A User-Centric Approach to Ensure Safe Browsing in E-commerce through Behavioral Economics

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Declaration

It is hereby declared that

1. The thesis submitted is my/our own original work while completing degree at Brac University.

2. The thesis does not contain material previously published or written by a third party, except where this is appropriately cited through full and accurate referencing.

3. The thesis does not contain material which has been accepted, or submitted, for any other degree or diploma at a university or other institution.

4. We have acknowledged all main sources of help.

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0.1 Ethics Statement

All the important steps were followed to ensure that the research method was ethical. This included:

1. **Informed Consent:** Participants in the surveys and interviews were clearly told how their information would be used. Before collecting any data, their proper consent was taken.

2. **Data Confidentiality and Anonymity:** All data, including personal and private information was gathered without revealing individual identities to protect participants' privacy and it was saved safely. Every effort was made to protect the name of the participants, so that no identifying information was shared at any stage of the study.

3. **Commitment to Relevant Laws and Regulations:** The research study followed every applicable law as well as all necessary institutional standards. The study conforms to all regional and international laws which protect data privacy rights.

4. **Research Integrity:** The authors affirm that all data presented is valid and accurate. The research contained only original results where no fabrication or falsification or plagiarism affected the work. All external work received appropriate citation. The research excluded both fabrication and falsification and plagiarism during its execution and its final presentation. This work includes proper citation of external materials whenever they were used as reference.

This research upholds the highest standards of ethical integrity by following these principles.

Abstract

In the last few decades, there has been a drastic growth in the field of technology which has resulted in a significant impact on the increase in usage of the internet, mobile phones, computers, and so on. This rapid advancement of technology has dramatically transformed the trade and e-commerce sector which open a new window of opportunities and risk. A major issue faced by online consumers is information asymmetry. Along with that, fake reviews, misleading advertisements, and poor customer support often results in irrational decision-making. Behavioral Economics proposes that human behavior is not always rational. Individuals are often influenced by emotions, cognitive bias, and environmental consequences. These biases lead to irrationality. Addressing these challenges our study explores the application of Behavioral Economics theories to mitigate these challenges and guide users toward more rational decisions in the context of E-Commerce using Behavioral Economics. We created a Google Chrome browser extension that uses Behavioral Economics ideas to lower information asymmetry as people cannot physically judge products along with integrating Bayesian Average and exponential time decay algorithms. The effectiveness of this research is evaluated through analysis of user behavior combined with hypothesis testing and semi-structured interview methods. In this respect, we focused on some Behavioral Economics (B.E) theories that drive human decision-making tendency, and implemented those into a chrome browser extension in order to investigate whether B.E reduces information gap. Along with this, we will investigate whether humans are able to make informed decisions for safe browsing in the e-commerce sector using the Chrome extension or not.

Keywords: E-commerce, Usability, Behavioral Economics, Bayesian Average Algorithm, Safe Browsing, Extension, Rating, Consumer Trust, HCI.

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Chapter 1

Introduction

Nowadays, more than half of the world's population are using the internet for their daily necessities [159]. Everyday millions of people are sharing millions of data in today's computerized world. With the advancement of the technologies there has been substantial growth in e-commerce. E-commerce brought a new wave right to the doorstep of customers with its unparalleled convenience and efficiency. Powered by better access to the Internet, advanced technological enhancements in the business, and personalized marketing, the industry is set to hit $4.89 trillion in global sales this year [160]. This impact of e-commerce has been remarkable in Bangladesh as well. According to "Bangladesh B2C E-commerce Market Report 2022" the e-commerce market size was about Tk 56,870 crore in 2021 and it will be around Tk 1.5 lac crore by 2026. And currently there are almost 2000 e-commerce based outlets and 50,000 Facebook commerce based outlets delivering 30, 000 products per day [142]. Therefore, a large number of people are engaged in buying products from online stores.

According to Bangladesh telecommunication regulatory commission (BTRC), latest statistics (November, 2024), the current number of internet users rose to 132.80 million (BTRC, www.btrc.gov.bd, 2024). Now an increase in technological usage has surely benefited the mass population but it is sad to be true that every coin has two sides. This engagement with online activities have facilitated a large number of fraudulent activities and online exploitations [85]. It is a matter of grief that e-commerce is no exception. 43% percent of e-commerce consumers are victims of fraudulent payment [155]. Because of that researchers, figured out consumers have trust issues on the authenticity of online shopping. Some revealed that there is so much false information scattered around this sector that it does not hesitate to disappoint the consumers. Accompanying that, user reviews, and rating are also deprecated, for which consumers can not assess their trustworthiness [157]. Several customers have complained that they failed to receive proper customer service, authentic products or sometimes undelivered products. Unreliable delivery service and digital payment failures also significantly affected in reducing the trust [157]. One of the main concerns faced by the consumer is uncertainty about online shopping. And it is created because people cannot physically judge any product before buying it from online stores. They have to rely on the available information in e-commerce sites and to buy products. This information asymmetry is a major issue which results in facing the scam. Humans tend to get influenced by external factors easily such as in e-commerce sectors, stores give a discount for a limited amount to influence customers to buy products [123]. So, if a fraudulent e-commerce store does that, humans will get easily influenced by that to buy products instead of thinking rationally. Earlier research shows that humans have certain cognitive biases that impact human decision-making which hinders rationality [30]. Though rational choice theory states that, if humans are presented with some options and asked to make decisions based on them, then humans will make rational calculations to decide and will choose the option that aligns with their ultimate goal [152]. But in reality that is not the case.

Therefore, it has become critical to educate consumers about safe online shopping in order to lessen the identified risks of digital transactions, manipulative information and becoming victims of fraudulence. In this respect, we will try to focus on human decision-making tendency, which factors drive them at the time to make decisions and how we can focus on those with a motive to help users towards safe browsing in e-commerce sites. We developed a Google Chrome browser extension focusing on the Behavioral Economics theory with a view to reduce information asymmetry and to analyze how users behave when we use the theories of Behavioral Economics in a positive way to influence their decisions. Our goal is to understand whether these interventions effectively guide users towards more rational decision-making.

1.1 Research Motivation

Over the past few years E-commerce has become a key part of economic growth in the global market. Due to the modernization of the internet, like all the other technological sectors online selling and buying took an immense transformation. Both consumers and retailers are satisfied with the unique features of online shopping like the round clock facilities and low travel cost, store visits have become a low priority option to them. More than 85% of the people have connected to online transactions and online ordering of products [94]. Recent research suggests that over a third of the customers spend around 200$ each on online shopping. Bangladesh is no different from that. As an emerging country it has almost 46 million active facebook users [149]. As a result many small businesses are growing as well. Around 300,000 f-commerce pages are present in the social media marketplace [149]. In Bangladesh the transaction value in Digital commerce is expected to touch $14.33 bn in 2024 with an annual growth of 11.34% [158]. As more people are concentrating on online activities, the same amount of pressure is also increasing on financial systems. To adapt to this increase many online payment systems have also been introduced.

Besides the development of the positive technical innovations, this has restored a notable amount of abuses such as anti-social activity, security-privacy issues for instance fraud, phishing etc. Data from IC3 shows that the complaint rate has increased to 10% by 2022. According to a news article presented by Daily Star in May, 2023 19,623 complaints have been filed against 50 e-commerce companies with the Directorate of National Consumer Rights Protection (DNCRP) involving about Tk 600 crore [143]. Some common types of e-commerce scam persist in Bangladesh are phishing scam, counterfeit products, fake websites, advanced fee scams and so on [146]. Therefore, it is a must to take steps to solve this issue. Now there can be a significant number of reasons why people are becoming victims. A huge number of technical steps are taken in order to increase safety but a question arises that do humans really take preventive measures to protect themselves from such scams? Humans are referred to as "The weakest link in the chain" in the system security [55]. Moreover, according to Behavioral Economics humans are driven away by emotion, heuristic, and mental shortcuts [112]. So, there might be a chance that it is humans who make wrong decisions or get influenced by external factors and so they are buying products from such scam online shops without having proper knowledge. For this reason, our research focuses on these humans irrationality which are explained by Behavioral Economics theories. We will apply Behavioral Economics theories to analyze how people make decisions and how these theories justify the factors that influence them. We aim to employ these theories and try to come up with a solution in the form of a usable Google Chrome browser extension to analyze whether human decision making tendencies can be influenced to ensure safe browsing or whether humans can make proper decisions to make themselves secure or not.

1.2 Research Objectives

Our research suggests a user centric approach using Behavioral Economics with a motive to influence user towards safe browsing in E-Commerce sector. Our objectives are:

- Explore Behavioral Economics concepts that can be leveraged in the Digital Environment to increase awareness and safe decision-making.
- Develop a Chrome Browser Extension that can help in real-time decision-making support and nudge users toward safer online behavior.
- Measure the impact of Behavioral Economics based nudges in alternating decision-making and reduce the information gap.
- Analyze user perception which alternates their decision-making tendencies.

1.3 Thesis Contributions

This research has significant contributions in the field of HCI (Human Computer Interaction), Behavioral Economics and E-Commerce Trust System to ensure consumer awareness and fraud prevention. There are the key contributions of this thesis outlined bellow:

- Incorporate Behavioral Economics in e-commerce risk awareness.
- Implementation of a dual stage awareness system (Active and Passive)
- Development an adaptive and dynamic reputation system.
- Incorporate AI driven sentimental analysis for selecting predefined options.

- Technological innovation to ensure safe browsing and take better decision through Chrome Extension.
- Experimental validation of user behavior to ensure fraud awareness.

1.4 Report Structure

This is an overview of the structure to be adopted for the report on Phase 3 of our thesis by identifying the main chapters to be used and giving an overview of what each chapter would contain to give a better understanding of how the research is organized.

Chapter 1-Introduction: This chapter overviews our research topic providing motivation, objectives and main aim of our research topic. Our work is set up for it, showing the increasing number of concerns regarding online shopping security and that our solution is supposed to tackle these concerns. The theoretical framework of our work involves an explanation of concepts such as usability, Behavioral Economics, and other works associated with e-commerce fraud detection.

Chapter 2-Background: This chapter overviews the description such topics which are relevant to our research. Additionally, a section with an overview of all the related works, prevailing ideas, themes and debates are explained thoroughly.

Chapter 3-Literature Review: This chapter overviews the existing research on Behavioral Economics, C-HIP model, E-Commerce sector in Bangladesh and highlights the relevant outcome that aligns with this study.

Chapter 4-Work Plan: This chapter overviews the work plan describes our research approach, broken into three phases, explained by the main activities: problem identification, design and development of the extension, and test and evaluation.

Chapter 5-Extension Design Architecture: This chapter overviews the technical details of our research, which includes System Architecture, Connection of Behavioral Economics and brief overview of technological stacks we have used.

Chapter 6-Rating System Development: This chapter overviews the exact model of Bayesian algorithm that was used and explain how the rating was calculated.

Chapter 7-User Testing: This chapter overviews elaborate explanation of our experimental setup, how we conducted semi-structured interview and how we collected observational data.

Chapter 8-Data Analysis and Result: This chapter overviews the exploratory data analysis part along with hypothesis testing with a motive to gain deeper insights of user behavior. It includes the expected outcomes from our proposed solution and gives an overview of some core features of the extension that have so far been implemented. Moreover, The effectiveness of the warning of the extension, which was evaluated with C-HIP model has also been described.

Chapter 9-Discussion: This chapter overviews elaborate explanation our research finding. It includes explanation regarding user feedback, their behavioral pattern and the role of our extension in influencing users decision making ability.

Chapter 10-Limitations and Future Work: The chapter overviews the possible limitations of our research along with the next steps of our research, detailing how improvements will be effected on the Chrome extension, further testing, and refinement of the algorithm using real-world data.

Chapter 11-Conclusion: This chapter overviews the findings of our research with a focus on the contribution that has been made through the Chrome extension, and sends a twofold message that both consumers and regulators are being assisted. This also serves as a notice for potential development and refinement into the final phase of the research.

Chapter 2

Background

Effective online safe browsing requires a balance between both usability and human behavior. Usability focuses on how easy and manageable a system is while understanding from Behavioral Economics explores how decision-making biases such as choice architecture, framing effects, loss aversion, etc influence user actions. The C-HIP model explains how a warning should be created to grab attention and make sense of the information. This research integrates these topics and tests through a prototype whether human behavior can be influenced or not.

2.1 Usability

We live in a world where we are deeply associated with technology every single moment. We are more engaged with such systems and technology which provides us with a good user experience or better usability. The term "usability" is a quality attribute that determines how flexible, simple, and easy the system is for a user. However, usability is not only related to the system rather it is also connected to user experience. There are several ways to interpret the quality of the interaction between end-users and technology. Usability is not confined to the user's perspective only. It is crucial at three fundamental levels. Firstly, from a user point of view, usability is doing a task efficiently without any errors or security issues. Secondly, from a developers point of view, usability is related to success or a system failure. Thirdly, from a management perspective, usability is connected to the security system of software [63]. According to ISO 9421 Standard (introduced by International Organization for Standardization in 1988; revised in 2018), usability is how easily, effectively and efficiently a user can use a system and achieve his desired outcome with satisfaction [133]. Efficiency depends on the particular goal of the user, it could depend on time, satisfaction after completion of a task [47]. Moreover, considering the limitations and the abilities of the users, they try to achieve some goals with the technology or at least think of doing something that requires less information and less labour. The more the system requires less resources to invest the more the usability of the system is. And so users prefer those systems which are less complex and have a more user-friendly interface [133]. A usable product is that product which meets specific usability criteria [21]. Now this specific usability criteria depends on user, environment and tasks. Thus, it is difficult to specify the criteria. One common solution is to compare a specific product to other available product and then measure the efficiency, satisfaction and effectiveness. Usability is fully dependent on interaction of the user. No product is usable of itself but it consist of attributes which is determine its usability for specific user, environment along with the task [24].

2.2 Behavioral Economics

In a perfect or ideal world, it is considered that human beings are optimal and always make favorable decisions that provide them with maximum satisfaction. Rational choice theory states that, if humans are presented with some options and asked to make decisions based on them, then humans will make rational calculations to decide and will choose the option that aligns with their ultimate goal [152]. This theory suggests that, people can make rational choices by determining the benefits of each option effectively. A rational person has control over his emotions and thus is not driven by any external factors while making decisions. It was Adam Smith, who was one of the first economists to say that humans often follow their self-interest and perform those actions which bring positive consequences [1]. Later in the 18th century, Adam Smith recognized that humans become overconfident within their limited abilities and thus their chances of gain are overvalued and their chance of loss is undervalued [54]. That is, human beings are not rational and their emotions often drive them away. This is where the discussion of Behavioral Economics started. The father of Behavioral Economics Richard Thaler, challenged the existing thought that human beings are rational. He stated that, anomalies are present in human behavior and people are greatly influenced by present, past experience along with emotion and mental state [115]. Thus, the field Behavioral Economics came into light which combines both economy and psychology to explain the fact that human beings are not always rational, easily distracted, and do not always make decisions of their self interest [138]. It is the study of psychology which relates with the economic decision making process that analyse people's decision making ability [148]. Behavioral Economics always deals with how people actually behave [96]. According to the field-defining work of University of Chicago scholar and Nobel laureate Richard Thaler, Behavioral Economics analyses the dissimilarity between what people should do in certain situations and what people actually do driven by emotion or external factors [148]. Now, human beings want to maximize benefits but at the time of decision-making, they can not control their emotions and get easily distracted by external factors. Behavioral Economics with the help of some theories and factors explains how people's decision-making capability gets affected because of externalities. Some of the remarkable theory of Behavioral Economics along with their practical implementation are discussed below.

2.2.1 Loss Aversion

Researchers within the vastly growing field of Behavioral Economics have identified that human beings tend to make irrational decisions and it is tied with their emotional shortcomings, biases towards a particular field, and social influence. Among many biases, the most mentioned bias is "Loss Aversion". Friedman and Savage stated that according to classical economics, the amount of happiness a person achieves from gaining should be equal to the amount of grief, a person receives after a loss [3]. However, in real-life scenarios, people are more averse to losses than an equivalent amount of gain [112]. This is an automatic thinking pattern of humans that reflects humans are more reluctant to lose negligible amounts of something rather than gaining something of considerable amount [108]. Some experts have also presented that loss aversion gradually evolved from early human beings. Because early human beings tended to protect their saved resources instead of taking risks to avoid losing something they already had. That is, they were more averse to loss [70]. Due to this loss aversion people sometimes make irrational decisions without thinking about the long-term effect even if it reduces utility.

For instance, in the e-commerce sector this loss aversion technique is used to manipulate human decisions. The stores give discounts and a time limit to purchase limited-stock products. This discount framing is done specifically to influence customers. Because of this, the customer will think about saving cost thus it will increase customers' urge to buy products [123]. Hence, they simply buy the product in order to avoid losing the opportunity. This same irrational decision-making tendency in order to avoid loss is also seen in the context of security. Grossklags and Acquisti in 2007 showed that people are willing to receive money in exchange for sharing personal information because they want to avoid the loss of ownership. That is why they set a high value for it. But they are not willing to pay that much to regain that information. This simply denotes that only due to loss of aversion they are making irrational decisions [112]. Consequently, loss aversion manipulates people into making decisions according to certain situations.

2.2.2 Asymmetric Information

Asymmetric information which is also known as "Information failure" occurs when one party has superior information in comparison to the other in a transaction [112]. Basically, the seller has more information about certain products than the buyers. But the opposite can also be true. In the context of buying some specific products from online or offline most of the cases buyers have more information of where they got the product from, how the product quality is, how much they bought it for. In the opposite scenario, let us say, a buyer wants to buy insurance keeping all the hidden problems of his. So, the person or party who has more information and better resources always remains in an advantageous position. This asymmetric information may lead to ineffective decision-making by the general public [112]. A classical example to describe this is "Market of Lemons" by Akerloaf made in 1970. For example, in a market of used cars, the seller of the cars knows more about the car's quality than the buyers of the market. Now the buyers have limited knowledge about the car's history and quality and so due to being uncertain they want to pay a price lower than the average price for the used cars thinking the used car can be a "lemon". Here, the term has been lemon used to refer to the poor quality product. Thus the owner of the cars that are actually in good quality tends to leave the market when they notice that the buyers' evaluated price is lower than their evaluated price. Thus in the market, only the bad quality car remains and so the risk of buying "lemons" from the market increases. Thus, it proves that asymmetrical information could lead to misjudgement and could lead to making wrong choices [7]. In real-life scenarios, asymmetric information is the main lead of causing privacy and security damage to the users [112]. The agent with whom we are sharing information has more knowledge about what he will do with our data than a data subject sharing the data. Here, the "Agent" refers to a person, group or people. Thus, how the personal information will be manipulated will only be known to a subset of agents making the decisions. [51], [112]. And so there arises a privacy issue regarding our personal data. Thus, asymmetric information manipulates our decision-making ability and sometimes raises concern regarding our privacy.

2.2.3 Bounded Rationality and Heuristic

In many situations in people's lives, they have to make decisions when the results of the consequences are uncertain. They do not get enough information, and time to judge the event to take proper steps. When an individual is out of their choices because they are bound by some constraints, they choose heuristics by default. Heuristics act as cognitive shortcuts in decision-making under uncertainty, quicker or more efficient means to a multitude of decision-making. These mental strategies, or "rules of thumb" allow the individual to make a judgment quickly, by simplifying a complex problem-solving process [88]. So, this basically helps people shorten the time span of decision-making and allows them to function instantly without thinking about the next step. Herbert Simon, who was an economist and cognitive psychologist, introduced the concept of heuristic. He explained that, when people are trying heart and soul to make rational choices, their judgment or decision-making gets limited because of cognitive limitations which then turn them into cognitive biases [50]. But if people can determine the possible benefits and costs of every alternative choice, they can make rational decisions. However, they are limited by some constraints, like enough information, time, etc. In 1957, Simon recognized bounded rationality and human shortcomings and interpreted them in a set of steps [6]. He refers to the decision-making process in an environment with limited knowledge and the limited cognitive capabilities of human thinking [4]. This would logically follow that, instead of maximizing, individuals more often choose acceptable solutions or "satisficing" judgments. Decisions are thus often made in part because of an incomplete understanding of the facts, solutions are thus "satisficing" practical, good enough under given circumstances rather than optimal. He said people's first choice is using heuristics, but it has nothing to do with rationality. They then select the best options among the choices.

This is where classical economics conflicts as here people are not being rational. Among some real-life examples of bounded rationality, one of them is people tend to buy certain products without analyzing all possible alternatives, which means checking the price or quality from other shops, checking payment methods, privacy policies etc. Whatever feels the most convenient to them at that time, they go with that option [112]. This behavior clearly reflects heuristics. Another mentionable scenario is sometimes people overlook warnings or information like spyware notification in software. It may happen because they fail to fully understand that or they may have time constraints. Now this behavior may not always serve the best interest because they may face risk or may get attacked with malware because of this irrational decision [112]. This clearly illustrates how humans make decisions having limited knowledge, time constraints, or because of less attention. Now bounded rationality is a vast field of research. The sub-parts of bounded rationality that are most relevant to our research are discussed below:

- **Availability Heuristic:** Availability is one kind of cognitive bias that says humans make decisions on the first information that comes into their mind or that is most available [134]. Suppose, there are some information stored in an individual's memory, and he will probably judge the outcomes and make decisions based on the experience and information he has in his mind. For example, a younger person will ignore the fact of being diagnosed with cancer because he does not have the information of what will happen if someone gets cancer nor he has any experience related to it. Whereas, if an adult hears this news and has already seen the poor consequences, he will start to think if he has already got it or not. Basically, that adult will overestimate. So in simple terms, availability heuristics refers to humans making decisions based on the information they currently experience or previous experience. Now this availability heuristic can significantly influence customer purchase decisions in the e-commerce sector. In the e-commerce sector, it is a crucial part to check and search the maximum number of stores and compare product quality before buying. However, that is very tiresome work to do. For that, online reviews serve the best purpose. Consumers consider online evaluations as the second most trustworthy source after recommendations from someone [78]. On the other hand, negative reviews tend to have a more significant impact than positive ones as customers try to overestimate risk level as they recall the memories of negative reviews [140]. That is, people tend to buy or make decisions with the available information or past experience and analyze the situation based on that. And so availability heuristic has a significant impact in people's decision-making.

- **Anchoring:** At the time of making a choice, we tend to consider information that is relevant to the current situation or previous experience that works as a reference point. This is known as anchoring [112]. According to a behavioral experiment conducted by Ariely related to anchoring, a group of people were asked to disclose the last two digits of their security numbers and after that, they were asked to estimate the price of a bottle of wine or chocolate. It was observed that the prices that they guessed were close to the security numbers provided by them earlier [48]. It proves that those security digits act as anchored points though they were not connected to the prices. In case of privacy and security, this anchoring has a significant impact. Acquisti surveyed a group of people asking about their personal information. The participants who were informed earlier about the information disclosure of other people were more likely to disclose information in comparison to those who were not informed [89]. That means, we are likely to consider a certain scenario as a reference point and make decisions from that even if it is a privacy-related issue. Similarly, in the e-commerce sector anchoring psychology is highly used to influence customer decisions. For example, when shopping online if a person sees a product with a price of $199, the first thought that will come to his/her mind is the product is expensive. However, if we see that there is a coupon which reduces the price to $99 then that person might get influenced to buy that. This coupon which reduces the price to $99 acts as a low anchor point.

Thus, this anchor point plays a great role in attracting customers to buy that product. Generally, people tend to give more value and weight to the information they perceive at first, that is they stick to a reference point [137]. That is how anchoring influences people's thoughts.

2.2.4 Herding Effect

Learning can be an effective way to develop rationality where it can shed light on when we are drowning in confusion. It can be more effective in decision making while people are in search of information. Behavioral Economics has made the understanding of the learning process mode easier by suggesting some behavioral model called Reinforcement Learning Model [85]. The main goal of this model is to shape the behavior of the human through rewards and punishment which can also be referred to as Token Economy [154]. Another important learning process that is receiving enough attention from behavioral economics is social learning theory. According to Bandura's (1977), people adopt new behavior by observing others and also by imitating them [12]. Social theory helps to understand how the environment a human living in helps to create and shape one's personality and behavior. When humans lack knowledge and arise a sense of uncertainty at that time they follow the crowds they find suitable. This is called Herding Effect. Both the theories closely align together, still they have some dissimilarity. Herding Effect is a one of the behavioral theories, which tells that human behavior likes to imitate others or rely on the decision of others rather than believing in themselves and their independent judgments [2]. This behavior tends to emerge when people are in an uncertain situation and think other's decisions are better informed. They think others have proper information and they might know more and so they follow the crowd [25]. Keynes considers this act as a rational choice in uncertainty.

In the perspective of Financial Markets, herding behavior can lead to stock market bubbles [26]. The theoretical research conducted by Bikhchandani and sharma (2001) highlighted that observing others can lead to market failure [42]. Beyond that, herding can also influence the behaviors of the consumer and decision-making. For example, in the online marketplace, visibility of the previous users activities, and reviews can roll the choice of the user that may lead to Bandwagon Effect. In Behavioral Economy, Bandwagon Effect refers to the tendency of adopting some certain behavior, belief or trends because others are doing so. Lederrey and West analyzed herding effects in online product ratings. They showed that early product reviews and rating can lead to biases to decision making and herding happens, they take a guess on the positive and negative reviews ignoring the quality of the product [120]. In physical stores, customers have the freedom to choose and evaluate their product by seeing and touching. However, this is impossible in online stores due to information asymmetry customers often face uncertainty [72]. According to Hu, Liu, Zhang (2008) this uncertainty is the "dissimilarity in the actual product and what is shown online" [69]. This is where herding is visible. This herding will be rational if users are uncertain and have no prior knowledge. If the user has prior knowledge but follows others without any judgement, it may lead to irrational decision making [85].

2.2.5 Attention Economy

The attention economy is a framework in which human attention is regarded as a valuable resource, similar to currency. In the modern digital environment, corporations, social media platforms, and advertisers compete for users' attention, since it influences decision-making, engagement, and profitability [9], [101]. The vast amount of information exceeding human processing ability makes attention an expensive and precious resource [153]. Platforms use notifications, modified content, and trending topics to sustain user interest and extend application usage [150]. The attention economy functions by combining technology and psychology to observe and influence individual behaviour. Websites and applications evaluate user preferences and present supplementary content accordingly, hence sustaining user engagement [156]. Social media platforms sustain user engagement via endless feeds and autoplaying videos, while advertisers produce exciting commercials [153]. The concept relates to Behavioral Economics since people do not operate using logical decision processes continuously. Companies apply human emotional responses alongside established behaviours and psychological aspects to maintain user engagement [156]. This clarifies why customers frequently allocate more time to digital platforms than intended, engaging with viral material or responding to notifications. This system influences individuals' concentration, efficiency, and psychological well-being. Excessive competition for attention results in information overload, distraction, and tension [101]. Understanding the attention economy clarifies the addictive design of digital platforms and the methods by which they manipulate user behaviour.

2.2.6 Nudge Theory

It is a behavioral economic theory that proposes that it is possible to manipulate people and influence their decisions in predictable ways. Thaler and Sunstein in 2008 stated nudge is "Altering and manipulating people's behavior through any aspect of the choice of architecture in a desired way without restricting the user to a certain choice or changing the economic choices" [112]. Making small changes in the way information is presented to them has a significant impact on influencing people's minds. Behavioral Economics might use "Nudge" to design systems in such a way as to mitigate users' biasing behavior by offering them more informed choices [76]. Because nudge recognizes that users are unaware of the system bias and can be affected by minimal changes in the system design [112]. Behavioral Economics also focused on "Soft Paternalism" which also helps to nudge because it also focuses on influencing people's behavior for their welfare [71], [73]. So, nudge and soft paternalism are on the same level that is to influence people's decisions. Soft paternalism approach influences people for their well being without limiting their individual choices because they preserve freedom of action. They re-frame the available choices in such a way so that the possibility of taking decisions by the user which is beneficial for them increases [112]. In fact, nudging interventions have six categories which are nudging through Information, Defaults, Demonstration, Incentives, Reversibility and Error Resiliency, and Timing [112]. A brief explanation of the following categories which are relevant to our research are provided below:

- **Nudging with Information:** It is the act of providing information in such a way that it mitigates the gap of information which is the hurdle of asymmetric information and availability heuristic aiming to take optimal decisions by the user [112]. Users are associated with different types of biases whether it is herding, emotion, availability heuristic. These biases can either lead to beneficial behavior or sometimes lead to irrational unexpected decisions. In the context of computer security, users are often required to make informed decisions about privacy and security. At the time of using a system it is necessary to let the users know about the risks and benefits associated with the system [112]. If they are informed about the associated risks through relevant information, their decision taking procedure could be more rational and well balanced as they are equipped with better information regarding the weight of potential losses.

However, it is important to keep in mind regarding the amount of information being presented and how it is displayed. Privacy policies mentioned by different websites are the clear example that notices with huge information might overwhelm the users [112]. Educating the user and informing them could be done through a better design. If information is provided in a concise manner then it can play a role in educating the user. However, it is not guaranteed that users will make informed decisions. Because users can ignore the salient information if biases enter into the process of decision making [112].

- **Nudging with Presentation:** Along with other factors of nudge, presentation plays a crucial role in influencing people. Presentation of an information can either mitigate the existing biases or increase the likelihood of getting more driven by the biases. The order in which the information is presented can affect decisions because of anchoring bias. Framing is a very important part of nudges with presentation. In such situations where users might underestimate the risks associated with their decision, in those cases if the potential losses are framed then it might affect the user in taking those risky decisions. Based on loss aversion risk could be framed by the designers such that users could understand the clear loss [112]. Researchers have shown that framing a certain privacy notice more or less has an effect on users willingness to disclose their personal information. Ordering is another important component of nudging with presentation. The order in which the information and options are presented has a strong influence on the user. It is seen that the first piece of information or option has an effect on users' perception regarding the rest of the choices or piece of information [112]. Besides this saliency is another necessary factor. It can either remove bias or increase making people more focus on a certain option ignoring others. Bravo Lillo found that, if the name of a software publisher was more salient, it could play a role in nudging people not to download risky and suspicious websites.

  Along with framing and ordering, structure is another crucial part. It helps users in making complex decisions when there are multiple alternatives and options. Structure helps to simplify the information and arrange those in such a way that users can focus on one factor at a time with less distractions. In summary, structuring along with framing and ordering information helps to reduce biases, and simplify information in an effective way with a motive to help users to make decisions in a balanced way.

- **Nudges with Timing:** Nudges, if strategically conveyed at specific times then the impact of nudging can be maximum. To be more specific, when a user needs guidance or when users are more responsive, if nudges are displayed in those moments then there is a high chance it will be noticed [112]. A study done by Egelman et al. where he found if the privacy policy of a website is shown to the user before visiting the site, it ensures that the user is more likely to trust that website rather than showing the policy afterwards [77]. Moreover, the context is also important. Nudge should be displayed at those moments where the displayed information is relevant to the context the user is going through [34]. For example, in the context of security, twitter gives prompts to users regarding reviewing application access when users are changing their password. It is because they are thinking about security factors at that time. Hence, nudging at the right time increases the likelihood of being noticed by the user and can play a role in affecting users' decisions.

- **Nudges with Incentives:** Incentives (rewards and punishments) can be used to nudge people's decisions. Nudging with the right incentive helps to reduce the bias of hyperbolic discounting that can help to limit the user to appreciate those things which have negative long term consequences [112]. We humans often give importance to those things which include social influence. Non-financial rewards, peer pressure and social influence has a strong influence on human behavior [34]. For example, the product in online shops which has better reviews often has a strong stand against other competitors [112]. Nudges with punishment have a strong effect in controlling user decisions. Increasing the difficulty level or the cost of selecting a particular configuration acts as a 'punishment' for the user. This is helpful as a form of preventing the naive or careless user from selecting the risky settings of a system. On the other hand, the options which are secured should be made easier to select which acts as a form of 'reward' to encourage users to select those [112]. Whether it is punishment or reward, nudges can be implemented with a view to impact user choice without hindering the freedom of choice.

2.2.7 Status quo bias

According to [20], status quo bias is sticking to a default choice or a predefined decision without making any further changes [22]. Even though the cost of changing from the default option is minimal, the after-effect will be great if the correct option is chosen. Still people tend to remain with default settings [22]. This mainly happens for two reasons. The first one is that people tend to remain with the default option thinking that the default option is correct. In another case, people do not want to take risks and choose other options thinking they might choose the wrong one and miss out on something [114]. However, this decision sometimes can be rational and sometimes can be irrational. In the context of privacy and security, information about privacy and security features can be complex and hard for an individual to understand and make rational decisions. So in this case the default setting seems more appropriate [112]. So if the default system setting is strong enough then sticking to the default option can be rational. However, if an individual is capable of understanding security features he may upgrade and change the setting. So, it can be stated that in terms of privacy and security, the status quo plays a role in making choices regarding security features.

2.2.8 Framing Effect

As we already know that cognitive biases are systematic errors in decision making. They are more tricky because they appear from incorrect, often unconscious, information processing [85]. The framing effect is a term commonly associated with Tversky and Kahneman that refers to how choices are presented in the frame, and affects decisions [16]. It suggests that people make decisions based on how the issues are shown to the user rather than the facts. It is humans' cognitive default bias that they like to choose those paths that are more positively shown. Framing Effect sometimes called "Framing Bias" in many human behavior articles [161]. Various methods of presenting the same choice produce different reactions because of the wording of the choices, whether there are gains or losses or because of how information is given. The framing effect is particularly powerful in marketing and consumer behaviors, where either the benefits or the costs of a product could be emphasized in various ways that influence purchase decisions.

For example, suppose an online e-commerce company has placed a discount offer in a different way. Let us say they announced, "Today is a 30% flash sale". Another day they showed the discounted offer by saying "You will lose 30% flash sale if you do not acquire it now". Here these two texts are framed in two different ways. In the context of the framing effect, something that is negatively framed will likely to impact a person more than a positively framed one. In the above example, people will more likely respond the second one, as people are loss averse and they do not want to lose the gains that are currently at hand. Another example could be the issue of overconfidence bias or optimism bias. There will be some individuals in personality traits, who are quite confident about their knowledge and very much optimistic about future events. Victims of online scams may be overconfident about the ability to distinguish a scam. Sometimes this leads to hard to assess the information they get. In the absence of available information which is also known as asymmetric information in Behavioral Economics can lead to a victim of vulnerability. The scammer could be framed in a way that is unknown to the user. So this over-optimism cannot help here and guide us to unpredictable situations [87].

2.2.9 Choice of Architecture

Cognitive and behavioral biases are systematic errors in judgments while making decisions. Here the term "systematic" does not necessarily mean wrong or odd. It means that the results of the decision deviating from the actual results of decisions are taken rationally according to economics theory [112]. According to Ariely in 2008, cognitive biases are non-random or systematic errors in thinking, that is, the judgment diverges from the desired outcomes in terms of rational logic [65]. These cognitive biases play a huge role in shaping and manipulating the decision-making ability of human beings. Now, these cognitive and behavioral biases are of different types. Some biases depend on emotion, and some on knowledge and previous experience. Considering these biases there is a tool that uses the knowledge of cognitive biases and nudges users to certain behaviors and decisions which is called the "Choice of Architecture".

Choice Architecture was first introduced by [73] that describes the practice of presenting choices which can influence human decision-making [73]. It is a metaphor that holds the idea that choices are structured with proper information and tasks. Together all of these features "form" a person's choice [49]. More precisely it is a way of "organizing a context based on which people make decisions" [91]. This tool is connected with liberal paternalism - which means freedom of choice, but encourages user actions in a certain way. From decades of behavioral research, it was discovered that people's preferences are not symmetric but malleable. Partition dependence is one illustration of the shapable preferences of the people. Partition dependency is a kind of cognitive tendency to give equal priority to different categories while judgment or in a specific work [104]. Categories can be changed like people's decisions. For example, in an experiment, the menu list of foods was grouped in terms of "fruits", "vegetables", "cookies & crackers". People are likely to buy fruits & vegetables from that list rather than when the same list was grouped as "Fruits & vegetables", "cookies", "crackers" [53]. Experimental findings reveal that these choice preferences change in different choice situations. These results prove that humans are not solely rational. However, their preferences are affected by many factors that are associated with a choice which do not result in a rational choice. So, it is obvious that there is no such thing as natural choice architecture.

Every unique choice is enclosed by a specific environment that will impact the choice [104]. Choice architecture is unavoidable; it is everywhere. One of the prominent fields among which "Choice Architecture" is being used is E-commerce [139]. When choice architecture is used online it is called OCA (Online Choice Architecture). One example of OCA would be Amazon's one-click invention. Users can set default shipping and payment information for future product purchases [139]. This leads to lower friction. Here, friction refers to the number of times a user gets resisted in a system to complete a task. Using this feature Online shopping friction can be reduced, which leads to smoother "conversion rates" for businesses. Still, when users are uncertain or due to bounded rationality(time pressure) they make faster decisions, reduction in the friction can lead to consuming products that they do not intend to buy [126]. In those cases, friction can be added into the OCA as part of it, which will pause the user's activity and help users in the decision-making process. Thereby reducing the negative impact of the faultless online shopping experience [139]. This behavior has been a proven benefit for consumers, increasing the number of decision points while making online transactions in online banking [135]. Choice architecture has both positive and negative sides to look at. But it depends on the design architect for what purpose they are using it. So, it is crucial to keep in mind before Designing any choice.

2.2.10 Hyperbolic Discounting

Hyperbolic discounting explains how individuals prioritizes instant reward over larger future benefits disproportionately and leading to dynamic inconsistency and present bias in decision making [132][84]. Apart from the traditional exponential discounting model [20] hyperbolic discounting assumes consistency preference over time. It introduces a short term impatience parameter (β) which heavily discounts upcoming rewards ensuring lower discount rate (δ) for future achievement [132]. Individuals struggle going through on long term plans because of the outcome in commitment problems for instance, making health conscious choices or making money due to shifting preference [84]. It has wide implication particularly in money savings behavior, public health and environmental economics where nudges and precommitment mechanisms are used to counteract present bias [84]. To explain procrastination, irrational short-term choices and addiction hyperbolic discounting is an essential theory in behavioral economics which offers insights into designing policies that rely on short-term actions with long-term goals [132].

2.2.11 Salience Effect

The salience effect explains how individuals focus on highly attention grabbing or visible information disproportionately while ignoring less noticeable but parallel important details [92]. The traditional rational choice theory assume that people measure all information equally suggested by salience theory. High contrast features like color-coded warnings, price in bold letter or prominent risk significantly influence while decision making [84]. This biasness effect on consumer behavior, policy making and financial decision. Research found that people react strongly to visually highlighted risks or costs. For instance, carbon emission warnings or tax-inclusive pricing revise their compliance or purchasing behavior [92]. At the time of financial decisions, individuals overwhelmed with highly visible risks while underestimate analytically significant but less prominent ones which lead to biased investment choice [92]. The behavioral nudging state the saline theory is widely applied. It represent information in significantly noticeable way that influences decision making without restricting options. The salience effect help to design effective policy investment that profoundly lead individuals towards better decision by enhancing the key information [92][84].

2.3 Colour Code Theory

Human behavior and thinking depend significantly on color as an essential feature that affects computer interface design and warning systems [111][103]. According to the color coding theory, Colors influence perception, memory retrieval and mental focus through distinct effects on both states and emotions. The use of colors serves as information-based triggers to stimulate psychological responses and build decision making strategies [111][103]. Through warning labels, we see how color coding proves essential for design communication. Research shows that red is strongly associated with high hazard levels because it culturally signifies danger and urgency. In contrast, colors like black, blue, and orange trigger different degrees of caution depending on the cultural and situational context. Yellow, for instance, is widely used in cautionary signs and hazard warnings, especially in traffic and workplace safety. Because it's highly visible and psychologically linked to alertness and vigilance [46][111]. Green is the most frequently used in secure environments, including first-aid areas and escape routes [100]. Signals within digital interfaces use colors to create clear detailed organization structures that help users spot important elements and monitor their noticing of essential items. Electronic warning notifications display red alerts to generate heightened user alertness yet use blue flags to encourage users toward peaceful decision-making. The Digital design supports completion and success indicators through green elements and warns users about requirements using yellow design features [111][100]. The color coding system maintains essential practical applications throughout various academic domains. Educational information processing benefits from the right color selections which leads to improved subjective learning achievements and enhanced instruction format design. Modern communication systems rely on Color Theory principles to achieve better usability through strategic color selection both in technology applications and safety measures [100][103].

2.4 C-HIP

The C-HIP model (Communication-Human Information Processing) is a framework that provides a complete understanding of how the warnings, and risk messages communicate with each other, processed and according to how individuals can individually take actions. It is widely used in Product safety, Health communication, Occupational safety, and HCI [37], [61], [122]. One of the most essential goals of warning is to bear safety information so that it can be perceived and adhered to. According to the C-HIP model, warning messages ought to be handled through several stages without a "bottleneck" that would stop the circulation. If there are any obstacles in the stages of C-HIP model then the main purpose of warning gets hurdled and this is what is called "Bottlenecks". It reduces the effectiveness of the warning outcomes. Wogalter suggests that, it can be used as an effective tool to reason out the effectiveness of a particular warning and make improvements accordingly[61]. The C-HIP has several stages. It basically starts with a source that delivers the warning message through a channel to a receiver. The receiver then receives it having many environmental stimuli that might distract the user from the message. This is not the end, the receiver goes through five more stages that determine whether a warning message is effective or not. Each step of the C-HIP model as per **Figure 2.1** has been described below:

- **Source:** The source is the main entity that starts with transmitting the warning message. It could change based on the different scenarios. It provides the necessity of the warning. Generally, this is the first stage where all the warnings will be conveyed.

- **Channel:** At this stage, it determines how the message is delivered. A message could be delivered in one or more sensory modalities. Generally, it is a better approach to arrange and show information in more than one format or modal rather than a single form. Thus, it gains more chances to reach more individuals with a significant impact [38].

- **Delivery:** Even though the warning is effective it would not matter if the message is not delivered. It needs to be reached to the receiver. Let us assume that a company has printed thousands of brochures that contain important warnings, but if they do not get distributed it would not make any difference

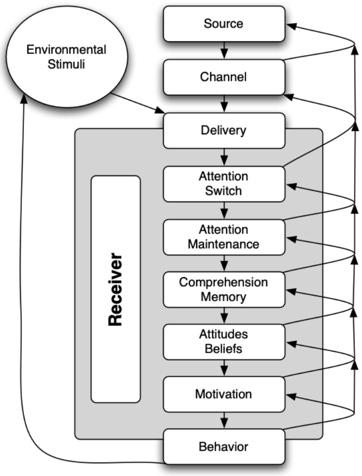


Figure 2.1: Communication-Human Information Processing (C-HIP) Model. [122]

and it would not be able to reach the end user who is at risk. So, it matters when and how it is delivered. Otherwise, this will fail to tune people at the right time.

- **Environmental Stimuli:** People react to different environmental stimuli. But the warning message shown to people has to compete with other sources that are present in the environment. Let us say, in an environment the red color is used frequently, so using red will lose its effectiveness. But if the use of red is not frequently used, then using red could flag a greater importance and is often more effective in signaling environments. As previously red was already used, it will lose in the competition for attention as it would not make any difference[107], [118].

- **Receiver:** Along with having similarities, people around the world have many dissimilarities also [39]. These differences can make changes in the processing of the warning message. Because of this, some people need to be shown particular characteristics of the warning that other people may not need. For example, older people might have a hard time reading the warnings in the small fonts. On the other hand, young people might not have any [39]. So, in order for warnings to be more effective it is necessary to consider the lowest denominator of capabilities and design it so that it reaches most people [122].

- **Attention Switch:** When a person moves, or changes his/her attention to something else then that phenomenon is called attention switch [58]. Some noticeable features that consist of larger text, different colors, and other stimulus changes promote attention switch. Besides these features the placement of this warning is an important factor. Basically, the warning should be salient enough to grab users' attention in order to be effective. So, it should be viewable as well and the timing should be appropriate so that the user has time to think and act accordingly. If the warning is bland and fails to create enough presence of itself in comparison to the environment, it is unlikely to grab the attention of the user.

- **Attention Maintenance:** To ensure enough information has been learned, attention should last long. However, how much information will be extracted depends on the environment. A few main factors of enable noticeable attention are adequate font size, high-contrast colors, and relevant details. The opposite of it affects attention maintenance. Other reasons that might affect attention maintenance are the complexity of the message, too lengthy, or hard-presented language. With the intention of warning to be effective, it should be "attractive" and "appealing" so that people keep with it long enough to grab the information from the warning. It has to be bold enough to compete with other stimuli and tasks so that users' attention does not get shifted. So, good design must be maintained with a view to help the user acquire information quickly that ties the connection with the next stages.

- **Memory/Comprehension:** Warnings are effective for conveying information about hazards, guiding to save actions, and safe decision-making. In order to do that, the attention must be grabbed, which then creates a new memory by extracting valuable information from it. If the information is too technical, that makes it hard for people to decode resulting in a quick attention switch. People cannot even remember what they actually saw due to the complexity. If they already know the information then they lose interest which then is converted to habituation. So, warnings should be designed in a way that is somewhat new and easier to understand and aligns with their existing knowledge helping to recall memories for better understanding. Another memory-related concept that cannot be overlooked is "Habituation". Habituation is a concept that says, repeated warning messages shown to people can produce the same type of content in the human brain [79]. Habituation is the proof that memory has been formed. If habituation is created it has an adverse effect on attention because the person who is habituated will be more likely to ignore those warnings which look similar even if the context is different. So, attention may not be grabbed for other same-looking warnings, because a person will think that nothing precious exists in the warning. In the C-HIP model due to habituation effects, later stages affect the earlier stages. So, in general the warning does not perform well.

- **Beliefs and Attitudes:** Belief is that kind of knowledge which is gathered through the lifetime experience of a person [59]. Belief is that background knowledge that a person always considers as true. If a warning is consistent and goes along with the belief of a person then it is easier to process that information. However, if the information does not fit with the existing belief or if it seems irrelevant then a person might not further process that. That is why warnings need to be highly attractive and salient to gain attention even if a person tends to ignore that.

- **Motivation:** Despite overcoming all the previous stages, still user might not comply with the warning because of limited motivation to process the information. Some reasons for limited motivation could be, that it takes too much time, cost of money, and too much effort etc. [122]. In addition to that, social influence is another factor. If an individual sees other people complying with a warning they are more likely to comply as well following them or vice versa. Moreover, motivation is also affected by mental stress, time, workload, and rushness [122].

- **Behavior:** Lastly, Behavior is the ultimate measurement of the effectiveness of a warning. Safe behavior might be impulsive however the chance of acting safely increases significantly due to well-designed warnings. It can be measured directly or indirectly, where directly means observing the actual behavior of the user and indirectly means using surveys and ratings to understand whether they are likely to follow the warning or not.

2.5 Warnings

In Human-Computer Interaction (HCI), warnings are intended to notify users of potential hazards, security vulnerabilities, or system malfunctions via visual, aural, or textual notifications. They are essential in influencing user behaviour, mitigating errors, and guaranteeing secure interactions with digital systems [67]. These alerts operate based on cognitive and attention paradigms, requiring users to notice, understand, and decide their response to the alert [121]. Warnings achieve the intended effectiveness based on how easy they are to use combined with their clear message presentation at the right time and how much risk a consumer already perceives. In HCI, warnings are classified as passive warnings, which convey information without disrupting user activity, and active warnings, which necessitate urgent user engagement prior to continuation. Effectively designed warnings augment general usability, diminish errors, and promote security compliance by clearly conveying hazards and directing users towards safer practices [67][121].

2.5.1 Active Warning

Active warnings in Human-Computer Interaction (HCI) are intentionally crafted to capture a user's immediate attention and need acknowledgement proactively, facilitating their progression [67]. Active warnings operate by directly intervening in a user's actions through modal dialogues, pop-ups, blockers, and audio-visual signals, therefore alerting users to potential security threats. The Communication-Human Information Processing (C-HIP) Model posits that for a warning to be effective, it must successfully redirect user attention, be perceived, and elicit appropriate behaviour [62]. Active warnings exhibit superior effectiveness since they need immediate cognitive engagement, resulting in reduced security breaches and user infractions. Research indicates that effectively designed active warnings substantially enhance compliance with security rules, achieving a compliance rate of 79% in web-browser interactions [67]. Effective warnings need user trust, urgent design features, and clear language; yet, overuse and inadequate warning design may lead to habituation and diminished compliance [62]. The goal of upcoming technology advancements in warning systems is to optimise their performance by including adaptive functionality that learns from user behaviours and risk assessments. Active warnings serve as crucial security elements that compel users to remain vigilant and undertake necessary measures during key moments [67][62].

2.5.2 Passive Warning

Passive warnings in Human-Computer Interaction (HCI) are security or system alarms that convey information without disrupting user activities. They appear as status bar messages, symbols, colour changes, or notification banners that users must recognise and understand on their own [121]. These warnings are based on the Communication-Human Information Processing (C-HIP) Model, which requires users to switch attention, grasp the message, and decide whether to act [67]. In online browsers, cybersecurity alerts, and system notifications, passive warnings are commonly used to advise users about potential hazards while ensuring workflow continuation. Their success is determined on visibility, user knowledge, comprehension, and trust, since many users may ignore or misinterpret them if they lack clear message [124]. According to research, user response to passive warnings is influenced by contextual circumstances, past experience, and site reputation, with some users rejecting them owing to familiarity or perceived low danger. Researchers recommend improved visual design, contextual adaption, and user education to raise awareness and engagement with passive warnings [67][124].

2.6 Bayesian Algorithm

The Bayesian Average Algorithm is a statistical technique that employs prior knowledge to obtain a weighted average in data sets with varying sample sizes. Unlike the arithmetic mean, which employs only the observed data and it can be skewed by small sample size, the Bayesian average combines observed ratings with a prior expectation to create a smoothed estimate. This approach restricts products with limited ratings from having an excessive influence on overall ratings and resolves data sparsity and bias issues [35]. For example, when there are not many ratings for a product on an e-commerce website, the Bayesian approach modifies the calculated average by considering a pre-defined prior average and returns a more stable and reliable score. The Bayesian average in e-commerce shopping platforms illustrates how it accurately predicts the rating by mitigating the bias sparse reviews [109]. In addition iterative Bayesian probability models which emphasize how Bayesian methods enhance the calibration of review helpfulness by integrating prior probabilities with observed data [128]. The environment of these prior and observed values provides more balanced results particularly in dynamic dataset like an e-commerce platform.

One of the most noticeable applications of the Bayesian Average Algorithm is in rating systems where reviews are allocated very unevenly. Websites like IMDb and online shopping sites employ this algorithm to rank movies or products in a more balanced way. For instance, a movie with one five-star review is not rated higher than one with hundreds of four-star reviews because the Bayesian approach employs a prior mean (e.g., the average rating overall) to moderate the effect of thin data. IMDB employs a Bayesian estimation approach to calculate aggregate product score while ensuring that items with limited ratings are not disproportionately represented. By weighting observed data with a prior belief, Bayesian averages allow more fair comparisons across items with varying numbers of reviews [113].

The advantages of the Bayesian approach in the recommendation are remarkable. These approaches not only aggregate user preferences effectively but also modify biased ratings, consequences in more robust and accurate outcomes. There detailed analysis of Bayesian aggregation approach which provided robustness in handling biased ratings in e-commerce platforms [75]. Furthermore, there is an adaptive Bayesian sentiment approach that improves classification accuracy for product reviews. The Bayesian average has thus become a foundation for many recommendation systems which significantly improved both accuracy and user satisfaction [131].

$$R_B = \frac{C \cdot \mu + \sum_{i=1}^{N}(r_i \times w_i)}{C + \sum_{i=1}^{N} w_i}$$

where:

- R_B = Final Bayesian average rating,
- C = Weight or confidence level (reflects how much weight we give to the prior),
- μ = Prior mean/Global average rating (e.g., the global average rating across all items),
- r_i = Individual ratings for the item,
- w_i = Category weight,
- N Number of ratings for the item.

Where C represents the weight assigned to the prior belief. This ensures that the item with fewer reviews relies more heavily on the prior mean while N controls the influence of the observed data [36].

2.7 Exponential Time Decay

The Exponential Time Decay Algorithm is a process that assigns greater weight to newer data points, thereby favoring temporal relevance in the dynamic systems. The algorithm takes its cue from the fact that new information is usually more indicative of current status, and is therefore particularly well-suited to environments where user preferences or product qualities change over time. According to the exponential weighted function older ratings gradually lose their impact on the overall score. By employing an exponentially weighted function, older ratings gradually lose their impact on the overall score, such that the system remains sensitive to recent feedback. This algorithm is frequently applied in time-sensitive rating systems such as e-commerce sites, where more recent reviews are important in deciding the current quality of a product or service. For example, a product with consistent five-star reviews two years ago but falling ratings in the past month should reflect this declining trend in its overall rating [95].

Exponential time decay achieves this by updating the rating in real time, and hence it is a suitable technique for modeling evolving user opinion. It is also a suitable application in recommendation systems and predictive modeling, where temporal trends significantly influence user behavior. One of the biggest advantages of the Exponential Time Decay Algorithm is its adaptability. By altering the decay rate (lambda), system designers can finely control how quickly older data fades in importance. A larger decay rate devalues older reviews more quickly, prioritizing only the most recent feedback. Conversely, a smaller decay rate clings to older data longer, providing a more balanced perspective. This flexibility makes exponential time decay particularly valuable for real-time adaptive systems such as product recommendation or financial modeling [145].

To improve sentiment classification for e-commerce product review the exponential decay in combination with the Naive Bayesian model is used and the result showed that considering recent reviews led to higher classification accuracy [127]. The exponential Decay model can be used to intelligently aggregate online reviews which ensures that recent feedback carries more weight in the final rating [75]. This approach can be extended by applying time decay in supervised learning systems.
The exponential time decay consists of decay functions that assign the weights to data based on their age(time). Where w(t) is the weight at a particular time, and the decay rate is (lambda). The overall rating calculator formula by aggregating the weight.
The Weight function is:

$$w(t_i) = e^{-\lambda t_i}$$

The Exponential Time Decay with weights:

$$R_E = \frac{\sum_{i=1}^{N} (r_i \times w_i) \cdot w(t_i)}{\sum_{i=1}^{N} w(t_i)}$$

where:

- R_E is the original rating score,
- r_i = Individual rating for the selected option,
- w_i = Category weight (same as Bayesian),
- $w(t_i)$ = Time decay weight
- e = Mathematical constant (approximately 2.718),
- λ = Decay rate, controlling how quickly the importance of older reviews diminishes,
- t_i = Time since the review was submitted.

The "Exponential Time Decay" provides a dynamic result, reducing the influence of backdated feedback while emphasizing recent feedback, which results in an outstanding rating system. Indeed, this trait is crucial in e-commerce platforms and provide up-to-date ratings [80].

Chapter 3

Literature Review

This literature review explores key research across various domains, including E-commerce Factors Influencing Consumer Decision, Behavioral Economics and Its Applications, and Reputation Systems. This study analyses existing studies to investigate how user behavior, decision-making processes, and trust mechanisms influence interactions in digital environments, offering insights into aspects that affect consumer choices and system effectiveness.

3.1 E-commerce Factor Influencing Consumer Decision

The E-commerce sector is an important sector boosting the economic growth all around the world. However, the trust of the consumer differs significantly in different markets. This study [157] explores the factors such as authenticity of product, customer review and rating, return policies, website design and usability, customer support and logistic solidity which influences the consumer trust in the e-commerce sector of Bangladesh. Issues like fake reviews, deceptive product descriptions, bad customer service are the reasons to erode customer trust. This study recommended that authentic product, digital security, post-purchase support, secured payment method, and logistic efficiency can play an important role in rebuilding trust of customers. Though their limitation was that they only focused on active online shoppers which excluded those people who engage themselves rarely in online shopping. Nevertheless, they mentioned that if more diverse groups are included into further study then this will lead to a better understanding of trust of online shoppers which can play a significant role in Bangladesh's rising e-commerce platform.

Online marketing thrives on developing good user experiences, which are contingent upon an understanding of the factors shaping consumer behavior while online shopping. Particularly, such factors will influence consumer attitudes about e-commerce purchases made from online shopping environments, as known from the study of [105]. This study identifies perceived trustworthiness, perceived ease of use, variety 10 of products, and customer service from previous research as factors that impact consumer satisfaction as well as online shopping willingness. They have conducted an interview with open ended questions to analyze factors like consumer behavior, future of online shopping process, payment transaction, goods return policy, and what other factors will affect online shopping more recently. From their analysis they found that quick delivery of goods, easy purchase option, attractive presentation, reasonable pricing, simple browsing of goods will stimulate the decision of online shopping. The study also emphasizes the need for easy-to-use interfaces, customer support, and, in general, drivers of repeat business in online retailing.

E-commerce is a very recent trend in Bangladesh. But during the COVID-19 pandemic, this sector has been affected around the world. It has also changed the perception of people on online shopping. The study done by (Tanjil Ahmed, 2023) has investigated the online challenges and provided probable solutions to them. They showed that in Bangladesh they had an environment to carry out e-commerce activities. After the survey, they found that 55% of the respondents took advantage of the online and 90% of them had a device to access online shopping along with a proper internet connection, 41% of the respondents were satisfied with the quality of the product in online shopping. They also found some challenges regarding trust issues. The statistics shows that 82.5% of the people faced dilemma of using unreliable online platforms and 60% faced fraudulent activities. However, they also suggested new technologies, building digital infrastructure, and establishing reliability as a solution [141].

3.2 Behavioral Economics and It's Application

Behavioral Economics have provided with some theories that talks about when and why people make irrational decisions when it comes financial decision making. A study was conducted by 7 authors including Tobias Seitz, Marion Koelle, Patrick Lindemann, Matthias Kranz, where they explored behavioral economics to leverage it in mobile application for financial decision making. They made a mobile application prototype considering behavioral theories (anchoring, loss aversion, mental accounting) and studied how people make decisions using it. After hypothesis testing they found "mental accounting" to be useful and can be supported by mobile app. Anchoring failed because of "anchoring overflow" as too many options were provided. While investigating loss aversion they have seen that people fear to lose the current acquired badge. They also planned to investigate asymmetric information, choice effects and deeper insights of loss aversion using the app [106].

Consumer behavior is complex and unpredictable. The behavior rarely aligns with the traditional rational choice theory. A study done by Elisha R. Frederiks, Karen Stenner1 and Elizabeth V. Hobman in 2014 with a view to analyze the complexity of household energy consumption behavior and showed the advantage of using key Behavioral Economics principles to predict and change such behavior. They have mentioned that in spite of knowing how to save energy, consumers do not take sufficient measures to conserve energy and it is because people are driven away by many cognitive biases. So, they have mentioned that if behavioral factors like loss aversion, sunk cost, risk aversion, temporal and spatial discounting, intrinsic and extrinsic rewards, normative social influence, perceived trust and availability heuristic can play role in effective designing of consumer-focused approach to improve household energy conservation. For example, framing energy saving information in terms of minimizing cost and losses will be more effective and motivating rather than only focusing on the benefits of saving energy. In addition to this, if energy saving practices are framed as socially desirable then people will tend more to be motivated and acquire those. Thus, this paper highlights the importance of applying key factors of psychology and Behavioral Economics to effective delivery of messages with an aim to encourage residential energy conservation [102].

Researchers have realized that people often struggle with decision making about online privacy and security due to many different factors, like anchoring, framing, overconfidence, etc. "Nudging" has came in to the place that can be leveraged with other behavioral economics theories to design such tools that can guide better decision-making. For example, a website could show security options in a way that encourages users to choose the safest option or gives a reminder to think about security before taking any decision. These "Nudges" are useful ways to make humans take better decision when many psychological barrier lead to poor decision making. This study suggested that Behavioral Economics theories like nudging, choice architecture, and framing can be implemented in a way that ensures better security and privacy decisions [112].

3.3 Effective Warning and C-HIP model

The study [66] by Serge Egelman, Jason Hong and Lorrie Cranor examined how users respond to specific phishing warnings in web browsers. They conducted an experiment where they showed participants different types of browser warning for spear-phishing attacks to analyze their response to those warnings. Their findings showed that 97% of participants were victims of at least one phishing attempt and 79% paid attention to active warning. However, when they were shown passive warning it was found that passive warning was ineffective in grabbing user attention. The researchers used the Communication Human Information Processing (C-HIP) model to analyze the effectiveness of warning, how users perceive information from warning and respond to those. From their analysis they have found that, active warning of Firefox worked better than active warning of Internet Explorer and both the working worked significantly better than passive warning of Internet Explorer. The study focused on the significance of active warnings in such a way to grab the attention of users to alert about phishing threats.

In this study [82] the researchers analyzed the reaction of users to different types of SSL warnings. They concluded a survey of 400 participants to examine their reaction and understanding of SSL warning. From their literature review they found that passive warning indicators often go unnoticed and so they are ineffective [58]. For this reason, many web browsers show active warning as they need users to pay attention to those and engage themselves in order to decide whether to dismiss the warning or not. They have mentioned that it is important for the warning to communicate clearly about the risk associated with it and clear instructions to avoid that risk. The researchers proposed two new approaches for the design which are warning will clearly explain the risk and after effects of preceding to the website and warning will appear more severe when participants had to enter their personal information. After the analysis they found that their newly designed warning performed better though some individuals were still exposed to dangerous situations. They found that users who understood the warning acted differently from those who did not understand the warning. Finally, they suggested that exposure of warning should be minimal and only shown for situations where user should be blocked from making risky connections

3.4 The Impact of Color on Cognitive Response: Effects on User Behavior and Interaction

The study by [130] examined how visual elements and user preferences affect how people rate things. The goal was to enhance the quality and accuracy of these ratings. The authors note that online systems heavily depend on user ratings and reviews since these elements strongly shape both consumer purchase decisions and evaluations of products and services. Rating scale design creates unintentional biases that undermine the validity of ratings. The experiment contrasts six rating scale designs differing in visual features, including icons (stars and emojis) and color schemes (traffic-light metaphors: red-yellow-green; warm-cool colors: red-yellow-blue). A user survey involving 187 participants was conducted with a view to investigating preferences, behavior, and the effect of these visual features on ratings [129]. The results showed that participants preferred rating scales with more intuitive visual designs, such as the traffic light metaphor in combination with emoji icons. Participants were also likely to provide accurate or "true" ratings with scales that they preferred. The implication is that the utilization of user-preferred designs can render ratings less prone to biases and more valid. Visual rating scales with eye-catching components induced users toward more optimistic and steady feedback decisions when compared to traditional yellow star configurations. Kruskal-Wallis analysis along with Apriori mining results demonstrated visual indicators and user preference leading to substantial changes in rating patterns. Research findings demonstrate how properly designed rating scales that incorporate visual elements create better user experiences while delivering improved measurement accuracy. Researchers emphasize that online decisions require both user involvement in designing rating scales and visual stimuli to deliver better results in this domain. By aligning rating scale designs with user attitudes and incorporating cognitive visual metaphors, we can render rating systems in platforms more efficient and reliable[129].

This study by [46] focuses on how the type of product and the style of warning symbols, including their colors, affect how people understand warning labels and view the risks. Signal words "DEADLY", "DANGER", and "CAUTION" are paired with the colors red, orange, blue, and black to identify the effects on salience and compliance by users. Study findings show hazard levels fluctuate enormously depending on how signal words and colors interact. "DEADLY" is considered the highest level of danger followed by "DANGER" and "WARNING" while black is considered the most hazardous color, followed by blue, red and orange. The study shows that mixing a dangerous product with a safety warning or a calming color results in people seeing it as moderately dangerous [46]. The authors note that factors like product type also significantly affect perceived hazard. Reflective warnings demonstrate that incorrect signal word choices combined with inadequate color selection can cause users to underestimate hazard levels leading to reduced warning compliance. Warnings that combine “DANGER” with a green color module result in decreased hazard perception even when the danger level remains unchanged thereby leading people to take insufficient cautionary measures. Warning labels achieve maximum effectiveness by precise integration between signal words and colors alongside product classes to properly communicate safety levels as well as improve behavioral compliance. As a concluding point, the study emphasizes the importance of integrating signal words and colors in warning labels as a means of providing clarity, salience, and appropriate hazard perception. By working on these factors, manufacturers are able to enhance warning effectiveness and minimize risks related to low compliance [46].

The study by [111] discussed how colored warning banner messages influence user compliance across different cultures while examining the natural psychological impact that colors have on human decision-making. According to this paper, color stands out as a critical element that attracts user attention while triggering emotional responses alongside cognitive responses to form behavioral intentions. Warning messages combined with their selected colors serve as a medium and form to affect users significantly under the Cognitive-Affective Model of Communication. Research demonstrates that psychological reversals explain how both red and blue colors generate varying degrees of psychological arousal which leads to different compliance results across different situations[111]. The study discusses that colors that are commonly associated with danger, such as red, are widely used in warning messages since they are universally perceived as signals of hazard. The study continues that exposure to the same color, such as red, on a frequent basis results in habituation, which lowers its effectiveness over time. The repeated exposure to blue hues endures longer because people associate this color with trust as well as calmness. This research demonstrates that color meanings differ enormously from one culture to another across the world. In Chinese culture, red stands for joy but Westerners understand it to signify dangerous situations. This cultural difference underscores the need for localized interface designs for the optimal effectiveness of warning messages. The investigation delivers significant findings about the relationship between color and user behavior along with cultural environment interaction. The research requires custom-colored warning sign usage to raise both user focus and safety compliance. The research explores psychological and cultural elements therefore deepening our understanding of color effects on decision-making in human-computer interaction[111].

The study by [83] analyzes the utilization of color within multimedia human-computer interfaces to describe its influence on interaction methods while examining processing information and usability. According to the authors, color serves as more than just visual decoration by functioning as an essential element which impacts on user perception and interface element interaction together. Their argument is that high color contrast is the basic property to move forward the perception of important information to enable users to easily find and interact with critical elements of the interface. Poor contrast on the other side, hides details and reduces usability, along with user satisfaction. The study also addresses the effect of visual illusions that are produced by ineffective color combinations, explaining how warm colors like red and yellow will “advance” or appear to move towards the viewer while cool colors like blue and green “recede” to create the feeling of depth. Designers manipulate these visual illusions for strategic control of interface elements which leads to successful user attention guidance. The enhancement of usability depends significantly on lightness contrast[83]. The authors state that interfaces with noticeable contrast in lightness between elements enhance comprehensibility leading to better interaction quality. The study reinforces that professionals working with color in design must fully comprehend visual perception together with psychological principles. The study demonstrates that strategically chosen colors in multimedia interfaces can improve both interface aesthetics and operational capabilities which promotes better user experiences. Research demonstrates color’s indispensable role in interface development because designers need to apply hexadecimal codes purposely to produce both usable and visually appealing systems [83].

The study by [130] focuses on color utilization on rating scales and discusses the influence that cultural background and personality traits have on user behavior. Users interact differently with rating system color codes which can potentially create systematic biases yet this bias appears inconsistently among users based on their individual characteristics. The research on Big Five Personality Traits and Individualism-Collectivism showed that extroverted people and those from collectivist countries can better change their neutral scores when using colorful rating scales, particularly those with red-yellow-green or red-yellow-blue colors. Individualists and other personality types did not show any significant biases[130]. The results indicate that cultural and personality differences play a big role in how people see and react to color-coded interfaces. We need to create personalized and culturally sensitive rating systems to reduce bias and make user rates more reliable[130].

The research conducted by [100] examines the significance of color in visual communication for human-computer interfaces, while also assessing graphics, icons, images, and the impact of color on user engagement and usability. According to the research, color functions being an aesthetic enhancement tool because it acts as a communication system which draws attention and improves both user experience and perceptions [100]. The study discusses how color, when employed effectively, can highlight logical information, distinguish sections of the screen, and enhance the visual appeal of the interface. The study has delineated the RGB, HSV, and HSL color models to illustrate how design interfaces manage color representation. The psychological aspects of color perception and cultural associations with color influence user reactions to interface designs [100]. The research primarily concerns the strategic application of color for grouping or dividing items, directing attention to specific interface components, and establishing a visual hierarchy. According to the study, it would be unwise to use multiple colors near each other in terms of brightness because it leads to visual confusion or overwhelm in users. The wise use of color helps communication through visual channels because it connects user needs with their total experience [100]. The study highlights the importance of considering psychological and cultural factors when creating color schemes for computer interfaces. This improves usability and user satisfaction [100].

3.5 Reputation System

The study [136] explains the development of a time-aware recommender system (TARS) for online shopping that integrates temporal features like buying history and user engagement to increase recommendation precision. As a model, TARS provides better performance across the board through its ability to collect implicit information alongside Bias and Decay functions that increase the weightage of new interactions. The study evaluates time-aware recommendation performances by using Matrix Factorization (MF) alongside K-Nearest Neighbor (KNN) and Sparse Linear Method (SLIM) algorithms [136]. Results indicate Decay-based models substantially improved recall and precision levels so Decay-MF and Decay-SLIM surpassed Bias-based approaches. However, Decay-KNN did not perform well, showing that time-awareness does not help all algorithms equally. The researched evidence demonstrates that online retail businesses benefit from time-aware recommendation approaches because these methods track changing markets and product fashion trends. Research shows that all recommendation systems require temporal data additions to achieve improved accuracy alongside enhanced personalization capabilities. Research results demonstrate that Decay functions increase recommendation accuracy for item-based models such as SLIM while helping businesses optimize customer interactions and decisions [136].

The study by [113] addresses the accuracy and stability of online rating systems and their influence on e-commerce decision-making. A research analysis compares rating methods from four categories including Naïve models (mean, median) and weighted averages along with fuzzy models and probabilistic models (BetaDR, Dirichlet, Bayesian) through performance metrics of Mean Absolute Errors (MAE), Mean Balanced Relative Error (MBRE) and Mean Inverse Balanced Relative Error (MIBRE). The research demonstrates that the combination of median and Dirichlet models achieves the highest accuracy across different data sets with BetaDR producing the most stable results. Naïve models present the greatest vulnerability to manipulation which results in unreliable manipulation-free ratings consolidation [113]. The article highlights the efficiency yet lack of transparency of IMDb's Bayesian rating system, and the greater applicability of Dirichlet and BetaDR models to sparse data and the median model to large datasets. Advanced aggregation techniques for online rating systems need further development to enhance validity and accuracy according to research findings which support weighted and probabilistic models for decreasing bias while strengthening credibility [113].

The work of [109] presents a computational intelligence solution to predict customer review ratings in e-commerce, bypassing the challenges of dimensionality and vagueness of text reviews. Researchers integrate Singular Value Decomposition (SVD), Fuzzy C-Means (FCM), and Adaptive Neuro-Fuzzy Inference System (ANFIS) to obtain a greater level of accuracy for sentiment analysis and rating prediction. The paper stresses that the majority of the existing rating prediction models, such as ANN-based models and SVM-based models, are poor in handling large unstructured text data. Through dimensionality reduction, the proposed framework acquires semantic features from reviews while using fuzzy clustering to group them before training the ANFIS system for better rating prediction [109].The study demonstrates that it is sufficient to utilize a subset of large datasets to build a robust predictive system, reducing computational costs without loss of accuracy. Experimental findings indicate that the model developed in this research exceeds conventional machine learning techniques by achieving prediction accuracy surpassing ANN, FCM and SVM models. The research model serves as a universal predictive solution which enables classification and prediction across multiple operational challenges for e-commerce decision making. This work stresses that the integration of neuro-fuzzy models together with dimensionality reduction techniques leads to better sentiment analysis and rating prediction performance. Research indicates that combining fuzzy clustering with machine learning algorithms creates substantial improvements in online rating system performance for both e-commerce companies and consumers[109].

The paper [125] uses Bayesian Model Averaging (BMA), a statistical method that deals with model uncertainty by averaging over a set of models rather than selecting a single best model. Classical approaches fail to consider uncertainty during modeling which leads to exaggerated and misaligned predictive results but BMA establishes model posterior probabilities to improve prediction stability. The study demonstrates how BMA achieves accuracy through its utilization in ANCOVA, meta-analysis and network analysis by accounting for competing-model uncertainty [125]. The practical implementation shows BMA reduces prediction errors by adding model consistency that stops unexpected statistical output fluctuations. The model-based approach maintains stability through ongoing updates of probabilities from newly collected data which drives decision-making toward data-driven certainty. The research demonstrates BMA's importance for improving statistical processing which creates particular advantages for psychology and economics alongside social science disciplines [125].

The study of [99] investigates the determinants of online shopping attitudes among Dhaka consumers by dissecting website features which affect purchase behavior. Through a survey of 199 online shoppers and the use of exploratory factor analysis, the study identifies four key factors that significantly impact consumer perceptions: website reliability, website design, customer service, and website competency. It also categorizes consumers into five groups prospective, trial, occasional, frequent, and regular buyers, then makes a comparison of their perception of these elements [125]. The findings demonstrate that although website design is equally rated by all groups of buyers, website reliability and security are viewed differently by them, with frequent and regular buyers showing higher trust levels. Security problems stand among the main challenges for potential customers to make trial purchases thus showing that improved website security and payment standards would lead to better customer retention rates. Customers increase their online shopping patterns because repetitive visits develop trust between users and vendors which drives increased buying behavior. Research results confirm customers require dependable online shopping systems equipped with user-friendly attributes to foster trust as well as increased engagement during transactions. The Online Retail market of Bangladesh can be strengthened by businesses addressing reliability concerns alongside security and usability issues which will transform occasional buyers into constant online customers [125].

The study [98] is on Rated Tags as an e-commerce decision support, examining their impact on decision quality, effort, and confidence. Rated Tags combine user-generated tags and a 5-star rating scale to enable customers to judge products efficiently by a summary of reviews. The study highlights how Rated Tags function as interactive decision support, allowing the sorting of reviews based on specific product attributes by the users, thereby reducing information overload and enriching the decision-making process [98]. The Empirical study deployed two groups: Rated Tags and the control group. Rated Tags group users could view reviews along with Rated Tags and could filter them by attributes, while the control group was presented with just regular reviews. It was discovered that Rated Tags significantly reduced decision-making effort. Rated Tags group users taking less time in making the choice. Additionally, Rated Tags resulted in higher decision quality, with the users in this group being more likely to pick the "dominating product" (the ideal product based on some attributes). Even though decision confidence was slightly higher for the Rated Tags users, the difference lacked statistical significance [98]. The study established that Rated Tags improve decision speed because they create standardized rating systems for product features. The Rated Tags feature serves as an efficient online shopping technology that minimizes mental workload and increases buying decision accuracy. The research demonstrates that product evaluation processes improve significantly when rating and tagging mechanisms work together with review systems to support customers' efficient purchasing decisions [98].

3.6 What Makes Our Work Unique

Apart from the traditional e-commerce awareness system which generally focuses on static reviews and ratings, in contrast, our study incorporates Behavioral Economics theories to actively influence to make decisions. By incorporating Loss Aversion, Framing Effect, Bounded Rationality and other theories our system provides a summarizes and well-structured information and also nudges individuals towards safe online behavior. The existing literature emphasizes on straight forward action to mitigate fraud, provide complex reputation system for product in the landscape of e-commerce. However, our study use B.E theories with a browser extension to provide a awareness more effectively. As user behavior has more impact on decision-making. We also incorporate two distinct algorithm (Bayesian Average and Exponential Time Decay) and dynamic predefined options with weight to calculate the overall rating.

Chapter 4

Work Plan

4.1 Existing problems in the E-Commerce sector and proposed solution

E-Commerce is a rising sector in Bangladesh. However, along with rising, it also has a dark side. With the increase in engagement in the e-commerce sector, fraudulence through misleading information, fake reviews, unsafe digital transactions etc. has increased significantly. These issues are already mentioned in Chapter 1 and Chapter 3. In our research, we first analysed the challenges in the e-commerce sector of Bangladesh. Then we tried to analyse the reason and at that moment one aspect caught our attention which is Behavioral Economics. Behavioral Economics claims that people are influenced by external factors at the time of making a decision. Chapter 2 offers a more comprehensive explanation. This completely aligns with the fact that e-commerce sites use many discount framing and choice of architecture to influence users to buy products. That is how we thought why not use Behavioral Economics to influence people in a positive way and help them to make informed decision. In order to implement that we thought of a user-centric approach and wanted to develop using the theories of Behavioral Economics with a motive to analyse human decision-making tendency.

4.2 Developing a User-Centric Approach using Behavioral Economics

In our research, we developed a chrome extension based on some key Behavioral Economics theories such as choice architecture, framing effects, loss aversion, etc. A more detailed explanation has been described in Chapter 2. By leveraging these theories, our chrome extension is designed to influence user decision-making in a more efficient and informed manner. Our system aims to analyse human behavior and their engagement in browsing e-commerce sites, we also aim to get a deeper understanding of Behavioral Economics principles that can be applied to real-world systems.

4.3 Proposal of Hypothesis

Our research hypothesizes that leveraging Behavioral Economics theories like choice architecture, framing effects, loss aversion, nudges, herding effect, etc can influence user-decision making and behavior. Basically what we have proposed is that these theories can actually be impactful in warning people and creating awareness. By testing the hypothesis we aim to prove that Behavioral Economics can be used to solve complex problems.

4.4 Hypothesis Testing

As we proposed some hypotheses in order to test our hypothesis we needed to conduct an experiment. After the experiment we conducted a semi-structured interview in order to gain deeper understanding of user behavior. After collecting the data from post experiment questions, we did data analysis and finally test our hypothesis using Chi-Square test.

4.4.1 User Testing

As explained in section 4.1, along with the growth of the e-commerce sector significant issues related to fraud are noticeable. And as humans are irrational, they are influenced by external factors along with the different types of constraints (eg. time constraints, asymmetry information, emotion, etc.) we proposed a solution in the form of an extension to reduce this information gap. Now our research focuses on how humans behave or do they make rational decisions when their information gap is reduced to some extent. We want to analyse how users act when they are provided with certain information regarding an e-commerce site through an extension, whether they are nudged towards a rational decision when they come across negative information and possible loss associated with an e-commerce site. Therefore, to understand user behavior and to test our proposed hypothesis we conducted an experiment, making our participants use extension unintentionally hiding the actual reason behind it. We will discuss how we conducted the experiment and what was our motive later in Chapter 7.

4.4.2 Semi-structured Interview

After the experiment we conducted a semi-structured interview to get a better understanding of user behavior and to get a detailed response from users. We provided a list of questions to users to understand the demographic first. Later on, we created a scenario where we asked the user to browse some e-commerce sites so that they come across certain information regarding an e-commerce site as a popup provided by our extension. After the experiment, we interviewed our user with some questionnaires which were prepared beforehand according to their actions. So, users went through two set of questionnaires:

- **Demographic Questionnaires:** Users were asked to fill out these questionnaires before the experiment so that we could get an idea about the demographics of our participants.

- **Post Experiment Questionnaire:** These questionnaires were asked after the experiment according to the actions they took during the experiment. It was done in order to gain deeper insights of their actions and proper reasons for such actions to analyse their behavior justifying Behavioral Economics.

Extended explanation of how we gathered participants, how we created the environment for the participants along with experiment design and questionnaires will be discussed in Chapter 7.

4.4.3 Exploratory Data Analysis (EDA)

EDA was conducted after collecting data from survey, observational study and semi-structured interview. The main purpose of this is to gain insights of the data we collected and find relationships between the variables, understand the data, understand any kind of outliers or any anomalies present in the data. Handling any missing values is also a part of EDA. Along with this, descriptive analysis, proper data visualization with graphs, charts are also important steps of EDA. As we did qualitative research, we did qualitative analysis on the interview responses which is discussed in Chapter 7. To understand the user response from the observation of using the proposed prototype and interview, the interview response was categorized into a form through qualitative analysis. So, performing EDA revealed some relation between the variables, based on which the hypothesis testing was able to be conducted which are discussed in Chapter 7. Lastly, result from the hypothesis testing, we got to know about the user's perception regarding our proposed solution.

4.4.4 Hypothesis Testing Method

Hypothesis testing is a statistical method which is used to make an informed decision on observed evidence. It is used to make a decision or make an assumption about the population parameter using the sample parameters. When we want to make an assumption about the large population but we do not have much data, in this case, sample data is collected and some statistical analysis is done in order to check the validity of any statistical claim of the unknown population parameter. The parameter basically consists of some statistical terms like mean, standard deviation, variance etc. So, using this parameter collected from the sample we use the testing methods that fits according to our data. Then the evaluation is made of the statements about the populations. Some key concepts that are frequently used in hypothesis testing are the two statements which is our main hypothesis, significance-level (α), p-value and test-statistics. Hypothesis testing is done in several steps.

Firstly, two mutual statement is made, one is null hypothesis (H_0), another one is alternate hypothesis(H_1). The initial guess is considered a null hypothesis, and the alternate hypothesis is the statement we want to prove considering some statistical tests. Secondly, the choosing an significance level (α) is one of the crucial steps.

Then, data is collected and based on the data and our goal appropriate test method is selected as well as the test statistic. Some familiar test methods are z-test, t-test, chi-square test, anova test etc. Depending on the test methods different test statistics are chosen. For example, t-score, z-score, chi-statistics, F-statistics. Then, test-statistics is computed. Lastly, the test statistic is compared with p-value and depending on the conditions, a certain assumption is made. In our research, we used the chi-square test. There are two types chi-square test, chi-square for independence and chi-square for good of fit. According to our goal, we will be using chi-square for independence. So we will be discussing it.

Null Hypothesis and Alternative hypothesis

In the chi-square test, we also have to formulate two hypothetical statements.

Null Hypothesis (H_0): It is a general statement that tell nothing unusual is happening or tells the default behavioral that nothing has occurred, there is no relation between two variables. This statement often leads to negative statements. For example, there is no significant difference between the two variables.

Alternate hypothesis (H_1): This statement opposes the null hypothesis. It is basically what has been claimed by the researchers. For example, there is a significant difference between the variables.

Test-Statistic:
As we are using chi-square, the test-statistic is called chi-statistic (χ^2). The test-statistic is calculated as:

$$\chi^2 = \sum \frac{(O_i - E_i)^2}{E_i}$$

where:

- O_i**:** i th Observed Frequency in the contingency table.
- E_i**:** i th Expected Frequency in the contingency table. The formula for expected frequency as follows:

$$E_i = \frac{(\text{row total} \times \text{column total})}{\text{grand total}}$$

Degree of Freedom:
It denotes the maximum number of independent variables. In other words, How many independent values can be filled before it gets filled automatically. Degree of Freedom (df) is used to find critical value from the chi-square distribution table. In chi-square for independence the value is calculated as:

$$df = (R - 1) \cdot (C - 1)$$

Where:

- R is the number of rows
- C is the number of columns

Significance value (α)

Significance value is a threshold to reject the null hypothesis when it is actually true. Commonly the significance level is 0.05 or 0.01. So, we can interpret that, we are willing to accept 5% of the risk to reject the null hypothesis.

P-value and critical value

P-value is a statistical metric which is used to measure the strength of the null hypothesis. Using chi-square statistic and degree of freedom (*df*) p-value is determined from chi-square distribution table. If the p-value is less than the significance level (α) we will reject the null hypothesis. There is another way to calculate. For that, we have to find the critical value using the degree of freedom (*df*) and significant level (α) from the distribution table. If chi-statistics is greater than critical value we will reject the null hypothesis (H_0).

- **For p-value:**

$$\text{p-value} < \alpha$$

- **For critical value:**

$$\text{Chi-statistic} > \text{critical value}$$

4.5 Usability Score

As we are trying to propose an user-centric approach in the form of an extension to assist users by providing all possible necessary information regarding an e-commerce site we decided to test the usability of our extension. In our study we selected two standard sets of questionnaires which are SUS (System Usability Scale) and SEQ (Single Ease Questionnaire) as these scales have created reliability as established by statistical methods. SUS scale has 10 sets of questions which was designed by John Brooke as a measure to usability that aligns with ISO standards. This measure of usability includes effectiveness, efficiency and satisfaction. Thus, SUS score aims to provide a global view of assessments of usability [30]. Among all other usability scales like SUS, QUIS, a variant of Microsoft's Product Reaction Cards, CSUQ, SUS turned out to be the most reliable. SUS is that only usability measure scale that helps to address all different aspects of users reaction to a website [60]. For these reasons, we choose SUS score to test the usability of our extension. After the experiment we provided our participants a set of 10 questions in order to measure the SUS score.

Score Calculation of SUS score

SUS score consists of 10 questions, each question has a range of scale 0 to 4. Question 1, 3, 5, 7 and 9 contribute a value of their scale position minus 1. Question 2, 4, 6, 8 and 10 the contribution to scale position minus 5. After that, the sum of scores should be multiplied by 2.5 to obtain the overall SUS score. **Figure 4.1** shows the adjective-based ratings to interpret SUS scores [30].

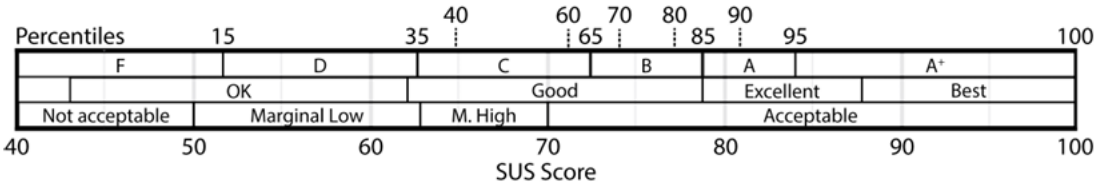


Figure 4.1: Adjective-based Ratings to Interpret SUS Scores. [110]

The average SUS score is 68 (50th percentile) [93]. Means any score below 68 is considered below average.

SEQ Score

Figure 4.2 shows The Single Ease Question (SEQ) range. It is a one question method that measures how satisfied users are after using a particular system. So, basically users are asked to rate the overall difficulty of using a system on a 7-likert scale and it is said to determine the ease of use [81]. Sometimes SEQ performs better than other measurements like Subjective Mental Effort Questionnaire (SMEQ) or Usability Magnitude Estimation (UME) which are considered complex to use [81]. Because of it's greater acceptance and it's easy of use we considered SEQ over other scaled that measure the satisfaction level.

Figure 4.2: SEQ scale.[90]

How we interpret the SUS and SEQ score and interpret it after collecting the SUS and SEQ scores from our participants will be explained in Chapter 7.

4.6 Flow Chart

Figure 4.3 demonstrates a structured approach of the overall methodology. To begin with problem identification and analysing hypothesis, the steps includes proposal of hypothesis, developing a user-centric approach for safe browsing, collecting data through interview and observational studies followed by data analysis to test hypothesis and analyse human behavior.

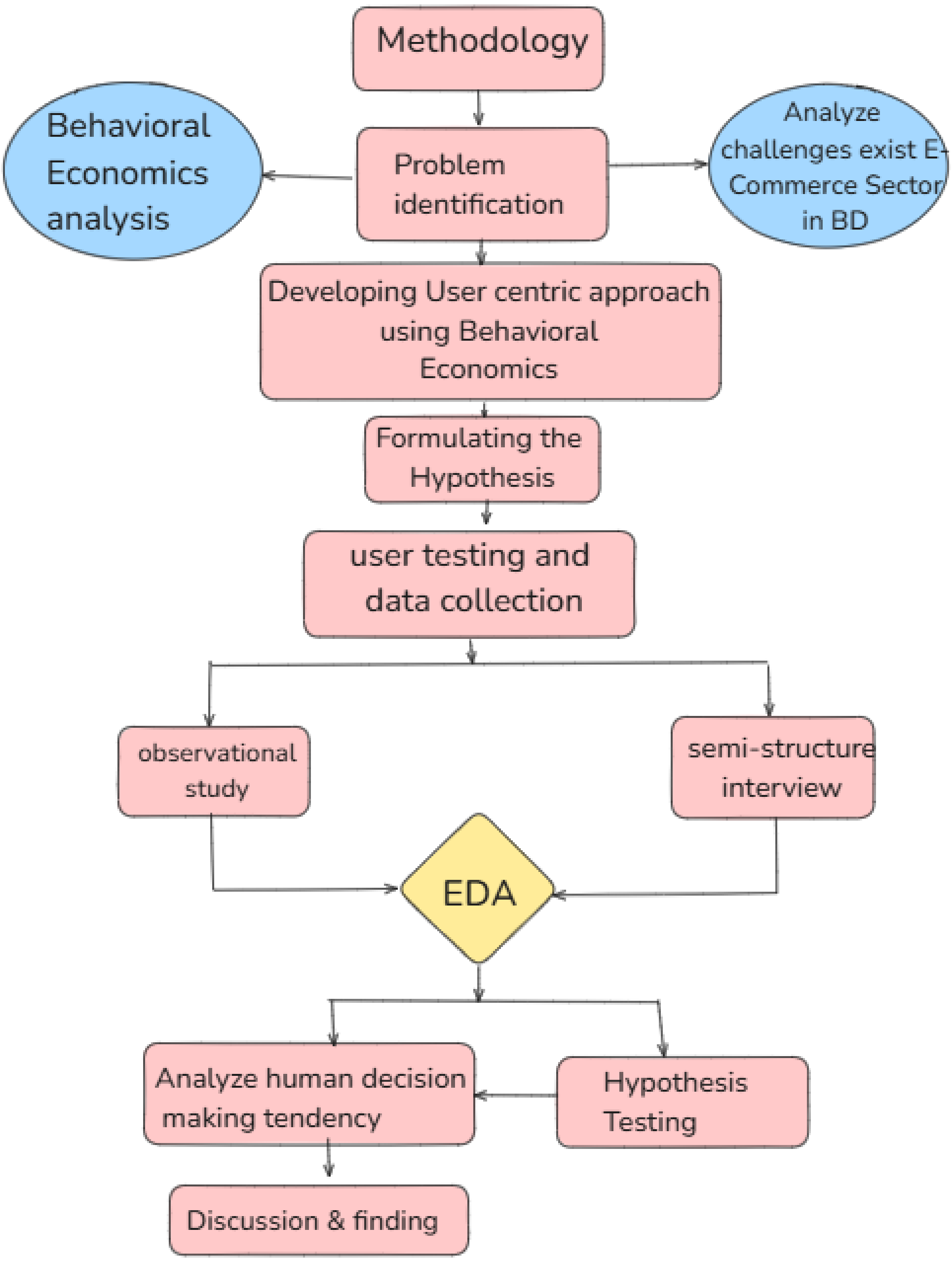


Figure 4.3: Work Plan Flow Chart.

Chapter 5

Extension Design Architecture

In the evolultion of e-commerce industry, it is a top priority to protect user security that requires new solutions. This chapter discusses how our innovation addresses this solutions that is a Google Chrome extension designed to reduce risks and improve decision-making during online shopping. We implemented the theories of *Behavioral Economics*, like *Bounded Rationality*, *Nudge Theory*, *Anchoring*, *Heuristic*, *Herding Effect*, *Hyperbolic Discounting*, *Salience Effect* and *Loss Aversion* into the development of this extension to help users make better and safer choices while shopping online. Here, we will also explore the connection between the extension's design elements and color model that influence user perception and behavior. The chapter showcases how to convert behavioral science ideas into digital solutions which resolve real e-commerce security and decision-making issues to improve user behavior.

5.1 Reason Behind Choosing Extension

Web extensions are considered superior in usability due to their seamless integration with browsers, allowing real-time interaction with web pages without requiring users to switch applications, which enhances productivity [165]. They consume less system resource, compared to standalone software and can simply be installed and updated through stores in a web browser, with ease in deploying them [164]. Extensions have cross-browser compatibility and a user can access settings and tools regardless of device, assuming a login through the same web browser [164]. Extensions enhance usability by offering instant practical functionality [165]. Users can access latest feature updates from extensions with minimal effort due to the fast deployment and development process combined with frequent update capabilities [164]. In 2025, Google Chrome boasts 3.45 billion worldwide users, and its Chrome Web Store holds approximately 111,933 extensions [151]. There have been over 346 million installed Chrome extensions between February 2023 and July 2020 according to the Stanford University and CISPA Helmholtz Center for Information Security studies [151]. In addition, behavior-changing factors such as confidence bars with colors, pop-up warnings, and heuristic cues can even be added in situ in the environment for browsing, and thus, will have a larger impact in creating safer choices [73]. These advantages collectively establish web extensions as an efficient, user-friendly, and scalable proposal solution for our problem.

5.2 Design of Extension

The proposed Chrome extension makes online shopping sites more secure by offering real-time trust ratings that users can access during their online shopping activities. Through active and passive operation this extension provides customized warning alerts and site trust ratings drawn from user feedback combined with website government registration information.

5.2.1 Passive Mode

If passive mode is turned on, the extension quietly monitors and analyzes the website in the background. It displays a minimalistic interface with two significant scrollable panels:

First Scrollable Panel: Slide 1

The design of the first part of the extension is meticulously planned to provide users with a rapid and intuitive summary of a website's trust when they enable it. The discussion below contains information on how each item is positioned within the part of the extension.

Section 1: Trustworthiness Signs

- **Website Logo and Numerical Rating:** A logo is displayed at the left border of the interface where users can immediately recognize the website's brand identity. Adjacent to the logo users will find a 5-point rating system that provides them with a numerical site evaluation.

- **Dynamic 5-Star Rating Bar:** Apart from the numerical rating, a dynamic 5-star rating bar graphically displays the average users' ratings, allowing users to instantly judge the overall impression of the service and the website's quality.

- **Dynamic Confidence Bar:** Below the star rating, the dynamic confidence bar is displayed horizontally across the interface. Real-time ratings are displayed through a color-coded system that moves from red to green based on the trust levels while showing different intensity stages between these colors.

- **Site URL and Government Registration Badge:** The website URL displays beneath the dynamic confidence bar to allow users to understand which domain they interact with. Users find a government registration badge positioned at the top-right corner to verify the site's legitimacy.

Section 2: Most Selected Reviews

Most Selected Review Positioned directly below Section 1, showcases the top five user-selected review tags in a tag format. This section is a quick snapshot of what existing users consider most important regarding the site, whether negative or positive aspects.

Section 3: Recent Feedback

Under *Most Selected Review* within Section 2, readers can find recent text reviews in the *Recent Feedback* subsection. Within this section, users can access the three most recent reviews presented in a vertical list that assists in a fast understanding of user sentiments and experiences. Each text review shows an attached date which helps users verify the novelty and reliable nature of the feedback. People can access all customer reviews by clicking *See All* located at the bottom of *Recent Feedback*.

Second Scrollable Panel: Slide 2

Section 4: Interactive User Review System

- **Scrollable Interface:** After users scroll down they can find this interface directly below the *Most Selected Review* section.
- **Multi-checkbox and Custom Review Field:** The section contains three main categories namely *Product Condition*, *Customer Service*, and *Overall Experience.* that include drop-down menus containing seven pre-defined options extending from positive to negative feedback. Users can check boxes to reflect their impressions of the e-commerce site. This section also includes an additional interactive customer review field named *Your Review* section that allows users to express their personal experience about sites manually.

5.2.2 Active Mode

Our Chrome extension engages with active mode when encountering a threshold website rating of 2.6 or lower indicating substantial reliability concerns. Active mode triggers an automatically imperative warning popup display to catch web users' attention. It briefly suspends user activity on the website to draw potential harm to their attention. The pop-up interface consists of two slides. The two slides are intended to present information and offer interactive options allowing users to make well-informed decisions when handling potentially risky situations.

Slide 1: Summary and Immediate Concerns

Section 1: Trustworthiness Indicator

The first slide of the popup presents the summary of the result of the user review which is collected from the passive warning (as discussed earlier) about the site. Section 1 includes the website logo, numerical rating, 5-star rating bar, dynamic confidence bar, and government registration verification badge, similar to *Section 1 - (see details at section 5.2.1)* of the passive warning.

Section 2: Detailed Concern

This section contains two distinct parts that are identified as *Most Concerning Issue* and *Most Selected Reviews.* The *Most Concerning Issue* subsection shows that users highlight distinguished problems through flags such as *'Not Government Authorized'* or suspected scam reports from many users.

Section 3: Review Overview

- **Pie Chart:** The pie chart shows the user's impressions about the sites by categorizing into *'Good', 'Bad', and 'Neutral'* ratings to deliver a quick visual overview.

- **Review Accessibility:** Users can access detailed textual reviews through the *View Review* button to explore monitored user experiences through passive observations.

Navigation Button

- **Continue:** An option on the user interface enables movement to the subsequent slide for further actions.

- **Close:** This button offers an option to exit the pop-up functionality and users can either leave the website or keep browsing.

Slide 2: Warning and Decision-Making

If the user chooses to click the continue button, it will go to the next slide that will show a warning message in clear terms: *"Warning: Proceeding Might Cause Potential Losses"* are presented in bold red text following this warning. In this slide, some messages on detailed bullet points that warn in a serious tone about the risks involved in continuing interaction with the site. Each warning message describes various risks including illegal financial transfers, security threats and service delivery problems.

User Decision Buttons
The slide has three navigation buttons to help users make knowledge-based decisions.

- **Safe Exit:** Users can safely exit the website through a button which resides at the bottom-left corner of the slide.

- **Proceed Anyway:** Users may proceed with the website surfing by clicking this button despite being aware of potential risks at the lowest-right portion of the window.

- **Go Home:** In the top-right corner, this button lets users return to the first slide. It provides an opportunity to review the information again before deciding how to proceed.

5.3 Extension Functionality

According to our extension's basic functionality the passive mode is designed in such a way to operate silently in the background to collect and analyze user reviews ensuring a comprehensive summarization. The active mode uses the same information to provide an effective warning to the user. Active mode triggers an imperative warning popup display to catch web users attention. However, detailed functionality will be discussed in the following sections.

Section 1: User Review Analysis and Summarization

Upon activation the extension begins to discreetly track and collect reviews from users of the website. The advanced system uses the reviews to extract important aspects while providing a summary of overall sentiments toward and attributes of the site. Users benefit from straightforward knowledge about site reputability through summations that analyze recent user experiences.

- **Numerical Ratings:** The extension calculates numerical ratings from the reviews that the users post. The ratings get updated dynamically as new feedback gets added which means the presented score is always relative to the opinions of the users at the given time.
- **Dynamic 5-Star Rating Bar:** Positioned next to the numerical rating, this graphical helper varies in real time based on the overall user numerical ratings.
- **Dynamic Confidence Bar:** A key element of our Chrome extension, the Dynamic Confidence Bar provides a graphical representation to users of the trust level of the site being visited. Positioned directly below the 5-star rating system, the bar displays trust levels through a sophisticated color gradient that runs from red to green.
  - **Color Dynamics:** The coloring of the Dynamic Confidence Bar is strongly tied to the numeric ratings from user reviews so that it reflects the current assessments of the trustworthiness of the site. User rating changes become visible through continuous color gradients in a way that delivers accurate feedback about small fluctuations in ratings. The confidence bar shows a dynamic color transformation when new user reviews enter the system and rating values transform. Real-time data processing allows the bar color to change dynamically after each new review changes the average rating. This is how the color is dynamically updated:
  - **Color Gradient System:** The bar uses a three-color gradient system—red, yellow, and green where, Red signifies low trust (ratings from 0 to 2.6), Yellow indicates moderate trust (ratings range from 2.7 to 3.5), Green represents high trust (ratings between 3.6-5).
- **Government Registration Verification:** Users can validate the site's legal status through a database comparison since the extension performs this task. Website legitimacy badges display to provide users essential information about registered business status which builds trust between users and sites.

Section 4: Multi-Checkbox Rating System and Custom Review Field

Section 4 of the passive mode has a highly interactive and user-driven review system.

- **Predefined Options:** In this section, there are three main categories, Product Condition, Customer Service and Overall Experience. Within each section, users have a selection dropdown with seven predefined choices. There are a combination of positive, negative and moderate options. However, there are two dynamic options that are auto-generated.

- **Custom Review Field:** The reviewers can submit their reviews in any language, which are passed through the API to generate meaningful, summarized tokens. These tokens are refreshed and updated at regular intervals in the dropdown menus, making it a dynamic and interactive user feedback system.
- **Dynamic options generation:** The system receives user reviews through the custom review field and sends it to the OpenAI API to create summarized tokens which capture the summary of review content. These tokens are then categorized and added as dynamic options under the appropriate main categories. The system ensures updated relevant options because this approach keeps user experiences up-to-date.

[*A detailed explanation and calculation about the rating system will be found in Chapter 6.*]

Section 2: Most Selected Reviews and Dynamic Update Mechanism

- *Most Selected Reviews* dynamically displays the top five most user-checked review tags in Section 4 i.e Multi-Checkbox Rating System. The users give input to the site by selecting the tags or composing reviews related to their experience. Each tag represents a specific quality of the user experience, such as *Easy to Use, Helpful Support,* or *Poor Quality.* Each time a user selects a tag, the system increments a counter for the corresponding tag. The extension tallies these selections ongoing in order to calculate which tags are most chosen by users. Five most frequently selected tags are automatically displayed in the *Most Selected Reviews* section. This list is updated in real-time reflecting any changes in user preferences or new emerging trends in feedback as more reviews are submitted.

5.4 Connecting BE Theories with Architecture

Now that we know about how the extension functions, now we will be connecting each component of our extension with the theories of Behavioral Economics.

5.4.1 Behavioral Economics: Reason Behind Choosing BE

Behavioral Economics (BE) is a study that acknowledges why human make irrational decisions. [*The detailed explanation can be found at section 2.2*]. Human beings are influenced by many external factors which led to irrational decision making. Similarly, in e-commerce sector human beings get influenced interesting discounts which often led to impulsive buying of products. The consequences lead to fraud susceptibility and unreasonable purchasing decisions. Apart from traditional economics, which assumes rational decision-making, BE explains how cognitive biases and heuristics influence consumer behavior [11].

One of the major reasons for choosing BE is loss aversion, where consumers fear losses more than they value gains. It makes them susceptible to deception such as limited-time offers and fake urgency tactics [13]. Similarly, the herding effect makes consumers trust online ratings and reviews without verifying their authenticity, which increases the number of fake reviews [27]. Framing effects also shape consumer perception positive wording in product descriptions can distort actual product value [15]. E-commerce scams also exploit asymmetric information [8], where sellers have more knowledge than buyers, leading to misleading product descriptions. Traditional consumer education is ineffective alone; behavioral interventions such as nudges, trust indicators, and warning alerts can significantly improve consumer awareness and decision-making [74]. By integrating BE principles, e-commerce platforms can design interventions that counteract fraud tactics, helping consumers make more informed and secure decisions. Our extension development followed behavioral economics principles to build each component and to reshape user behaviors and improve decision outcomes. Given the rise in online scams, BE-driven solutions are critical for fostering trust and transparency in digital transactions. A complete outline of how each section of our extension incorporates specific behavioral theories, which substantiate the practical application of these theories are given below.

5.4.2 Bounded Rationality

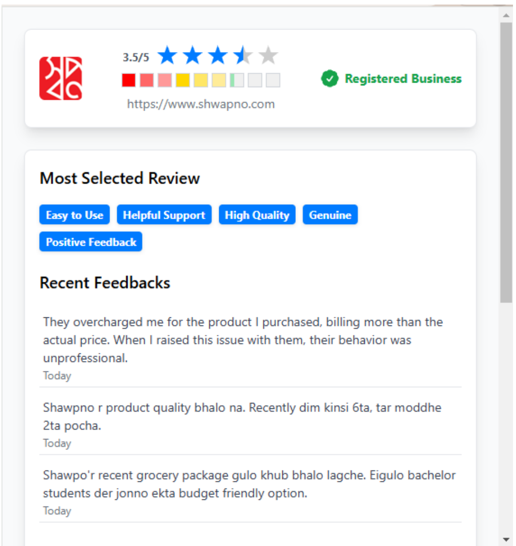
The extension starts with displaying the summarization of the sites indicated as "Slide 1" in both passive and active modes (shown in the **Figure 5.1a and 5.1b**) of our extension. According to bounded rationality (see at **subsection 2.2.3**) individuals make decisions within the constraints of limited information, cognitive capacity, and time [5]. In e-commerce shopping, the vast amount of scattered and incomplete information exacerbates users' vulnerability towards fraud, as they may not have access to all the necessary details to make fully informed decisions. Consumers generally look for a solution that is adequate rather than optimal one due to the limits of their cognitive resources while dealing with complex decisions and a lot of information, primarily [5]. The extension simplifies decision-making by taking scattered data and condensing it into actionable insights by summarizing and presenting important information such as ratings, government registration status, *Most Concerning Issues*, and user reviews. This significantly reduces the cognitive load. Therefore, users can make effective decisions within their cognitive limitations and become more sensitive to the potential for fraud.

5.4.3 Section 1: Anchoring, Heuristic, Salience Effect

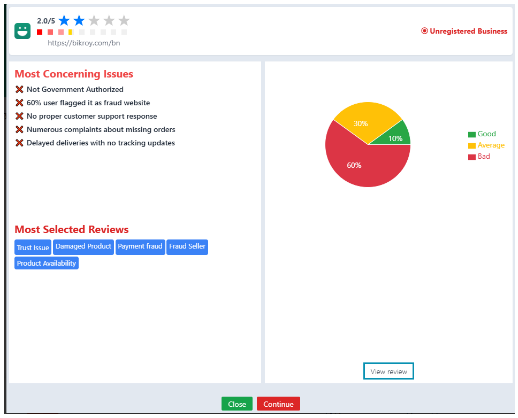
Through *Section 1* of passive and active mode of our extension with the combination of Anchoring, Heuristic and Salience Effect we organize the flow in such a way with a motive to help users to make decisions easily. It is arranged in such a way so that users can easily understand and take decisions while looking at the *Color Coded Confidence bar, Registered Business.*

Anchoring

Our extension implements *Section 1* through anchoring theory to shape user preliminary perceptions while driving decision–making processes as shown in **Figure 5.2.** A cognitive heuristic called anchoring (see **subsection 2.2.3**) demonstrates how humans disproportionately rely on the first accessible information during their decision-making process [13]. In the passive and active modes of our extension, the



(a) First Scroll Panel of Passive Mode



(b) Slide 1 of Active Mode

Figure 5.1: Bounded Rationality of both Active and Passive

numeric rating, star rating, dynamic confidence bar, and government registration badge comprise this anchor. These attributes become conspicuous at once when a new user accesses this site to form an instant minimum impression of the trust of this site. Numerical and star-based ratings provide them with a fast objective metric of goodness, while the color-coded confidence bar graphically expressed levels of security utilize a red for caution through the green for trust spectrum. The government-registration badge also is available to ground user trust by proclaiming official supervision or recognition. This anchoring is crucial because it sets the tone for all subsequent interactions with the site. One of the tendencies of consumers is they are more likely to approach additional information through the lens of initial judgment [16]. An initial credible anchor forces users to accept further content with more positive feelings about making decisions online. Conversely, if the initial ratings are low, users may be more cautious and vigilant which will make them to seek further verification than if the initial rating had been higher before proceeding. Anchoring serves to simplify the decision-making process with easily understandable and instant options while combating digital information overload according to bounded rationality principles by enabling efficient constrained cognitive decision-making.

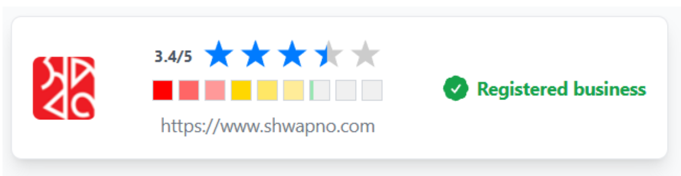


Figure 5.2: Visual Representation of Anchoring in Decision-Making

(a) Heuristic of Passive Mode (b) Heuristic of Active Mode

Figure 5.3: Heuristic Decision-Making Through the "Registered Business" Badge

Heuristic

The *Registered Business* badge in the passive and active modes of our extension is a good application of heuristics since it is an immediate visual cue that indicates government registration and compliance with legal regulations. Heuristics *(see more at* ***subsection 2.2.3****)* in behavioral economics are mental shortcuts that allow individuals to make efficient decisions in the face of complex information or uncertainty [13]. As shown in **Figure 5.3**, heuristic plays a crucial role in e-commerce platforms. In the online market, as there is plenty of information and choices that can be overwhelming, these mental shortcuts are useful. The *Registered Business* badge accelerates decision-making through its instant signal of security and trustworthiness. This heuristic cue guarantees the users that the business attains some standards that reduce the amount of cognitive effort required to decide whether it is legitimate. A prominent display of this badge takes advantage of the authority heuristic creating a perceived authority effect from government or regulatory bodies in users' minds. The heuristic plays an essential role in establishing trust as users glimpse content online for brief periods.

Salience Effect

Our extension uses a dynamic color-coded *Confidence Bar* system that modifies color intensity to guide users toward vital trust and quality information cues. We inherit this approach from the salience effect theory *(see details in* ***subsection 2.2.11****)* of Behavioral Economics. Salience effect theory claims that while making decisions people tend to focus excessively on the most visually prominent or emotionally striking components [13]. In digital platforms, this bias becomes critical as users often face cognitive overload because of plenty of information. The confidence bar follows the principles of behavioral economics in enhancing user's experience and decision quality. Through the hypotheses of the Salience Effect introduced by Tversky and Kahneman (1974), the bar employs the affective cues of color to create efficient anchors, pre-conditioning users to judge subsequent information within the frame of our extension. Building on Simon's (1957) concept of bounded rationality,

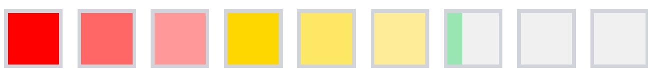


Figure 5.4: The Salience Effect Applied through the Confidence Bar

the intuitive design of our extension as shown in **Figure 5.4** decreases cognitive load by converting abstract numeric ratings into brief visual cues, enabling users to make efficient decisions within their cognitive and informational limitations. Design-integrated nudging elements according to Thaler and Sunstein's (2008) theory guide users towards safer choices [74]. With the utilization of a salience-based color palette, the bar enables users to make more informed and quicker decisions.

Color Code Model

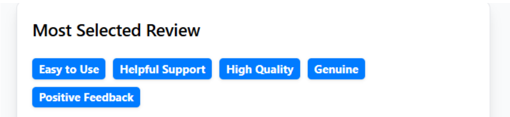
The deliberate application of color in our extension is informed by recognized color models and psychological theories, facilitating users' comprehension of danger levels, safety indicators, and decision-making routes. Studies demonstrate that red indicates a sensation of urgency and avoidance, whereas green induces emotions of security and affirmation [31][97]. *The Dynamic Confidence* bar utilizes a model that associates red with danger, yellow with caution, and green with safety, adjusting in real-time according on the site's trust score. Likewise, the *pie chart* in Section 3 (Active Mode) utilizes *HSV (Hue-Saturation-Value)* color gradients, facilitating a smooth transition between risk levels, which is especially helpful in depicting risk intensities [56]. The active warning system enhances the *Color Code Model* by employing red alerts, as indicated in the title of the second slide - "*Warning: Proceeding Might Cause Potential Losses*," in bold red for low-trust sites (e.g., "Potential Fraud"), thereby underscoring urgency and augmenting user adherence to safety recommendations. Red-framed warnings have been shown to enhance user attention and risk-aversion [64][17]. The green *Safe Exit* button gently highlights a safe and logical choice, The red *Proceed Anyway* button presents advancing as a risky action, hence increasing users' tendency to self-doubt due to their loss aversion. This extension improves risk communication, decision clarity, and user compliance with safety-oriented actions by combining color psychology, the *RGB* and *HSV* models, and behavioral framing effects.

5.4.4 Section 2: Choice Architecture, Attention Economy

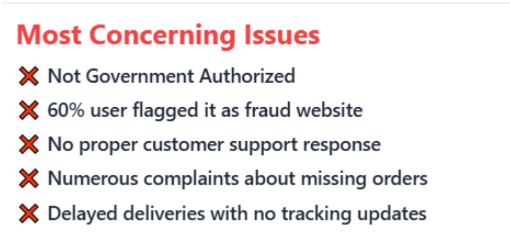
Through *Section 2*, *Most Selected Reviews* & *Most Concerning Issue* our extension applies principles of Choice Architecture and Attention Economy to deliver user feedback in an interactive and open manner.

Choice Architecture

Choice architecture *(see more at **subsection 2.2.9**)* denotes the way of presentation of information and alternatives designed to affect decision-making [74]. This notion is utilized in our extension to shape user perceptions via the strategic display of information as shown in **Figure 5.5**. The *Most Selected Reviews* area constantly updates tags according to real-time user selections ensuring that consumers encounter the most crucial and often emphasized elements which facilitates quick decision-making. In order to eliminate bias or manual curation, this dynamic mechanism makes sure the interface shows true trends based on user feedback. The interface emphasizes these tags visually ensuring users can easily identify the most common sentiments about the product or service. Similarly, the *Most Concerning Issue* subsection of active mode emphasises the most urgent issues from a website's feedback. This allows users to immediately identify potential risks. The information is presented in a clear and concise format such as *Not Government Authorized* or 60% *flagged this as a fraud website*. This presentation helps user to process key details quickly and make informed decisions with minimal effort. These subsections of our extension use Choice architecture to anonymously direct users towards prioritising safety while preserving their autonomy in decision-making. This method enables customers to acquire a comprehensive picture of a product's value and drawbacks, obtained from aggregated feedback without flooding them with irrelevant data.



(a) Most Selected Review of Section 2 (Passive Mode)



(b) Most Concerning Issues of Section 2 (Active Mode)

Figure 5.5: Choice Architecture Implementation of both Passive and Active Mode

Attention Economy

In the design of this section, we use attention economy theory *(see details at **subsection 2.2.5**)* by utilizing color and recurring design to make prominent feedback labels easily noticed and processed. Attention economy principles state that user attention retention requires placement of items with clear visual presence and easy interpretation at the forefront [43]. In a digital environment where user attention is limited, information has to be presented in such a way that it captures attention without causing cognitive overload. The use of blue, a stable and neutral color creates harmony and focuses user attention on each review tag without emotional bias. The design maintains structural integrity through equal tag dimensions and text format which results in distraction-free presentation. The design of this section with the implementation of attention encourages users to focus on the aggregated feedback helping them process critical information quickly and efficiently. The organization of this section is underpinned by [44] Cognitive-affective model of communication which recognizes the synergy of logical and emotional elements in effective communication. According to the model effective communication occurs when rational presentation (cognitive) maintains equality with emotional involvement (affective). Three main things influence the process in accordance with this model:

- The inputs such as the purpose of the communication, the receiver-sender relationship.
- The process includes both (cognitive) thinking logical and (affective) emotional feelings.
- The outcome is the impact of communication on relationships and actions.

The application of this model to this section:

- **Inputs:** Selected tags from users deliver authentic feedback which helps other users make informed decisions.
- **Process:** The combination of cognitively clear blue visual tokens with consistent visual presentation enables cognitive clarity while the system's dynamic update process develops emotional trust in system authenticity.
- **Outcome:** The section establishes a relationship between the user and the message, facilitating knowledgeable action according to collective views.

The *Most Selected Reviews* section effectively applies Choice architecture and Attention economy to provide a dynamic, user-generated presentation of reviews. Supported by the Cognitive-affective model of communication, the layout supports the clear and transparent presentation of user-chosen tags, developing trust and ensuring speedy decision-making.

5.4.5 Section 4: Hyperbolic Discounting, Information Asymmetry

Hyperbolic Discounting

The section *Recent Feedback* applies the behavioral economics theory of Hyperbolic Discounting *(see details at **subsection 2.2.10**)* to emphasize and present the most recent user feedback shown in **Figure 5.6**. Hyperbolic discounting highlights the tendency of humans to assign greater value to current or recent incentives and information compared to things regarded as temporally distant, despite the latter being more extensive or advantageous [33]. The system incorporates this interface style because it represents users' natural preference to prioritize fresh data over storied data thus maintaining interface user involvement linked to real-time focus. The system shows reviews from today's date and those recently posted. The functional design drives users to believe the feedback maintains a current and important connectivity with recent activities. The immediacy of the information encourages users to trust and act upon it, leveraging their preference for recent data. Although summarised data or trends over time could provide a greater insight, we have expressly designed this section without including such aggregated data. This approach correlates with research on information overload, as noted by Eppler and Mengis (2004), and guarantees that readers may concentrate on the most current and relevant reviews without feeling overwhelmed.

Information Asymmetry

The data provided by the complete chrome extension corresponds with the behavioral economics concept of Information Asymmetry *(See more at **subsection 2.2.2**)*. According to information asymmetry, during the decision-making process when one participant possesses superior or more comprehensive knowledge than another, resulting in possible disadvantages for the less informed participant [8]. Individuals become victims of fraudulent services due to an inadequate understanding of

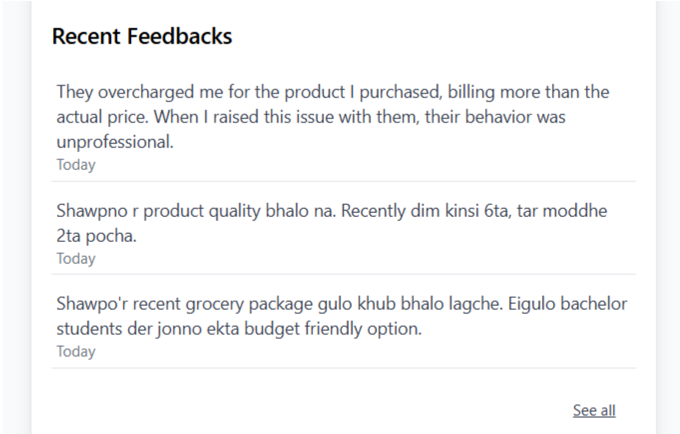


Figure 5.6: Hyperbolic Discounting Application through the Recent Feedback

risk assessment [10]. Our comprehensive chrome extension functions as an interface to bridge the information gap. Research on consumer behaviour and digital trust indicates that offering accessible, organised, and transparent information might markedly decrease the probability of consumers succumbing to fraud and deceptive services [19]. Our extension equips users with the required facts to avoid fraudulent platforms and make more educated decisions by summarizing crucial variables such as website ratings, government registration status, aggregated user reviews, and significant concerns. In our extension, users can access all the reviews given by other users by the *View All* option in *section 3* for both passive and active modes. Consumers interested delving more into the service or product can find comprehensive reviews that go beyond summarizing recent feedback. By providing access to more information, the design also mitigates the risks of decision-making based solely on a narrow set of recent reviews. Thus, our extension exemplifies the application of information asymmetry theory by reducing the knowledge gap and providing enough information to prevent users from becoming fraud victims due to information scarcity.

Loss Aversion

In the active mode of our extension, *Slide 2* incorporates the loss aversion theory of behavioral economics *(see details at subsection 2.2.1)* shown in **Figure 5.7**. Loss aversion describes individuals' tendency to prefer avoiding losses over acquiring gains [13]. Our system implements dedicated warning messages that alert users about unauthorized transactions as well as financial protection risks and service quality problems to match their instinctive damage avoidance needs. Our design incorporates specific warning elements about risks including unauthorized transactions alongside financial security loss and poor service quality to match users' natural need to minimize harm. Alerts located within interfaces lead users to evaluate their decisions prior to movement which ultimately prevents sudden choices that result in subsequent regret. The slide prominently displays a warning message in bold red text that reads *Warning: Proceeding might cause potential LossesD* to emphasize strongly the severity of risks that users will face. The cautious message shown through bullet point details gives users direct visibility into particular risks that clarify actual monetary losses. On the *slide 2*, *Safe Exit* button is positioned prominently to appeal to users' instinct to minimize exposure to potential losses by safely exiting the website. The *Proceed Anyway* button allows users to continue by signaling their acceptance of encountered risks specifically for individuals who choose urgency over likely losses. *Go Home* button offers to revisit the *Slide 1* so that users can review material for further clarification before making decisions which helps to reduce anxiety during your decision-making process. The entire slide frames the decision-making process around the concept of avoiding losses. Users encounter potential risks while watching content because the system directs users toward safer choices by placing these risks at the forefront. This ensures users are guided toward safer choices while still retaining their freedom to proceed if desired.

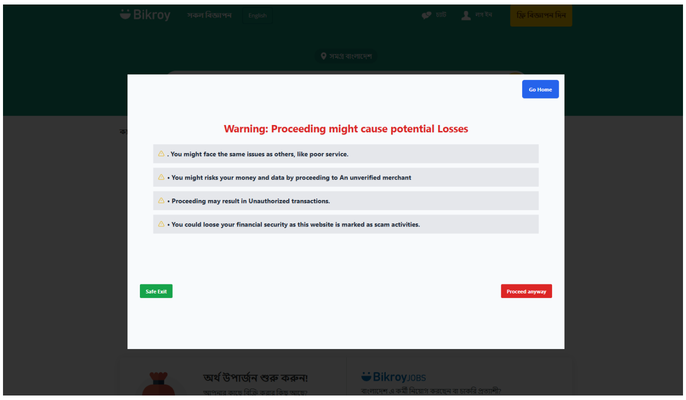


Figure 5.7: Loss Aversion Application through Active Mode

Herding Effect

The herding effect *(see more at **subsection 2.2.4**)* has been intentionally utilized in the extension to direct users towards safer online buying choices by leveraging user reviews, numerical ratings, and a *Confidence Bar*. According to the herding effect, in uncertainty people are more likely to take suggestions from others behavior [40] the interface can be shown in **Figure 5.8**. The herding effect arises from the presumption that a large group contains greater information, making it rational to emulate collective behavior[40]. In the extension, the user review section is included because humans have the tendency to follow a crowd. This section is added to take advantage of the herding effect, which occurs when people rationally choose to follow the lead of others when they are uncertain about their own choices. Empirical studies confirm that user feedback acts to serve as an anchorage for decision-making, reducing individual uncertainty through aggregated feedback [69]. By offering a view of *Recent Feedback* and an option *View all* through which one can see all textual feedback of others. The extension brings limelight over the aggregated feelings of users, urging individual users to follow in the view of most. The active warning mechanism for low-rated websites exploits the herding effect via its use of collective feedback in terms of a high percentage of visitors having rated the site not safe (e.g., 60% rated this site a fraud). Another part of our extension is *Most Selected Reviews* which presents the user's textual feedback in tag form through aggregation, facilitating the user's ability to discern the predominant conclusions without the necessity of examining individual feedback in detail. Behavior economics studies have uncovered that graphical cues for collective opinion reduce the cognitive burden and promote efficiency in decision-making [13]. The extension effectively leverages the herding effect that tries to counteract uncertainty and stimulate users to act in agreement with collective feedback. Studies demonstrate that warning information enhances the extent to which users follow system protocols specifically when decision risks are involved [40]. With individual decisions guided through aggregated trust statistics, safer behavior is enhanced and trust in e-commerce experiences is heightened [68].

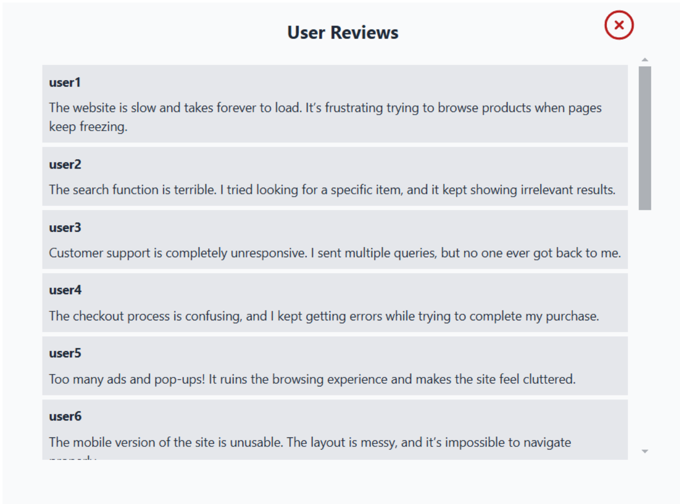


Figure 5.8: Herding Effect Application through the User Reviews

Framing Effect

The extension makes great use of the framing effect *(see more at* ***subsection 2.2.8****)* with its dynamic confidence bar, registration business badge and active warning systems. The framing effect is a cognitive bias in which people' decisions are influenced more by how information is displayed rather than its content[11]. The dynamic confidence bar employs visual framing by linking color-coded danger levels to site trustworthiness. Psychological studies indicate that individuals perceive red as an urgent warning or danger signal, whereas green signifies safety and approval [86]. By delineating trustworthiness through this color gradient (red, yellow, green), the extension influences user perception prior to their evaluation of numerical ratings or reviews, hence increasing the likelihood of emotional rather than rational responses to risk levels. By highlighting the possible losses, the active warning mode of our extension illustrates negative framing. When a user tries to engage with a low-rated website, the extension halts their action with an alert message that enhances risk awareness using clear framing language such as *Warning: Proceeding Might Cause Potential Losses*. Behavioral research indicates that individuals respond more intensely to loss-framed communications compared to gain-framed messages, hence increasing their likelihood of adhering to safety recommendations [86]. The decision routes in the warning popup utilize framing effects by presenting alternatives as a distinct risk-aversion scenario. To nudge the user for a safe decision, the design of *Safe Exit* button is designed done to appear more prominent than *Proceed Anyway*. The extension affects user perceptions of trustworthiness by combining visual, linguistic and structural framing strategies to nudge the user's decision-making towards safer behaviors and improve compliance with recommended actions.

5.4.6 Connecting BE with Active Mechanism

Status Quo Bias

The warning system integrated into our Chrome Extension that applies the behavioral economic principle called status quo bias, the interface can be shown in **Figure 5.9**. People show preference toward their initial choice rather than making changes to them despite better prospects emerging [20] *(check **subsection 2.2.7** for more details)*. This bias is particularly relevant in privacy and security decisions, where users often accept default settings instead of modifying them [52]. By automatically displaying an imperative pop-up message when a website's rating drops below 2.7, the extension directly engages with users' natural inclination to stick with default settings. Security warnings that users encounter for the first time often lead them to hesitate before taking any action because they worry about selecting the incorrect option [45]. Our extension provides a mandatory warning that disrupts normal browsing to prevent users from automating their actions. Thus users gain time to review potential security risks. The active warning system serves as a built-in security safeguard that guided naturally to users toward caution in risky situations. By providing crucial security alerts proactively, the system eliminates the need for users to look for risk assessments on their own, making default compliance the most sensible option.

Nudge

The process of whole active warning through our extension is done with an intention to nudge users towards a more rational decision (learn more about Nudge theory at subsection 2.2.6). The information presented in each layer of the extension satisfies the theory 'Nudge with Information'. Just as 'Nudge with Information' claims itself as the act of providing information in order to reduce information gap, our motive was also the same. Necessary information such as summarised token, rating, reviews, potential risks etc. relevant to an e-commerce site is provided in every UI of our extension with a view to reduce the problem of asymmetric information faced by the customers of e-commerce sites. Moreover, how the information is ordered and framed in a certain way, and how the options are presented satisfies the theory of 'Nudge with Presentation'. According to 'Nudge with Presentation', ordering, framing, saliency has a role in grabbing user focus reducing distraction. 'Nudges with Timing' says that nudge should be done at the right timing relevant to the context so that it can affect users' decisions. The reason our popup is shown when users are visiting a low rated website is because we wanted to warn our user with all the necessary information at the time of visiting the website so that the user can make informed decisions. That is the main reason for our active popup. Users are bound to pause their usual activities and take a look at our active popup so that they can receive relevant information to make informed decisions. 'Nudge with incentive' to be specified we have focused on 'Nudge with Punishment' because it claims that increasing difficulty for certain configurations act as a form of punishment for the users. When users are trying to click 'continue' from the first UI of active popup to visit the website even after being low rated, they have to face a second UI describing all the possible consequences of visiting the website. That means they have to go through two layers of UI in order to visit the website which acts a friction and a form of punishment as they want to visit a low rated website even after knowing it is low rated. The reason for implementing this is nothing but to increase friction and to give users a chance of second thought so that they can take a while to think and make informed decisions. That is now nudge is implemented in our extension. Elaborate description of nudge can be found in Chapter 2.

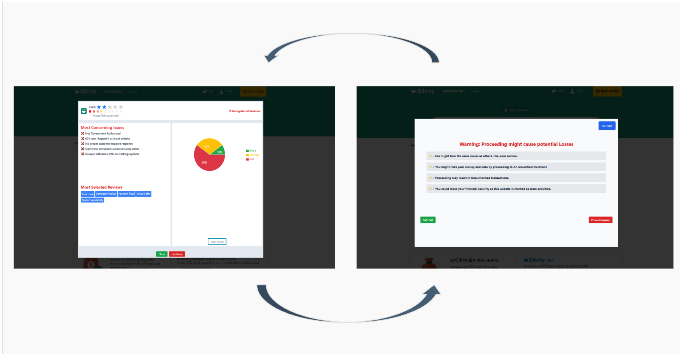


Figure 5.9: Mechanism of Active Mode with Nudges with Timing and Nudges with Incentives

5.5 Proposal of Hypothesis

As we have already explained the connection of Behavioral Economics principles with each component of our extension the hypothesis we are proposing are mentioned below:

- H_0: Potential Risky Information has a significant effect on user buying decision that is users will prioritize to not buying from the website due to fear of loss after knowing the potential risks.
- H_1: Displaying a popup at the time of website entry grabs user attention which increases awareness and the chance of taking cautious actions.
- H_2: Summarized information gives users an overall overview of the website which helps them to make more informed decisions within a short time reducing the information gap and effect of bounded rationality.

5.6 Uniqueness of our Extension

The extension is unique because of the collaboration of Behavioral Economics (BE) theories, ensuring the user awareness, decision-making and helpful for fraud prevention in the context of e-commerce. Apart from the traditional awareness system we effectively leverage cognitive biases and decision-making heuristics to guide the user to make more rational decisions. Incorporating BE theories with focusing on awareness mechanisms our system will inform users and also nudges them toward safe purchases.
[Detailed BE theory can be found at ***section 2.2****]*

5.6.1 Behavioral Economics: Foundation of Awareness

The traditional warning system comes with a static alert users may often ignore the message due to human habituation [11]. Our extension becomes unique with loss aversion, framing effect and bounded rationality to design an attention-grabbing and persuasive warning system which actively influences user behavior. Therefore, potential financial losses triggered loss aversion, making users reconsider unsafe purchasing action [14].

Behavioral Economics: Warning System Enhance User Response

Traditional standard warning systems are often ignored due to alert fatigue. Incorporating anchoring, nudge theory and framing in our extension makes the risk information more digestible and actionable.

- **Herding Effect:** Users are generally influenced by previous review and fraud reports according to caution behavior [27].
- **Framing Effect:** Apart from the traditional alerts our warnings are framed with emotional triggers, for instance, a warning message can be, (90% of fraud victims ignored this warning) to increase impact.

5.6.2 Dual Stage Awareness System: Active and Passive

Our extension performs two distinct ways to maximize effectiveness for different platforms.

- **Active Mode:** It presents immediate pop-up warnings when a user visits a potential fraud e-commerce platform. This mode emphasizes nudge theory to prevent impulsive decisions.
- **Passive Mode:** A user can get detailed risk breakdown and see other reviews manually while interacting with an e-commerce platform. However, users can provide their own experience in this mode. This approach supports asymmetric information providing the summarized insights that reduce decision uncertainty [8].

5.6.3 Personalized Review: Dynamic Reputation System

The traditional reputation system uses numeric star rating and custom text review separately, our system incorporates two distinct algorithms (Bayesian & Exponential) which make sure up to date rating. Moreover, our system uses predefined options with custom review. Among the 7 options, 2 options will dynamically update from the recent user reviews. Find more details about the dynamic options in **section 6.2.**

- **Bayesian Average:** It ensures ratings are stabilized and remain unbiased to prevent rating manipulation for fewer reviews [109]. See more explanation in **section 2.6**.

- **Exponential Time Decay:** It prioritizes recent feedback and provides weight according to time since the user submitted. It makes our system more adaptive than the traditional static reputation system [95]. See more explanation in **section 2.7**.

To provide awareness where potential risk may occur and to prevent this our extension comes with effective and necessary summarized information to help the user before taking any decision from a suspected e-commerce platform according to the BE theories. We build a smarter user-centric fraud prevention system through nudges, dynamic reputation adjustment and C-HIP based awareness. This innovative awareness system with the combination of Behavioral Economics keeps us apart from the traditional scattered information provider.

5.7 Technology Stack

Our extension development for e-commerce platforms requires scalable, efficient and real time adaptable technology. Our system has frontend and backend technologies and NoSQL database and AI driven sentiment analysis to provide and optimize experience. Bellow the structured breakdown of the technologies we have used to develop the extension.

5.7.1 Front-End Development

The front-end was developed using TypeScript to strong type safety and maintainability in our extension. The user interface were designed in such a way that it stays lightweight and interactive. It ensures a smooth experience while displaying the dynamic rating and warnings.

- **Technology:** TypeScript
- **Key Features:**
  - Better error handling and type checking.
  - Code maintainability and scalability.
  - Facilitate efficient UI interaction.

5.7.2 Back-End Development

The back-end server build in NodeJS run time environment with Express JS enabling fast, scalable and efficient RESTful API for handling user review and rating calculations.

- **Techonoligy:** NodeJS with ExpressJS
- **Key Features:**
  - Handle rating calculation and user review submission.
  - Scalable API for fetching risk assessment.
  - Ensure efficient connection between databases.

5.7.3 Database Management

A NoSQL database like MongoDB database were chosen for storing user reviews, dynamic rating calculation, dynamic predefined options. MongoDB provides flexibility in handling both unstructured and structured data which make it ideal for our extension.

- **Techonology:** MongoDB
- **Key Features:**
  - Scalable storage for user review and websites details.
  - Efficient querying of rating and historical data.
  - Enable real-time data updates.

5.7.4 Sentiment Analysis with AI

To strengthen our reputation system we use AI powered generated predefined option to make our system more realiale and up-to-date. This AI use to generate token from the long text provided by the user. The generated token add to the dynamic predefined section. It categorized the data in positive negative as state and then categorized into three main category enhance the reliability of the of our system.

- **Technology:** OpenAI
- **Key Features:**
  - OpenAI ensures high availability and reliability.
  - Automatic scaling for traffic.
  - Secure API communication between service.

Chapter 6

Rating System Development

The Rating system is arranged to evaluate the performance of an e-commerce site based on user feedback, this ensures a fair, robust and adaptive reputation system. Here we have predefined options in this system and a collection of dynamic options from the user textual reviews. Our system leverages two distinct algorithms **Bayesian Average Algorithm** and **Exponential Time Decay Algorithm**, which ensure both statistically balanced and prioritize recent user feedback. In this system, we assign weight to different categories and options. It also ensures that critical factors have a greater influence on the final rating. Therefore, this section illustrates how the rating system is organized and calculates the rating.

6.1 Categories and Predefined Options

The system evaluates any e-commerce platform based on three major categories *Product Condition, Customer Service, Overall Experience*, each of these major categories has a total of seven predefined options that represent the user experience. These predefined options are divided into *Positive, Negative* and *Moderate*. Below, the description of all the major categories with their predefined options within list structure.

Category 1: Product Condition

Positive Options:

- High-Quality Product
- Genuine and Authentic

Negative Options:

- Poor Quality/Defective Item
- Counterfeit/Imitation Product

Moderate Option:

- Average Quality

Dynamic Options (Generated):

- Durable Product
- Substandard Packaging

Category 2: Customer Service

Positive Options:

- Friendly and Helpful Support
- Prompt Response to Queries

Negative Options:

- Unhelpful or Rude Staff
- Delayed or No Response

Moderate Option:

- Basic/Standard Support Experience

Dynamic Options (Generated):

- Clear Issue Resolution
- Misleading or Confusing Information

Category 3: Overall Experience

Positive Options:

- Easy to Use
- Smooth Shopping

Negative Options:

- Hard to Use
- Payment Problems

Moderate Option:

- Average Experience

Dynamic Options (Generated):

- Fast Delivery
- Privacy Concerns

6.2 Generating and Adding Dynamic Options

In the main category, the dynamic options come from user text review. These options are auto-generated by OpenAI's API to summarize and sentiment analysis for positive and negative. Based on the analysis we assigned it to the relevant category. Significantly we prioritize user-preferred language(Bangla). However, a user can provide their detailed review both in Bangla and English or a mix of languages. Below, we have a detailed step-by-step explanation of how this process works:

Step 1: User Input

1. **Predefined Options**
    - User can select any predefined options from the dropdown menu from each category.
2. **Custom Text Review Field**
    - User also can type a review of their experience with the platform.
    - This review can be the user's preferred language as the OpenAI's API supports multilingual texts.

Step 2: Token Generate and Category Identification

1. **OpenAI's API**
    - **API:** The custom text review will initially send to the OpenAI's API for processing. We have used a custom prompt to generate this token.
      Prompt:
      Please analyze the following review message and perform the following tasks:
      (a) Provide a 2-3 word summary of the review.
      (b) Categorize the review into one of these categories:
        - Product Condition
        - Customer Service
        - Overall Experience
      (c) Assign a base rating ± 2 based on the overall sentiment of the review. For Positive provide $+2$ and Negative provide -2.

      Review Message: `"${message}"`

      Respond in JSON format as follows:

```
{
    "class": "<summary in Pascal Case>",
    "category": "<selected category>",
    "baseRating": <numeric rating>
}
```

- **API task:** According to the prompt summarize the review into concise, meaningful one or two word token. Also analyze the sentiment and tone of the review to distinguish between positive, negative or moderate.

2. **Category Identification**

   - After the token generation the system analyzes which main category it belongs to.
     - If the provided review mentions anything about product quality: **Product Condition**
     - If the provided review mentions anything about customer support: **Customer Service**
     - If the provided review mentions anything about usability and other experiences that are not related to product conditions and customer support: **Overall Experience**

3. **Update the Dynamic Options, Validation and Weight Assignment**

   (a) **Dynamic Options**

   - Each category has two dynamic options at the end of the list. When a new token is generated it replaces with the oldest option in that category. It is similar to FIFO (First in First Out). This mechanism ensures the dynamic options are up-to-date to reflect recent user feedback.

   (b) **Validation**

   - Once a token is generated the system performs a basic quality check to ensure the token is meaningful and not redundant.
   - The generated token will be eliminated if it is irrelevant, or nonsensical the dynamic option remains unchanged.

   (c) **Assigning Weight**

   - The API-generated token might be wrong so we can not give the same weight as the fixed option. So we provide an average weight so that if it is wrong then it will not have greater impact on the overall rating (The full process will be described in the following section).

6.3 Dynamic Option Selection Flowchart

The **Figure 6.1** shows the selection of dynamic option and weight assignment.

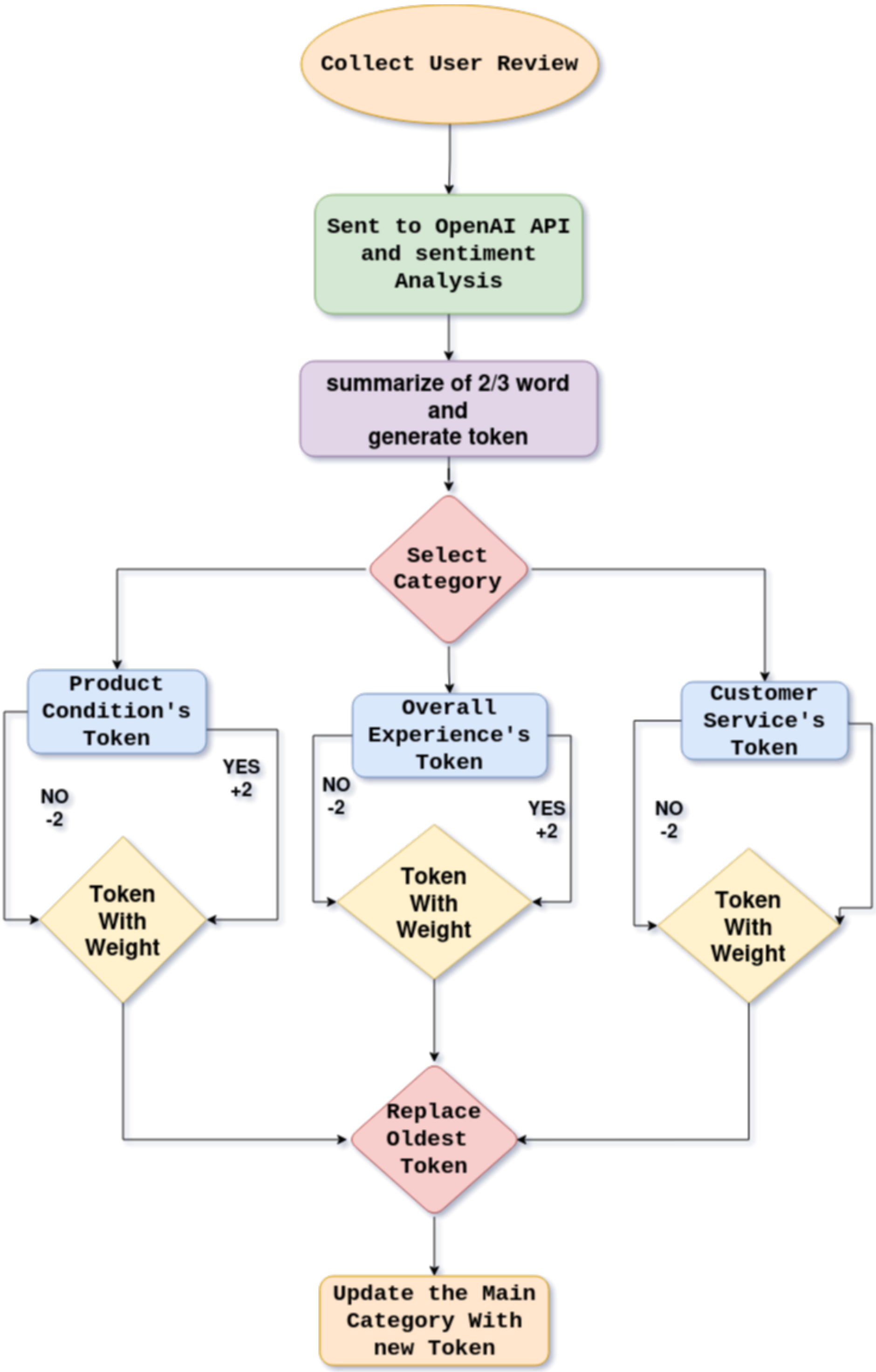


Figure 6.1: Dynamic Option Selection Flowchart

6.4 Weight Value: Assignment Process & Rational

In our rating system, one of the crucial portions is assigning weight values to predefined and dynamic options that ensure the final rating is accurately presented to the user. All of the weight values were determined meticulously based on two factors.

The relative importance of each category, the nature (*Positive, negative, moderate or dynamic*) of the predefined options. Therefore, this section discloses a detailed explanation of the methodology of how the weight values were assigned for both factors.

6.4.1 Relative Importance: Categorical Weight

Each of the categories plays a distinguished role in shaping the user perception of an e-commerce site. The Relative importance of - **Product Condition, Customer Service** and **Overall Experience** was determined by user satisfaction and decision making in e-commerce. This ranking variance is supported by the existing research and the study of consumer behavior. These categorical weight acts as multiplier when calculating the overall rating which ensure critical factor have greater influence.

1. **Product Condition: Weight(0.5)**

   - **Significance:** The most critical factor for user satisfaction and gaining the trust of an e-commerce platform is product quality. Anything related to a product count as a significant factor. The product quality directly impacts on user decisions which can lead to purchase or dissatisfaction. Product quality is a major identifier for building customer trust and satisfaction, especially when it comes to online platforms where building trust is necessary before purchasing [32]. In addition, tangible elements like product quality are the most crucial elements of services even in the digital marketplace [18]. Research proves that product quality influences customer satisfaction and it had a substantial effect on customer satisfaction [147].
   - **Impact:** Users are more likely to judge an e-commerce site based on this category than others. A poor experience with product quality will severely damage the trust while a positive experience will significantly increase the confidence.

2. **Customer Service: Weight (0.3)**

   - **Significance:** To establish a sense of reliability, resolve issues, address concerns and trust customer service plays a significant role. However, customers are considered as secondary to product quality as users tolerate suboptimal service if the product quality meets. A study indicates that product quality has a significant effect while service quality contributes minimally [147]. In addition, customer service is a key aspect of customer satisfaction in service industry including e-commerce [23]. Responsive customer service significantly increases user trust and long-term loyalty [28]. According to a research on Dhaka city customer service is one of the key point out of four in customer satisfaction [99].
   - **Impact:** User can tolerate suboptimal service if product quality is satisfactory while good service can enhance user satisfaction.

3. **Overall Experience: Weight (0.2)**

- **Significance:** The overall experience consists of usability, navigation and general impression about the experienced platform. Though these factors are important they have less influence on user satisfaction. A user may tolerate usability, and navigation errors as long as the desired product and support meet expectations. Usability is an important factor for digital platforms but the impact on user satisfaction is often overshadowed by the quality of core offering [29]. However, web design is one of the factor out of four in customer satisfaction [99]. In addition, a positive impression can be created at the initial stage because of a good user experience [41].
- **Impact:** This category have the lowest weight as it has minor impact on user satisfaction compared to other categories.

6.4.2 Nature of Options: Predefined Weight

We have different natures of the predefined options **positive, negative, moderate** and **dynamic**. Based on these different kinds, there are different values. Now we will discuss how we assign weight to the predefined values.

1. **Positive Option: High Weight**
   - **Rationale:** Positive option must have the higher weight as it has a significant amount of impact on customer satisfaction. However, the value will be different based on their category importance.
   - **Category Specific Weight**
     - **Product Condition:** For higher influence on customer satisfaction the relevant weight is +5 and +4 gradually.
     - **Customer Service:** As a secondary importance the weight is +4 and +3 gradually.
     - **Overall Experience:** Due to less impact the weight is +3 and +2 gradually.
2. **Negative Option: Low Weight**
   - **Rationale:** The negative options have significantly lower user satisfaction therefore the weight must be negative. To reflect the relative importance similar to the positive option the weight varies by the category of each aspect.
   - **Category Specific Weight**
     - **Product Condition:** Due to severe consequences in product quality the weight must be -5 and -4 gradually for two options.
     - **Customer Service:** Based on the impact the preferable weight is -4 and -3 gradually.
     - **Overall Experience:** Due to less concern the weight is -3 and -2 gradually.
3. **Moderate Option: Middle Weight**

- **Rationale:** The moderate option indicates those options are which represent neutral experience consequence it to provide a middle-ground weight to get a balanced influence in the overall rating.
- **Category Specific Weight**
  - **Product Condition:** To align with the high category the weight is +3.
  - **Customer Service:** For lower impact the weight must be +2.
  - **Overall Experience:** Due to minor impact the weight is +1.

4. **Dynamic Option:** We are familiar how the dynamic option were generated and take place there relevant categories. The goal is to make it up-to-date an adaptive system with recent feedback. Since the options are auto-generated there might be a chance of being wrong so the weights are moderate to mitigate potential inaccuracies. The value will be the same for each category and the generated token will be either positive or negative.

   - **Rationale:** The assigned weight of the dynamic options are lower than the fixed positive and negative weights to prevent the potential influence if the generated token is inaccurate or overlay. This approach ensures to contribute the rating parallelly do not overshadow predefined options.
   - **Specific Weight**
     - **Positive Tokens:** A moderate positive weight of +2.
     - **Negative Tokens:** A moderate negative weight of -2.

6.4.3 Summary of Weight and Example

- **Importance of the Category:** Categories are rearranged based on their perceived impact on customer/user satisfaction.

  Product Condition > Customer Service > Overall Experience

- **Sentiment of the Options:** The positive options have the highest weight followed by the moderate, negative.

- **Dynamic Option:** This value was intentionally given moderate weight as it is less reliable compared to fixed options.

6.4.4 Weight Value Summarization Tables:

Here are the weight summarization in tabular format. The Table 6.1 shows the weight regarding product condition, the Table 6.2 shows the weight of the customer services and the Table 6.3 shows the Overall experience of our system.

Category 1: Product Condition		
Type	**Options**	**Weight**
Positive	High-Quality Product	+5
Positive	Genuine and Authentic	+4
Negative	Poor Quality/Defective Item	-5
Negative	Counterfeit/Imitation Product	-4
Moderate	Average Quality	+3
Dynamic (Generated)	Durable Product	+2
Dynamic (Generated)	Substandard Packaging	+2

Table 6.1: Product Condition Category

Category 2: Customer Service		
Type	**Options**	**Weight**
Positive	Friendly and Helpful Support	+4
Positive	Prompt Response to Queries	+3
Negative	Unhelpful or Rude Staff	-4
Negative	Delayed or No Response	-3
Moderate	Basic/Standard Support Experience	+2
Dynamic (Generated)	Clear Issue Resolution	+2
Dynamic (Generated)	Misleading or Confusing Information	-2

Table 6.2: Customer Service Category

Category 3: Overall Experience		
Type	**Options**	**Weight**
Positive	Easy to Use	+3
Positive	Smooth Shopping	+2
Negative	Hard to Use	-3
Negative	Payment Problems	-2
Moderate	Average Experience	+1
Dynamic (Generated)	Fast Delivery	+2
Dynamic (Generated)	Privacy Concerns	-2

Table 6.3: Overall Experience Category

6.5 Calculation Guide: Formulae

As we bit familiar with the formulas for both Bayesian Average and Exponential Time Decay, here we will have detailed explanation for some special parameter. We choose both of this statistical approach from the existing research. Both of the algorithm calculates the rating separately and then for final rating we will take the arithmetic mean.

6.5.1 Bayesian Average Algorithm

This algorithm is used to get a stabilize ratings that ensure platform with fewer reviews do not receive extreme score. The formula is:

$$R_B = \frac{C \cdot \mu + \sum_{i=1}^{N}(r_i \times w_i)}{C + \sum_{i=1}^{N} w_i}$$

where:

- R_B = Bayesian average rating,
- C = Weight or confidence level (constant value),
- μ = Prior mean/Global average rating (constant value),
- r_i = Individual ratings for the item,
- N Number of ratings for the item,
- w_i = Category weight,
  - **Product Quality = 0.5**
  - **Customer Service = 0.3**
  - **Platform Experience = 0.2**

6.5.2 Exponential Time Decay Algorithm

The Exponential Time Decay ensure the recent reviews have stronger impact on the overall rating than older ones. There is a weight function to calculate the weight based on time and then the average rating function.
The Weight function is:

$$w(t_i) = e^{-\lambda t_i}$$

The Exponential Time Decay with weights:

$$R_E = \frac{\sum_{i=1}^{N}(r_i \times w_i) \cdot w(t_i)}{\sum_{i=1}^{N} w(t_i)}$$

where:

- R_E is the original rating score,
- r_i = Individual rating for the selected option,
- w_i = Category weight (same as Bayesian),
- $w(t_i)$ = Time decay weight
- e = Mathematical constant (approximately 2.718),
- λ = Decay rate, controlling how quickly the importance of older reviews diminishes,
- t_i = Time since the review was submitted.

6.5.3 Final Rating Calculation

We can obtain the final rating by taking the arithmetic mean of the Bayesian and Exponential ratings.

$$R_{\text{final}} = \frac{R_B + R_E}{2}$$

6.5.4 Justification of Constant Parameter C, μ, λ

1. **Confidence level C = 25**

   - This value is scalable value based on different circumstances. As we are evaluating a e-commerce site itself the confidence level 25 ensure that a reasonable baseline while allowing actual reviews to progressively shape the rating [162].

2. **Global Average** $(\mu) = 4.0$

   - The global average value (μ) for en e-commerce site is set to 4 on experimental analysis of major rating system such as Amazon, Yelp, etc [162]. The Bayesian average based rating system often use the arithmetic mean as prior assumption for better stability [109].

3. **Decay Rate** $(\lambda = 0.0058)$

   - The decay rate control how quickly the importance oof older review will mitigate. The rate with 0.0058 ensure that the review lose 50% of their impact after **120** days ($4 months$), balancing with long-term stability. In recommended system a half-life decay model significantly improves adaption [80].

6.6 Example with Real Data

Now we will see an example of a rating with 5 user. The input data were taken from the Extension. The table 6.4 shows the user input in different cases.

6.6.1 Bayesian Average Calculation Step

The Bayesian Average formula is:

$$R_B = \frac{C \cdot \mu + \sum_{i=1}^{N}(r_i \times w_i)}{C + \sum_{i=1}^{N} w_i}$$

where:

- $C = 25 =$ Confidence level.
- $\mu = 4.0 =$ Global average rating.
- $r_i =$ User rating.
- w_i the category weight:

Customer	Product Condition Rating	Customer Service Rating	Platform Experience Rating	Time Since Review (Days)
User 1	5 (High-Quality Product)	4 (Friendly Support)	3 (Smooth Shopping)	30
User 2	4 (Authentic Product)	3 (Prompt Response)	2 (Average Experience)	10
User 3	2 (Defective Item)	1 (Delayed Response)	1 (Hard to Use)	90
User 4	-5 (Counterfeit Product)	-4 (Rude Staff)	-3 (Payment Problems)	120
User 5	3 (Average Quality)	2 (Standard Support)	1 (Average Experience)	60

Table 6.4: Customer Input Data for Rating Calculation

  - Product Condition = 0.5
  - Customer Service = 0.3
  - Platform Experience = 0.2

- $N = 5$ = Number of total reviews.

Step 1: Calculate Weighted Ratings

This Table 6.5 shows the Bayesian average with weighted calculation for each user.

Customer	Product Condition $(r_i \times w_i)$	Customer Service $(r_i \times w_i)$	Platform Experience $(r_i \times w_i)$	Total Weighted Score
User 1	$5 \times 0.5 = 2.5$	$4 \times 0.3 = 1.2$	$3 \times 0.2 = 0.6$	4.3
User 2	$4 \times 0.5 = 2.0$	$3 \times 0.3 = 0.9$	$2 \times 0.2 = 0.4$	3.3
User 3	$2 \times 0.5 = 1.0$	$1 \times 0.3 = 0.3$	$1 \times 0.2 = 0.2$	1.5
User 4	$-5 \times 0.5 = -2.5$	$-4 \times 0.3 = -1.2$	$-3 \times 0.2 = -0.6$	-4.3
User 5	$3 \times 0.5 = 1.5$	$2 \times 0.3 = 0.6$	$1 \times 0.2 = 0.2$	2.3

Table 6.5: Bayesian Average Calculation with Weights

Step 2: Calculate the Bayesian Average Rating

$$R_B = \frac{C \cdot \mu + \sum (r_i \times w_i)}{C + \sum w_i}$$

Substituting with the values:

$$R_B = \frac{25 \times 4.0 + (4.3 + 3.3 + 1.5 - 4.3 + 2.3)}{25 + (0.5 + 0.3 + 0.2)}$$

$$R_B = \frac{100 + 7.1}{25 + 1.0}$$

$$R_B = \frac{107.1}{26} \approx 3.68$$

Therefore, the Bayesian average rating is **3.68**

6.6.2 Exponential Time Decay Calculation Step

The Exponential Time Decay formula is:

$$R_E = \frac{\sum_{i=1}^{N} (r_i \times w_i) \cdot w(t_i)}{\sum_{i=1}^{N} w(t_i)}$$

where:

- r_i = User provided rating .
- w_i The category weight:
  - Product Condition = 0.5
  - Customer Service = 0.3
  - Platform Experience = 0.2
- $w(t_i)$ = Time decay weight calculated as:

  $$w(t_i) = e^{-\lambda t_i}$$

  where $\lambda = 0.0058$ ensures a (120) day half-life.
- t_i = Time, since the review was submitted (in days).
- $N = 5$ = Number of total reviews.

Step 1: Calculate the Time Decay Weights

The Table 6.6 shows the calculation of the time decay weights.

Customer	**Review Age (t_i) in Days**	**Decay Weight** $w(t_i) = e^{-\lambda t_i}$
User 1	30	$e^{-0.0058 \times 30} = 0.835$
User 2	10	$e^{-0.0058 \times 10} = 0.943$
User 3	90	$e^{-0.0058 \times 90} = 0.567$
User 4	120	$e^{-0.0058 \times 120} = 0.456$
User 5	60	$e^{-0.0058 \times 60} = 0.689$

Table 6.6: Calculate Decay Weights

Step 2: Calculate Weighted Ratings with Decay Weights

The user review's rating weight is calculate with the weighted time. The Table 6.7 show the calculation

$$(r_i \times w_i) \cdot w(t_i)$$

Customer	Product Condition Score	Customer Service Score	Platform Experience Score	Total Weighted Score
User 1	$5 \times 0.5 \times 0.835 = 2.0875$	$4 \times 0.3 \times 0.835 = 1.002$	$3 \times 0.2 \times 0.835 = 0.501$	3.5905
User 2	$4 \times 0.5 \times 0.943 = 1.886$	$3 \times 0.3 \times 0.943 = 0.849$	$2 \times 0.2 \times 0.943 = 0.377$	3.112
User 3	$2 \times 0.5 \times 0.567 = 0.567$	$1 \times 0.3 \times 0.567 = 0.170$	$1 \times 0.2 \times 0.567 = 0.113$	0.850
User 4	$-5 \times 0.5 \times 0.456 = -1.14$	$-4 \times 0.3 \times 0.456 = -0.547$	$-3 \times 0.2 \times 0.456 = -0.274$	-1.961
User 5	$3 \times 0.5 \times 0.689 = 1.033$	$2 \times 0.3 \times 0.689 = 0.414$	$1 \times 0.2 \times 0.689 = 0.138$	1.585

Table 6.7: Weighted Ratings with Time Decay

Step 3: Calculate Exponential Time Decay Average Rating

$$R_E = \frac{\sum (r_i \times w_i) \cdot w(t_i)}{\sum w(t_i)}$$

Substituting with the values:

$$R_E = \frac{3.5905 + 3.112 + 0.850 - 1.961 + 1.585}{0.835 + 0.943 + 0.567 + 0.456 + 0.689}$$

$$R_E = \frac{7.1765}{3.49} \approx 3.74$$

Therefore, the Exponential Time Decay rating is **3.74**

6.6.3 Final Rating Calculation

Now the final rating is calculated by taking the arithmetic average of the Bayesian Average (R_B) and the Exponential Time Decay (R_E) ratings:

$$R_{\text{final}} = \frac{R_B + R_E}{2}$$

Substituting the computed values:

$$R_{\text{final}} = \frac{3.68 + 3.74}{2}$$

$$R_{\text{final}} = \frac{7.42}{2} = 3.71$$

Therefore, the overall final rating for the e-commerce site is **3.71**

The Calculation Summary

The following Table 6.8 shows the overall final ration calculation summary of an e-commerce site.

Customer	Bayesian Weighted Rating	Exponential Decay Weighted Rating	Final Rating
User 1	4.3	3.5905	3.95
User 2	3.3	3.112	3.21
User 3	1.5	0.850	1.18
User 4	-4.3	-1.961	-3.13
User 5	2.3	1.585	1.94
Overall Rating	**3.68**	**3.74**	**3.71**

Table 6.8: Calculation Summary of Final Rating

6.6.4 Calculation Flowchart

Initially, the system collects value from the user selected predefined options. Following this, the system calculates the rating separately according to Bayesian Average and Exponential Time Decay algorithm. Finally, the system provides overall rating by calculating arithmetic mean, the flow is given in **Figure 6.2**.

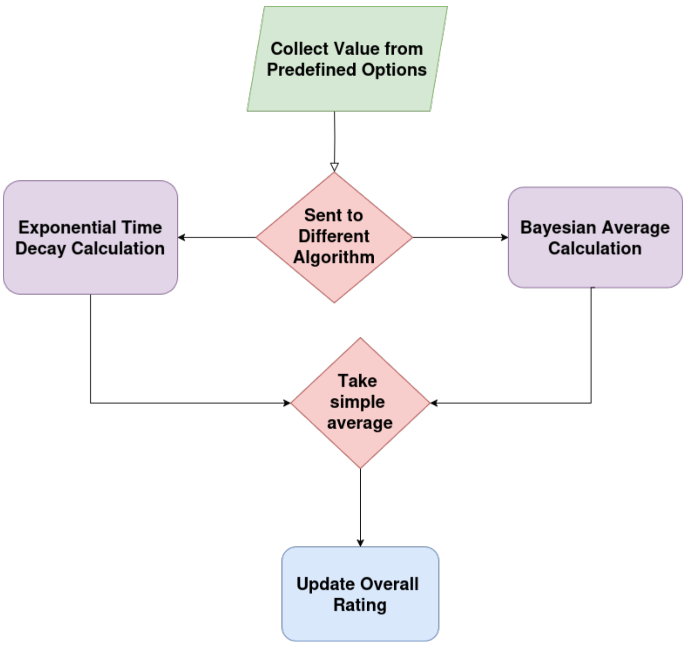


Figure 6.2: Calculation Flow

6.6.5 Summary

The Bayesian average algorithm and Exponential Time Decay algorithm is a established algorithm from existing research and this study accurately integrated two distinct approach to develop a robust e-commerce rating system. By incorporating dynamically generated tokens extracted from OpenAI API enhance the system ability to reflect the up-to-date consumers feedback. The weighted predefined option ensure balance evaluation of online platform. These ratings represent to the user in two different manner to effectively guide the user to make safe decision. Therefore the adaptive reputation system provides a robust and user-centric approach to strengthen user trust and transparency in e-commerce.

Chapter 7

User Testing

In order to test our hypothesis, we had to conduct an experiment so that we can collect the required data to prove our proposed hypothesis. As per we discussed in Chapter 4, we conducted a experiment with a motive to have in depth understanding of our participants decision making behavior. Along with that we also conducted an observational study that means when our participants were engaging themselves with specific tasks we observed how they behave in response to certain scenarios. The reason for doing this observational study is it allows us to analyse and understand complex organizational dynamics [117]. Along with that, interviews are helpful to understand user needs, perception and reactions [117]. For this reason we conducted a semi-structured interview after the experiment. The recruitment process, scenario of experiment and type of data collection is explained in following sections:

7.1 Recruitment

For our experiment we recruited 29 participants. In HCI the number of participants may vary with as few as 12 is not uncommon however, 20 or more than that is usually convincing [116]. We extended that number a bit and recruited 29. Due to time constraints, we could not extend that number a bit more. We selected students and staff from different departments from Brac University in order to ensure diversity and to reduce potential biases. We reached university students as they were more accessible in a shorter period of time. Participants were approached to take part in our experiment via email. The time period of our interview was January 21, 2025, to January 24, 2025, between 11:00 AM - 9:00 PM.

Participation was totally voluntary along with an option to participate without any incentive or receive an incentive for the amount of time they are spending for our study. Each interview along with the participation in our experiment lasted approximately 25 to 30 minutes. Before starting our experiment, consent of our participants were confirmed as we were provided with a consent form. We informed them that the interview sessions will be recorded for analysis purposes and their data would remain completely anonymous. We ensured that this data will be permanently deleted after a specified period of time. Our participants also had the right to withdraw from the experiment at any moment if they wanted to. Our recruitment process ensured that privacy and confidentiality were sustained throughout the whole study.

7.2 Experiment Scenario

To capture the natural behavior of our participants, we framed our experimental environment in such a way that would prevent them from realizing that their behavior was being actively observed and studied. We just instructed our participants to browse a list of e-commerce websites and navigate those. We told them we were just going to analyse user-experience of e-commerce websites. The list of e-commerce websites was provided beforehand. It contained two sites which were highly rated and one low-rated website. Before conducting the experiment, participants were informed that an extension was pre-installed in their browser with which they were browsing. If they click on that extension information related to e-commerce sites would be visible. It was informed because otherwise they would not know about the passive form of our extension which would be visible upon clicking. However, they were not explicitly informed about the display of active popup which would be visible upon visiting poorly rated websites. Two good rated websites were instructed to browse at first because for that active popup will not be visible and participants would only interact with the passive form of popup containing some information regarding the website. And after that the low-rated was instructed to navigate so that they would face the active popup. The passive form of popup was still visible for the low-rated website too. If they encounter both active and passive forms of popup by visiting the low-rated website first, then for a good-rated website they would have already known how the system works. For that reason, we asked them to visit the good-rated website first and then the low-rated website so that we could observe their reaction and spontaneous decision-making process when they encounter risky information displayed in an active popup.

7.3 Observational Study

During the experiment we observed the whole process about how they are interacting with our extension in order to analyse their behavior. Such as

- Time spent on different page of our active popup (eg, user review page, page containing potential risk factors, summarised information page).
- Click interactions with popup (eg. whether they avoid popup or engage with it).

7.4 Post-Experiment Interview

After participants were done interacting with the extension, we arranged a interview based on the actions of our participants. For example:

- We inquired about the reason behind their particular action at the time of interaction with the extension.

- We inquire about their perception regarding the popup.
- We asked about their experience with the extension.

Another mentioned fact is whether these questions are enough for our study or not were tested through a pilot study. Before diving into the actual experiment we conducted a pilot study with 2 participants. From the pilot study, we realized our questions were a bit biased, such as "Do you think our information was informative enough?". So we changed the format of such questions to avoid any biases. Along with that in our pre-experiment survey questions which contains questions for demographic analysis, we did not provide our participants with any predefined options to select for questions like "What is your age?". It was open ended at first but later on we realized that if we provide them with some predefined options, it would be easier for us to group our participants.

After the participants were done with the semi-structured interview, we asked them to complete a usability survey which contains 10 sets of questions (SUS scale) to measure the usability of our extension. Along with that, they were asked to fill up a single question asking their satisfaction level (SEQ scale) for us to measure their satisfaction level. So, altogether we collected three categories of data:

- **Demographic Data**: Participants were asked to fill up some questions before the experiment which contained questions like age, gender, profession, how frequently they shop online etc.
- **Observational Data:** We observed how our participants interact with our extension. This would help us to analyze how they were reacting to the components we placed in our extension combining with Behavioral Economics theory.
- **Post-Experiment Data:** Through our interview we inquired about certain reasons behind their action, and their perception regarding certain components with our extension. We did this to analyse how effective a certain component of our extension is, that we implemented using Behavioral Economics theory; what was the user perception, how they react and behave and whether their responses and action align with Behavioral Economics theory or not. Along with that we asked our participants to complete a 10 set of questions for us to calculate the SUS score and a single ease question for us to calculate SEQ score. It was included because SEQ score will help us to measure the usability of our system and SUS score will help us to measure the user satisfaction level.

Our experiment helped us to understand the effectiveness of our nudge based intervention and how it helped users to influence their decision-making process.

Chapter 8

Data Analysis and Result

As a part of our hypothesis testing, we aim to conduct an exploratory data analysis in order to identify underlying patterns and relationship between different demographic patterns. By hypothesis testing and statistical analysis, we aim to analyse human decision-making tendency.

8.1 Data Analysis

In this section the study will conduct exploratory data analysis from the data collected from our 29 participants. After that the study aims to conduct hypothesis testing along with data analysis to gain deeper understanding about the demographics and the response collected from the participants. After first demographic analysis will be done and then participants' perspective regarding the extension and how Behavioral Economics impact their decision-making will be analysed.

8.1.1 Demographic Analysis

Before the experiment, some demographic questions like age, profession, gender, how frequently do they shop online were asked to our participants in order to gain background information regarding them. The relationship between different demographics and frequency of online shopping is shown below through some visual diagrams with a motive to get deeper insights about how demographics are connected to shopping frequency. Table 8.1 shows the frequency count of the demographics of our participants.

Age vs Shopping frequency

The bar chart in **Figure 8.1**, explains the relation between age and shopping frequency. In the x-axis, the age group is shown and in the y-axis the frequency count is shown. The blue color bar is used to highlight "Shopping-once a month", the dark green color bar is used to highlight "Shopping-once a week" and the light green color bar is used to highlight "Shopping once a year". From our collected data we can clearly see that almost 14 participants from the age group 18-24 shop once a

Gender	Count
Male	23
Female	6
Age Range	**Count**
18-24	18
25-34	10
35+	1
Profession	**Count**
Student	16
Job Holder	8
Faculty	2
Businessman	1
Housewife	1
Student/Part time job	1

Table 8.1: Demographics of Respondents

month. This frequency is the highest among all. And from the age group 25-34, the frequency of shopping once a month is also the highest. The number of participants is 6 from that group. From group 35 and older a single participant shops once a month. No other participant is visible from that group. Now coming to the other two categories "Shopping once a year and once a week", 2 participants from both the age group of 18-24 and 25-34 are seen shopping "once a year and once a week".

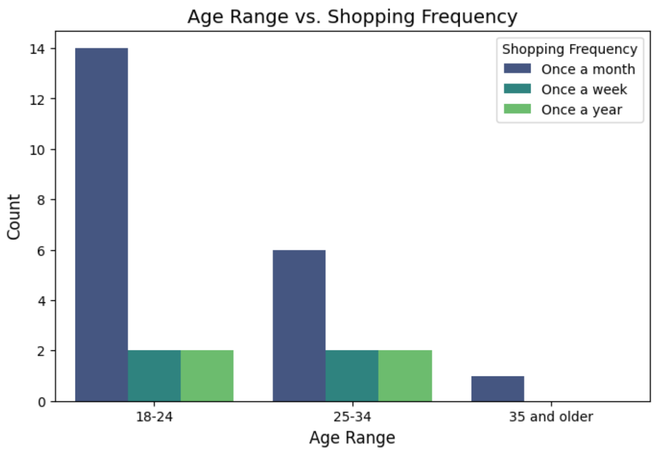


Figure 8.1: Age vs Shopping Frequency.

Therefore, this analysis highlights that people are generally more inclined to shop once a month rather than once a week or once a year. Along with that people from the age range 18-24 are more inclined to online shopping rather than the other two groups which are 25-34 and 35 and older. A study [144] also highlighted the same factor that young adults, particularly those aged 18-30, are more attracted to online shopping. Hence, it is clear from our results also that young adults are more attracted to online shopping.

Gender-Profession vs Shopping frequency

The bar chart in **Figure 8.2** explains the relation between shopping frequency across different professions which is further categorized by gender. It is observed that people from different professions like students, Job holders, businessmen, and teachers are engaged in buying things online.In the x-axis of the bar chart, the profession is plotted and in the y-axis, the frequency of online shopping is plotted. It is clearly visible that Students have the maximum number of shopping frequency. Job Holders also show a noticeable trend in hopping from online. On the other hand, housewives, Faculty, and businessmen shops relatively less. But to mention the fact that our participants were mostly students this could be a reason for certain biases. So we can't come to a clear conclusion from this.

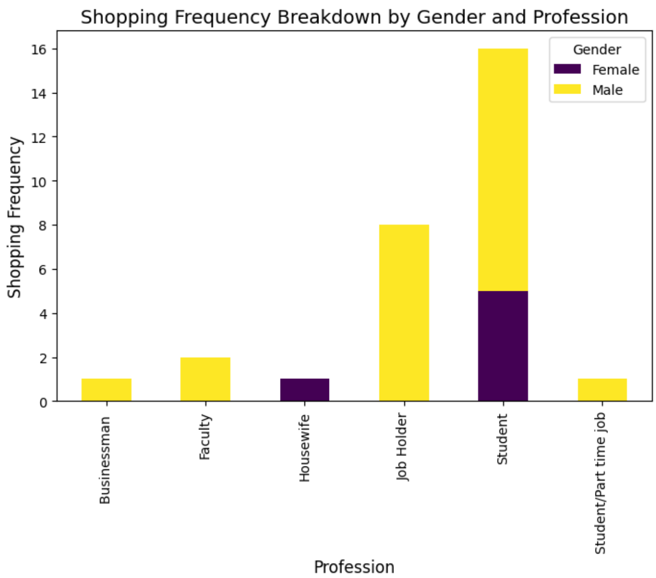


Figure 8.2: Gender-Profession vs Shopping Frequency.

The yellow color of the bar shows the representation of males and purple represents females. It is visible that the male shopping frequency exceeds the female shopping frequency in almost all professions to be specific in the Student and Job Holder categories. However, again to be mentioned that as our demographic was mostly students we cannot come to the conclusion that Job Holder and other categories shop significantly less than students.

Profession-Gender vs Shopping Category Frequency

Now as in we got an idea about the tendency of online shopping of people across different gender and professions now we will cover an in-depth analysis regarding how people shop across different genders and professions and categorize then some categories of shopping (eg. once a month, once a year, once a week). In the bar, "Once a month" is represented through color purple, "Once a week" is represented through color teal, "Once a year" is represented through color yellow.

In the following bar chart in **Figure 8.3** it is seen that Female-Students have a diverse shopping experience as they shop across all three categories (weekly, monthly,

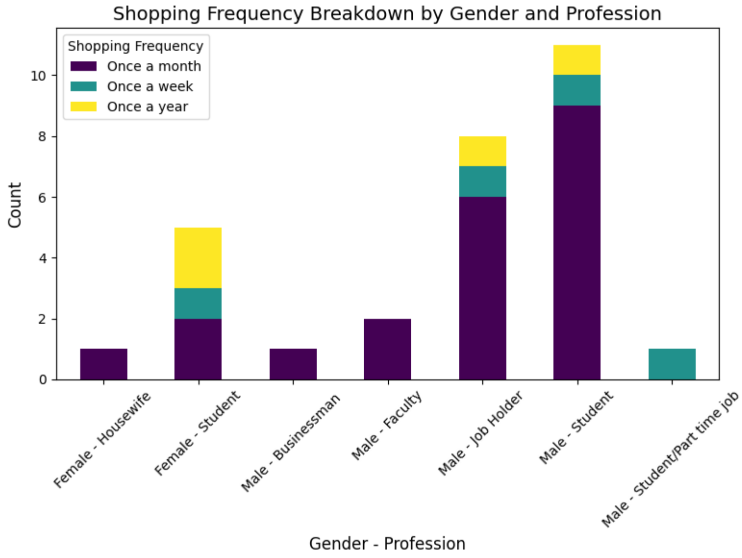


Figure 8.3: Gender-Profession vs Shopping Category Frequency.

yearly). Though in the weekly category they shop the least. Male Student category is seen to be the most significant shopper out of all the categories. "Once a month" category is the most dominant one in this section. Male Job Holders also shop notably. It is seen that they shop highest in the category "Once a month". Male-Faculty is only seen shopping in the category "Once a month". Rest of the categories like Housewife, Businessman are limiter online shoppers. Again to be mentioned that as our demographic was mostly students we cannot come to the conclusion that Housewife, Businessman and other categories shop significantly less than students. To summarize, Students (both male and female) reveal the highest amount of shopping. And Male in particular professional roles such as Job Holder and Student exhibit diverse shopping frequencies.

To conclude, the bar chart highlights different shopping behaviors across demand demographics (gender, profession). Shopping Frequency of "Once in a month" dominates other categories mostly.

8.2 Hypothesis Testing and Interpreting the Result

The main motive of our research is to analyze human behavior, how they react when the information gap they faced in reduced and whether safe browsing of e-commerce site can be ensured or not. We showed all possible information regarding an e-commerce site through an extension to check whether these information which are placed based on theories of Behavioral Economics has any effect on them to make informed decision. For that we proposed some hypothesis. In the following section for particular theory of Behavioral Economics theories we analyzed human decision making tendency and test our proposed hypothesis.

8.2.1 Bounded Rationality, Asymmetric Information and Heuristic

Bounded Rationality of Behavioral Economics tells that people face different type of constrains (eg. Time constraints, asymmetric information, emotion, stress etc.). And because of that constraints, human tend to take shortcut decision which is justified by the term "Heuristic" of Behavioral Economics. More elaborately about the terms are explained in Chapter 2. Our motive was to reduce the information gap which is asymmetric information and to provide user with such information which helps them to make decision easily even if they are bounded with different type of constraints. For this reason when user visited a low-rated website we present them with an active popup through our extension. And when they visit a good rated website the information related to that e-commerce site are visible in passive version of our extension. Now we are claiming that the problem of asymmetric information is faced by maximum number of e-commerce users. However, we got to see the same scenario among our participants. We inquired them about their perception regarding e-commerce site in order to gain insight regarding the available information presented in e-commerce sites. Our question was, *"What is your perception regarding the available information present in an e-commerce site?"*. In response to this one of our participant replied- *"They usually hide their cons for their business purpose"*. Another participant replied- *"I think they provide manipulative information"*.

Analyzing the response of other participants, we found that, our participants are claiming, e-commerce sites tend to hide cons of their business, they provide manipulative and misleading information. Moreover, our participants face a huge information gap as they assume e-commerce sites do not provide all necessary information which are required for shopping. As we are confirmed that the problem of asymmetric information exist, we tried to reduce that by providing all necessary information (eg. rating, summarized information as tags, user reviews, most concerning issues etc) which will help them to make informed-decision. To analyse how our presented information affected them, we conducted an experiment as explained in Chapter 7 and presented them with necessary information regarding an e-commerce site through a popup. Now, after the experiment every participant responded that they the information presented in the popup were helpful. The UI of our active popup is shown below in **Figure 8.4**.

Though some people thought of it as a random alert and thought this would hinder their decision-making. Further analysis about this is discussed in the Section 8.2.2. However, after analysing the information presented in UI, they agreed that the information which are presented is helpful. Now we have some components in our UI as shown in **Figure 8.4**. We asked our participants after the experiment which component among the components presented in the UI affected them the most. Some participants mentioned about "rating" whereas some mentioned about "Summarized tags". Now which components among "Summarized tags", "User reviews", "Registered business tag", "Pie-chart", "Rating" etc. affected user decision the most are visualized below **Figure 8.5** through a bar plot.

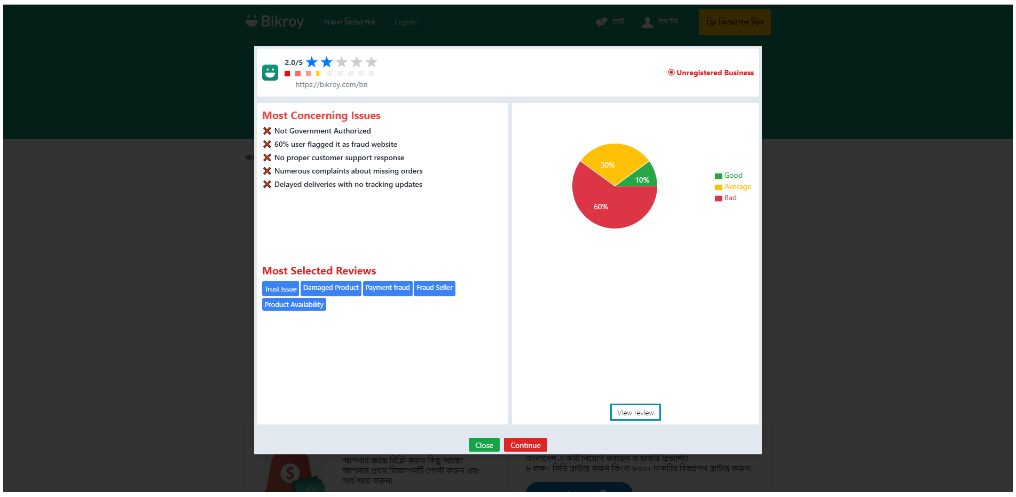


Figure 8.4: Active Popup UI

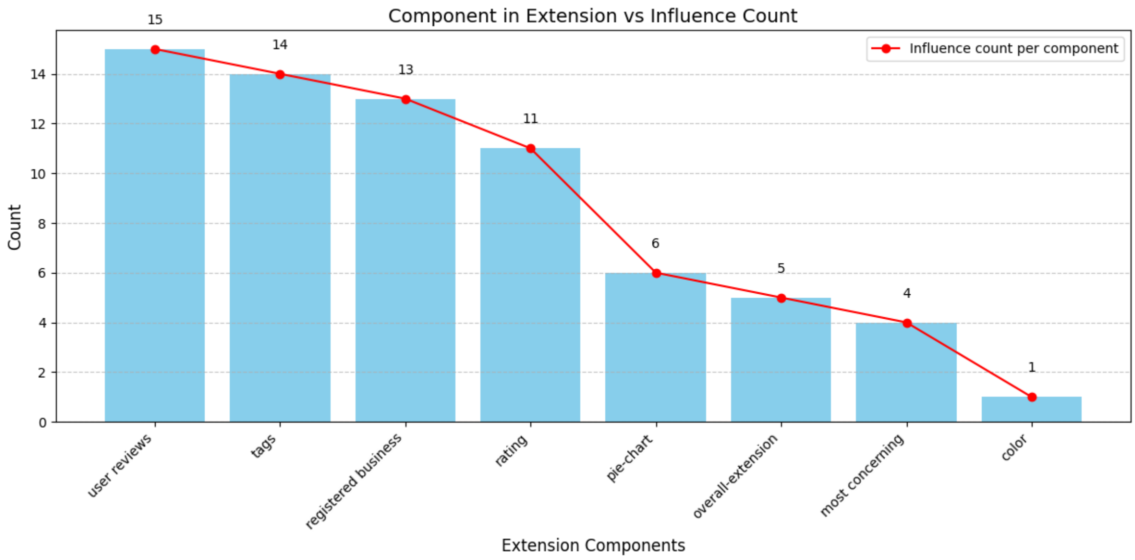


Figure 8.5: Component in Extension vs Influence Count

From the bar plot in **Figure 8.5**, maximum user mentioned that reviews of other users impacted most in influencing their buying decision. It actually proves that we human being tend to follow others and walk along in that path. The second most selected component by the user is the summarized tags generated from user reviews. Our motive of showing summarized tags was to help users to take decision in an instant. As human always want to take shortcut decisions, we thought presenting the summarized information as tags generating from user review, will assist user in making shortcut decisions. The information regarding “Registered Business” and “Rating” shown in the UI also plays an important role in alternating people decision of buying product as we can see from the bar chart that significant amount of our participants mentioned those as their source of confidence. Our motive of showing the rating was, we wanted to show such an information through which user will get an overall idea regarding their visited website. On the other hand, the other components like “pie-chart”, “most concerning issue section” affected significantly less than other components.

From the above analysis, we can clearly see that the problem of information gap is largely visible in e-commerce sector. We also got the same insights from our participants. Most of them feel that e-commerce tends to hide their cons and provide misleading information to manipulate customers. In order to solve this problem we took an approach to provide all necessary information like website rating, summarized tags generated from user review, user review section, a section of most concerning issues etc. Moreover, as user tend to take shortcut method for taking decision, so we thought that providing necessary information in a concise way will help them to do so. Hence, after the experiment, we got to know that our participants find our method of showing information was helpful. Some of then responded that- *"I got a short and precise idea about the e-commerce site"*, *"I got the summarization and instantly take the decision to leave the site"*. Moreover, we also got a brief idea about which components of our UI mostly affected our participants. Therefore, we can come to a conclusion that, summarized information gives users an overall overview of the website which helps them to make more informed decisions within a short time reducing the information gap and effect of bounded rationality.

8.2.2 Loss Aversion

One of the main important focus of our research is to analyze whether user fears loss and make informed decisions whenever they are informed about potential risk of visiting a website. In the UI of our active popup shown in **Figure 8.6**, whenever user clicked "Continue" button we navigate then to the following **Figure 8.6** UI to inform them about potential risk of visiting a low rated website.

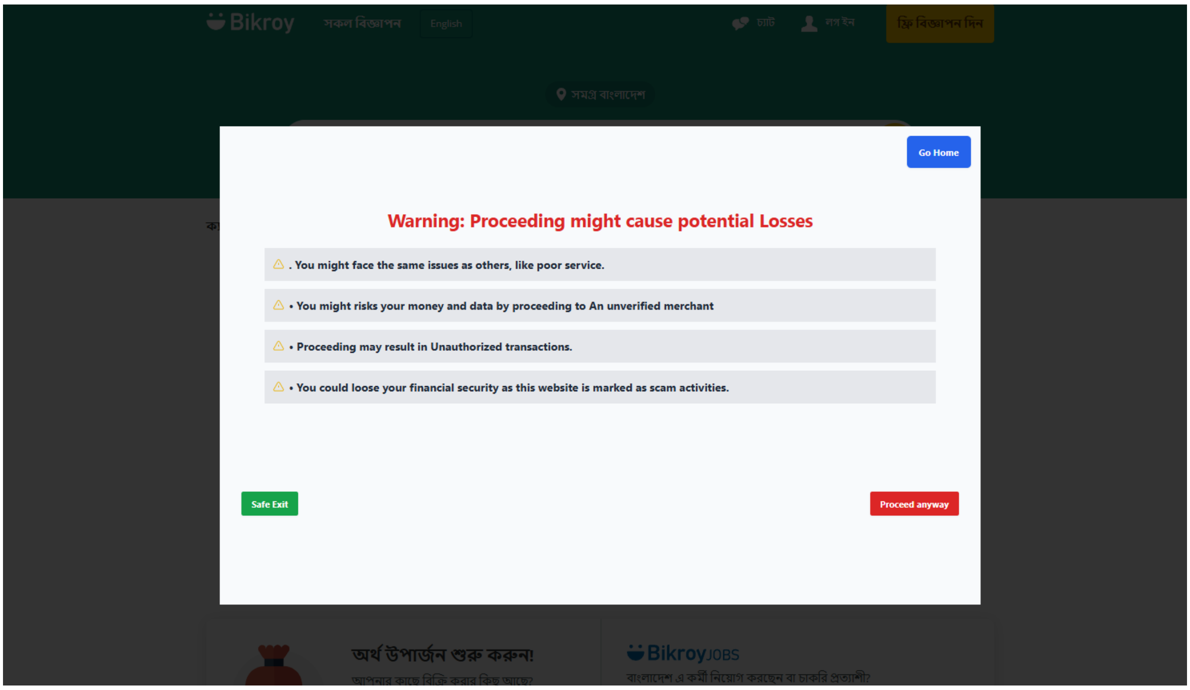


Figure 8.6: UI mentioning potential risk of visiting a low rated e-commerce site

Our motive was to prevent user to visit a site when they will know about potential losses. However, if user at least still visited we wanted them to influence their buying decision so that they can prevent themselves from fraud websites.

Proposal of Hypothesis

To analyze whether the risk associated information presented in this UI Figure 8.6 has an impact on user buying decision we proposed a null hypothesis and an alternate hypothesis which are mentioned down below.

Null Hypothesis(H_0): Potential Risky Information does not have a significant effect on user buying decision that is users will not prioritize to not buying from the website due to fear of loss after knowing the potential risks.

Alternate hypothesis(H_1): Potential Risky Information has a significant effect on user buying decision that is users will prioritize to not buying from the website due to fear of loss after knowing the potential risks.

Hypothesis Testing

To check whether that explains the potential risk of visiting a website has any effect on user buying decision or not we run Chi-Square test to test our hypothesis. The reason of choosing Chi-Square test is explained at the end of this paragraph. Before that we cleaned our data and make sure to remove any null values. We selected those participants who visited this particular UI. Then we group the participants into two group. Participants who clicked *"Safe Exit"* were kept to *"Safe Exit"* group, and participants who clicked *"Proceed Anyway"* were kept to *"Proceed Anyway"* group. After that we analysed and find out the frequency count of participants who still want to buy product, who do not and who are not sure what to do from these groups. We marked them as "YES" group, "NO" group and "NEUTRAL" group. After that we created a contingency table from those data to run our hypothesis test. As we are trying to find an association between two categorical data means people who clicked *"Safe Exit"* and "Proceed Anyway" and their decision regarding buying products, we thought Chi-Square would be the best test to check this association. The contingency table is presented in Table 8.2 below.

Table 8.2: Observed Values

Action \ Buying	Neutral	No	Yes
Proceed anyway	2.0	5.0	4.0
Safe Exit	0.0	8.0	0.0

The table shows the frequency count to measure the association among different variables. Here "Proceed Anyway" and "Safe Exit" is our independent variables and "NEUTRAL", "NO", "YES" is our dependent variables. In Table 8.3, displays the expected values which we calculated using the observed values.
The Chi-Square value is then calculated using the standard formula of Chi-Square

Table 8.3: Expected Values

Buying / Action	Neutral	No	Yes
Proceed anyway	1.1579	7.5263	2.3158
Safe Exit	0.8421	5.4737	1.6842

testing. The formula is referred in Chapter 4.

$$\chi^2 = \sum \frac{(O - E)^2}{E} \tag{8.1}$$

From our dataset, the computed Chi-Square value is:

$$\chi^2 = 6.3776 \tag{8.2}$$

And our calculated p-value, degree of freedom is shown in Table 8.4

Table 8.4: Chi-Square Test Results

Chi-Square (χ^2)	p-value	Degrees of Freedom
6.3776	0.0412	2

From the calculated value as our p-value = 0.04 is less than significance value (α = 0.05), we can reject our null hypothesis and accept the alternate hypothesis. So we can say there is a significant association between action taken “safe exit” or “proceed anyway” with buying product. However whether people are more inclined to buying product or to not buying product after knowing about potential risks is still not clear. For that, we will try to analyze further and check from our observational study how did the user behave when they were informed about potential risks.

Analysing User Action

Just like we mentioned above we grouped out our participants who engaged themselves with the UI explaining potential risks into two groups “Proceed Anyway” and “Safe Exit”. We did a descriptive analysis about how many people choose to proceed anyway and how many people choose to safe exit knowing the potential risk, whats is the average time they took to analyze the potential risk information, etc. The Table 8.5 contains the descriptive analysis.

From the Table 8.5, we can see that 11 participants choose to proceed and 10 participants out of 21 choose to safe exit even after knowing the potential risks. We have considered 21 participants out of 29 because only 21 participants wanted to continue even after knowing all the summarized information from the first page of our active popup. And only 21 participants were engaged with this second UI of our popup. From the standard deviation(std) we can see the value of “Proceed Anyway”(PA) group is larger than “Safe Exit”(SE) group. It means time taken by the people who choose to proceed varies larger than people who decided to safe exit. Some people

Table 8.5: Descriptive Statistics for Proceed Anyway (PA) and Safe Exit (SE) group

Statistic	Proceed Anyway (PA)	Safe Exit (SE)
Count	11.000	10.000
Mean	14.737	18.336
Standard Deviation	13.892	8.887
Minimum	1.510	7.000
25th Percentile	5.115	11.558
Median (50th Percentile)	8.000	19.000
75th Percentile	18.330	23.250
Maximum	45.000	33.000

quickly proceed, some people took more time to think before proceeding. On the other hand, the people who choose to safe exit took almost same time to decide. The minimum and maximum time for deciding to safe exit was 7 and 33 seconds, where as for proceed group minimum time was 1.5 seconds and maximum was 45 seconds. It means some people take very quick decision and some people spend significant time in understanding the risk. From the percentile values, we can see that 25 % of people of PA group spent 5 or less than 5 seconds and on the other hand, people of SE group spend 11.5 seconds or less than that. 50 % of people of PA group spent 8 or less than 8 seconds and on the other hand, people of SE group spend 19 seconds or less than that. 75 % of people of PA group spent 18.33 or less than that and on the other hand, people of SE group spend 23.25 seconds or less than that. To summarize, people of SE spends large amount of time to decide and analyze the risk before safe exit rather than who choose to proceed. A visual representation of people spending time to decide in shown in a box plot **Figure 8.7** below.

From the **Figure 8.7** PA denotes "Proceed Anyway" group and SE denotes "Safe Exit" group. It is clear that SE group spends significant amount of time in deciding rather than PA group. The explanation of the percentile that we have already explained above clearly aligns with this box plot. Now we got to know that people spend larger time to think about safe exit understanding potential risk. Though significant number of people choose to proceed. The percentage is shown in a pie chart in **Figure 8.8** below.

We can clearly see that 52.4 % of our participants wished to enter the website even if it is red marked after knowing the potential losses and 47.7 percent choose not to visit. However, entering the red marked e-commerce site does not mean they are exposed to risk. Out of 11 participants who choose to proceed, one thought that it was a random alert, three participant had the urgency of buying product and rest 7 participants entered only because they were curious and wanted to explore further. Now what really matters is, whether their buying decision is changed or not after knowing about the risks. So, below **Figure 8.10** we provided a pie chart representing people of both SE (Safe Exit) and PA (Proceed Anyway) groups and their buying decisions.

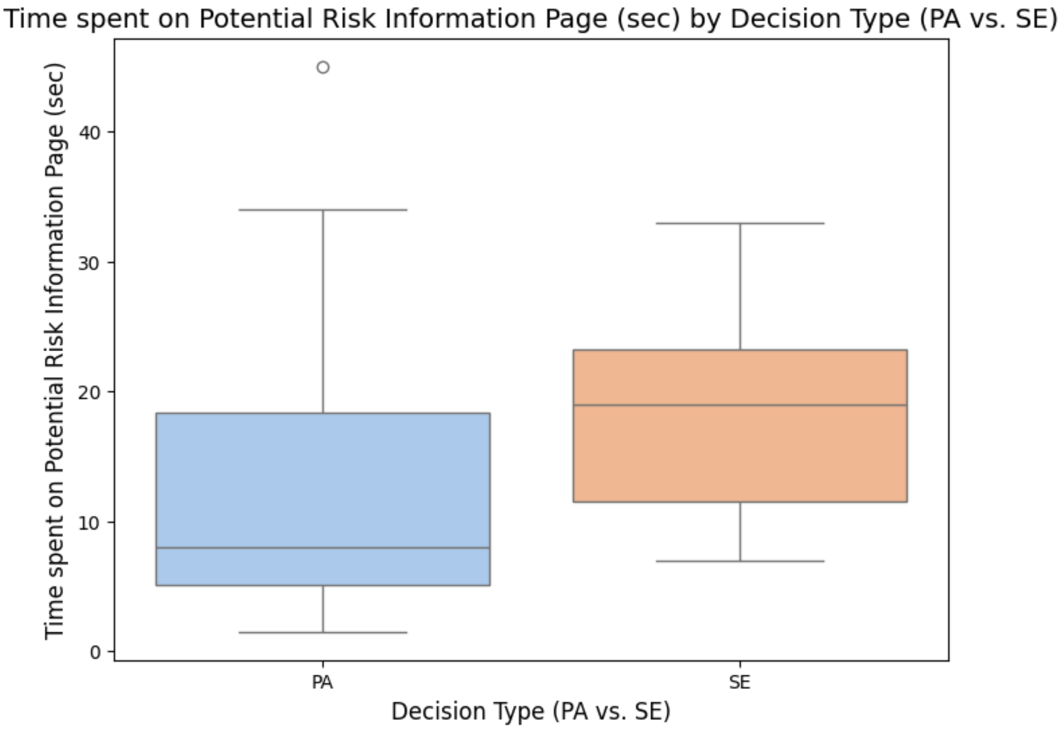


Figure 8.7: Box plot showing average time taken by user to proceed into a red marked website or to safe exit

From the **Figure 8.10** it is visible that 45.5 % of PA group and 100 % of SE group did not want to buy product. Only 36.4 % wanted to buy product as for some people it was urgent and some considered our popup as a random alert. And only 18% of people are neutral. That means a significant amount of people do not want to buy product after knowing the potential risk. The percentage of people buying and not buying irrespective of any group is shown through a pie chart below.

Here in **Figure 8.10** we can see that total 68.4 % of people do not want to buy products, 21.1% of people wanted to buy and 10.5% was confused whether to buy or not. It means though a significant amount of people wanted to visit the red marked due to curiosity, they would not have bought any product as they were informed about potential risks.

It was our goal to inform the user about the risks of visiting website and to influence their behavior towards an informed decision. Through the hypothesis testing, we got to know that there is association between their actions of proceeding vs safe exit and with buying decisions. And now from further analysis of user behavior, we got an in-depth understanding that even though people want to visit the red marked e-commerce site due to exploration they would not have buy anything as they know the potential risks. From the post-interview, we got to know how they got influenced by the texts. One of the participants said, "*I thought I might get deceived by this website as I do not have previous knowledge about it. So, I can not judge properly. But as this warning suggests what i might loose, I preferred not to go there*". Another participant stated that, "*I got to about the the potential risks, but*

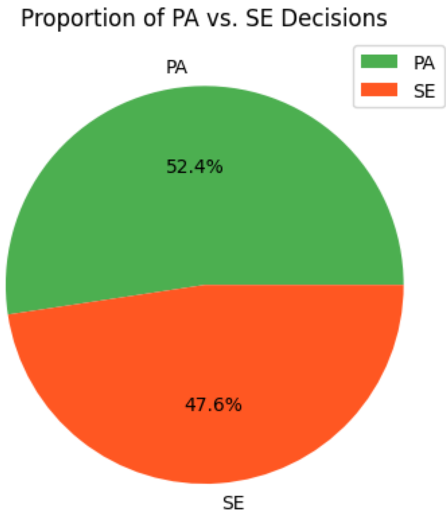


Figure 8.8: Percentage of people to proceed into a red marked website or to safe exit

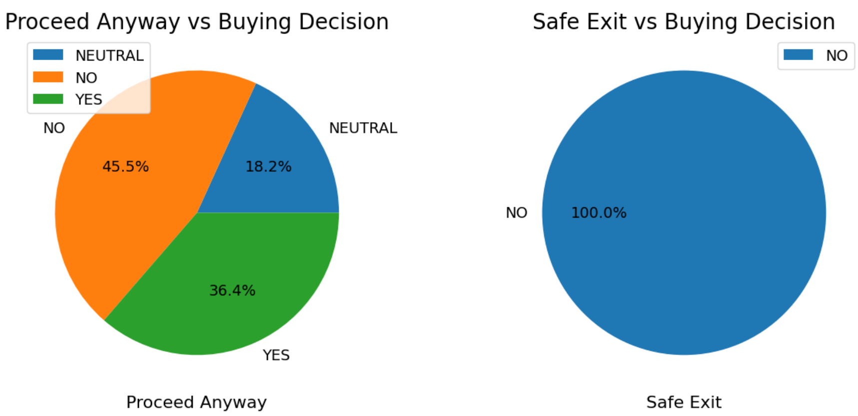


Figure 8.9: Product Buying Decision of Proceed Anyway and Safe Exit group

I still want to visit the website to get to know about the site. But while surfing the website, I will remain aware of the risks I have been warned about". So information regarding potential risks helped users to make informed decision. That means we can claim that our alternate hypothesis is satisfied which is Potential Risky Information has a significant effect on user buying decision that is users will prioritize not to buy from the website due to fear of loss after knowing the potential risks.

8.2.3 Nudge Theory

Another main goal of our research was to nudge user towards safe browsing by providing them relevant information regarding an E-commerce site using the theories of Behavioral Economics.

Proposal of Hypothesis

To analyse user perception regarding our overall popup, whether the information presented through our popup has influenced users positively or negatively and how

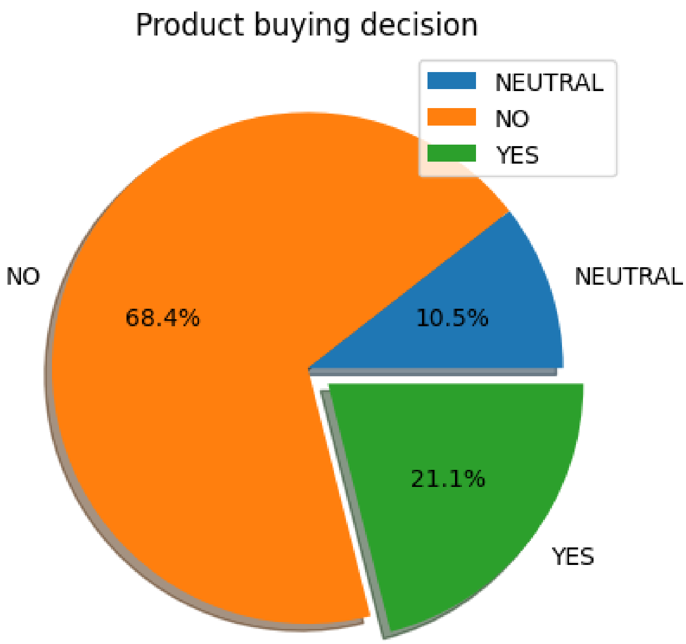


Figure 8.10: Product Buying Decision those of PA and SE group altogether

it affects user buying decision we proposed a null hypothesis and an alternate hypothesis which are mentioned down below:

Null Hypothesis (H_0): Displaying a popup at the time of website entry fails to grabs user attention and fails to increases awareness and the chance of taking cautious actions.

Alternate hypothesis (H_1): Displaying a popup at the time of website entry grabs user attention which increases awareness and the chance of taking cautious actions.

Thematic Analysis

To run our hypothesis testing, we first need to analyse user response that we collected from user through the post-experiment interview phase. As we asked open ended questions, we received a very detailed response from them. To analyse whether how the information we presented nudged the user, whether it has a positive impact, negative impact or neutral we asked user regarding their perception of the overall popup that appeared when they visited a low rated website. In response to that some told it was useful, informative whereas some replied they mistook it as a random alert. Now as the response was very detailed we conducted an thematic analysis manually analysing each response. We decided to run inductive coding at first. For that we collected the user response, manually went through each response and tried to find keywords that align with their response. After finding out the codes from each response we then categorize it keeping it align with our research theme which is deductive coding. After second level of coding we generated three themes from that- “Positive”, “Negative”, “Neutral”. The coding process is visualized below in **Figure 8.11** shortly.

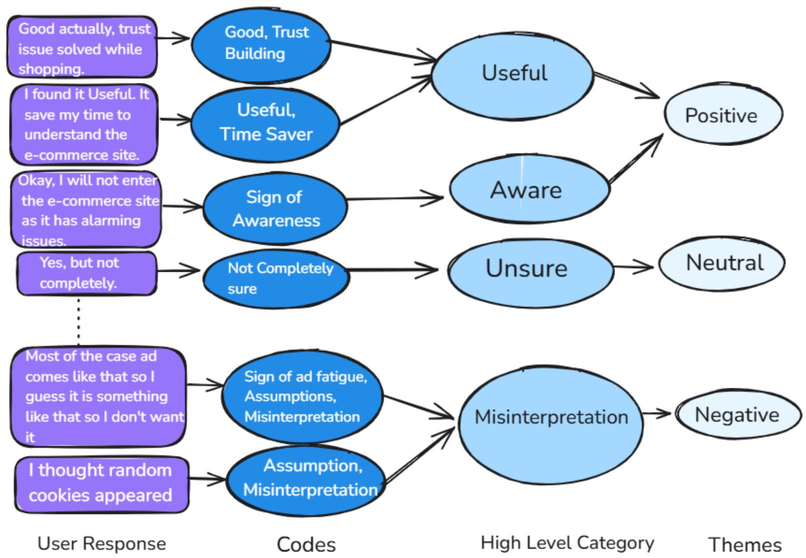


Figure 8.11: Thematic Analysis

Figure 8.11 presents the coding process using thematic analysis. After collecting the response, codes are generated then they are categorized and then into themes. “Positive” means our overall popup had a positive impact on the participants, “Negative” means our overall popup had a negative impact on the participants, “Neutral” means our overall popup had an neutral impact on the participants. With this info we will run the hypothesis testing whether the impacts had an effect on their buying decisions.

Hypothesis Testing

After we achieved the final codes which are “Positive”, “Negative”, “Neutral” we started our hypothesis testing. We conducted Chi-Square test as we want to find association between two categorical variables. We want to find whether the positive or negative or neutral impact (as per explanation of our participants), of our overall information which were displayed in our popup had any association with the buying decision of our participants. Here, “No” in Table 8.6 means user will not buy from the low rated website after getting informed with all available information, “Yes” means they will still continue to buy and “Neutral” means they are not quite sure about their decision. So we created a contingency table with the impact of popup and buying decision of our participants in order to find association between them. This Table 8.6 shows the frequency count to measure the association among different variables. Here, “Negative“ and “Neutral“ and “Positive” are our independent variables and “NEUTRAL”, “NO”, “YES” are our dependent variables. Using these observed values we calculated the expected values which is shown in Table 8.7.

The Chi square value is then calculated using the standard formula of Chi square

Popup Impact \ Buying	Neutral	No	Yes
Negative	0	1	0
Neutral	0	2	3
Positive	2	20	1

Table 8.6: Contingency Table of Popup Impact vs. Buying Decision

Popup Impact \ Buying	Neutral	No	Yes
Negative	0.069	0.793	0.138
Neutral	0.345	3.966	0.690
Positive	1.586	18.241	3.172

Table 8.7: Expected Values for Popup Impact vs. Buying Decision

testing. The formula is referred in Chapter 4.

$$\chi^2 = \sum \frac{(O - E)^2}{E} \tag{8.3}$$

From our dataset, the computed Chi-Square value is:

$$\chi^2 = 11.084 \tag{8.4}$$

And our calculated p value, degree of freedom is shown in Table 8.8

Chi-square (χ^2)	**p-value**	**Degree of Freedom**
11.084	0.0032	4

Table 8.8: Chi-square test results

From the calculated value as our p value = 0.0032 is less than significance value ($\alpha = 0.05$), we can reject our null hypothesis and accept the alternate hypothesis. So, we can say there is a significant association between Popup Impact with buying product. However we will try to analyse further and check from our observational study how did the user behave when they were informed about all the information associated within an e-commerce site.

Analysing User Behavior

Along with hypothesis testing we tried to analyse user behavior, what is their perception regarding our popup, how it impacted them and how much time they overall spent with our extension. **Figure 8.12** displays the percentage of how our popup impacted our participants through a pie chart.

Here in **Figure 8.12** we can see that 79.3 % of our participants responded that our popup had an positive impact upon them, 3.4 % of our participants told that it had an negative impact and 17.3% of participants were not sure about their perception about the popup. Clearly, it proves that the information of our popup helped our

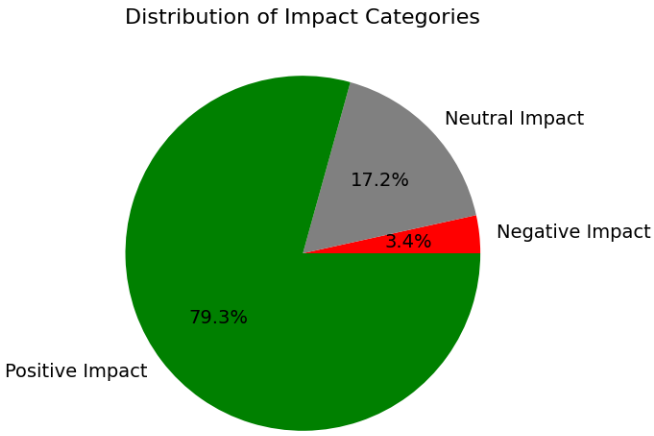


Figure 8.12: Impact of our popup on our participants

participants and had an positive impact. How much time our participants spent with our extension is visualized using a box plot below **Figure 8.13**.

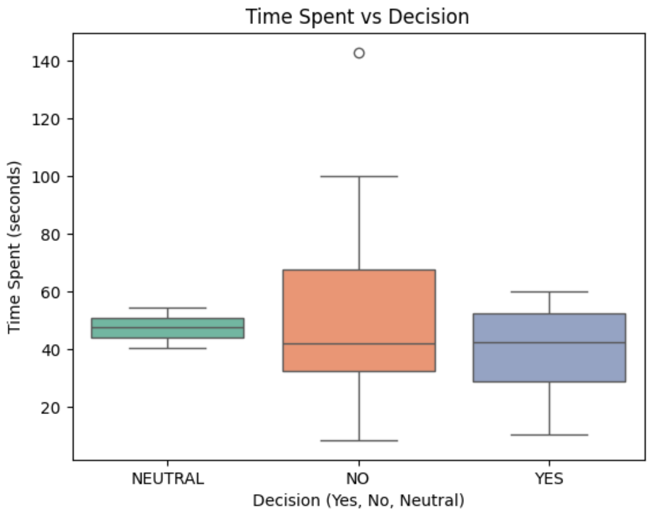


Figure 8.13: Time spent with overall extension vs Buying decision

From the box plot **Figure 8.13** it is clear that the participants of "NO" group spent maximum time with the extension comparing to other groups. It means they properly analysed every information and they decided not to buy product which is the perfect choice as the website was red marked and unsafe. One outlier is seen means one person spent maximum amount of time around 140 seconds with the extension.

From hypothesis we got the result that the impact of our popup has an association with the buying decision of our participants. And when we analysed in depth we got to know what our popup significantly impacted positively our participants. Moreover, those who chose not to buy from the unsafe website spend the most time in understanding the information that we presented. So our claim is true that Displaying a popup at the time of website entry grabs user attention which increases awareness and the chance of taking cautious actions.

8.2.4 SUS SCORE and SEQ SCORE

Just like we mentioned in Chapter 4 we asked our participants to rate their overall experience. For measuring the effectiveness of our extension we asked our participants to answer 10 set of predefined questions. The process of calculating the SUS (System Usability Scale) score is described elaborately in Chapter 4. We also calculated the SEQ score to measure the user satisfaction rate. However, Figure **Figure 8.14** represents each SUS score calculated for the individual users.

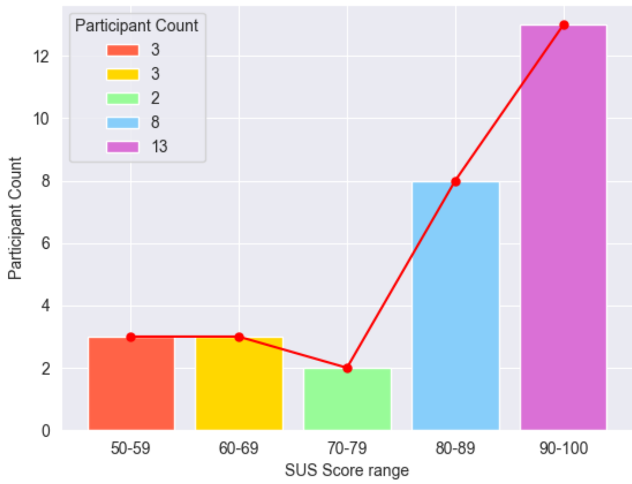


Figure 8.14: SUS score Range vs Participant Count

We can see that on most of the participants rated the usability in a range of 90-100 which is significantly good. It proves our approach is an user-friendly approach. Moreover, in **Figure 8.15** the calculated SEQ score of each participants can be found.

We can see that around 44.8% of the participants rated their satisfaction level as 7 on a scale of 7, which is a high rated score. Hence, it proves users are highly satisfied at the time of engaging with our extension.

Therefore, Table 8.9 represents the overall SUS and SEQ scores.

Total SUS Score	**Total Seq Score**
85.77	6.17

Table 8.9: SUS and Seq Scores

The average SUS score is considered 68 and ours is 85.77 which is significantly larger [119]. This means the usability of our system is very good. Moreover in a scale of 7, the average SEQ score of 4.3-7 interprets that the system is easy to use and users are satisfied [163]. Our SEQ score is 6.17 means users are satisfied with our extension.

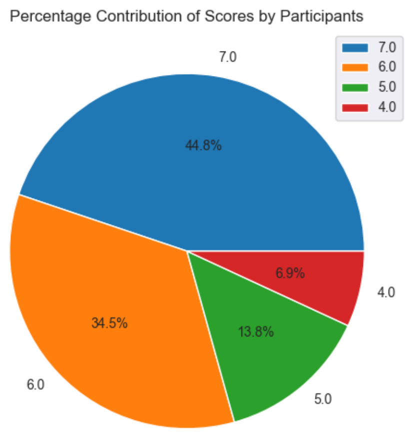


Figure 8.15: Percentage Contribution of SEQ scores by participants

8.2.5 Evaluation of Effectiveness of Extension using C-HIP Model

The extension is focused on acting as an effective user-centric safe-browsing guide which will eventually work as a warning with information that will help users in better decision-making. As this extension will be working as a warning, we need to evaluate the effectiveness of this extension on user behavior. To examine the effectiveness of warning we will be using the C-HIP model [122]. To measure the effectiveness we followed some questionnaires suggested by Wogalters model that align with the stages of the C-HIP model [57].

- **Attention Switch and Maintenance** — *Do users notice the indicators?*
- **Comprehension/Memory** — *Do users know what the indicators mean?*
- **Comprehension/Memory** — *Do users know what they are supposed to do when they see the indicators?*
- **Attitudes/Beliefs** — *Do they believe the indicators?*
- **Motivation** — *Are They Motivated To Take The Recommended actions ?*
- **Behavior** — *Will they actually perform those actions?*
- **Environmental Stimuli** — *How do the indicators interact with other indicators and other stimuli?*

To analyze whether our extension meets the criteria, we observe the users while they are engaging themselves with our extension. Users were asked to participate in an interview immediately after the experiment so that they can remember what they did and why they did certain actions. Based on the questions we tried to find the answers. They are discussed below:

Attention Switch and Maintenance

In a warning, how a warning is received by the users is important. In the C-HIP model the first stage is "Attention Switch". It says that a warning should grab the attention of the user and should compete with other external stimuli effects, otherwise it will remain useless. A warning could be shown in two ways; one is "Passive Warning" and the other one is "Active Warning". A study showed that the active warning performs better than the passive [122]. The researchers noticed that if a warning that appears has some delay and at that time if any user starts typing the warning message unwillingly gets dismissed and fails to grab the attention of the users. On the other hand, maintenance is also a crucial part. It says that the warning should persist long enough so that the user can avail necessary information. According to their research, active warnings were able to grab the user's attention and lasted enough time.

In accordance with it, when our participants were undergoing the experiment of engaging themselves with the extension, we observed whether our active popup grabs user attention or. We observed whether they avoided our active popup or actually tried to analyze the information of the active popup. We measured the time each participant spent without active popup and we saw that on average they spent 49.73 seconds with our extension. This actually proves that our active popup was successful in grabbing user attention. This also proves that we could successfully achieve maintenance means, our active popup was successful in holding used attention span. From the post-experiment interview we got responses from our participants like -"*I found it Useful. It saves me time to understand the e-commerce site*", "*It grabs my attention because of the UI. It provides necessary information*". Thus, we can understand that users were actually paying attention to the provided information of our extension.

Warning Comprehension and Memory

A warning would be more effective if users can extract information from it and can easily decode what the warning conveys. Our extension had pie charts, ratings, summarized information and tokenized information. Our goal is to reduce the information gap and that's why we kept these elements focusing on Behavioral Economics. In order to keep everything simpler, our tokenized information and summarized information was introduced so that it can help users to make quick decisions. In a post-survey interview one user claimed, "*I got the summary and instantly made the decision to leave the site*". Another user also added that, " *I can understand the risk here precisely. This was effective*". But the answers also varied from user to user. For example, some included that, "*It was a bit confusing to grab everything, I think I need to see it twice. I think I can not make a quick decision.*", "*Actually it is a little bit annoying to suddenly rise up in the middle and the color is so overwhelming*". Though they complained about the information, they gave a positive vibe at the end. One said, "*I understand there is a risk but it takes time to realise. So it is actually useful*". So it is useful as they are able to digest the information and understand what we were actually trying to convey. Moreover, as our provided information was clear and concise enough they know what to do.

Attitudes and Beliefs

Users tend to avoid warnings that do not align with their trust and belief. In our extension warning users active participation to be specific reviews of other users has been provided, government registered information has also been provided. Also, the extension provides information about what a user might lose if they visit a low-rated website. Based on that potential risk, the user had the freedom of choosing what to do. For example, there are options through which users can make their own decision, so two buttons were provided: "safe exit", "proceed anyway" in order to safely exit from a red marked website or proceed into. When we asked our participants regarding their perception of the summarised information along with risky information, they responded - "*Yes, I have understood the possible risk because the information presented was clear enough*", "*Due to the tag of registered business verification, I have found enough confidence*", "*I thought I could be a victim of any fraud. So i decided not to buy anything from this site and exit*". So, this expresses the scenes of trust and belief of what they are seeing and according to that they took their decision not to enter the website.

Motivation and Behavior

Sometimes user's can not make decisions for themselves due to many constraints. So they lack motivation and seek it. They seek guidance of what they should do when they are uncertain. Sometimes the effectiveness of the color displayed and text presented also play a role as a motivation. In our interview, we found some participants, who used a safe exit or closed the website as they paid heed to the warnings. Their statements were - "*After seeing the pop-up, I realize that there are multiple issues to be specific the potential risk information and so I thought not to buys*","*After seeing the potential loss, I do not want to be a victim of scam for which I choose to click safe exit*".

Therefore, it is clear that the users who were uncertain got to understand the risk through the information presented through our extension and had the chance to take steps accordingly. It proves that our information created enough motivation for them to take such steps.

Environmental Stimuli

Appearance of warning, timing of warning is very important to grab user attention. Warning should be able to compete with other external distractions for the user to be notified. This aligns with the first condition of CHIP that is "Attention Seeking". This aligns completely with our approach of showing warning as we showed our warning at that moment when the user is visiting a low-rated website. When our participants engaged themselves with our active warning, their perception was - "*Yes, It triggered my decision while I was watching the rating red colored. I feel like warning.*", "*It shows the alert information effectively. I found it helpful*". From these perceptions it can be claimed the appearance of our warning helped users to be informed. Moreover, our extension competed with other external stimuli and created a presence of itself.

As we were trying to nudge people towards a safer decision-making and we are trying to warn people regarding certain risks of visiting a low-rated website, we decided to measure the effectiveness of our extension using the C-HIP model because if our extension meets the criteria then we can claim that we can effectively warn the user. From the above discussion, it is clear from users response that we are successful in meeting the criteria of an effective warning message.

Chapter 9

Discussion

To ensure safe browsing in the e-commerce sector of Bangladesh is a challenging factor in the digital era as users are frequently associated with deceptive websites. Our research focuses on analyzing user behavior, how human behavior can be influenced at the time of decision-making. Our study focuses on evaluating the effectiveness of our Chrome browser extension which is designed using the principles of Behavioral Economics with a motive to influence user decision-making to warn them from getting associated with risky websites. We aim to analyze whether users can make informed decisions if they are presented with clear and summarized information regarding an e-commerce website.

C-HIP Model

To evaluate the effectiveness of our active popup we measured the effectiveness using the C-HIP model. The C-HIP model is used to evaluate whether a warning message is successfully able to warn users or not. As we are trying to warn users using specific information when they are visiting any low-rated website, we measured the effectiveness of our active popup to check whether our approach is effective or not. After analyzing each step of the C-HIP model we clearly saw that our active popup is an effective way to warn users by grabbing their attention and presenting summarized information.

Asymmetric Information & Summarized Information

As our research focuses on whether our approach to assist users to make informed decisions towards safe browsing or not. For that we conducted an experiment where we analyzed user behavior when they were engaging with our extension. From our collected data we got some interesting results. As user face the issue of asymmetric information along with facing different types of constraints during decision-making, we provided them with concise summarized information regarding an e-commerce site in the form of rating, short sentences as most concerning issues, tokenized information generated from user reviews, and a pie chart giving an overall idea of user review. When we asked our user what their perception is regarding this information their responses were - "I can make a quick decision after seeing the summarized information. Because I think most of the necessary information is present there", "I got a short and precise idea about the e-commerce site". Most of them said that this information was helpful and it saves their time as they get all types of information all at once in a summarized format. When we again asked our participants which element impacted them the most, we got to know the user reviews and tokenized information were the top two in the list. From this result, it is clear that, summarized information really helped users to make quick decisions which satisfies the principle "Heuristic" of Behavioral Economics overcoming the constraint of bounded rationality and asymmetric information.

Loss aversion

However, when users still want to visit the website, we present them the information related to potential risks they might face. After getting exposed to that information still almost 52.4% of the participants who were exposed to this risk related information still wants to visit the website overcoming the popup. And rest 47.6% safely exited from the website. However, we could not come to a conclusion that those who visited are exposed to risk because when we further asked the reason for their visit, most of them responded that they wanted to visit out of curiosity and they wanted to explore. 3 of them said they had the urgency of buying a product. However, when we asked them about their buying decision 45.5% of them did not want to buy the product, 36.5% wanted to buy and 18.2% remained neutral. On the other hand 100% of the participants who safely exited the website did not want to buy products. This actually proves that a significant number of people do not want to buy products after knowing the potential risk as they fear loss due to getting scammed. Some of our participants response when we asked about not buying products are - *"I thought I could be a victim of any fraud. So I decided not to buy anything from this site"*, *"After seeing the potential loss, I do not want to be a victim of scam for which I choose to click safe exit"*. From this, it is clear that people fear loss and thus, they changed their mind and do not want to buy products. Thus, loss aversion principle is justified through our popup.

Nudging user decision

Our main goal was to analyze whether our extension which is built on the principle of Behavioral Economics can nudge users towards a more rational decision making. After the user was done engaging with our extension we inquired how they felt when a popup appeared in front of their website they were visiting. Some of our participants thought it was a random alert while most of our participants thought it was very useful and informative. Their responses were like these - *"It helps to think and it is easy to make decisions using this information"*, *"I become aware by getting enough information together. It is a positive initiative. I will remain aware and will not buy the product from this low rated site*". As we wanted to nudge users towards an informed decision, analyzing the user response we can conclude that the inclusion of Behavioral Economics principles greatly helped in nudging the user.

Usability & Conclusion

As we were claiming that our approach is a user-centric approach, to measure the usability of our system, we calculated SUS score for each participant and then found the average score. The SUS score of our system is 85.77 which is significantly larger than the average score of 68. Means our system has a good usability and is user friendly. In addition to this the SEQ score is 6.17 in a range of 7. This was measured to check the user satisfaction level. This also proves that our participants were satisfied in using our extension. Therefore, to conclude, from our observation we saw that users' decision-making can be influenced in a positive way if they are provided with necessary information aligning with the theories of Behavioral Economics to ensure safe browsing in E-Commerce of Bangladesh.

Chapter 10

Limitations and Future Work

10.1 Limitations

Our research provides valuable insights into e-commerce awareness decision making through behavioral economics, however, certain limitations must be acknowledged. These limitations arose due to sample constraints and technological factors. Acknowledging this limitation allows for more objective evaluation of the study and highlights the area of future improvements.

- **Limited Demography:** For our survey we collected participants from our University premises for which our participant were mostly students and a limited number of staffs. So people outside of this demographics were excluded from our study.

- **Sample Size Constrain:** The sample size considered may be sufficient for exploratory research but it is not appropriate for the broader populations each human being is different so to study human behavior and decision-making ability, more diverse and broader population is required.

- **Time Constrain:** We had time limitations as well. As we are analysing human behavior and how humans interact with our system, it is a long-term study to analyse how the principles of Behavioral Economics that we have applied affects human being in their decision-making in the long run.

- **Technological Barriers:** As this is an extension so a user must install this in their browser therefore, he/she might not know about the extension or do not know how to install. In addition, there is a strong demographic with technological shortcomings in terms of the Bangladeshi region where digitalization remains a challenge. Moreover, we have developed this system as a Chrome extension but there are alternative browsers available and users might use other browsers (Mozilla, Edge or Safari).

- **Optimize Reputation System:** In terms of the reputation system that we have implemented is still evolving, there are improvements required. Due to time limitation we were unable to conduct particular test such performance and scalability test. However, the system re-calculate the ratings from scratch for each review submitted which may lead to inefficiency as the volume increases. Further improvements need to focus on optimization and handle large scale.

10.2 Future work

To address the limitation of our research, future work is needed according to the following areas:

- **Demographic Expansion:** Future study is needed with more diverse population such as elderly users, job holders, working professionals and most significantly in rural population to improve our findings.
- **Increase Sample:** To get deeper insights about human behavior and decision-making the study need large scale of representative.
- **Long Term Analysis:** Increasing the time of the study will provide greater understanding of how users actually acts and how much they are influenced by the theories of Behavioral Economics if it is implemented in a system.
- **Improve Accessibility:** The system needs to be adaptive for multiple browsers to improve user interaction and increase awareness in the greater context.
- **Optimize Reputation System:** Performance and scalability improvements need to be adaptive with the system and ensure to handle larger datasets efficiently.

Chapter 11

Conclusion

The Chrome extension we have developed and pilot-tested in Phase 3 of our research helps us to advance our knowledge of how technological interventions may support trust and better decision-making in e-commerce. This extension embeds the key insights from Behavioral Economics into pragmatic technology solutions that address a strongly pervasive deficiency in trust about online shopping, manifested by user and government registration data. Blending review information from users alongside regulatory compliance into one seamless rating system has made site ratings reliable via a combination of the Bayesian Average Algorithm and Exponential Time Decay Algorithm. The upcoming function of the extension that can validate government registration and compliance marks the precedent for how such digital tools can be of assistance to the regulatory bodies in handling the increasing pace within the e-commerce space. It goes up with dual functionality, which not only helps consumers to make better purchasing decisions but also fortifies governments in their efforts toward enforcement mechanisms of e-regulations through e-commerce. This will involve heavy testing in the real environment during these final stages of research, and further refinement of the algorithm with diverse user feedback. It is also intended to make the extension fully comply with technical and user experience standards, turning out to be adaptable to dynamic requirements related to online trade and regulatory frameworks. This part of the study emphasizes how much the innovative technological solution can contribute to overcoming fraudulent issues in e-commerce and form the very basement for further development to make another revolutionary step regarding measures of security in digital marketplaces.

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