"A STUDY ON EFFECT OF SHOPBOTS ON PURCHASE INTENTION OF MOBILES"

Dissertation Submitted to Mahatma Gandhi University, Kottayam in Partial Fulfillment of the Requirement for the Degree of

MASTER OF COMMERCE

Submitted by

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DECLARATION

I hereby declare that the project work titled **"A STUDY ON EFFECT OF SHOPBOTS ON PURCHASE INTENTION OF MOBILES"** is a bonafide record of the project work done by me under the supervision of Dr. Ajay Joseph, Assistant Professor, Department of Commerce, Bharata Mata College Thrikkakara for the partial fulfillment of the requirement for the award of master of Commerce. This project report has not been submitted previously by me for the award of any degree, diploma, fellowship or other similar titles of any other University or Board.

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CERTIFICATE

This is to certify that the dissertation titled **"A STUDY ON EFFECT OF SHOPBOTS ON PURCHASE INTENTION OF MOBILES"** submitted by CHRISTY PAUL in partial fulfillment of Master of Commerce to Mahatma Gandhi University, Kottayam is a bonafide record of the work carried out under my guidance and supervision at Bharata Mata College, Thrikkakara, Cochin.

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A STUDY ON EFFECT OF SHOPBOTS ON PURCHASE INTENTION OF MOBILES

ABSTRACT

The most effective tools for customers to quickly compare costs and find offers for desired products are online price comparison websites (shopbots), such as PriceGrabber.com. Shopbots like NexTag.com have now released price charts (line charts) that show a product's whole price history in addition to distributions of actual prices in price comparison tables. Consumers should be assisted by pricing charts in generating expectations about future prices. However, it is not yet known how price charts affect consumer perceptions of prices and purchasing choices. The findings of this study demonstrate that, depending on price chart parameters, providing prior prices causes significant revisions to price predictions. Particularly, price expectations and timing decisions are significantly influenced by the trend, variation, and range of historical prices in the chart. The aim of the study is to analyse factors influencing purchase intention of mobiles. The information for the study were collected be means of structured questionnaire with the sample of 80 respondents,

Keywords: Shopbots, Price comparison sites, Purchase intention

CHAPTER 1

INTRODUCTION

INTRODUCTION

Customers now have more options for stores to shop at as internet businesses expand, making it harder for them to choose the best one. As a result, customers who know exactly what they want to buy still have to do a lot of searching to find a business with the right price and selection to buy from, with acceptable product and service quality. A consumer's search volume increases as She expects to find a more perfect balance between price and quality offers. However, looking through internet shops is time-consuming, which makes it expensive. The presence of search fees has been cited as a primary cause of pricing variation across online retailers (Brynjolfsson and Smith, 2000; Clay, et al. 2001). The introduction of shopbots has almost eliminated the expense for potential customers to view the prices of numerous online vendors. Shopbots, often known as price comparison engines, are software agents that automatically search a large number of online sellers to compile information on their goods and services a certain item. Since shopbots can more easily gather and compare price data than humans, shopbots are largely made to improve service quality and reliability price aggregation and presentation for the largest online merchants (Harrington and Leahey, 2006; Smith, 2002).

According to Nielsen NetRatings (2007), 62% of those polled said that being able to compare offers effectively is one of the most common reasons why people shop online. The most effective tools for consumers to quickly compare costs and find offers for desired products are hence online price comparison websites (shopbots), such as PriceGrabber.com and YahooShopping.com. Shopbots enable better and more effective buying selections by lowering the cost of product information search. Since price history information is a source of external reference pricing, it should influence consumer behaviour. Price charts should therefore assist consumers in setting expectations for future prices. Research indicates a conceptual link between buying timing and price expectations. The price chart's price history information may consequently encourage smart buying decisions regarding when to buy now and when to buy later. Since behavioural finance research have shown that some investors base their buy- or sell-decisions on specific chart patterns of prior stock values, one might also anticipate that the impact of visualisation on consumer expectations and the timing of purchases. Depending on the features of price charts and as a result, price history.

The purpose of the project to investigate how the price chart provided by online shopbots affect the purchase intention of mobile phones. The impact of price chart attributes is also examined in this study. To know the factors which generating purchase intention of mobiles a survey is conducted. The study on the factors affecting purchase intention is limited in the existing literature and this study tries to examine the effect of shopbots on purchase intention of mobiles. The variables used to measure the factors effecting purchase intention are deal proneness, perceived usefulness, expertise, shopbot relevancy and perceived expensiveness.

1.1 STATEMENT OF THE PROBLEM

There were factors which influence purchase intention. This study attempts to identify the factors which have effect on purchase intention of mobiles on online shopbots. This study was undertaken based on the review of available literature which revealed that a researcher has not been conducted to study the factors that influence the purchase intention on shopbots. The current study therefore is an attempt to analyse the various uses of shopbots and to establish relationship between factors that influence purchase intention of mobiles on shopbots. The study raises the following questions for investigation

- What are the uses of shopbots in mobile purchase?
- How these factors affect purchase intention of mobiles?

1.2 SIGNIFICANCE AND NEED OF THE STUDY

Shopbots help customers make informed decisions before making a purchase by displaying a list of pricing given by various businesses. Users will use this website as a resource to confirm the cost of goods being sold and to find out whether any promotions are currently running. Additionally, it can assist vendors in promoting new products. Shopbots offered a better solution by gathering all the prices so users only needed to go online and select which product

they wanted to know about, and the list of retailers and the price offered will be shown. This saved time and energy compared to taking hours to visit each shop just to check on the price.

1.3 SCOPE OF THE PROBLEM

The factors that influence the purchase intention of mobiles such as Deal proneness, perceived usefulness, expertise, shopbot relevancy and perceived expensiveness are different from one respondent to another. Hence such factors may negatively or positively affect the purchase intention of mobiles.

1.4 OBJECTIVE OF THE STUDY

The study on the effect of shopbots on purchase intention of mobiles is undertaken with the following specific objectives :

- To explore the various uses of shopbots in mobile purchase
- To study the impact of shopbots antecedents on generating purchase intention of mobiles.

1.5 HYPOTHESIS OF THE STUDY

Following are the null hypothesis for the study:

HO1 : There is no significant relationship between Deal proneness and Purchase intention

HO2 : There is no significant relationship between Perceived usefulness and Purchase intention

HO3 : There is no significant relationship between Expertise and Purchase intention

HO4 : There is no significant relationship between shopbot relevancy and Purchase intention

HO5 : There is no significant relationship between Perceived expensiveness and Purchase intention

Figure 1.1 Hypothesized Model


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┌─────────────────────┐
│   DEAL PRONENESS     │
│       (HO1)          │
└─────────────────────┘

┌─────────────────────┐
│     PERCEIVED        │
│    USEFULNESS        │
│       (HO2)          │
└─────────────────────┘
                                            ┌─────────────────┐
┌─────────────────────┐                     │                 │
│     EXPERTISE        │                     │    PURCHASE      │
│       (HO3)          │ ──────────────────→ │   INTENTION      │
└─────────────────────┘                     │                 │
                                            └─────────────────┘
┌─────────────────────┐
│     SHOPBOT          │
│    RELEVANCY         │
│       (HO4)          │
└─────────────────────┘

┌─────────────────────┐
│     PERCEIVED        │
│   EXPENIVENESS       │
│       (HO5)          │
└─────────────────────┘
```
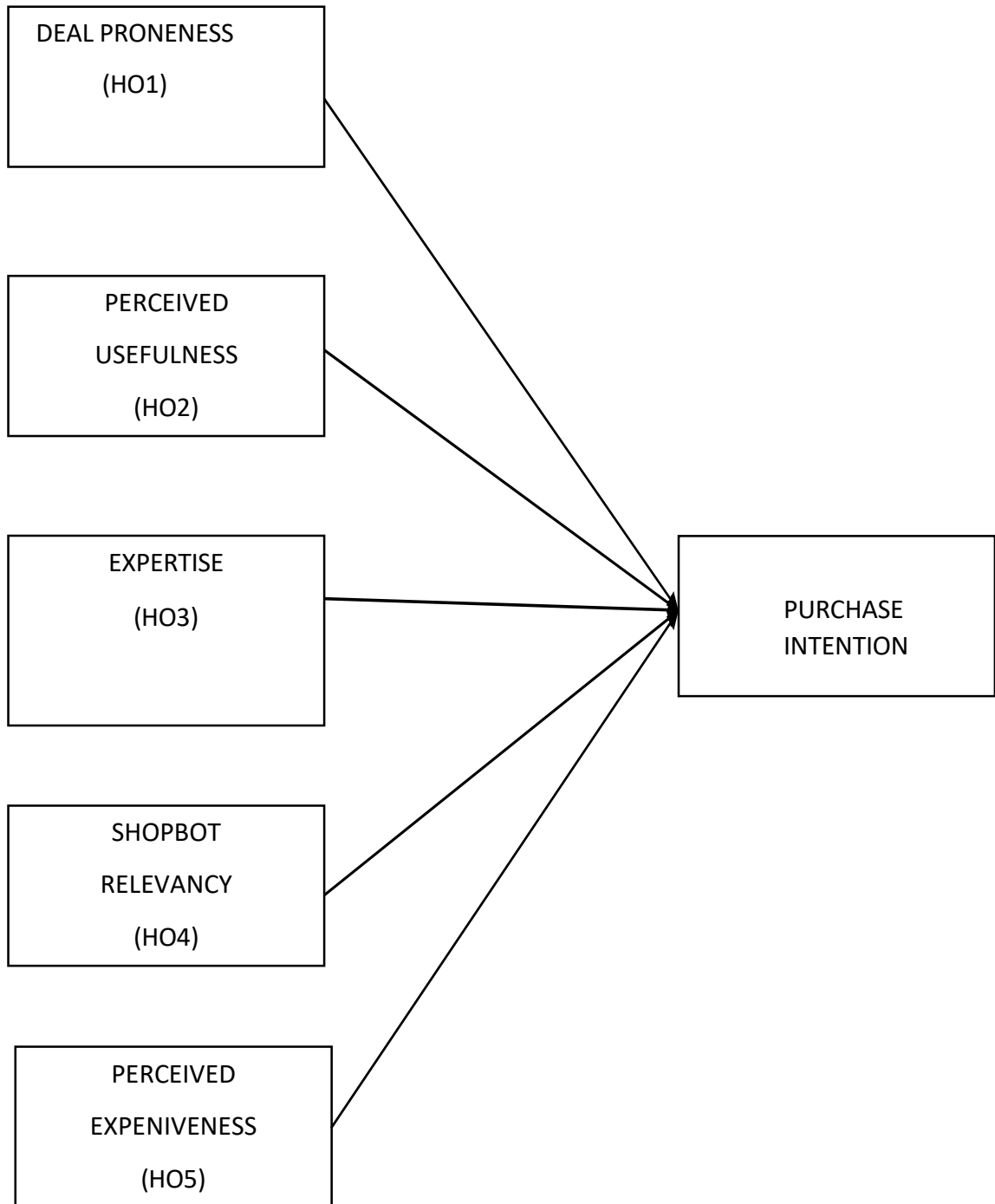
Source : Complied by the researcher based on extensive review

1.6 RESEARCH METHODOLOGY OF THE STUDY

Research methodology is a science of studying how research is carried out. This study tries to look out the influence of factors that influence shopbots on purchase intention. During this study, five independent variables and one dependent variable are tested. Dependent variable is purchase intention, and independent variables are deal proneness, perceived usefulness, expertise, shopbot relevancy, perceived expensiveness.

1.6.1 Sample

A sample is a finite subset of population, selected from it with the objective of investigating its properties. A sample of respondents who use shopbots in Kerala irrespective of district, is taken for the study.

1.6.2 Sample Design

Sampling design is a design that specifies the sample frame, sample size, sample selection and estimation method in detail. For this study, the 80 samples were selected by using the convenience sampling method from the total population.

1.6.3 Method Of Data Collection

Data was collected from the respondents irrespective of the age and gender using structured questionnaire prepared digitally in Google forms. Google Forms Questionnaire were sent to the respondents and responses were taken from the Google response sheet.

1.6.4 Source Of Data

Data are characteristics or information, usually numerical, that are collected through observation. In an exceedingly very more technical sense, data could even be a bunch of values of qualitative or quantitative variables about one or more persons or objects, while a datum (singular of data) could even be one value of one variable. Data is an uninterpreted quite information and its complete only through valid interpretation. There are various methods for interpreting data. Sources of information are mainly classified into two:

1.7.4.2 Primary data

Primary data are the first-hand information collected specifically for a purpose through surveys, questionnaires and direct interviews. In this study, the primary data was collected using structured Google form questionnaire. Out of the responded questionnaire 80 were selected after sorting the incomplete and incorrect questionnaire forms for conducting the research. Responses on various measures used in the study were obtained on 5-point scale on basis of frequency of visit as very frequently (1), frequently (2), occasionally (3) and rarely (4) and based on agreements as strongly agree (5), agree (4), neutral (3), disagree (2) and strongly disagree (1).

1.7.4.3 Secondary data

Secondary data are the information that are already collected by and readily available from other sources. Such data are more quickly obtainable than primary data. Secondary data for the study was collected from various books, various articles published in online journals, Magazines, and websites.

1.7.5 Tools For Analysis

The primary data collected were statistically coded, processed, classified, tabulated and analysed by using statistical and mathematical tools and techniques like percentages, mean, mode and standard deviation. In this study table and statistical results were derived with the help of the software called Statistical Package for Social Science (SPSS).

1.8   LIMITATIONS OF THE STUDY

Some of the limitations of the study:

- Time and resources factors are the most limiting one for the study

- The sample size was limited to 80 respondents only.

- The findings of the study are based on the response of the respondents, which might have their own limitations. The attempted objectivity has naturally been constrained.

- It is assumed that the information given by the respondents is true as per their knowledge and hence the chances of biased information is remote but definitely cannot be ruled out

- Due to the limited number of respondents, the findings may not be the same for the whole population.

1.9   CHAPTERISATION

For the convenience of the study and the analysis the work is divided into four different chapters.

1st chapter – Introduction

This gives an introduction to the study. It gives details including the statement of problem, relevance, scope, objectives, hypothesis, research methodology, limitations, method of analysing of data of the study and scheme of chapter presentation.

2nd chapter – Review of literature and Theoretical Framework

It includes various previous studies related to the topic and also includes the concept, definition, meaning of Shopbot and purchase intention which has been obtained from various published sources and act as secondary data for the study.

3rd chapter – Data Analysis and Interpretation

This explains the examination and analysis of the data to obtain objectives of the study. Analysis of the study is carried out with the help of a software called Statistical Package for Social Science (SPSS).

4th chapter – Findings, suggestion and conclusion

It is the final chapter which gives findings, suggestions and conclusion derived from the study.

CHAPTER II

REVIEW OF LITERATURE

AND

THEORETICAL FRAMWEORK

THEORETICAL FRAMEWORK & REVIEW OF LITERATURE

2.1 THEROTICAL FRAMEWORK

2.1.1 SHOPBOTS – MEANING

A shopping bot is an intelligent software programme that automatically searches the products of numerous online retailers to get the best prices for customers. These shopping bots often list things according to price and allow customers to click over to an online retailer's website. An intelligent software agent that can automatically search a large number of online stores for a certain product is known as a "shopping robot," thus the abbreviation. Shopbots make it possible for customers to compare products by showing the costs and characteristics of each one on a single page. A comparison shopping website, also known as a price comparison website, price analysis tool, shopbot, aggregator, comparison shopping agent, or comparison shopping engine, is a vertical search engine that customers use to filter and compare products based on price, features, reviews, and other factors. The majority of comparison shopping websites collect product listings from numerous shops, but they don't actually sell anything themselves; instead, they make money through affiliate marketing deals.

2.1.2 HISTORY OF SHOPBOTS

BargainFinder, created by Andersen Consulting, was the first well known comparison shopping tool (now Accenture). In 1995, the team, under the direction of researcher Bruce Krulwich, developed BargainFinder as an experiment and released it online without informing the e-commerce sites under comparison. The University of Washington academics Oren Etzioni and Daniel S. Weld launched the Seattle startup company Netbot, which created the first commercial shopping agent under the name Jango. In late 1997, the Excite site purchased Netbot. A Bay Area business named Junglee also invented comparison shopping technology and was quickly purchased by Amazon.com. Pricewatch.com and killerapp.com were a couple of further early comparison shopping websites. Another comparison-shopping website, NexTag, was ranked among the top 50 websites worldwide by Times magazine in 2008 before

closing in 2018. PriceGrabber's acquisition by Experian in 2005 for $485 million was arranged by the company's then-CEO and founder, Kamran Pourzanjani, and Tamim Mourad, in 1999.

The price comparison websites entered emerging markets about 2010. Many new comparison websites have been developed, particularly in South-East Asia. When CompareXpress launched in Singapore in 2010, other nations soon followed, including Baoxian in China, Jirnexu in Malaysia, and AskHanuman in Thailand. In the meantime, Google has been accused of undermining competitors in developed economies by favouring Froogle and its replacement, the paid-placement-only Google Shopping, over them in search results, thereby reducing traffic to rival websites and even forcing some of them out of business. A 2010 inquiry by the European Commission resulted in a €2.42 fine in July 2017.

2.1.3 TYPES OF SHOPBOTS

When customers use shopping bots to do a product search, the bots locate the items and report back with details such as prices and descriptions. On the other hand, there are actually lots of bots with slightly varied features. Therefore, shopping bots might be browser-based, websites, plugins, price comparison tools, etc.

Some popular shopping bots are:

- MySimon: The most well-liked shopping bot, with excellent reviewer reviews. More than 1,700 retailers across many categories are questioned.

- DealPilot : It is a browser-based bot that displays price comparisons on bars near the bottom of the browser. It does the web search and then provides the user with information on where to get the best price as well as specifics on availability and shipping.

- iChoose: This free application sends a consultant with consumers as they browse and shop on their chosen websites. When buyers identify a desired product, it

alerts them if there is a better offer available, along with details on the cost, delivery, and taxes.

- Shoppinglist.com: This website gives users the most recent details on sales and exclusive offers at physical stores in their area.

- StoreRunner.com: This website aids users in discovering goods and services from more than 1,000 brands. The choice therefore rests with the customers as to whether they should shop locally or online in order to find the greatest deals in their area.

2.1.4 PURCHASE INTENTION - MEANING & DEFINITION

Purchase intent refers to a customer's willingness to purchase a specific good or service. The dependent variable, purchase intention, is influenced by both internal and external variables. An indicator of a respondent's attitude toward making a purchase or using a service is their purchase intentions.

A crucial marketing metric is purchase intentions. In fact, marketing based on intentions, also known as intent marketing, is the practise of promoting goods and services based on consumer intentions, or the consumer's intent to accept, purchase, or utilise a specific good or service that may or may not have been explicitly mentioned by the business or brand. Measurements of purchase intentions are useful when creating marketing campaigns or promotions. It can be extremely simple to precisely repeat what kind of material should be displayed in an advertisement based on the intent of a customer. The intentions may reveal details about the consumer's mental understanding levels. And the design of marketing activities can be created based on this measurement. Purchase intentions of a customer base can be analyzed to make an integrated map of how to go about an advertising campaign.

2.1.5 IMPORTANCE OF PURCHASE INTENTION

The increase in return on investment for marketing efforts results from marketing that uses purchase intentions as a measurement. Knowing a customer's intentions in advance or being able to measure them precisely would enable you to better target your marketing efforts and provide the intended outcomes, such as stronger customer engagement and return on investment. This occurs because there is no requirement that a brand first raise consumer awareness of a product or service provided by it before advertising it. When a consumer wants to make a purchase of a good or service, their purchase intentions are explicitly recorded in the interaction database or projected based on behaviour data.

Search marketing, also referred to as search engine marketing and search engine optimization, is one source of how purchase intention is measured. Site data, off-site online activity, point of sale data, and customer relationship managers are a few additional sources of intent information. Social data—information gathered from social networks—can also be quite useful. Data or patterns about content consumption are highly helpful in that the purpose information gleaned from them serves as a digital footprint because these are linked to specific key words on a search engine. These are a result of engagements when users connect on social media platforms or visit websites, and they provide us with a quick snapshot of the customer's present and potential future purchase intentions. These intent measurements individually tell us a lot about how the design of engagement activities can be made effective so that the platforms can become more interactive and fruitful.

2.1.6 FACTORS AFFECTING PURCHASE INTENTION

The factors affecting purchase intention are:

- **Seasonality**

  Various seasons of the year tend to see the sale of particular commodities. However, since this is not always clear, be sure to ask your customers directly if and how seasonality is affecting their intention to buy your items. For instance, some individuals purchase rain boots immediately it starts to rain, but other people are more clever and wait until the off-season to purchase in order to save money.

- **Existing customer satisfaction**

  This is a significant factor in purchase intention. Believe us when we say that unhappy customers are more likely to want to shop elsewhere. In the section below, we'll demonstrate how to use customer satisfaction surveys to gather information about how satisfied your consumers are with your current offerings and your brand as a whole. Additional details can be found in our comprehensive market research guide.

- **Customer demographics**

  Customer demographics may influence purchasing intent depending on your product or service. Customers from different socioeconomic classes, for instance, might buy particular products more frequently. We advise getting a number of consumer demographic metrics when gathering data on buy intent so that you can compare intent across various customer categories.

- **Advertising**

  Since advertising is intended to increase sales, you should anticipate that it will have an impact on your decision to buy, preferably in a good way. Read a recent article about brand tracking surveys to learn more about how you may assess your advertising efforts and their impact on purchase intent.

2.1.7 STAGES OF PURCHASE INTENTION

```
┌─────────────┐
│ Awareness or│
│ Need        │
│ recognition │
└─────────────┘
        ⬊
        ┌─────────────┐
        │ Interest or │
        │ Search      │
        └─────────────┘
                ⬊
                ┌─────────────┐
                │ Desire      │
                └─────────────┘
                        ⬊
                        ┌─────────────┐
                        │ Action      │
                        └─────────────┘
```
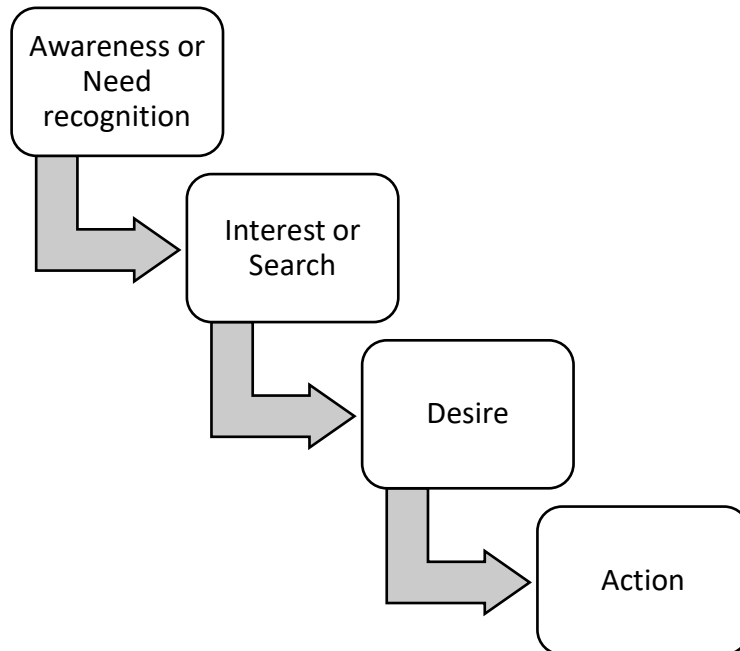
Stage 1: Awareness or need recognition

 The customer becomes aware of their need to buy a certain product at the awareness stage of the customer journey. For instance, a consumer can realise that their sofa is worn out, doesn't fit in their ideal room design, is broken, or both. At this point, the consumer is aware of the need for a purchase, but due to the necessity for preliminary research, they may not yet be prepared to convert this awareness into intent.

Stage 2: Interest or search

Information search is the second step in the customer purchasing process. Before making a final selection, the consumer now starts to hunt for and research information about various goods and services available on the market. The sources of information available to customers are numerous. Customers might order catalogues, browse websites for various furniture retailers, or ask friends and family about their prior purchases, for instance, in our sofa example. The customer may not be certain which merchant to buy from and may only have a tentative

intent to buy. Knowing where customers are in the buying cycle will help you tailor marketing initiatives like your advertising or efforts to increase brand recognition.

Stage 3: Desire

The consumer can assess the various items that are accessible to them once they have gathered enough information to support their buying decision. Purchase intentions are firm at this point, so you're interested in if clients are thinking about purchasing from you.

Stage 4: Action

The consumer actually purchases the product and consumes it toward the conclusion of the customer journey, either away or at a later time. However, research demonstrates that there are occasionally discrepancies between a consumer's plans and actions. Customers might have decided to buy a sectional sofa, for instance, but change their minds as soon as they go inside the store to complete the transaction. Therefore, at this point, you should learn as much as you can about the specifics of the intended purchase decision, such as how much the buyers anticipate spending. You can better address their requirements if you do this.

2.2 REVIEW OF LITERATURE

2.2.1 Shopbot

Shopping robots or shopbots for short, are thought to be a significant driver of these lower search costs. Internet shopbots are automated programmes that let clients quickly and easily search for prices and product details from online merchants. Customers can assess the features of available products and navigate straight to their preferred retailer by clicking through to structured pricing comparison tables that display product information that has been directly retrieved from retailers. For marketing scholars examining electronic markets, shopbots raise a number of intriguing issues. How will customers react to the availability of shopbot services and the information they provide? Many investigations have discovered that the search intensity in electronic markets is remarkably low (Johnson, Moe, Fader, Bellman, and Lohse 2000). Will the use of shopbots significantly change how people conduct searches? How much

will buyers who utilise shopbots choose their products based on price, brand, and other factors of the product bundle?

Shopbots are software intelligent agents that automatically question many online merchants to acquire details about costs and other product characteristics at a specific point in time. Typically, the information is made available to customers for free (Smith 2002). Shopbots serve as a central "clearinghouse" for businesses and customers to communicate and exchange information in this way (Baye and Morgan 2001).

Shopbots are web-based services that enable 'one click' access to price and product data from a variety of rival merchants. By doing this, they lower the cost for consumers to research products and prices compared to phone-based purchasing and even more so compared to visiting the stores in person (Brynjolfsson and Smith,2000)

2.2.1.1 DEAL PRONENESS

Deal proneness is described as "a greater propensity to respond to a buy offer since the structure of the purchase offer positively influences purchase assessments" (Lichtenstein, Netemeyer and Burton 2016). It is seen as a latent consumer trait and an individual factor impacting customer perceptions because it refers to the inclination to buy rather than actual buying activity (Buil, De Chernatony, and Montaner 2013). Deal proneness is therefore a key characteristic that influences the inclination to buy a phone.

A general propensity to respond to promotions because they are in deal form has been described as the concept of deal proneness, first used by Webster in 1965. (Lichtenstein,1995). This concept provides a conventional method for analysing people's behaviour in relation to promotions (Henderson, 2000). Deal proneness is crucially defined in this definition as the psychological predisposition to buy rather than the actual acquisition of things on sale (Delvecchio,2005).

HO1: There is no significant relationship between deal proneness and purchase intention

Table No. 2.2.1.1 Measure of Deal proneness

Sl.No	Measures/Items	Reference
1	I wait till there is an advertised sale before purchase the product	Roy, 2016
2	I hunt around till I find a real bargain	
3	If a product is on sale, discount can be the reason to buy it	Henderson, 2000
4	I am more likely to buy brands that are on sale	Lichtenstein,1995

Source : From existing Review of Literature

2.2.1.2 PERCEIVED USEFULNESS

Lai and Wang (2012) state that customers' perceptions of the effectiveness of online price comparison sites as a resource for them when making online purchases. A person's perception of the system's usefulness can be used to gauge whether they believe it would be preferable to carry out certain tasks if they used it (Lim, Osman 2016).

When a person discovers that using a recommender system might boost their performance, as opposed to when they had not previously experienced the benefit of a recommender, they are viewed as being more effective (Pursel , 2016). It is necessary to get the users' perspectives on the utility or lack thereof of this system. Common recommenders in e-commerce environments primarily assist consumers in finding relevant information to support their purchasing decision. The process of selecting relevant things is best demonstrated by shopping in an online setting. Overall, decision technologies seek to overcome consumers' limited capacity for logic in an effort to help them make more persuading decisions (Zhang, 2011).

Users in particular use recommender systems to manage a large amount of information and make better selections while working within time and knowledge constraints. Furthermore, the effectiveness of system-mediated judgments can be evaluated using a confidence criterion. The

criterion outlines the degree to which a user is confident that using a recommender enabled them to make the right decision (Pu & Chen, 2011).

HO2: There is no significant relationship between Perceived usefulness and Purchase intention

Table No. 2.2.1.2 Measure of Perceived usefulness

Sl No.	Measures/Items	Reference
1	Shopbots will help to search more quickly for information about price of a product	Lai and Wang , 2012
2	Shopbots would make it easier to purchase products at lowest price	
3	Using shopbots would enable me to accomplish purchase timing task more quickly	
4	I would find shopbots is useful to purchase products	Pursel,2016
5	Shopbots would make my search for information about price of a product more effective	Zhang, 2011

Source : From existing review literature

2.2.1.3 EXPERTISE

When evaluating consumers' opinions of this medium and their online shopping habits, it is important to take into account their level of familiarity with or experience with using shopbots on the internet (Balabanis and Vassileiou, 1999; Helander and Khalid, 2000; Hoffman,1996; Hoffmal,1999b; Liao and Cheung, 2001; Maignan and Lukas, 1997; Montoya-Weil, 2003; Novak et al., 2000). Studies have even shown that a consumer's level of internet proficiency may be a factor in determining how widely they use online price comparison channels (Montoya-Weis,2003).

The advantage provided by base expertise can be connected to the different basis knowledge structures that beginners and professionals have. According to Alba and Hutchinson (1987), experts have a solid basis of knowledge that is well-endowed with attribute information as well as abstract knowledge regarding structural relations. Experts will probably use this information

in their decision-making as well. Experts, as opposed to beginners, "employ more effective top-down tactics starting with known variables to deduce unknowns," according to Spence and Brucks (1997)

HO3: There is no significant relationship between Expertise and Purchase intention

Table No. 2.2.1.3 Measures of Expertise

Sl No.	Measures/Items	Reference
1	I strongly recommend shopbot to others	Roehm and Sternthal, 2011
2	Prior knowledge about shopbots helps to judge its credibility and quality	
3	I consult friends on electronic media before making a purchase decision	Montoyo weis, 2003

Source : From existing review literature

2.2.1.4 SHOPBOT RELEVANCY

Although customers frequently rely on knowledge from their recollections to shape their product assessments and purchases (Costley and Brucks 1992), they may first do an information search (Alba,2018). Shopbots, merchants, and producers should be interested in how customers react to pricing chart information. Price charts may become more popular if people consider them to be important information. According to research, a shift in pricing expectations has a significant impact on demand elasticities when it comes to timing of purchases (Erdemet , 2005).

According to certain ideas, price information influences consumer perceptions when it is deemed acceptable or realistic in comparison to the consumers' internal price standards (Monroe 2003; Urbany, Bearden). Additionally, these processes take place when customers are presented with a price that is outside of their expectations but still reasonable. Consumers integrate and lower this pricing information to a level more appropriate for the product category rather than simply rejecting it (Urbany, Bearden). When considered collectively, these facts show that customers who receive new pricing information tend to revise their earlier price

assumptions (Yadav and Seiders 2016). Therefore, we anticipate that customers would update their earlier pricing expectations using price charts that reflect the evolution of historical prices.

HO4: There is no significant relationship between Shopbot relevancy and Purchase intention

Table No. 2.2.1.4 Measures of Shopbot relevancy

Sl No.	Measures /Items	Reference
1	Information provided by the shopbot was relevant for purchase timing decision	Alba,2018
2	Information provided by the shopbot would helps me in purchase timing decision	
3	Information's are always up-to-date and fit the users criteria	

Source : From existing review literature

2.2.1.5 PERCEIVED EXPENSIVENESS

According to Zeithaml (1988), from the standpoint of the customer, price is what is given up or sacrificed in order to receive a thing, and that pricing is made up of three components: sacrifice, perceived nonmonetary price, and objective price (sometimes known as the actual price of a product). Consumers sacrifice their money and gain from other competing brands, according to Parvin and Chowdury (2006), in order to acquire the most utility out of a brand whose items they buy. Geçti (2014) noted that a number of factors, including price, could influence customers' decision-making. One of the many significant market cues that customers typically consider while making choices is price. As many individuals consumers often have different reactions to price.

HO5: There is no significant difference between Perceived expensiveness and Purchase intention

Table No. 2.2.1.5 Measures of Perceived expensiveness

Sl No.	Measures/Items	Reference
1	Actual price in shopbots are high	Yoo,Donthu, and Lee, 2002

Source : From existing review literature

2.2.1.6 PURCHASE INTENTION

Purchase intention describes a user's intentions to buy a specific good or service. Customer intention can be used to predict actual user behaviour. The best indicator of a person's behaviour is their goal as a customer. This goal then contributes to understanding a customer's real behaviour (Eid,2011). Purchase intention is a customer's commitment to returning to a business to buy further goods and services as well as to spread word of mouth recommendations. (2012) Khan, Naumann, and Williams.

The intention to purchase a specific good or service within a certain time frame is known as a purchase intention (Hair, 2011). The consumers' resolve to make a purchase from an e-commerce company also influences their intention to make an online buy (Salisbury ,2001)

Table No. 2.2.1.6 Measures of Purchase intention

Sl No.	Measures/Items	Reference
1	Product price has significant impact on purchase intention	Khan, Naumann, and Williams, 2012
2	I will purchase products by comparing price in shopbots in future	

Source : From existing review literature

2.3 MODEL FOR VALIDATION

Based on the above identified variables and review, the following model was developed for validation.

Figure 2.1 Model for validation


```
┌──────────────────────┐
│   DEAL PRONENESS      │
└──────────────────────┘

┌──────────────────────┐
│     PERCEIVED        │
│     USEFULNESS       │
└──────────────────────┘
                                              ┌──────────────────────┐
┌──────────────────────┐                      │     PURCHASE         │
│     EXPERTISE        │──────────────────────│     INTENTION        │
└──────────────────────┘                      └──────────────────────┘

┌──────────────────────┐
│     SHOPBOT          │
│     RELEVANCY        │
└──────────────────────┘

┌──────────────────────┐
│     PERCEIVED        │
│     EXPENIVENESS     │
└──────────────────────┘
```
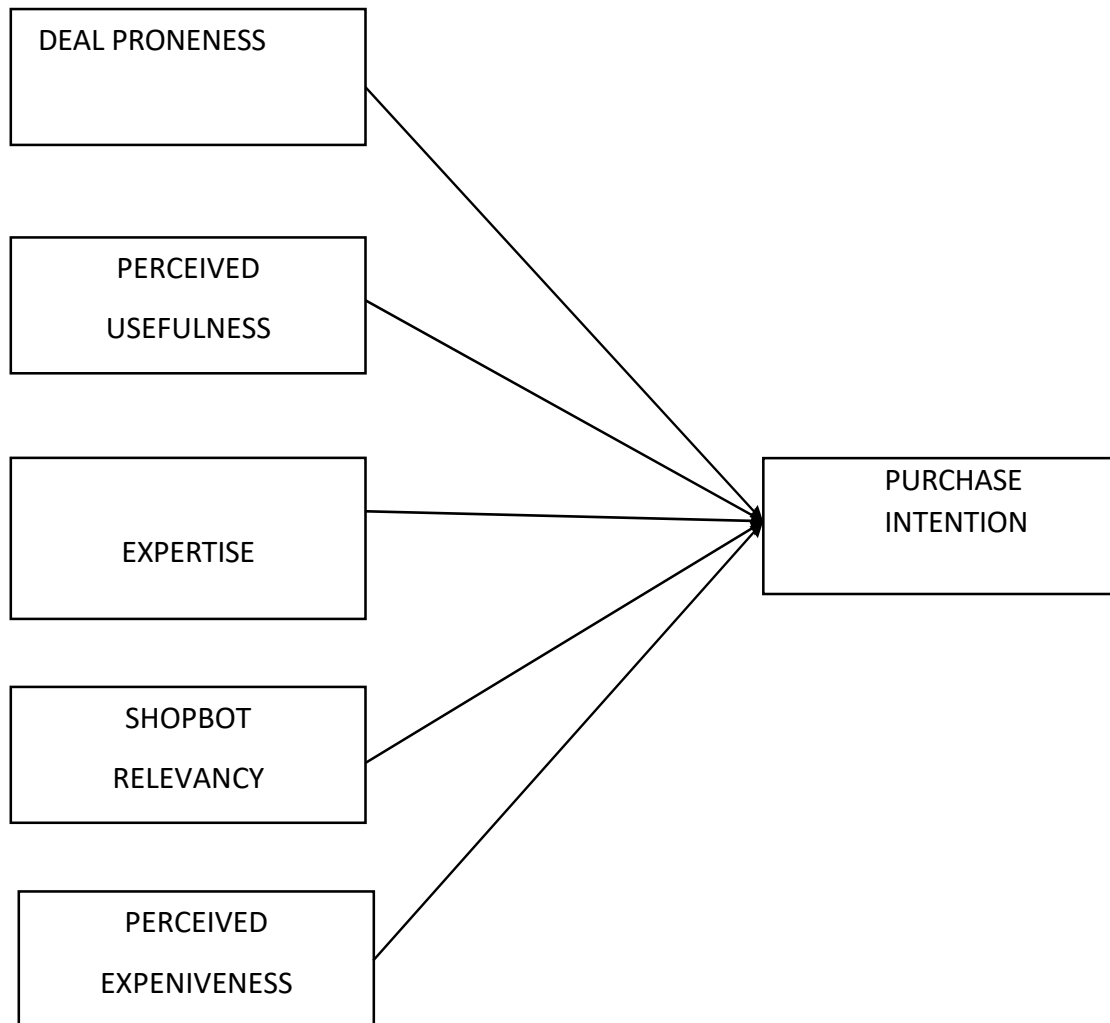
Source : Complied by the researcher based on extensive review

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2.4 SUMMARY

In this chapter we are dealt with literature review and theoretical framework. This chapter was mainly divided into three sections as theoretical framework, Literature Review and Model Development. In theoretical framework the theory related to the topic of study were identified from secondary data related to the topic. After that lots of previous study were reviewed from various sources and measures used for the study were identified. Then the model development was made according to the review regarding the constructs used in the study. This provides a comprehensive idea and structure to accomplish the objectives of the project. Exploring the literature has helped in developing the questionnaire in tune with the objectives. The variables or construct mentioned here were measured using items identified in the previous review itself. To conclude, all the available previous studies were reviewed to make a meaning full hypothesized model and to bridge the void in literature.

CHAPTER III
DATA ANALYSIS AND INTERPRETATION

DATA ANALYSIS AND INTERPRETATAION

This chapter deals with the analysis of the data collected. The data is analysed in three different stages. The first section is the profile analysis which includes a brief analysis of the Demographic profile of the sample respondents. In the second section the descriptive analysis and reliability test of the measure of the measures are done. In the third section the hypothesis formed at the outset were tested and model validation.

Section I

3.1 DEMPGRAPHIC PROFILE OF THE RESPONDENTS

3.1.1 FREQUENCY OF VISIT

Table 3.2.1 Frequency of visit

Frequency of visit	Frequency	Percentage
Very frequently	8	10.0
Frequently	17	21.3
Occasionally	30	37.5
Rarely	25	31.3
Total	**80**	100.0

Source : Primary Data

Table 4.2.1 presents the frequency of visit composition of respondents. It can be conclude that from the total of 80 respondents, respondents who visit shopbots very frequently were 10.0 percent, frequently were 21.3 percent, occasionally were 37.5 percent and rarely were 31.3 percent. Majority of the respondents visit shopbots occasionally.

Section II

3.2 RELIABILITY ANALYSIS

A Reliability test was carried out using Cronbach's Alpha, which measures the internal consistency of research constructs and the result is exhibited in Table 3.2.1. The Alpha value for the seven factors are above 0.70, the threshold suggested by Nunnally (1978). Thus, it can be concluded that the Scale has internal consistency and reliability. In the other words, the item that are used in it measures what are intended to measure.

Table 3.2.1

Cronbach's Co-efficent Alpha – DP,PU,EP,SR,PU,PI

Factors	Number of items	Cronbach's Alpha
Deal proneness	4	.800
Perceived usefulness	5	.769
Expertise	3	.750
Shopbot relevancy	3	.754
Perceived expensiveness	1	.915
Purchase intention	2	.769

Source : Author's calculation

3.3 DESCRIPTIVE ANALYSIS I

3.3.1 DEAL PRONENESS

Deal proneness is described as "a greater propensity to respond to a buy offer since the structure of the purchase offer positively influences purchase assessments" (Lichtenstein, Netemeyer and Burton 2016). It is seen as a latent consumer trait and an individual factor impacting customer perceptions because it refers to the inclination to buy rather than actual buying activity (Buil, De Chernatony, and Montaner 2013). Deal proneness is therefore a key characteristic that influences the inclination to buy a phone.

Table 3.3.1 Measures of Deal proneness

Measures	Item Acronym	Mean	Mode	SD
I wait till there is an advertised sale before purchase the product	DP1	4.03	5	.993
I hunt around till I find a real bargain	DP2	3.74	4	.924
If a product is on sale, discount can be the reason to buy it	DP3	4.09	5	.983
I am more likely to buy brands that are on sale	DP4	4.00	4	.842

Source : Primary data

The mean, mode and SD for DP1, DP2, DP3 and DP4 are given in the table 3.3.1. Mean for the DP3 is the highest. Mode for DP1 and DP3 is 5 and for DP2 and DP4 the mode is 4. From the above statistics we can conclude that respondents are willing wait for an advertised sale before purchase the mobile phones and discounts can be the reason to purchase the mobile phones but they not much interested to hunt around to find a real bargain and and not much likely to buy brands that are on sale.

3.3.2 PERCEIVED USEFULNESS

Lai and Wang (2012) state that customers' perceptions of the effectiveness of online price comparison sites as a resource for them when making online purchases. A person's perception of the system's usefulness can be used to gauge whether they believe it would be preferable to carry out certain tasks if they used it (Lim, Osman 2016).

When a person discovers that using a recommender system might boost their performance, as opposed to when they had not previously experienced the benefit of a recommender, they are viewed as being more effective (Pursel , 2016). It is necessary to get the users' perspectives on the utility or lack thereof of this system. Common recommenders in e-commerce environments primarily assist consumers in finding relevant information to support their purchasing decision. The process of selecting relevant things is best demonstrated by shopping in an online setting. Overall, decision technologies seek to overcome consumers' limited capacity for logic in an effort to help them make more persuading decisions (Zhang, 2011).

Table 3.3.2 Measures of Perceived usefulness

Measures	Item Acronym	Mean	Mode	SD
Shopbots will help to search more quickly for information about price of a product	PU1	4.19	5	.843
Shopbots would make it easier to purchase products at lowest price	PU2	4.11	5	.928
Using shopbots would enable me to accomplish purchase timing task more quickly	PU3	3.94	4	.891
I would find shopbots is useful to purchase products	PU4	4.06	4	.876
Shopbots would make my search for information about price of a product more effective	PU5	3.98	4	.941

Source : Primary data

From Table 3.3.2 it is understood that majority of the respondents is Agree towards perceived usefulness that all measures has a mean nearing 4. The highest mean was reported for PU1 which indicate shopbots will help to search more quickly for information about price of mobiles. The least mean was found on PU3 which indicate respondents are neutral towards using shopbots that would enable to accomplish purchase timing task more quickly. Standard deviation is lowest for the measure PU1.

3.3.3 EXPERTISE

When evaluating consumers' opinions of this medium and their online shopping habits, it is important to take into account their level of familiarity with or experience with using shopbots on the internet (Balabanis and Vassileiou, 1999; Helander and Khalid, 2000; Hoffman et al., 1996; Hoffman et al., 1999b; Liao and Cheung, 2001; Maignan and Lukas, 1997; Montoya-Weis et al., 2003; Novak et al., 2000). Studies have even shown that a consumer's level of

internet proficiency may be a factor in determining how widely they use online price comparison channels (Montoya-Weis et al., 2003).

Table 3.3.3 Measures of Expertise

Measure	Item Acronym	Mean	Mode	SD
I strongly recommend shopbot to others	EP1	4.09	4	.903
Prior knowledge about shopbots helps to judge its credibility and quality	EP2	4.01	4	.914
I consult friends on electronic media before making a purchase decision	EP3	4.03	4	.914

Source : Primary data

The mean, mode and standard deviation of the measure of the variable. Expertise are displayed in the table. Mean stands the highest for EP1 with a value of 4.09. Mode value is same for all the three measures. Standard deviation is lowest for the measure EP1 with a value of .903. Since all the mean values are above 4 which clearly indicates that respondents have strong expertise towards shopbots.

3.3.4 SHOPBOT RELEVANCY

Although customers frequently rely on knowledge from their recollections to shape their product assessments and purchases (Costley and Brucks 1992), they may first do an information search (Alba et al. 1991). Shopbots, merchants, and producers should be interested in how customers react to pricing chart information. Price charts may become more popular if people consider them to be important information. According to research, a shift in pricing expectations has a significant impact on demand elasticities when it comes to timing of purchases (Erdemet al. 2005)

Table 3.3.4 Measure of shopbot relevancy

Measure	Item Acronym	Mean	Mode	SD
Information provided by the shopbot was relevant for purchase timing decision	SR1	3.89	4	.857
Information provided by the shopbot would helps me in purchase timing decision	SR2	4.03	4	.914
Information's are always up-to-date and fit the users criteria	SR3	3.86	4	.910

Source : Primary data

This table shows the mean, mode and standard deviation of the different measures of shopbot relevancy. The measure SR2 has the highest mean of 4.03. The mode value is same for all three measures. Standard deviation is the lowest for the measure SR1 with a value of .857. Since all the mean values of measures are near to 4 which clearly indicates that shopbots are relevant for purchase timing decision.

3.3.5 PERCEIVED EXPENSIVENESS

According to Zeithaml (1988), from the standpoint of the customer, price is what is given up or sacrificed in order to receive a thing, and that pricing is made up of three components: sacrifice, perceived nonmonetary price, and objective price (sometimes known as the actual price of a product). Consumers sacrifice their money and gain from other competing brands, according to Parvin and Chowdury (2006), in order to acquire the most utility out of a brand whose items they buy. Geçti (2014) noted that a number of factors, including price, could influence customers' decision-making. One of the many significant market cues that customers typically consider while making choices is price. As many individuals consumers often have different reactions to price.

Table 3.3.5 Measure of Perceived expensiveness

Measure	Item Acronym	Mean	Mode	SD
Actual price in shopbots are high	EP1	3.13	3	1.296

Source : Primary data

The above table shows the measure of perceived expensiveness. The respondents are neutral towards perceived expensiveness were the actual price in shopbots are high. The mode value is 3 and the standard deviation value is 1.296.

3.3.6 PURCHASE INTENTION

Purchase intention describes a user's intentions to buy a specific good or service. Customer intention can be used to predict actual user behaviour. The best indicator of a person's behaviour is their goal as a customer. This goal then contributes to understanding a customer's real behaviour (Eid,2011). Purchase intention is a customer's commitment to returning to a business to buy further goods and services as well as to spread word of mouth recommendations. (2012) Khan, Naumann, and Williams

Table 3.3.6 Measure of Purchase intention

Measure	Item	Mean	Mode	SD
Product price has significant impact on purchase intention	PI1	4.11	4	.914
I will purchase products by comparing price in shopbots in future	PI2	4.04	4	.892

Source : Primary data

The above list of items were used to measure the purchase intention. This table shows the mean, mode and standard deviation of the different measures of purchase intention. The measure PI1 with a value of 4.11 has the highest mean which is followed by PI2 with a value 4.04. Mode value is same for all measures. Standard deviation is lowest for the measure PI2 with a value of .892. From the above statistics we can conclude that product price has a significant impact on purchase intention.

3.4 DESCRIPTIVE ANALYSIS II

3.4.1 ONE SAMPLE T TEST FOR INDEPENDENT AND DEPENDENT VARIABLES

The mean scores of the 6 main variables are calculated and compared with the second quartile (i.e, Central value or Q2). The opinion of the respondents is treated as poor or very poor when the mean is less than the second quartile. It is treated as average when the mean score is equal to the second quartile. The responses of the respondents are treated as good or very good when the mean score is above the second quartile (Jojo,2008). The below table shows the criteria fixed in this regard.

Table 3.4.1 Criteria for comparison – Mean score and central value

Mean score	Opinion
Less than Q1(<2)	Very low
Between Q1 and Q2(2-3)	Low
Equal to Q2(=3)	Medium
Between Q2 and Q3(3-4)	High
More than Q3(>4)	Very high

To check whether the response of the respondents significantly differ from the moderate or neutral state of response, one sample T test were carried out (second quartile).

Table 3.4.2 One Sample T test

Measure	Item Acronym	Mean value	Q2	T value	P value	Inference
Deal proneness	DP	3.9325	3	11.469	.000	High
Perceived usefulness	PU	4.0550	3	12.773	.000	Very high
Expertise	EP	4.0375	3	11.823	.000	Very high
Shopbot relevancy	SR	3.9250	3	1.264	.000	High
Perceived expensiveness	PE	3.1286	3	3.830	.409	High
Purchase intention	PI	4.0750	3	11.789	.000	Very high

Source : Field survey

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- Based on the above table the mean score of Deal proneness is 3.9325. It is statistically significant from Q2 (3). Based on the developed scale, the value falls between Q2 and Q3 (3-4). The value denoted as high. There exist a high level of deal proneness among respondents regarding the aspects of shopbots.

- From the above table, the mean score of Perceived usefulness is 4.0550. It is statistically significant from Q2 (3). Based on the developed scale, the value lies more than Q3 (Q3) (>4). It is denoted as very high. It can concluded from table that there exists high level of perceived usefulness regarding shopbots.

- From the above table, the mean score of expertise is 4.0375. It is statistically significant from Q2 (3). Based on the developed scale, the value lies more than Q3 (Q3) (>4). It is denoted as very high. It can concluded from table that there exists high level of expertise regarding shopbots.

- Based on the above table the mean score of shopbot relevancy is 3.9250. It is statistically significant from Q2 (3). Based on the developed scale, the value falls between Q2 and Q3 (3-4). The value denoted as high. This indicates that shopbots are relevant.

- Based on the above table the mean score of perceived expensiveness is 3.1286. It is statistically significant from Q2 (3). Based on the developed scale, the value falls between Q2 and Q3 (3-4). The value denoted as high. These states perceived expensiveness has a high impact on purchase intention.

- From the above table, the mean score of Purchase intention is 4.0750. It is statistically significant from Q2 (3). Based on the developed scale, the value lies more than Q3 (Q3) (>4). It is denoted as very high. It can concluded from table that there exists high purchase intention from the part of respondents regarding shopbots.

SECTION III

3.5 HYPOTHESIS TESTING AND MODEL VALIDATION

3.5.1 CORRELATION ANALYSIS

Correlation analysis is carried out before conducting regression analysis in order to quantify the strength of relationship between variables. It tests the linear relationship between the variables. Each correlation appears twice: above and below the main diagonal. The correlation on the main diagonal are the correlation between each variable itself.

Table 3.5.1 Correlation between independent and dependent variable

Variable	DP	PU	EP	SR	PE	PI
Deal proneness	1					
Perceived usefulness	.666**	1				
Expertise	.579**	.785**	1			
Shopbot relevancy	.571**	.701**	.807**	1		
Perceived expensiveness	.016**	.165**	.206*	.244*	1	
Purchase intention	.501**	.588**	.727**	.730**	.748**	1

Source : Complied by the researcher

**Correlation is significant at the 0.01 level
*Correlation is significant at the 0.05 level

The correlation coefficients between the independent variables like Deal proneness, Perceived usefulness, Expertise, Shopbot relevancy, Perceived expensiveness and dependent variable Purchase intention are reported in the table 3.5.1. Then correlation coefficient are always be in the range -1 to 1. A correlation is ststistically significant if its P value < 0.005 and P value <0.01. From the above table we can understand that there exists a high positive correlation between all variables with deal proneness.

The correlation between various variables are as follows:

- ➢ The correlation between deal proneness and perceived usefulness is 66.6 percent

- The correlation between deal proneness and expertise is 57.9 percent
- The correlation between deal proneness and shopbot relevancy is 57.1 percent
- The correlation between deal proneness and perceived expensiveness is 16 percent
- The correlation between deal proneness and purchase intention is 50.1 percent
- The correlation between perceived usefulness and expertise is 7.01 percent
- The correlation between perceived usefulness and shopbot relevancy is
- The correlation between perceived usefulness and perceived expensiveness is 16.5 percent
- The correlation between perceived usefulness and purchase intention is 58.8 percent
- The correlation between expertise and shopbot relevancy is 80.7 percent
- The correlation between expertise and perceived expensiveness is 20.6 percent
- The correlation between expertise and purchase intention is 72.7 percent
- The correlation between shopbot relevancy and perceived expensiveness is 24.4 percent
- The correlation between shopbot relevancy and purchase intention is 73 percent
- The correlation between perceived expensivess and purchase intention is 74.8 percent

3.5.2 REGRESSION ANALYSIS

Regression analysis conducted to measure the influence of DP, PU, EP, SR and PE on PI. The independent variables are DP, PU, EP, SR and PE and dependent variable is PI. The main objective of regression analysis is to explain the variation in one variable (called dependent variable) based on the variation in one or more other variables (independent variables.) If multiple independent variables are used to explain variation in a dependent variable, it is called a multiple regression model. The output of linear regression was used to test the hypothesis.

3.5.2 REGRESSION ANALYSIS BETWEEN DP, PU, EP, PE AND PI

Table 3.5.2 Model summary

Model	R	R Square	Adjusted R Square	Standard error of the estimate
1	.760ª	.577	.544	.5680

a.Predictors: (Constant)

R square is the percent of the variance in the dependent explained uniquely or jointly by the independents. The R square and adjusted R square will be same when used for the case of few independents. The R square and adjusted R square shown in Table 3.5.3 is almost the same. Hence, adjusted R square value is used for interpreting the results.

Table 3.5.3 shows that 56.80 percent variation in PI is explained by DP, PU, EP, PE.

Table 3.5.3 ANOVA of regression model

Model		Sum of square	df	Mean square	F	Sig.
1	Regression	28.165	5	5.633	17.456	.013*
	Residual	20.653	64	.323		
	Total	48.818	69			

a. Predictors : (constant), DP, PU, EP. SR, PE
b. Dependent variable : PI

*denotes significant at 5 percent level

ANOVA table showing the regression model fit presented in Table 3.5.3 shows that the model is statistically significant at 5 percent significance level (F= 17.456)

Table 3.5.4 Coefficient of Regression analysis

Factors (constructs)	Item Acronym	Standardised Beta coefficient (β)	Sig. (P value)
Deal proneness	DP	.12	.019*
Perceived usefulness	PU	.55	.021*
Expertise	EP	.543	.017*
Shopbot relevancy	SR	.292	.041*
Perceived expensiveness	PE	.097	.032*

Source : Complied by researcher

*Denotes significance at 5 percent level

Table 3.5.4 percent the standardized Beta coefficient values and the significant values of independent variables deal proneness, perceived usefulness, expertise, shopbot relevancy and perceived expensiveness. The independent variable deal proneness (DP), perceived usefulness (PU), expertise (EP), shopbot relevancy (SR), perceived expensiveness (PE) are statistically at 5 percent significance level. Therefore, it is clear that these five independent variables have significant effect on purchase intention. **Hence, HO1, HO2, HO3, HO4, HO5 are rejected**

From the standard Beta coefficient values of the independent variables, we can understand that all independent variables have positive effect on purchase intention.

The beta coefficient give a measure of the contribution of each variable to the model. Higher the beta value, greater the effect of independent variable on the dependent variable. Among the independent variables perceived usefulness (PU) has the greatest effect.

3.5.5 VALIDATED MODEL

Figure 3.1 : Validated model
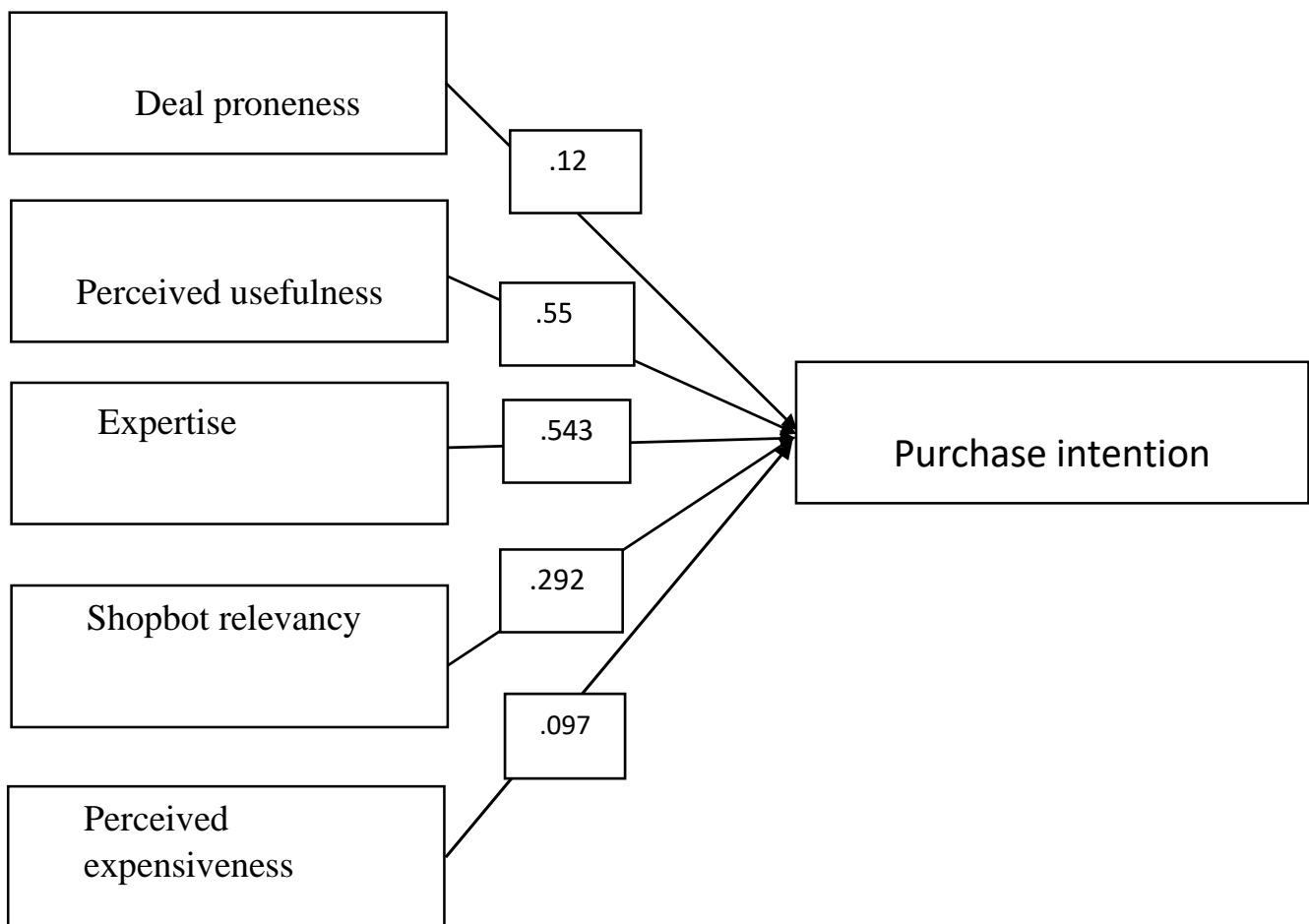
Empirically validated model in figure 3.1 perceived usefulness (β =.55) has the highest beta coefficient followed by expertise (β =.543), shopbot relevancy (β =.293), deal proneness (β =.12) and perceived expensiveness (β =.097). The beta coefficient of all independent variables are statistically significant at 5 percent significance level (P<0.05). Based on the above model it is understood that 5 null hypothesis are rejected and their strong relation between variables. Based on the standardised beta co efficient given in the above table following interpretations can be made:

➢ HO1 : Deal proneness – Purchase intention: Since the P value is .019, the beta coefficient of the variable is significant and the coefficient (.012) being positive proves there exist positive relation between deal proneness and purchase intention. In short deal proneness has positive relationship of 12 percent over purchase intention.

- ➢ HO2 : Perceived usefulness – Purchase intention: Since the P value is .021, the beta coefficient of the variable is significant and the coefficient (.55) being positive proves there exist positive relation between perceived usefulness and purchase intention. In short perceived usefulness has positive relationship of 55 percent over purchase intention.

- ➢ HO3 : Expertise – Purchase intention: Since the P value is .017, the beta coefficient of the variable is significant and the coefficient (.543) being positive proves there exist positive relation between expertise and purchase intention. In short expertise has positive relationship of 54.3 percent over purchase intention.

- ➢ HO4 : Shopbot relevancy – Purchase intention: Since the P value is .041, the beta coefficient of the variable is significant and the coefficient (.292) being positive proves there exist positive relation between shopbot relevancy and purchase intention. In short shopbot relevancy has positive relationship of 29.2 percent over purchase intention.

- ➢ HO5 : Perceived expensiveness – Purchase intention: Since the P value is .032, the beta coefficient of the variable is significant and the coefficient (.097) being positive proves there exist positive relation between perceived expensiveness and purchase intention. In short perceived expensiveness has positive relationship of 9.7 percent over purchase intention.

3.6 SUMMARY

This chapter deals with the analysis of the data collected. The data was analyzed in three different stages. The first section displays the profile analysis which includes a brief analysis of the demographic profile of the respondents. In the second section the reliability of the measures was tested and found satisfactory. Descriptive analysis of the measures was done as two sections: Descriptive analysis I and Descriptive analysis II. Descriptive analysis I includes analysis of each measures belong to the particular variable where as in Descriptive analysis II one sample T test were carried to check whether the responses of the respondents significantly differ from the moderate or neutral state of responses. The Linear regression analysis of the measures was done in the third section and hypothesis formed at the outset were tested.

It was found that the Independent variable deal proneness, perceived usefulness, expertise, shopbot relevancy and perceived expensiveness has effect on purchase intention of mobile phones.

CHAPTER IV

FINDINGS, RECOMMENDATIONS AND CONCLUSIONS

4.1 INTRODUCTION

Businesses are looking for novel solutions to automate online shopping due to the worldwide rapid growth of online transactions. Online ordering has been more simpler thanks to the development of business systems for shopping bots that can handle the amount of orders, client inquiries, and transactions. Computer programmes known as "shopping bots" automate online ordering and self-service shopping for users. A shopping bot speeds up checkout, helps customers select the right products, compares costs, and offers real-time customer care while placing an online order. By speeding up the search process and enhancing the online ordering experience for clients, a bot also assists users in having a simpler online purchasing experience.

A shopping bot offers users a wide range of features, and there are numerous varieties of online ordering bots. Users are familiar with Chatbots, one particular kind of bot. An automated computer software called a chatbot is created to offer customer service by responding to their questions and interacting with them in real-time. Chatbot expedites the ordering and buying process online and gives users quick answers to questions regarding goods, specials, and store restrictions. Online chatbots help businesses run more efficiently, increase customer happiness, and boost revenue.

Shopbot speeds up the online ordering and purchasing process and provides users with prompt replies to queries about products, offers, and store policies. Online shopbots improve operational efficiency, promote client satisfaction, and increase sales for enterprises. Businesses who use shopping bots in their online ordering process have a competitive advantage over those that do not thanks to the artificial intelligence of chatbots. To improve their ability to serve customers, win over users' loyalty, and enhance earnings, shopping bot business owners typically use systems like a Chatbot.

We have so far talked about the advantages that these shopping applications offer their customers. These consist of quicker checkouts, easier item ordering, and price comparison. However, the advantages for company go far beyond more sales. Shopping bots reduce the financial investment that companies must make to hire staff. These chatbots function as leaner,

more productive digital workers. They save a corporation money at the price of insurance, pay, and health plans. Additionally, they are less likely to experience staffing problems like order mistakes, unplanned absences, displeased workers, or ineffective staff. Businesses that are able to access and use the essential client data can grow more lucrative and stay competitive. Businesses can build marketing campaigns around this data by using the virtually infinite library of insights provided by some sophisticated bots. The bots may build extensive profiles of the best reward programmes and products for their target customers based on the shopping information they have access to. They can even forecast potential customer behaviour. With the information provided by the bots, businesses may also quickly pinpoint problems with their supply chain, product quality, or pricing strategy.

4.2 OBJECTIVES OF THE STUDY

The study " A STUDY ON EFFECT OF SHOPBOTS ON PURCHASE INTENTION OF MOBILES" is carried out with the following objectives:

- To explore the various uses of shopbots in mobile purchase
- To study the impact of shopbot antecedents on generating purchase intention of mobiles

4.3 METHODOLOGY OF THE STUDY

The project " A STUDY ON EFFECT OF SHOPBOTS ON PURCHASE INTENTION OF MOBILES" is a study based on information collected from both primary and secondary data. Google form questionnaire where send to the respondents, out of these only respond back and after sorting the incomplete and incorrect questionnaire forms were selected for conducting research.

4.4 SUMMARIZED FINDINGS

i. The effects of shopbots which have significant relationship with purchase intention are Deal proneness, Perceived usefulness, Expertise, Shopbot relevancy and Perceived expensiveness.

ii. Deal proneness, perceived usefulness, expertise, shopbot relevancy, perceived expensiveness have significant impact on Purchase intention of mobiles.

iii. All independent variables which are deal proneness, perceibved usefulness, expertise, shopbot relevancy and perceived expensiveness have positive relationship with purchase intention

iv. From the analysis we can come to an inference that the price charts provided by the shopbots have an effect on the purchase intention of mobiles.

4.4.1 Demographic findings

i. Majority of the respondents visits online shopbots occasionally

ii. Reliability Test were carried out shows the Alpha values for all the six factors and it can be concluded that the scale has internal consistency and reliability.

4.4.2 Deal proneness

i. Most of the respondents are willing to wait for an advertised sale before purchase the mobile phones

ii. They also opinioned that the discounts can be the reason to purchase the mobiles

iii. They not much interested to hunt around to find a real bargain and and not much likely to buy brands that are on sale.

iv. All the mean scores are above three shows their high perceptions regarding the variable Deal proneness

4.4.3 Perceived Usefulness

i. The highest mean was reported for PU1 which indicate shopbots will help to search more quickly for information about price of mobiles.

ii. The least mean was found on PU3 which indicate respondents are neutral towards using shopbots that would enable to accomplish purchase timing task more quickly

iii. Most of the respondents find shopbots is useful to purchase mobiles by comparing price

iv. Majority of the respondents agreed that shopbots are effective to search for an information about price of mobiles.

4.4.4 Expertise

i. All the mean values are above 4 which clearly indicates that respondents have strong expertise towards shopbots.

ii. Majority of the respondents are in the opinion that they recommend shopbots to others.

iii. The mode value of majority of the measures shows the highest perception of respondents regarding expertise

4.4.5 Shopbot relevancy

i. All the mean values of measures are near to 4 which clearly indicates that shopbots are relevant for purchase timing decision.

ii. Most of the respondents feels that the informations on shopbots are up do date and it fits users criteria

iii. The mode value of majority of the measures shows the highest perception of respondents regarding Shopbot relevancy.

4.4.6 Perceived expensiveness

i. The respondents are neutral towards perceived expensiveness were the actual price in shopbots are high.

ii. The mean above three shows their high perception regarding the variable perceived expensiveness

4.4.7 Purchase intention

i.   Majority have the opinion that product price has a significant impact on purchase intention.

ii. Mean score shows that price chart provided by shopbots has influence on purchase intention of mobiles

4.4.8 T test

This section deals with findings relating to the T test carried out:

i.   It was found that there exist very high effect of perceived usefulness and expertise in purchase intention

ii. Deal proneness has high effect on purchase intention

iii. Perceived expensiveness has high effect on purchase intention

iv. Perceived usefulness, expertise and purchase intention has mean above second quartile shows good response from respondents.

4.4.9 Regression Analysis

Linear regression analysis was conducted to measure the influence of independent variable deal proneness, perceived usefulness, expertise, shopbot relevancy and perceived expensiveness on purchase intention. Following are the results and findings:

i.   The correlation coefficient between the independent variable and the dependent variable exhibits a positive correlation.

ii. The R square adjusted R square were almost the same. The adjusted R square shows that 54.4 percent variation in purchase intention is explained by deal proneness, perceived usefulness, expertise, shopbot relevancy and perceived expensiveness.

iii. The model is statistically significant at 5 percent significance level with F value at 17.456

iv. The beta coefficient of deal proneness, perceived usefulness, expertise, shopbot relevancy and perceived expensiveness are statistically significant at 5 percent significance level ($p < 0.05$).

v. Perceived usefulness is found to be strong positive impact on purchase intention. It is evident from the beta coefficient of 55 percent. Thus, perceived usefulness establishes strong positive relation over purchase intention of mobiles.

vi. There exist a positive effect of expertise over purchase intention with its beta coefficient of 54.4 percent.

4.5 THEROTICAL CONTRIBUTION

This study examines the various uses of shopbot in mobiles purchse and various factors on generating purchase intention through the validation of theoretical model. For further research, there is a need to search for additional measures and constructs to improve the validity of the model. Findings of the study might be useful for students and academicians as an input for doing similar nature of research in academic field in future.

4.6 SUGGESTIONS (Practical contribution or managerial implications)

This study could aid shopbots in their efforts to increase the effectiveness of official websites in encouraging visitors to make more purchases. To feed a calibrated continuous improvement process on company objectives, businesses should carefully plan and manage chatbots. They should pay attention to time, communication tone, information quality, contact staff training, and control of the channels of instant messaging applications by feeding ongoing relationships with their customers. Companies must develop the necessary digital and artificial intelligence skills and understanding in order to maximise the data obtained from conversations with shopbots and more precisely create digital relational sales strategies.

4.7 SCOPE OF FURTHER STUDY

The research study is limited to a few factors. It explores only the relationship between a short-listed factor influencing purchase intention of mobiles on shopbots. The scale of experiment can be further enlarged. Some extraneous variables which ignored in the present study can be further controlled and the experiment can be strengthened as a standardized research tool. There are various factors that affect the purchase intention other than those mentioned in the study.

4.8 CONCLUSIONS

Shopbots make it possible for customers to compare products by showing the costs and characteristics of each one on a single page. "A STUDY ON EFFECT OF SHOPBOTS ON PURCHASE IONTENTION OF MOBILES" had its objective to study the various uses of shopbots in mobile purchase. The study focuses on understanding the impact of shopbots antecedents on generating purchase intention of mobiles.

The study is mainly conducted as four chapters namely Introduction, Theoretical Framework and Literature Review, Analysis and finally Findings, suggestion and conclusion. First chapter is the introduction part which mainly dealt with overall view of the topic of study and it includes objectives of the study, statement of the problem, scope, methodology, hypothesis and chapterisation.

The second chapter is divided into three section as Theoretical Framework, Literature Review and Model Development. Theoretical framework mainly includes the concerned theory of the subject which is under the study. Theories were framed and collected from various secondary sources. From the theory portion one can simply get the subject very clearly. The second section of the chapter contains various review of past studies connected with the area of our topic. And it also includes review of variables which is used for conducting this research. All this literature review is been framed by reading and searching various articles published in

journals. Third section of the chapter contains Model Development of the research. Model Development is done from the extensive literature review.

Third chapter is mainly divided into three as Analysis of Demographic profile, Descriptive analysis and Regression Analysis, Model validation and Hypothesis testing. In analysis of demographic profile various demographic measures used in the study were analysed. And for that frequencies were framed out to show the number of respondents belongs to each demographic feature. Reliability analysis was carried out using Cronbach's Alpha which proved the internal consistency of the research constructs. The Descriptive analysis includes the analysis of the variables used in the study. It is carried with identifying the mean, mode and standard deviation.

A one sample T test were conducted to check whether the responses of the respondents significantly differ from the moderate or neutral state. And a one-way Anova test were carried out to determine whether there are any statistically differences between the means of two or more independent groups. In the final section we conducted Correlation analysis to quantify the strength of relationships between variables. And from the analysis we understood that there exists a high positive correlation between all variables except the variable. Then Regression analysis is done to measure the influence of independent variables with the dependent variables. From the regression analysis it was proved that five independent variables have significant relationship with purchase intention. As the result of all these analyses all hypothesis is rejected.

The fourth chapter of the study denotes Findings, Suggestions and Conclusions. It includes the demographic findings, descriptive findings and regression analysis findings. The study makes significant contribution to the existing literature by examining the measures of purchase intention. In this context the present study attempts to unearth the answers to the research questions factors influencing purchase intention. It was purchase intention found that is dependent on various measures such as deal proneness, perceived usefulness, expertise, shopbot relevancy and perceived expensiveness. Hence, the study is quite relevant and timely from the view of both academics and authorities.

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APPENDIX

A STUDY ON EFFECT OF SHOPBOTS ON PUCHASE INTENTION OF MOBILES

I DEMOGRAPHIC PROFILE

1. Have you ever visited online shopbots
   - Yes
   - No
2. Frequency of visit
   - Very frequently
   - Frequently
   - Occasionally
   - Rarely

II DEAL PRONENESS

Sl No.	Measures	Strongly agree	Agree	Neutral	Disagree	Strongly Disagree
1	I wait till there is an advertised sale before purchase the product					
2	I hunt around till I find a real bargain					
3	If a product is on sale, discount can be the reason to buy it					
4	I am more likely to buy brands that are on sale					

III PERCEIVED USEFULNESS

Sl No	Measure	Strongly agree	Agree	Neutral	disagree	Strongly disagree
1	Shopbots will help to search more quickly for information about price of a product.					
2	Shopbots would make it easier to purchase prroducts at lowest price					
3	Using shopbots would enable me to accomplish purchase timing task more quickly					
4	I would find shopbots is useful to purchase products					
5	Shopbots would make my search for information about price of a product more effective					

IV EXPERTISE

Sl No	Measure	Strongly agree	Agree	Neutral	Disagree	Strongly disagree
1	I strongly recommend shopbot to others					
2	Prior knowledge about shopbots helps me to judge its credibility and quality					
3	I consult friends on electronic media before making a purchase decision					

V SHOPBOT RELEVANCY

Sl No	Measure	Strongly agree	Agree	Neutral	Disagree	Strongly disagree
1	Information provided by the online shopbot was relevant for purchase timing decision					
2	Information provided by the shopbot would helps me in purchase timing decision					

3	Information are always up-to-date and fit users criteria					

VI PERCEIVED EXPENSIVENESS

Sl No	Measure	Strongly agree	Agree	Neutral	Disagree	Strongly disagree
1	Actual price in shopbots are high					

VII PURCHASE INTENTION

Sl No	Measure	Strongly agree	Agree	Neutral	Disagree	Strongly disagree
1	Product price has significant impact on purchase intention					
2	I will purchase products by comparing price on shopbots in future					