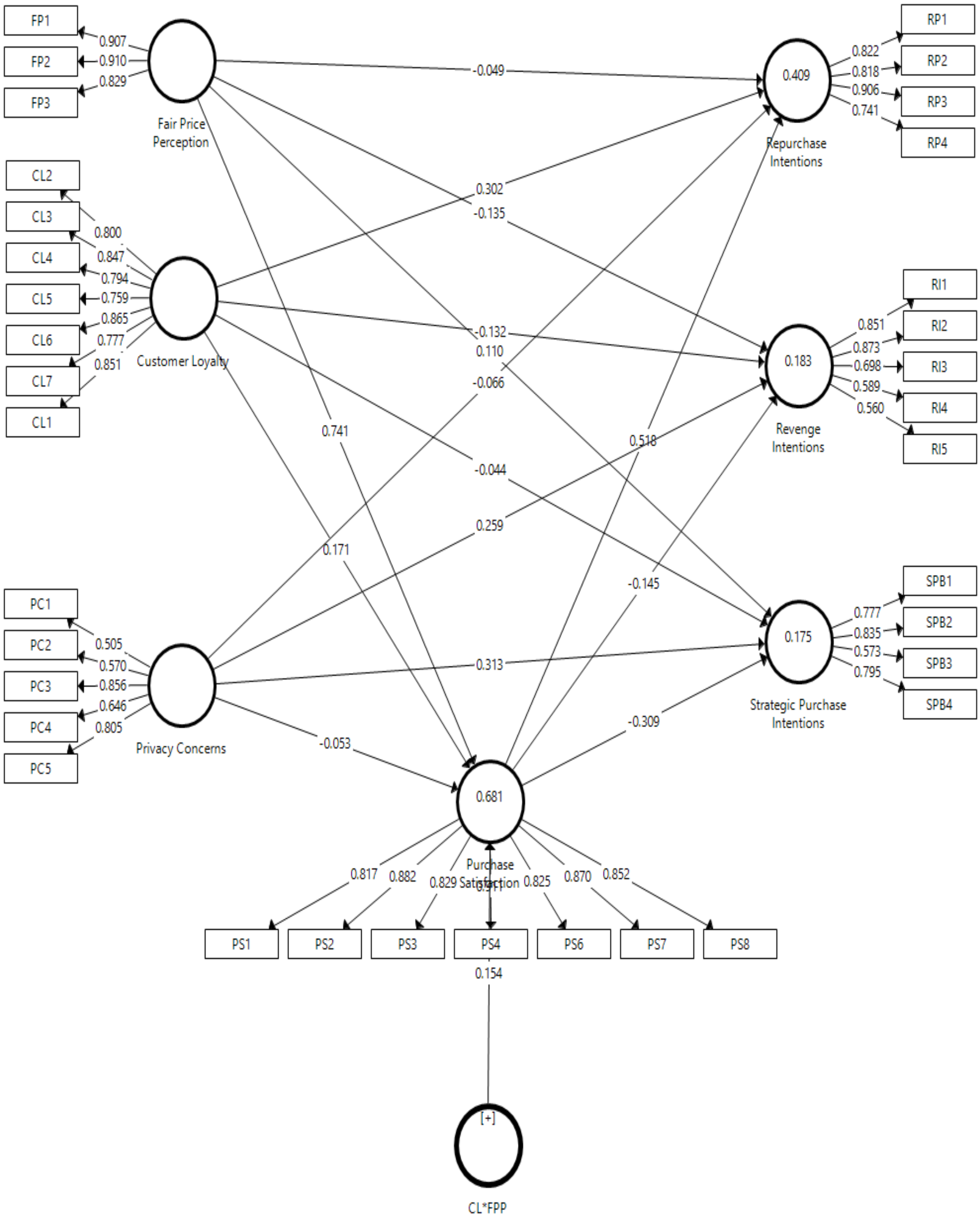
Appendix (5). Item statistics for Reprisal intentions, Repurchase Intentions and Strategic Purchase Intentions – Malaysian Purchase Scenarios

Items	Mean		Median		Standard Deviation		Excess Kurtosis		Skewness	
	Mal_Neg	Mal_Pos	Mal_Neg	Mal_Pos	Mal_Neg	Mal_Pos	Mal_Neg	Mal_Pos	Mal_Neg	Mal_Pos
RI1	2.91	2.89	3.00	3	1.12	1.14	-0.85	-0.68	0.08	0.14
RI2	3.09	2.97	3.00	3	1.13	1.28	-0.81	-0.50	-0.08	0.03
RI3	2.71	2.86	3.00	3	1.01	1.01	-0.53	-0.22	-0.07	-0.29
RI4	2.85	3.49	3.00	3	1.07	1.11	-0.51	-0.54	0.27	0.09
RI5	3.39	3.19	3.00	4	1.01	0.96	-0.36	0.30	-0.40	-0.71
RP1	2.71	2.46	3.00	3	1.06	1.05	-0.52	-0.32	-0.08	-0.28
RP2	3.33	2.98	3.00	4	1.11	1.17	-0.65	-0.85	0.31	0.37
RP3	2.52	3.47	3.00	3	1.06	1.04	-0.60	-0.52	0.29	0.00
RP4	2.85	2.82	2.00	2	1.00	1.13	-0.45	-0.75	-0.30	-0.30
SPB1	3.88	4.15	4.00	4	1.12	1.10	0.25	-0.45	-0.76	0.22
SPB2	3.80	4.05	4.00	4	0.99	0.94	0.33	0.68	-0.72	-1.02
SPB3	3.62	3.68	4.00	4	0.97	0.93	-0.22	0.66	-0.55	-0.93
SPB4	3.94	4.15	4.00	4	0.98	1.055	0.25	1.27	-0.81	-0.98

Appendix (6). Outer Loadings Obtained from the Confirmatory Composite Analysis - Indian Negative Purchase Scenario

	CL	FPP	PC	PS	RP	RI	SPI
CL2	0.800						
CL3	0.847						
CL4	0.794						
CL5	0.759						
CL6	0.865						
CL7	0.777						
FP1		0.907					
FP2		0.910					
FP3		0.829					
PC1			0.505				
PC2			0.570				
PC3			0.856				
PC4			0.646				
PC5			0.805				
PS1				0.817			
PS2				0.882			
PS3				0.829			
PS4				0.911			
PS6				0.825			
PS7				0.870			
PS8				0.852			
RI1						0.851	
RI2						0.873	
RI3						0.698	
RI4						0.589	
RI5						0.560	
RP1					0.822		
RP2					0.818		
RP3					0.906		
RP4					0.741		
SPB1							0.777
SPB2							0.835
SPB3							0.573
SPB4							0.795
CL1	0.852						

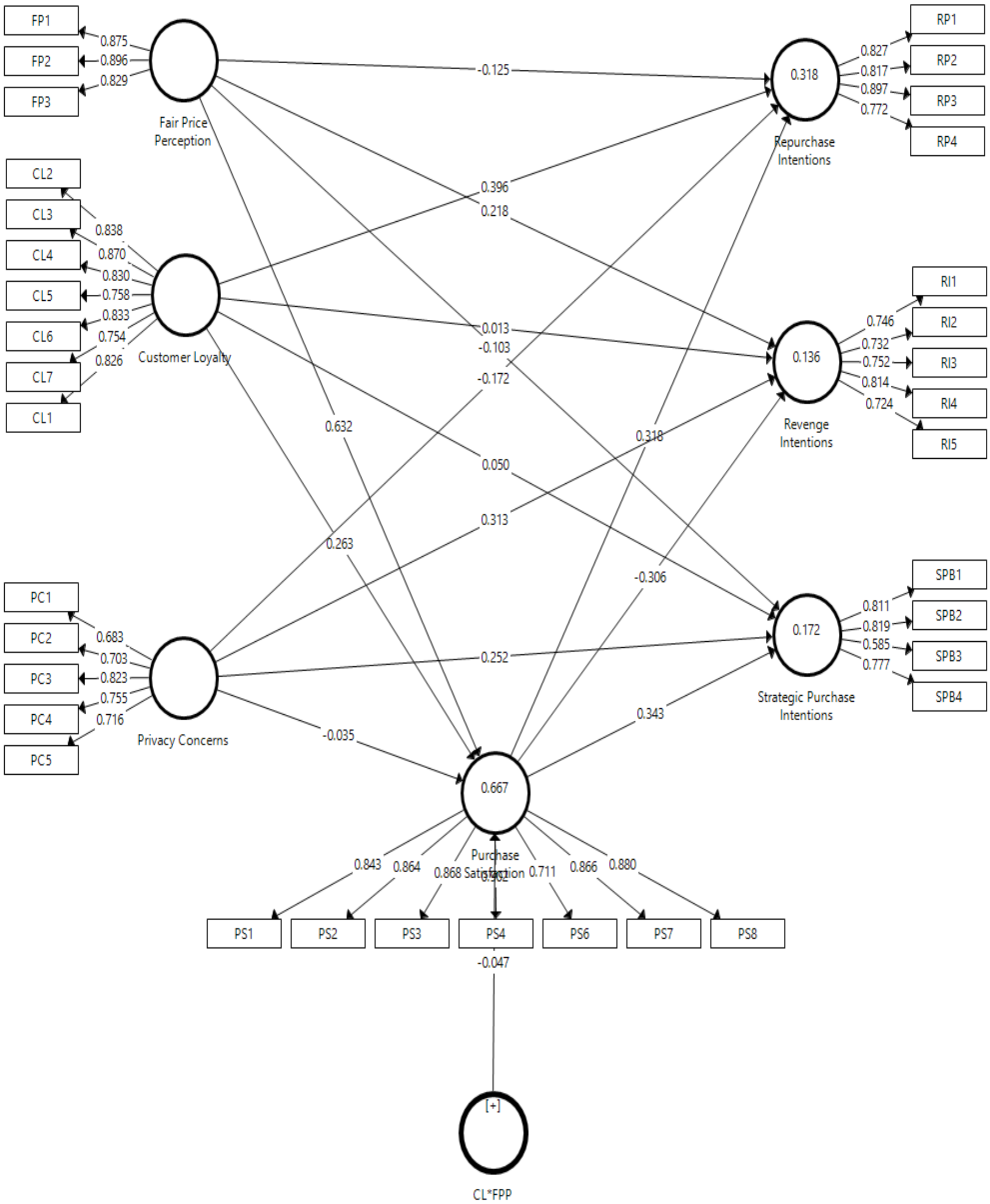
Appendix (7). Model with Outer Loadings Path Coefficients and R Square values for Indian Negative Purchase Scenario



Appendix (8). Outer Loadings Obtained from the Confirmatory Composite Analysis - Indian Positive Purchase Scenario

	CL	FPP	PC	PS	RP	RI	SPI
CL2	0.838						
CL3	0.870						
CL4	0.830						
CL5	0.758						
CL6	0.833						
CL7	0.754						
FP1		0.875					
FP2		0.896					
FP3		0.829					
PC1			0.683				
PC2			0.703				
PC3			0.823				
PC4			0.755				
PC5			0.716				
PS1				0.843			
PS2				0.864			
PS3				0.868			
PS4				0.902			
PS6				0.711			
PS7				0.866			
PS8				0.880			
RI1						0.746	
RI2						0.732	
RI3						0.752	
RI4						0.814	
RI5						0.724	
RP1					0.827		
RP2					0.817		
RP3					0.897		
RP4					0.772		
SPB1							0.811
SPB2							0.819
SPB3							0.585
SPB4							0.777
CL1	0.826						

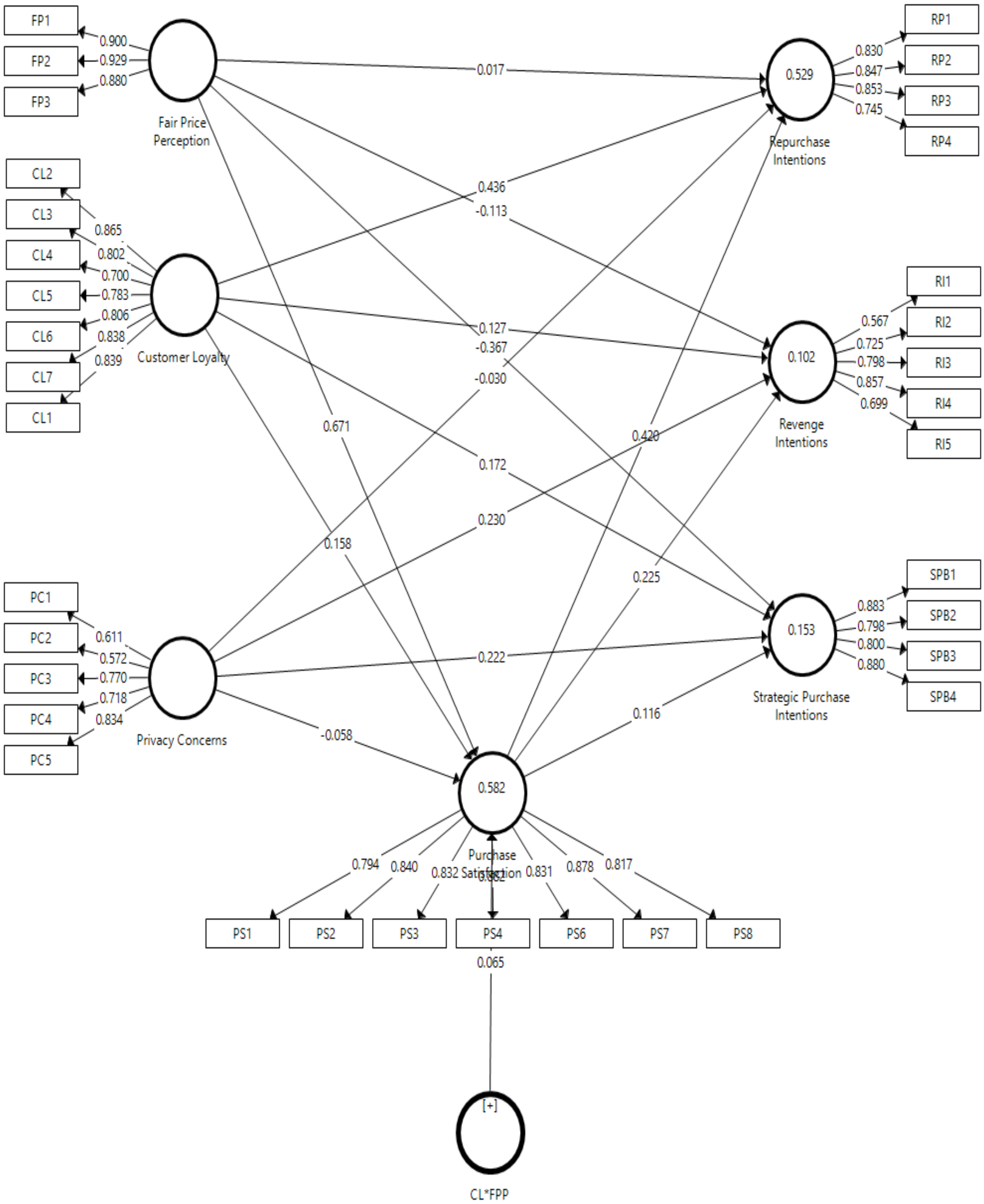
Appendix (9). Model with Outer Loadings, Path Coefficients and R Square Values for Indian Negative Purchase Scenario



Appendix (10). Outer Loadings Obtained from the Confirmatory Composite Analysis - Malaysian Negative Purchase Scenario

	CL	FPP	PC	PS	RP	RI	SPI
CL2	0.865						
CL3	0.802						
CL4	0.700						
CL5	0.783						
CL6	0.806						
CL7	0.838						
FP1		0.900					
FP2		0.929					
FP3		0.880					
PC1			0.611				
PC2			0.572				
PC3			0.770				
PC4			0.718				
PC5			0.834				
PS1				0.794			
PS2				0.840			
PS3				0.832			
PS4				0.882			
PS6				0.831			
PS7				0.878			
PS8				0.817			
RI1						0.567	
RI2						0.725	
RI3						0.798	
RI4						0.857	
RI5						0.699	
RP1					0.830		
RP2					0.847		
RP3					0.853		
RP4					0.745		
SPB1							0.883
SPB2							0.798
SPB3							0.800
SPB4							0.880
CL1	0.839						

Appendix (11). Model with Outer Loadings, Path Coefficients and R Square Values for the Malaysian Negative Purchase Scenario

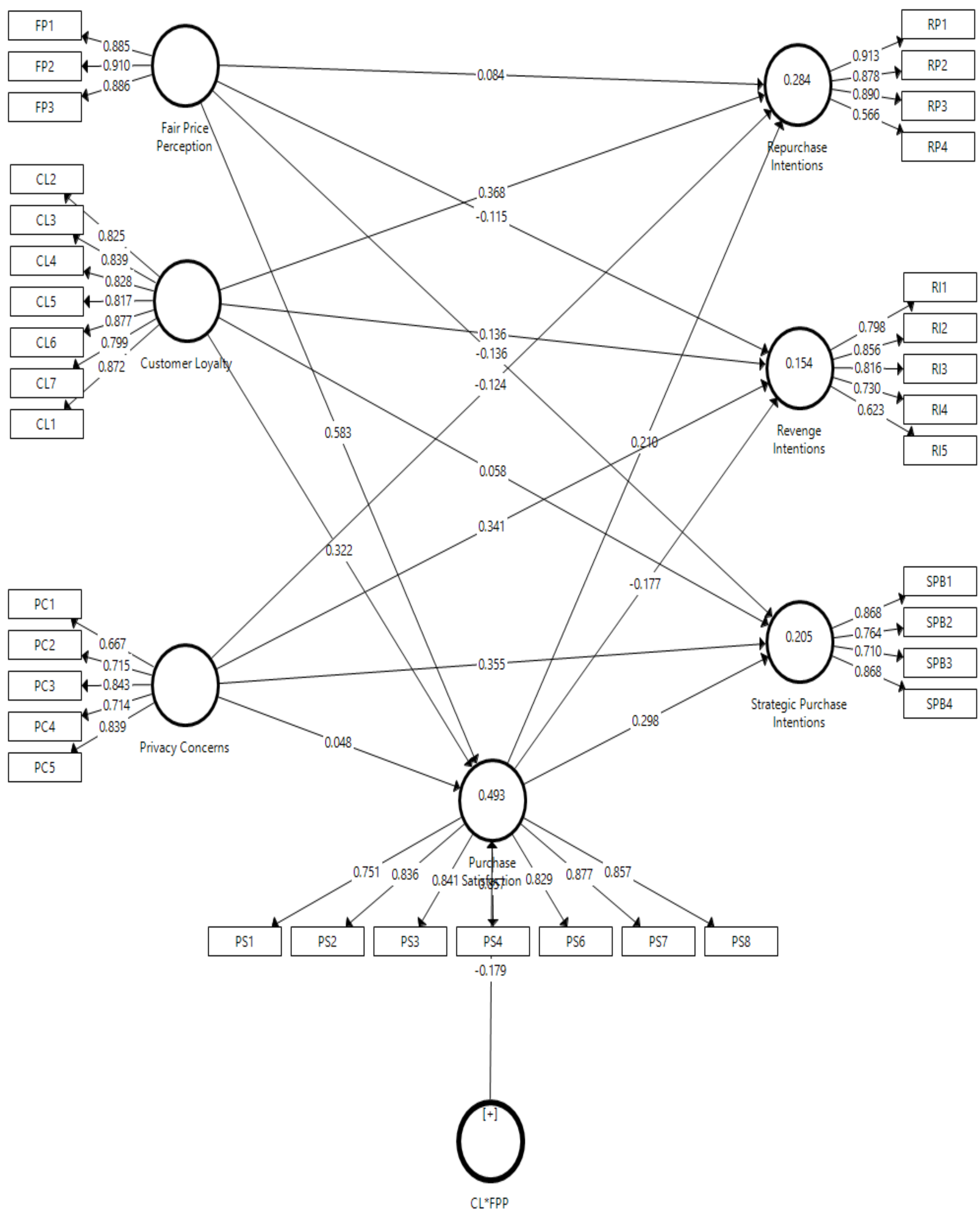


Source: Author’s own work using SmartPLS

Appendix (12). Outer Loadings Obtained from the Confirmatory Composite Analysis - Malaysian Positive Purchase Scenario

	CL	FPP	PC	PS	RP	RI	SPI
CL2	0.825						
CL3	0.839						
CL4	0.828						
CL5	0.817						
CL6	0.877						
CL7	0.799						
FP1		0.885					
FP2		0.910					
FP3		0.886					
PC1			0.667				
PC2			0.715				
PC3			0.843				
PC4			0.714				
PC5			0.839				
PS1				0.751			
PS2				0.836			
PS3				0.841			
PS4				0.857			
PS6				0.829			
PS7				0.877			
PS8				0.857			
RI1						0.798	
RI2						0.856	
RI3						0.816	
RI4						0.730	
RI5						0.623	
RP1					0.913		
RP2					0.878		
RP3					0.890		
RP4					0.566		
SPB1							0.868
SPB2							0.764
SPB3							0.710
SPB4							0.868
CL1	0.872						

Appendix (13). Model with Outer Loadings, Path Coefficients and R Square Values for the Malaysian Positive Purchase Scenario



Appendix (14). Cover Letter for the Questionnaires

Dear Sir/Madam,

Greetings!

My name is Vijay Victor, a second year PhD student at Szent Istvan University, Hungary. I am approaching you with a request to fill this questionnaire as part of completion of the PhD dissertation requirements of Szent Istvan University. The purpose of this questionnaire is to examine the perceived changes in consumer behaviour in a personalised pricing context in the E-Commerce Sector. The questionnaire consists of a hypothetical purchase scenario and some questions based on it. This questionnaire shouldn't take longer than 5 to 10 minutes to complete. The research is being conducted on an anonymous basis among the online consumers in India and Malaysia. Your responses will be kept confidential and will only be used for academic purposes. Your participation is entirely voluntary.

In case of any questions, please don't hesitate to contact me on any of the contact details given below.

Thank you for your contribution and time in advance.

Szent Istvan University,
Faculty of Economics and Social Sciences,
Doctoral School of Management and Business Administration,
Pater Karoly. u 1. Godollo, 2100, Hungary.

Email address: Victor.Vijay@phd.uni-szie.hu
Ph. Nbr - +36 202957628/+91 7012071713

Appendix (15). Indian Questionnaire Set 1 with Complete Questionnaire and Purchase Scenario

Attitude towards the seller

For the following statements please indicate your level of agreement with each of the following statements.

Note: If you have never purchased from Amazon.com, kindly consider any other online stores from where you have made purchases previously and mark your responses.

	Strongly Disagree 1	2	3	4	Strongly Agree 5
I prefer buying products from Amazon.in	☐	☐	☐	☐	☐
Amazon.in is a retailer that Interests me.	☐	☐	☐	☐	☐
I would recommend Amazon.in to others.	☐	☐	☐	☐	☐
I feel it is safer to buy products from Amazon.in.	☐	☐	☐	☐	☐
I frequently purchase products from Amazon.in.	☐	☐	☐	☐	☐
I would encourage others to use Amazon.in.	☐	☐	☐	☐	☐
I would consider Amazon.in as first choice when buying products online	☐	☐	☐	☐	☐

Purchase Scenario

You are about to read a purchase scenario describing the purchase of a specific product from amazon.in. This scenario is hypothetically developed for the study and thus, may or may not depict the actual business practice of amazon.in. Please carefully read the scenario and answer the following questions.

Read the Scenario

You wanted a new American Tourister© Comet Black Laptop Backpack and decided exactly what colour and model you will buy (as shown in the picture below). You purchased the bag for 3500 Rupees from Amazon.in with your own money. Later the same day, your friend told you that he just bought the same bag for 1400 Rupees (60% lower) from Amazon.com. You came to know that this price discrepancy is due to Amazon's practice of charging different buyers different prices for the same product using each customer's personal and observed information such as age, location, browsing habits, previous purchases, number of clicks on a product etc received from the browser cookies.

American Tourister© Comet Black Laptop Backpack

(Source - https://www.amazon.in/American-Tourister-Comet-Backpack-03_8901836135312/dp/B01CQZ5FBA)

Which of the following statements is true based upon the scenario you just read?

☐ My friend had to pay Rs.3500 and I paid only Rs.1400 for the same backpack.

☐ I had to pay Rs.3500 and my friend paid only Rs.1400 for the same backpack.

Which of the following statements is true based upon the scenario you just read?

☐ The difference between the price I paid and the price my friend paid occurred within the same day as I purchased the backpack

☐ The difference between the price I paid and the price my friend paid occurred one week after I purchased the backpack.

Attitude Towards Personalised Pricing

Kindly answer the following questions based on the purchase scenario you just read. Please indicate your level of agreement with each of the statements using the scale below.

	Strongly Agree 1	2	3	4	Strongly Disagree 5
The price I paid was fair	☐	☐	☐	☐	☐
The price I paid was justified.	☐	☐	☐	☐	☐
The price I paid was honest.	☐	☐	☐	☐	☐
The price I paid was Equitable	☐	☐	☐	☐	☐
am satisfied with the price I paid	☐	☐	☐	☐	☐
My choice was wise.	☐	☐	☐	☐	☐
I am satisfied with my purchase decision.	☐	☐	☐	☐	☐
I think I selected the right retailer.	☐	☐	☐	☐	☐
I am happy with my purchase decision.	☐	☐	☐	☐	☐
I feel badly about my purchase decision.	☐	☐	☐	☐	☐
I am satisfied with the purchasing process through Amazon.com.	☐	☐	☐	☐	☐
Overall, I am satisfied with the purchase experience.	☐	☐	☐	☐	☐
Overall, I am pleased with my purchase experience.	☐	☐	☐	☐	☐

Privacy Concerns

Kindly answer the following questions based on the purchase scenario you read. Please indicate your level of agreement with each of the statements using the scale below.

	Strongly Disagree. 1	2	3	4	Strongly Agree 5
I am not interested in sharing my personal information to get personalised prices	☐	☐	☐	☐	☐
I am not interested in sharing my personal information to get personalised product recommendations	☐	☐	☐	☐	☐
I fear that my personal information used for online purchases may attract the attention of cyber criminals	☐	☐	☐	☐	☐
I would be happy if there is an option to not share my personal information with the seller	☐	☐	☐	☐	☐
I fear that my personal information about payment method may be stolen	☐	☐	☐	☐	☐

Post Purchase Reactions

Please indicate your likelihood to take actions described below based upon the scenario you just read

	Strongly Disagree 1	2	3	4	Strongly Agree 5
I will say negative things about Amazon.in's pricing policy to other people.	☐	☐	☐	☐	☐
I will complain to other customers about Amazon.in's pricing policy.	☐	☐	☐	☐	☐
I will complain to governmental agencies about Amazon.in's pricing policy.	☐	☐	☐	☐	☐

I will complain about Amazon.in’s pricing policy through online social networking channels	☐	☐	☐	☐	☐
I will switch to Amazon.in’s competitor after my experiencewith their pricing policy	☐	☐	☐	☐	☐
I will stop buying products from Amazon.in.	☐	☐	☐	☐	☐
I will continue to buy products from Amazon.in regardless of their pricing policy.	☐	☐	☐	☐	☐
I will continue to buy products from Amazon.in if I need the product in the future.	☐	☐	☐	☐	☐
I will buy more products from Amazon.com in the next few years regardless of their pricing policy.	☐	☐	☐	☐	☐
I will continue to buy products from Amazon.in even if the prices are somewhat higher than those of Amazon.com’s competitors.	☐	☐	☐	☐	☐
Having witnessed my friend’s situation, I will track the price of the products before future purchases to avoid paying higher prices	☐	☐	☐	☐	☐
I will consider the changing prices as an opportunity to buy products at lower prices	☐	☐	☐	☐	☐
I will use some software applications or browser extensions to track the changes in the price of the product.	☐	☐	☐	☐	☐
I will motivate my friends & family to track the prices to avoid paying higher prices	☐	☐	☐	☐	☐

Personal Information

I am ------------------ years old

15 – 25 ☐
26 – 35 ☐
36 – 45 ☐
46 – 55 ☐
56 and above ☐

Gender

Female ☐
Male ☐

Educational background

High School ☐
Graduate ☐
University Degree ☐
PhD ☐

Monthly Family Income

Below Rs. 10,000 ☐
Rs. 10,000 - Rs. 25,000 ☐
Rs. 26,000 - Rs. 50,000 ☐
Rs. 50,000 - Rs. 75,000 ☐
Rs. 75,000 and above ☐

Have you purchased products online?

Yes ☐
No ☐

Appendix (16). Indian Questionnaire Set 2. Purchase Scenario

Purchase Scenario

You are about to read a purchase scenario describing the purchase of a specific product from amazon.in. This scenario is hypothetically developed for the study and thus, may or may not depict the actual business practice of amazon.in. Please carefully read the scenario and answer the following questions.

Read the Scenario

You wanted a new American Tourister© Comet Black Laptop Backpack and decided exactly what colour and model you will buy (as shown in the picture below). You purchased the bag for 1400 Rupees from Amazon.in Later the same day, your friend purchased the same backpack and told you that he had to pay 3500 Rupees to buy it from Amazon.com. You came to know that this price discrepancy is due to Amazon’s practice of charging different buyers different prices for the same product using each customer's personal and observed information such as age, location, browsing habits, previous purchases, number of clicks on a product etc received from the browser cookies.

American Tourister© Comet Black Laptop Backpack

(Source - https://www.amazon.in/American-Tourister-Comet-Backpack-03_8901836135312/dp/B01CQZ5FBA)

Which of the following statements is true based upon the scenario you just read?

☐ My friend had to pay Rs.3500 and I paid only Rs.1400 for the same backpack

☐ I had to pay Rs.3500 and my friend paid only Rs.1400 for the same backpack

Which of the following statements is true based upon the scenario you just read?

☐ The difference between the price I paid and the price my friend paid occurred within the same day as I purchased the backpack

☐ The difference between the price I paid and the price my friend paid occurred one week after I purchased the backpack.

Appendix (17). Malaysian Questionnaire Set 1 with Complete Questionnaire and Purchase Scenario

Attitude towards the seller

For the following statements please indicate your level of agreement with each of the following statements.

Note: If you have never purchased from Lazada.com.my, kindly consider any other online stores from where you have made purchases previously and mark your responses.

	Strongly Disagree 1	2	3	4	Strongly Agree 5
I prefer buying products from Lazada.com.my.	☐	☐	☐	☐	☐
Lazada.com.my.in is a retailer that interests me.	☐	☐	☐	☐	☐
I would recommend Lazada.com.my to others.	☐	☐	☐	☐	☐
I feel it is safer to buy products from Lazada.com.my.	☐	☐	☐	☐	☐
I frequently purchase products from Lazada.com.my.	☐	☐	☐	☐	☐
I would encourage others to use Lazada.com.my.	☐	☐	☐	☐	☐
I would consider Lazada.com.my.as first choice when buying products online	☐	☐	☐	☐	☐

Purchase Scenario

You are about to read a purchase scenario describing the purchase of a specific product from amazon.in. This scenario is hypothetically developed for the study and thus, may or may not depict the actual business practice of Lazada.com.my. Please carefully read the scenario and answer the following questions.

Read the Scenario

You wanted a new American Tourister© Comet Black Laptop Backpack and decided exactly what colour and model you will buy (as shown in the picture below). You purchased the bag for RM 139 from Lazada.com.my. Later the same day, your friend told you that he paid only RM 94 for the same backpack from Lazada.com.my You came to know that this price discrepancy is due to new the pricing practice of charging different buyers different prices for the same product using each customer's personal and observed information such as age, location, browsing habits, previous purchases, number of clicks on a product etc received from the browser cookies.

American Tourister© Comet Black Laptop Backpack

(Source - https://www.amazon.in/American-Tourister-Comet-Backpack-03_8901836135312/dp/B01CQZ5FBA)

Which of the following statements is true based upon the scenario you just read?

- [ ] My friend had to pay RM 139 and I paid only RM 94 for the same backpack
- [ ] I had to pay RM 139 and my friend paid only RM 94 for the same backpack

Which of the following statements is true based upon the scenario you just read?

- [ ] The difference between the price I paid and the price my friend paid occurred within the same day as I purchased the backpack
- [ ] The difference between the price I paid and the price my friend paid occurred one week after I purchased the backpack.

Attitude Towards Personalised Pricing

Kindly answer the following questions based on the purchase scenario you just read. Please indicate your level of agreement with each of the statements using the scale below.

	Strongly Agree 1	2	3	4	Strongly Disagree 5
The price I paid was fair	☐	☐	☐	☐	☐
The price I paid was justified.	☐	☐	☐	☐	☐
The price I paid was honest.	☐	☐	☐	☐	☐
The price I paid was Equitable	☐	☐	☐	☐	☐
am satisfied with the price I paid	☐	☐	☐	☐	☐
My choice was wise.	☐	☐	☐	☐	☐
I am satisfied with my purchase decision.	☐	☐	☐	☐	☐
I think I selected the right retailer.	☐	☐	☐	☐	☐
I am happy with my purchase decision.	☐	☐	☐	☐	☐
I feel badly about my purchase decision.	☐	☐	☐	☐	☐
I am satisfied with the purchasing process through Amazon.com.	☐	☐	☐	☐	☐
Overall, I am satisfied with the purchase experience.	☐	☐	☐	☐	☐
Overall, I am pleased with my purchase experience.	☐	☐	☐	☐	☐

Privacy Concerns

Kindly answer the following questions based on the purchase scenario you read. Please indicate your level of agreement with each of the statements using the scale below.

	Strongly Disagree. 1	2	3	4	**Strongly Agree** 5
I am not interested in sharing my personal information to get personalised prices	☐	☐	☐	☐	☐
I am not interested in sharing my personal information to get personalised product recommendations	☐	☐	☐	☐	☐
I fear that my personal information used for online purchases may attract the attention of cyber criminals	☐	☐	☐	☐	☐
I would be happy if there is an option to not share my personal information with the seller	☐	☐	☐	☐	☐
I fear that my personal information about payment method may be stolen	☐	☐	☐	☐	☐

Post Purchase Reactions

Please indicate your likelihood to take actions described below based upon the scenario you just read

	Strongly Disagree 1	2	3	4	**Strongly Agree** 5
I will say negative things about Lazada.com.my's pricing policy to other people.	☐	☐	☐	☐	☐
I will complain to other customers about Lazada.com.my's pricing policy.	☐	☐	☐	☐	☐
I will complain to governmental agencies about Lazada.com.my's pricing policy.	☐	☐	☐	☐	☐
I will complain about Lazada.com.my's pricing	☐	☐	☐	☐	☐

policy through online social networking channels					
I will switch to Lazada.com.my's competitor after my experiencewith their pricing policy	☐	☐	☐	☐	☐
I will stop buying products from Lazada.com.my.	☐	☐	☐	☐	☐
I will continue to buy products from Lazada.com.my regardless of their pricing policy.	☐	☐	☐	☐	☐
I will continue to buy products from Lazada.com.my if I need the product in the future.	☐	☐	☐	☐	☐
I will buy more products from Lazada.com.my in the next few years regardless of their pricing policy.	☐	☐	☐	☐	☐
I will continue to buy products from Lazada.com.my even if the prices are somewhat higher than those of Amazon.com's competitors.	☐	☐	☐	☐	☐
Having witnessed my friend's situation, I will track the price of the products before future purchases to avoid paying higher prices	☐	☐	☐	☐	☐
I will consider the changing prices as an opportunity to buy products at lower prices	☐	☐	☐	☐	☐
I will use some software applications or browser extensions to track the changes in the price of the product.	☐	☐	☐	☐	☐
I will motivate my friends & family to track the prices to avoid paying higher prices.	☐	☐	☐	☐	☐

Personal Information

I am ------------------ years old

15 – 25 ☐
26 – 35 ☐
36 – 45 ☐
46 – 55 ☐
56 and above ☐

Gender

Female ☐
Male ☐

Educational background

High School ☐
Graduate ☐
University Degree ☐
PhD ☐

Monthly Family Income

Below RM2000 ☐
RM2001 - RM4000 ☐
RM4001 - RM6000 ☐
RM6001 - RM8000 ☐
RM8000 and above ☐

Have you purchased products online?

Yes ☐
No ☐

Appendix (18). Malaysian Questionnaire Set 2. Purchase Scenario

Purchase Scenario

You are about to read a purchase scenario describing the purchase of a specific product from amazon.in. This scenario is hypothetically developed for the study and thus, may or may not depict the actual business practice of Lazada.com.my. Please carefully read the scenario and answer the following questions.

Read the Scenario

You wanted a new American Tourister© Comet Black Laptop Backpack and decided exactly what colour and model you will buy (as shown in the picture below). You purchased the bag for RM 94 from Lazada.com.my Later the same day, your friend purchased the same backpack and told you that he had to pay RM 139 to buy it from Lazada.com. You came to know that this price discrepancy is due to new the pricing practice of charging different buyers different prices for the same product using each customer's personal and observed information such as age, location, browsing habits, previous purchases, number of clicks on a product etc received from the browser cookies.

American Tourister© Comet Black Laptop Backpack

(Source - https://www.amazon.in/American-Tourister-Comet-Backpack-03_8901836135312/dp/B01CQZ5FBA)

Which of the following statements is true based upon the scenario you just read?

☐ My friend had to pay RM 139 and I paid only RM 94 for the same backpack
☐ I had to pay RM 139 and my friend paid only RM 94 for the same backpack

Which of the following statements is true based upon the scenario you just read?

☐ The difference between the price I paid and the price my friend paid occurred within the same day as I purchased the backpack
☐ The difference between the price I paid and the price my friend paid occurred one week after I purchased the backpack.

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