INFLUENCE OF DEMOGRAPHIC CHARACTERISTICS ON CONSUMERS' ONLINE REVIEW-BASED PURCHASE BEHAVIOR

Kaniz Fatima [1*]
Rezwanul Huque Khan [2]

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Abstract

Consumers nowadays are being increasingly influenced by online reviews (ORs) of different review platforms on the web for making a purchase decision about a product or service. While existing literature has shed light on different factors of ORs that influence consumers' purchase decisions, this study aims to find out the influence of consumers' demographic characteristics on their purchase behavior based on ORs. By analyzing the data collected from 454 participants in Dhaka city, we found that consumers read the ORs for food, drink, and related services like restaurants followed by clothing, accessories, beauty, and personal care products. The study shows that most consumers search various channels for reviews, including search engines, social media, content communities, and review aggregators on merchants' websites, instead of relying on just one platform. We also found that besides online purchases, ORs are useful for traditional offline purchases and such behavior varies across consumers' demographic profiles like gender, age, and household monthly income. The study reveals that demographic characteristics, like age and household monthly income, influence how frequently consumers alter their decisions based on online reviews. Thus, this study is the first to explore how demographic factors affect consumers' choice of shopping channels as well as the degree of variability in their purchase decisions both based on ORs. Finally, the implications of these findings for theory and practitioners have been outlined.

Keywords : *Credibility, Demographic Characteristics, Online Review, Online Review Platform, Purchase Decisions, Shopping Behavior*

JEL Classification : *C12, C14, C83, D12, J10, M21, O14, R20*

1. INTRODUCTION

With the proliferation of the Internet, online reviews (ORs) or electronic word of mouth (e-WOM) have emerged as a prominent source of information for many consumers across the world. While electronic word-of-mouth (e-WOM) recommendations or advice are limited to the immediate social circle, ORs provide a wide range of opinions and experiences from various users yielding a more comprehensive and broader perspective on a product or service (Moore & Lafreniere, 2020; Babić Rosario

1 Lecturer, Institute of Business Administration (IBA), University of Dhaka, Bangladesh
2 Professor, Institute of Business Administration (IBA), University of Dhaka, Bangladesh
* *Corresponding Author: Kaniz Fatima, Lecturer, Institute of Business Administration (IBA), University of Dhaka, Bangladesh*

et al., 2020; Romero & Ruiz-Equihua, 2020; Akbari et al., 2022). Again, WOM recommendations can be biased, based on individual preferences, or influenced by personal relationships whereas ORs are free from such biases. Consequently, about 95% of consumers are reported to read ORs before making a purchase decision (Collinger et al., 2017) and consider it to be the second most trusted source of information after friends and family (Sikdar et al., 2022). Potential consumers, to reduce the risk of loss and improve the accuracy of purchase decisions, compare and try to validate the product information provided by the sellers on their official website with the ORs shared by experienced consumers (Zhong-Gang et al., 2015). As such, ORs, being an influential content that leads to conversion (Sikdar et al., 2022) and plays a catalytic role in the outcomes of the businesses (Rese et al., 2014; Konig et al., 2022), have recently received mentionable attention among the researchers. Given the backdrop, the focus of this study is also on OR, a dynamic and ongoing information exchange process that is accessible to many people and organizations via the Internet.

Researchers (Rajani & Nakhat, 2019; Naujoks & Benkenstein, 2020; Zhang et al., 2020; Chen et al., 2022; Fang, 2022; Ma et al., 2022) argued that even though ORs can influence the purchase decision of consumers, the overall effect depends on many factors (Fang, 2022) of the reviews, reviewers, review platforms, product category, etc., and only the top reviews among thousands of written reviews on a product in different online review platforms (ORPs) exert significant influence (Sikdar et al., 2022). For example, Lackermair et al. (2013) showed that review comments (i.e., positive or negative) and ratings are important sources of information for consumers while Naujoks and Benkenstein (2020) found that overall aggregated rating and perceived expertise of the review writer are important attributes for reviews to be credible, hence affecting purchase decision. In other studies, valence and volume of reviews (Xiang et al., 2017; Fang, 2022), user-supplied photos, the reviewer's personal information, the explicit mention of the type of product in a review (Xiang et al., 2017), and average paragraph length of review (Shen et al., 2022) were found to build credibility on review and influence the consumers' decision. In this regard, a few researchers (Zhang et al., 2020; Ma et al., 2022) also investigated how users can be motivated to contribute with honest and unbiased quality reviews on online platforms. Again, given the myriad design options available for ORPs, König et al. (2022) stated that the credibility of reviews may be affected by how the platforms are designed and suggested more studies on ORPs. As such, existing literature has focused on different factors of online reviews that influence consumers' purchase decisions, mostly ignoring how this influence is affected by gender (Shen et al., 2022; Sikdar et al., 2022) and other demographic characteristics of consumers.

To address this gap, this study aims to find out the influence of consumers' demographic characteristics on their purchase behavior based on online reviews. This work is backed by the consumer behavior theory by Michael and Backer (1973) which is a reformulated theory of consumer behavior, founded on the household production function theory proposed in "A Theory of the Allocation of Time" (Becker, 1965).

In this study, we try to understand the phenomena by exploring the online platforms where online reviews are looked at, the goods/services for which online reviews are searched for, whether online reviews are read for only online, offline, or both types of shopping, how those reviews impact purchase decision, and how demographic characteristics of consumers influence these purchase behaviors. Relevant data from 454 participants of Dhaka city were collected and analyzed to unearth how the purchase behavior of consumers varies due to their differences in demographic characteristics.

The rest of the paper is structured as follows. The next section gives an overview of online reviews, review platforms, and the products searched for on those platforms followed by a discussion on online review-based purchase decisions and the impact of demographic variables on it. Then the research methodology and the analysis and findings of the study are provided. Finally, the paper ends with a discussion of contributions while outlining implications for theory and practice.

2. LITERATURE REVIEW, HYPOTHESES DEVELOPMENT, AND RESEARCH MODEL

This section reviews the relevant literature on online reviews, review platforms, products searched for review, the influence of online reviews on purchase decisions, and the effect of demographic characteristics on such influence. Based on the review, hypotheses are formulated and a research model is created.

2.1 Online Review, Products Searched for, and Platforms Preferred for Review

Online review refers to the feedback submitted by consumers on an online platform after they have purchased or used a certain product or service (Fang, 2022). These reviews, mostly posted by genuine and experienced consumers, are rich in information on product or service attributes and qualities, which can alleviate information asymmetry in the online market (Burtch et al., 2018) and facilitate potential consumers to reduce their risk of loss (i.e., purchasing a low-quality product or at a high price) by improving the accuracy of their purchase decision (Zhong-Gang et al., 2015). That is why, consumers, nowadays, are heavily relying on reviews of different online platforms before they make decisions to purchase a product or service.

In a recent study, Xiang et al. (2017) mentioned that for online review-based consumption, some product categories are more suitable than others, i.e., online purchase based on consumer reviews varies based on product category. In the same line, Ma et al. (2022) stated that, to choose a restaurant, hotel, movie, book, or news, consumers are increasingly relying on online reviews. According to Freddie (2020), a recent survey of US consumers found that 68% of the consumers read online reviews before they purchase a technological product like a mobile phone, e-book reader, video game console, or laptop while a large percentage of consumers go through online reviews before purchasing durables such as household appliances (55%) and automobiles (52%). Extant literature has mostly mentioned consumers' intention to read reviews for hotels, restaurants, destination places, electronic devices, home appliances, movies, books, etc.

In this regard, Elliot and Fowell (2000) stated that consumers rely on e-WOM (hence, online review) more for high-involvement products like computers, cars, and products and also for products that require in-person experience like perfume, lotion, etc. In another study, Grewal and Dharwadkar (2002) mentioned that properly standardized products, for which there is no quality uncertainty and no requirement for physical assistance (e.g., book, groceries, etc.), are less considered for purchase based on online review. Investigating the effects of review source and product type, Bae and Lee (2011) concluded that reviews of established products are more credible to the consumers, indicating that consumers seek more information of established products on online review platforms. According to Girard (2003), consumers' willingness to read the reviews in ORPs may be influenced by their shopping orientation (i.e., price-consciousness, risk-aversion, innovativeness, brand-consciousness, importance of convenience, variety-seeking inclination, and impulsiveness), as it does for online shopping (Girard, 2003). Again, Vermeulen and Seegers (2008) stated that consumers seek information more on ORPs for products whose utility can only be evaluated after consumption (e.g., travel services). It reflects that consumers seek information more for some product categories than others on different online review platforms.

Online review platform (ORP) refers to an online channel e.g., social media, retailers' site, or a third-party channel, where consumers submit their reviews on a product or service they have consumed (Chen et al., 2019; Fang, 2022). On one hand, ORPs have emerged as a very popular and useful aid for potential consumers to make an informed purchase decision, on the other hand, online retailers and subsequently traditional companies operating online channels are now increasingly focusing on ORPs for active review management (König et al., 2022) considering its significant effect on the decision-making process of the consumers. While the purpose of the ORPs is the same (i.e., assisting customers), there are many ORPs that are diverse in nature and vary in terms of their focused product or service category (Constantinides & Holleschovsky, 2016; Chen et al., 2019).

According to Xiang et al. (2017), ORPs may range from community-based review sites such as Yelp and TripAdvisor to transaction-based online travel agencies like Booking.com, Expedia, etc. where customer reviews are incorporated. Online retailers like Amazon.com, Walmart, and eBay enable consumers not only to buy products and services from their e-stores, but also to write comments on their sites about the products purchased (Fan & Gordon, 2014). In these retailers' sites, review content can be in the form of open-ended comments as well as aggregated, numerical star ratings about the product (Constantinides & Holleschovsky, 2016). A survey by Review Monitoring had also found such *retailers' sites* as a popular platform among US citizens for reading online reviews (Freddie, 2020). This survey also identified that many consumers seek information through *search engines* like Google and *social media* like Facebook about a product they want to purchase. Many researchers (e.g., Ye et al., 2009; Yin et al., 2014) noted *search engines* like Yahoo and Google as popular ORPs that enable users to find the reviews they need. Similarly, Fritsch and Sigmund (2016), by investigating social media for hotel reviews, stated that social media like Facebook or Google+ are increasingly gaining popularity for hotel reviews and the boundaries between these media and the traditional hotel review portals are getting blurred. In a survey of US citizens, Freddie (2020) found online review readers are very active in social media like LinkedIn (89%), Instagram (87%), Pinterest (87%), Twitter (86%), and Facebook (81%), and these social media sites could be widely used as ORPs by brands.

Due to the intensive engagement of consumers in social media, specific interest-driven communities like blogs, social bookmarking sites, and photo and video-sharing communities have risen as content communities where users consume, generate, and share multimedia content (Thompson, 2011). Consumers view content communities as a means of diverse media sharing content such as videos (YouTube), photos (Instagram and Flickr), bookmarking (del.icio.us), text (BookCrossing), presentations (Slideshare), and audio (postcasts) (Du Plessis, 2017). Noguti (2016) stated that content communities differ from social media in the sense that the content posted by users is most likely to be unknown to the viewers, but they still might be engaged with the community by replying, sharing, and liking the content (Rowe & Alani, 2014). In the case of bloggers, their identity is mostly very detailed and communication with them is often possible (Constantinides & Holleschovsky, 2016). Similarly, YouTube review offers multiple advantages like number of views, subscribers, or downloads of the video indicate the popularity of the review, others' comments on the review can be observed, other videos for similar products are displayed nearby, profile of the reviewer is visible, and link to other videos posted by that reviewer can also be found from YouTube or other video sharing platforms (Chang & Lewis, 2013). As such, these *content communities* have emerged as vital reference ORP in decision making for potential consumers (Fan & Gordon, 2014; Lu et al., 2014).

Again, Burtona and Khammash (2010) mentioned about consumers' preference of independent consumer review platforms (e.g., yelp.com, tripadvisor.com, rotten tomatoes) where customer reviews are displayed without having a direct or indirect interest in businesses, and product comparisons are facilitated. These sites are also called *review aggregator sites* which collect large number of reviews about a product, service, or business from different sources, compile those to an average score or ranking (Renderio, 2022), and play critical roles in helping consumers to compare products or services based on the reviews in the platform (Freddie, 2020).

As the ORPs vary in feature, nature, and focus, the consumers may prefer one platform over another to read the reviews of the products or services to be purchased. Again, since huge discrepancies in representations of the same products or services over different platforms are noticeable (Xiang et al., 2017), consumers may go through multiple ORPs to cross check the information found in one platform and may intend to build more confidence though this process. However, the extant literature barely sheds light on ORP industry in general (König et al., 2022) or on the consumers' preference of ORPs. But for devising the platform's strategy, it is critical for the business organizations to understand how their targeted audience prefer one ORP (Xiang et al., 2017) over its competitors. Hence, one of the aims of this study is to find out consumers' most preferred ORPs and consider retailers' site, content communities, search engine, social media, review aggregators site, and multiple ORPs as consumers' available options to select.

2.2 Online Review-based Purchase Decision, Channel of Purchase, and Demographic Variables

A multitude of studies (e.g., Naujoks & Benkenstein, 2020; Rajani & Nakhat, 2019; Fang, 2022; Sikdar et al., 2022) have investigated the influencing factors of online reviews from different perspectives. However, these studies mostly considered the effect of online reviews on making shopping decisions for shopping online (Li et al., 2020; Chen et al., 2022) ignoring the fact that online reviews can be read by consumers who purchase from traditional offline channels too. In a study by Lewis and Reiley (2014), they found that online advertising can have a large effect on offline sales. Through an experiment, these researchers estimated that 93% of the treatment effect was offline and the retailer recorded 85% of its sales volume offline rather than online. This finding reflects that like the significant impact online advertisements can have on online consumers, online reviews might have a similar impact on the consumers who shop offline indicating a huge readership of online reviews by offline consumers. In a study, Constantinides and Holleschovsky (2016) stated that personal blog reviews by bloggers are quite popular among both online and offline consumers. However, given the paucity of study, we have tried to distinctively understand the influence of online reviews on offline consumers' purchase decisions and the effect of demographic characteristics on that usage (i.e., online purchase, offline purchase, or both).

Extant literature has identified several factors relating to reviews, reviewers, review platforms, and product categories that play a critical role in influencing consumers' purchase decisions. For example, Lackermair et al. (2013) showed that review comments and ratings are important sources of information for consumers while Naujoks and Benkenstein (2020) found overall aggregated rating and perceived expertise of the review writer to be important attributes for reviews to be credible, hence affecting the purchase decision. Xiang et al. (2017) opined that valence and volume play a critical role in influencing consumers. Similarly, Fang (2022), in a study, showed the vital influence of the valence intensity of online reviews on purchasing intention. It was found that the consumers, especially the female consumers, pay more attention to negative comments than to positive comments and they were not able to identify the false comments. User-supplied photos and the reviewer's personal information were also found to build credibility and influence consumers' decisions (Xiang et al., 2017). They also mentioned that the explicit mention of the type of product in a review affects consumers' decision to buy that product. Again, given the myriad design options available for ORPs, König et al. (2022) highlighted that the credibility of reviews may be affected by how the platforms are designed.

Again, it is well-established that the consumption pattern of most of the products and services vary across consumers having different demographic characteristics. Researchers even found that demographic variables like age, gender, income, profession, family structure, education, and marital status have a substantial impact on online shopping behavior or intention to purchase online (Girard et al., 2003; Kalia, 2016; Bhat et al., 2021). While the intention to shop online varies across demographic characteristics, it might be argued that there should be some degree of relationship/association between those demographic characteristics and the credibility of online reviews, i.e., the credibility of online reviews might be more or less, depending on the demographic profile of the consumers.

In this regard, a few of the researchers recently focused on various issues of online review relating to gender differences. For example, Shen et al. (2022) examined how various message features of online product reviews are evaluated by female and male consumers. They showed that female consumers consider online product reviews helpful which have pictures, negative viewpoints, and average paragraph length while male consumers are found to value positive viewpoints and ratings more in evaluating those reviews. In another study, Luo and Ye (2019) found that females' intention to continue the use of international online shopping website varies depending on the quantity of online reviews while the same varies for male consumers based on the quality of online reviews. Sikdar et al. (2022) examined whether the success of online product reviews differed in case it was generated by males or females and found no general trend in overall review success. However, if the gender signal of the review was noticed, strong context-specific (e.g., product category) effects were observed in that study. Similarly, Fang (2022), by investigating the online reviews of restaurants, showed the effect of gender "for the first time" on the influence of those reviews on restaurant revenue.

Based on the discussion, it is clearly understood that while there has been very limited research relating gender and online reviews, the impact of other demographic characteristics hardly received any attention in the context of online reviews. However, according to Michael and Becker (1973)'s consumer behavior theory, demographic factors like gender, age, education level, income level, etc., directly influence consumers' motivation and purchase decisions. A deeper comprehension of observable human behavior has been made possible by this idea. To explain consumer behavior, the classic theory of choice focused on just three variables: income, prices, and tastes where taste can account for the portion of consumer behavior that cannot be explained by price or money. The theory suggests that numerous non-financial variables, such as age, gender, family size, religion, and the state of the political and/or social environment, influence this preference as well. According to the new idea, environmental factors like age, education, weather, political stability, etc., may also have an impact on utility derived from the consumption of any product and/or services. Apart from gender, not much research has been done on the influence of other demographic characteristics on consumers' attitudes about making purchases online. As such, we argue that it is important to observe the impact of different demographic factors on the use of ORs and OR-driven purchase behavior of the customers. In this research, we define OR-based purchase behavior in terms of the frequency with which judgments are changed regarding purchases based on ORs. This research investigates if ORs are exclusively used for online purchasing or whether they are also utilized for traditional media shopping, as well as how this usage varies depending on the demographics of the clients. Another purpose of this study is to examine the impact of several demographic factors, including age, gender, education, income, and occupation on OR-based purchasing behavior. Additionally, this research illuminates whether such action is impulsive or whether people genuinely believe these reviews to be reliable. Therefore, the study proposes the following hypotheses:

H_{01}: *There is no difference between the proportion of males and females checking online reviews for shopping through various channels.*

H_{02}: *There is no difference among the age groups in checking online reviews for various channels of purchases.*

H_{03}: *There is no difference among the customers having different educational backgrounds in checking online reviews for various types of purchases.*

H_{04}: *There is no difference among the customers from various occupations in checking online reviews for buying via different shopping channels.*

H_{05}: *There is no difference among the customers having different household monthly incomes in checking online reviews for various purchase channels.*

H_{06}: *There is no difference among the mean ranks of males and females altering their purchase decisions based on online reviews.*

H_{07}: *There is no difference among the mean ranks of different age groups in altering their purchase decisions based on online reviews.*

H_{08}: *There is no difference among the mean ranks of different education groups in altering their purchase decisions based on online reviews.*

H_{09}: *There is no difference among the mean ranks of customers having different professions in altering their purchase decisions based on online reviews.*

H_{010}: *There is no difference among the mean ranks of different monthly household income groups in altering their purchase decisions based on online reviews.*

H_{011}: *There is no monotonic association between the frequency of shifting purchasing decisions and the credibility of online reviews.*

Figure 1 demonstrates the conceptual framework of the study.

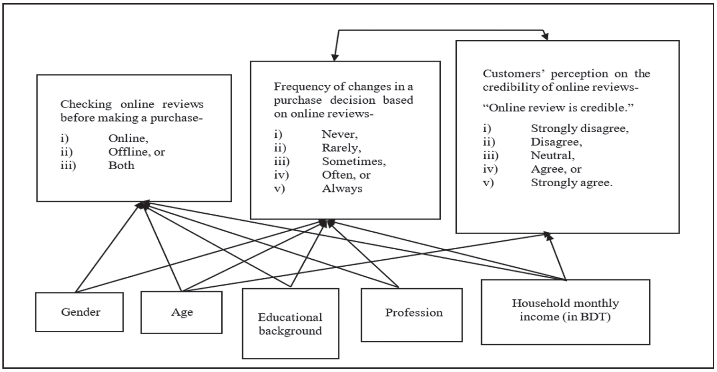

Figure 1 : Conceptual Framework

3. METHODOLOGY

3.1 Population and Sample

The research population encompasses all consumers who purchase products physically and/or via online platforms in Dhaka. However, the relevance of the findings has been ensured by selecting participants who have access to the Internet to check online reviews before buying goods or services.

3.2 Sample Size and Data Collection Technique

Both primary and secondary data, as well as pertinent literature studies, were used in the study. The core data was gathered by a structured questionnaire survey and 20 respondents were pre-tested before the final questionnaire was created. Samples were chosen using a convenience, quota, and non-probabilistic judgmental sampling mix. 560 Dhaka city inhabitants participated in the survey among which 454 participants responded that they checked online reviews before buying any product. With a 5% level of significance, 5% level of precision, 50% proportion, 10% non-response rate, and around 10% non-adoption rate, this sample size is justifiable. The non-adoption rate refers to the proportion of respondents who do not look for internet reviews before making a purchase of any goods or services.

Online surveys were used to gather responses from a self-administered questionnaire. Participants in the sampled group were given questionnaires about whether they bought things online or through offline media. But in this study, only the data from 454 respondents— who utilize internet reviews to decide what to buy— were included for analysis. To provide a framework for the study, secondary materials including numerous research reports, publications, and websites have been examined. To comprehend the necessity and usefulness of such a demographic factor-based study on the impact of online reviews on the purchasing choice of consumers dwelling in Dhaka city, a thorough literature review was conducted.

Only Dhaka city inhabitants were used to collect the data so a study of all Bangladeshis falls outside the purview of this investigation. The data used for this study are just from the two months of January and February 2023. The research's findings will make it possible for business owners, service providers, online marketers, social media page administrators, and even content creators to understand the value of online reviews in boosting sales of their goods and/or services and maintaining their brands' reputation. They will therefore focus more on ensuring, maintaining, and improving quality at every stage of the creation of goods and services.

3.3 Analytical Techniques

Statistical tools including frequency distribution, cross-tabulation, Chi-square test of association, Mann Whitney U-test, Kruskal Wallis H test, and Kendall's Tau-b have been used to conduct in-depth investigations. The survey questionnaire used in this study does not contain any construct or latent variable with multiple observed variables. No indicator variables are used to measure or predict any construct of interest. Rather some observed variables are directly used to collect nominal or ordinal responses from the participants. Since these dimensions are somewhat independent, a measure of internal consistency, reliability, and validity computed across dimensions would be inappropriate (Sijtsma & Pfadt, 2021; Tavakol & Dennick, 2011). The statistical software used were Statistical Package for Social Sciences (SPSS) 26 and Microsoft Excel.

4. FINDINGS AND ANALYSIS

4.1 Descriptive Statistics

Table 1 summarizes the respondent profile in terms of gender, age group, educational qualification, profession, and income group. The majority of respondents (53.3%) are male and 46.7% are female. According to age, the dominant group is from the age range of 20-29 years corresponding to 40.5% of the total participants. The second largest group, in terms of age, is 30-39 years (22%). However, fewer responses have been found from those who are within the 10-19 years age group (4.6%) and people who are older than 60 years (2.9%). A big chunk of participants (39.9%) has academic background up to the bachelor level and the next large group (38.5%) in this category has completed their master's degree. 2% of the participants' educational qualifications fall in other categories like Ph.D., post-doctorate, diploma, below SSC, etc. Approximately half of the participants are working in the private sector. The next prominent group consists of students (21.1%). Furthermore, 2.4% are related to other professions like white and pink color job holders. Around one-fourth (24.4%) of the respondents' household monthly earnings fall between BDT 30,001 to BDT 50,000 level.

Table 1 : Respondent Profile

Characteristics	**Category**	**Frequency**	**Percentage**
Gender	Male	242	53.3
	Female	212	46.7
Age Group	10-19	21	4.6
	20-29	184	40.5
	30-39	100	22
	40-49	75	16.5
	50-59	61	13.4
	>=60	13	2.9
Educational Qualification	Secondary level (SSC/O-level)	21	4.6
	Higher Secondary level (HSC/A-level)	59	13
	Bachelor	190	39.9
	Masters	175	38.5
	Other	9	2
Profession	Public Service	50	11
	Private Service	214	47.1
	Student	96	21.1
	Business	44	9.7
	Homemaker	39	8.6
	Other	11	2.4
Household Monthly Income (in BDT)	=<10,000	80	17.6
	10,001-30,000	84	18.5
	30,001-50,000	111	24.4
	50,001-70,000	76	16.7
	70,001-90,000	34	7.5
	90,001-1,10,000	48	10.6
	>=1,10,001	21	4.6
	Total	**454**	**100**

4.2 Products for Which Online Reviews Are Searched

Figure 2 shows that 87.4% of customers in Dhaka, who are shopping for food, beverages, groceries, restaurants, and packaged food products, utilize online reviews. Of these, 56.7% use online reviews to choose restaurants for eating out. On the other hand, only 12.7% of participants choose online MOOC (massive open online course) services after reading online reviews. The data also makes it abundantly evident that apparel and fashion accessories are very popular items for online review checking (76.3%). Products for personal care and beauty are right behind it (65.5%). It is also noteworthy how frequently electronic gadgets (58.8%), accommodations (57.4%), home appliances (48.1%), and service delivery apps (42.6%) are reviewed online. Dress receives 51.4% of evaluations under the category of apparel and fashion accessories, which also includes shoes, bags, jewelry, perfume, watches, and other items. The electronic equipment or gadgets category, where smartphone reviews are checked the most (26.4%), includes smartphones, phone accessories, laptops, desktops, computer accessories, digital cameras, and other gadgets. 29.4% of the participants check hotel reviews online before booking. The detailed product/service categories are presented in Table A1.

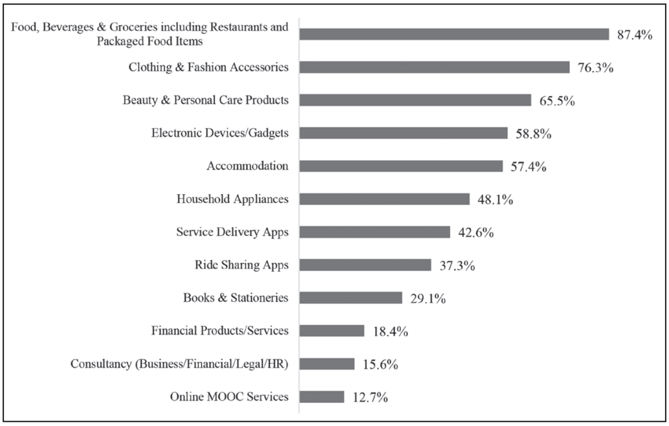

Figure 2 : Products for which Online Reviews are Searched

4.3 Platforms Used for Checking Online Reviews

Customers search online reviews on several platforms, e.g., search engines, review aggregators, retailers' sites, content communities, social media, and a combination of multiple platforms or 'multiple ORPs' (Figure 3). Customers in Bangladesh use different search engines, e.g., Google, Yahoo, Microsoft Bing, Microsoft Edge, Duck Duck Go, etc. for product reviews. However, only 15% of the respondents depend on such search engines for reviewing products. The next highly used platform (39%) is review aggregator sites like Product Review BD, Review Bangla, Food Story, Dhaka Foodster, Google Play Store/App Store, etc. Moreover, 43% of the sampled customers take the help of the retailers' sites to make purchase decisions of products.

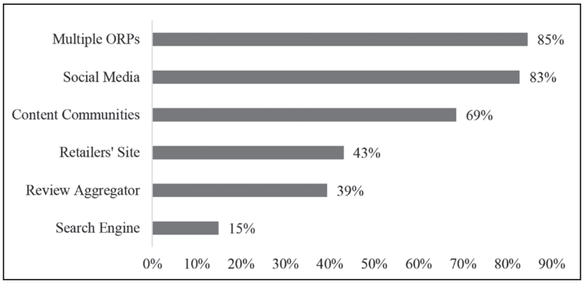

Figure 3 : Platforms used for Checking Online Reviews

Different company websites, online store product comments, and ratings fall under this category. In addition, there are several content communities in Bangladesh such as YouTube videos on specific brands or products, YouTube blogs, food blogs named Khudalagse, Petuk Couple, Rafsan The ChotoVai, Metroman, Khai-dai.com, Bangladeshi Food Reviewer, Zoltan BD, etc. 69% customers rely on such content communities to collect product reviews before buying. The second highest used platform (83%) after multiple ORPs (85%) is social media like Facebook pages and groups, Instagram, Flickr, LinkedIn, etc. Hence, social media platforms are the most significant in circulating product reviews. Notably, most people check more than one review site to get product reviews.

4.4 Effect of Demographic Factors on the Use of ORPs in Different Shopping Channels

In this section, the effect of different demographic factors is examined on how consumers use ORPs for purchasing products through different channels. The chosen demographic factors are- gender, age, educational background, profession, and household monthly income. The channels considered in this article are only online, only offline, or both, which indicate that the three categories are mutually exclusive. 56.2% of participants mentioned that they check online reviews for online shopping only, whereas only 9% check reviews for offline shopping. 34.8% use online reviews to make sure they are buying the right product via both online and offline media (Table A2).

A. Gender on Shopping Channels

To observe the difference in the use of online reviews by male and female customers, the Chi-square test of association is used. The nature of the data led to the choice of this association test (Agresti, 2013; Blalock, 1999; Conover, 1999; Howell, 2010). Analysis reveals that more male customers (64.9%) check online reviews before they purchase products online compared to females (46.2%) whereas female customers rely on online reviews even while purchasing products physically and that proportion is slightly more than males (9.9% as opposed to 8.3%). Considering the groups who seek online reviews regardless of the media for buying products, females (43.9%) are ahead of males (26.9%) (Table A3). Analysis shows that there is a statistically significant association between gender and the use of online reviews for different types of purchases, $\chi^2(2) = 16.728$, $p = 0.000233$, and this association is moderately strong [Cramer's V = 0.193, p = 0.000233] (Table 2). Hence, H_{01} is rejected, and it is found that females search online reviews before making a purchase, either online or offline, more than males.

B. Age on Shopping Channels

A chi-square test has been employed to understand the impact of age on different purchase patterns. Analysis reveals that the 20-29 age group is the largest user of online reviews for online shopping (67.4%) whereas, for offline shopping, the 40-49 age group is the most prominent user (14.7%). On the other hand, the 50-59 age group is the most concerned group as they check reviews the most (59%) for both types of purchases. Thus, for the age group, analysis shows that 3 cells have an expected count of less than 5 because of inadequate samples in one/two of the categories of purchase types for the 10-19, 50-59, and >= 60 age groups (Table A3). Removing these three age groups from the samples leaves 359 responses where 207 participants use online reviews for online shopping, 40 for offline, and 112 for both (Table A4). As a result, a statistically significant association is found among age groups and checking online reviews for different types of purchases, [$\chi^2(4) = 18.555$, $p = 0.001$] and the association is moderately strong [Cramer's V = 0.161, p = 0.001] (Table 2). Hence, H_{02} is rejected, and it is observed that the 20-29 age group prefers to check online reviews for online shopping the most, while consumers aged 50-59 read reviews in case of both online and offline shopping, and the 40-49 group for offline shopping the most.

C. Educational Qualification on Shopping Channels

Table A3 explores that three cells have an expected count of less than 5. Excluding the SSC (n = 21) and other groups (n = 9), 424 responses are left where 61% of the HSC pass respondents (n = 59) use online reviews for online shopping, 15.3% of them use those for offline purchases, and 23.7% for both (Table A4). Among the 190 participants with a bachelor's degree, 58.4% search reviews before online purchases and 32.6% for both. For both types of shopping, online reviews are sought the most by master's degree holders (41.1%). However, no statistically significant association is observed among educational qualification (HSC, bachelor, and master's) and online review checking for types of purchases, $\chi^2(4) = 8.423$, $p = 0.077$. The results are summarized in Table 2.

D. Profession on Shopping Channels

88.6% of businesspeople depend on online reviews for online purchases (Table A3). Similarly, half of the public service holders check such reviews before buying products online. In fact, online reviews are sought for online purchases by customers from all occupational groups. However, no responses have been received from business owners for online and offline purchases together. They check online reviews for either online purchases or offline purchases but not for both. Proportions of homemakers checking online reviews for online shopping and offline shopping are the same (46.2%). Students mostly seek online reviews for online purchases (69.8%). The tendency to check reviews for only online and both types of purchases is very close to 46.7% and 46.3% respectively among the private service holders. Whereas only 7% of them look for reviews for physical shopping (Table A3). The statistical test will not generate meaningful results since 5 cells have an expected count of less than 5.

E. Household Monthly Income on Shopping Channels

For examining the impact of household monthly income on types of purchases where online reviews are searched, the Chi-square test has been employed. Customers from all income groups prefer to check online reviews before purchasing only online items except for the BDT 50,001-70,000 and 70,001-90,000 income ranges. These two groups check the reviews for both types of purchases and the proportions are 57.9% and 41.2% respectively (Table A3). Customers with a family income of less than BDT 10,000 use reviews for online shopping significantly (78.8%). People whose household monthly earnings are in the range of BDT 70,001-90,000 are the largest users of online reviews only for offline shopping (20.6%). Nevertheless, crosstabulation shows 3 cells have an expected count of less than 5 in the ranges of BDT 70,001-90,000, 90,001-1,10,000, and >= 1,10,001. Hence, a Chi-square test has been run deselecting these 3 income groups (Table A4), and significant associations have been found between household monthly income group and types of purchases [$\chi^2(6) = 47.481$, $p = 0.000$]. A strong association exists between household monthly income groups and online reviews for channels of purchase, as reflected in Cramer's V = 0.260, p = 0.000 (Table 2).

Table 2 : Results of Hypotheses Tests for the Chi-square Test of Association

Hypothesis	χ^2	df	Sig. (2-tailed)	Decision at α=5%
H_{01}	16.728	2	0.000233	Reject the null
H_{02}	51.059	10	0.000	3 cells have an expected count of less than 5 (All age groups)
	18.555	4	0.001	Reject the null (3 age groups, n = 359)
H_{03}	17.062	8	0.029	3 cells have an expected count of less than 5
	8.423	4	0.077	Fail to reject the null (3 educational qualification groups, n = 424)
H_{04}	120.453	10	0.000	5 cells have an expected count less than 5
H_{05}	56.826	12	0.453	3 cells have an expected count less than 5
	47.481	6	0.000	Reject the null (4 income groups, n = 351)

4.5 Effect of Demographic Factors on Frequency of Altering Purchase Decisions

Respondents have been asked how often they change their decision to purchase a product based on online reviews and responses have been collected on a 5-point Likert scale: Always (2), Often (1), Sometimes (0), Rarely (-1), Never (-2).

36.1% of respondents say that they alter their purchase decisions based on online reviews (Table A5). The order of such alteration in purchase decisions according to the survey is- sometimes (22.2%), always (17.8%), rarely (15%), and never (8.8%). Nonparametric tests like Mann Whitney U-test and Kruskal Wallis H-test have been applied since the dependent variable– frequency of altering purchase decisions because of online reviews- is an ordinal variable. Mann-Whitney U-test has been performed to observe the effect of gender and Kruskal Wallis H-test has been applied to detect the influence of other demographic factors.

A. Gender on Frequency of Decision Alteration

Mann-Whitney U-test has been executed to determine if there is any difference in online review-based purchase decision changes between males and females. This is because two groups of the ordinal level responses for frequency of altering purchase decisions are to be compared (Agresti, 2013; Daniel, 1990; Dineen & Blakesley, 1973). Since distributions of the frequency for males and females are not similar, as assessed by visual inspection (Figure 4), the mean ranks are to be compared (Dineen & Blakesley, 1973).

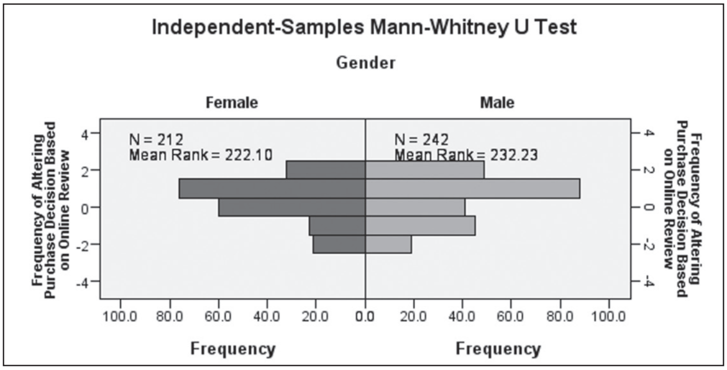

Figure 4 : Population Pyramid of the Mean Ranks of Males and Females

The test result retains the null hypothesis (Table 3). Hence, there is no statistically significant difference between males (mean rank = 232.23) and females (mean rank = 222.1) in altering their buying decision based on online reviews [$U = 24508$, $z = -.850$, $p = 0.396$], using an exact sampling distribution for U (Dineen & Blakesley, 1973).

Table 3 : Results of Mann Whitney U-test

Hypothesis	Mann Whitney U	Wilcoxon W	Sig. (2-tailed)	Decision at α=5%
H_{06}	24508	47086	0.396	Fail to reject the null

B. Age on Frequency of Decision Alteration

A Kruskal Wallis H-test has been conducted to determine if there are any differences in the number of times customers of various ages alter their buying decisions. Multiple nominal or ordinal categories of age and other demographic factors in the following sections led to the choice of such a non-parametric technique (MacFarland et al., 2016). Distributions of alteration frequencies are not similar for all age groups, as assessed by visual inspection of a boxplot (Figure A1). Separate age groups alter their purchase decisions significantly differently when they read online reviews [$\chi^2(5) = 21.559$, $p = 0.001$] (Table 4). Subsequently, pairwise comparisons are performed with a Bonferroni correction for multiple comparisons (Figure A2). This post hoc analysis (Table A6) reveals statistically significant differences in the frequency of decision alteration based on online reviews between 20-29 (mean rank = 253.95) and 40-49 (mean rank = 184.44) ($p = 0.001$) age groups, and 20-29 and 30-39 (mean rank = 205.96), ($p = 0.034$) age groups.

C. Education on Frequency of Decision Alteration

A Kruskal Wallis H-test has been run to determine if there are any differences in the number of times customers of various academic backgrounds alter their buying decisions. Distributions of frequency of decision alteration are not similar for all groups, as assessed by visual inspection of a boxplot (Figure A3). The mean ranks of frequencies are not statistically significantly different between education levels [$\chi^2(4) = 3.952$, $p = .413$] (Table 4).

D. Profession on Frequency of Decision Alteration

To determine if there are any differences in the number of times customers of various professions alter their buying decisions, a Kruskal Wallis H-test has been run. Distributions of frequency of decision alteration are not similar for all groups, as assessed by visual inspection of a boxplot (Figure A4). The mean ranks of frequencies are not statistically significantly different among professions [$\chi^2(5) = 8.239$, $p = .144$] (Table 4).

E. Household Monthly Income on Frequency of Decision Alteration

A Kruskal Wallis H-test has been conducted to determine if there are any differences in the number of times customers having different household earnings alter their buying decisions. Distributions of different income groups are not similar for all groups, as deemed by visual inspection of a boxplot (Figure A5). Separate income groups alter their purchase decisions significantly differently when they go through online reviews [$\chi^2(6) = 44.861$, $p = 0.000$] (Table 4). Subsequently, pairwise comparisons are performed with a Bonferroni correction for multiple comparisons (Figure A6). This post hoc analysis (Table A7) reveals statistically significant differences in frequency of decision alteration based on online reviews between BDT 90,001-1,10,000 (mean rank = 145.92) and BDT 70,001-90,000 (mean rank = 234.63) (p = 0.037); BDT 90,001-110,000 and BDT 10,001-30,000 (mean rank = 261.14) (p = 0.000); BDT 90,001-110,000 and BDT 30,001-50,000 (mean rank = 262.85) (p = 0.000); BDT 90,001-1,10,000 and >= BDT 1,10,001 (mean rank = 268.05), (p = 0.005); BDT 50,001-70,000 (mean rank = 185.75) and BDT 10,001-30,000 (p = 0.005); and BDT 50,001-70,000 and BDT 30,001-50,000 (p = 0.001) income groups.

Table 4 : Results of Kruskal Wallis H-tests

Hypothesis	**χ^2**	**df**	**Sig. (2-tailed)**	**Decision at α=5%**
H_{07}	21.559	5	0.001	Reject the null
H_{08}	3.952	4	0.413	Fail to reject the null
H_{09}	8.239	5	0.144	Fail to reject the null
H_{010}	44.861	6	0.000	Reject the null

4.6 Relationship between Frequency of Decision Alteration and Credibility of Online Reviews

To observe if there is any correlation between the frequency in which customers alter their purchase decision and their perception of the credibility of online reviews, Kendall's Tau-b has been applied since it measures ordinal association between concordant and discordant pairs (Kendall,1945; Siegel & Castellan, 1988). The results are summarized in Table 5. A statistically significant, positive, and moderately strong relationship has been found between the frequency of altering decisions based on online reviews and people's perception of the credibility of online reviews, τ_b = 0.306, p = 0.000. Hence, we reject H_{011} (Table 6).

In addition, correlations between age groups and income groups have been observed with frequency and credibility. Though weak, age groups reflect a statistically significant, negative association with both frequencies of choice alteration (τ_b = - 0.122, p = 0.002) and credibility of online reviews (τ_b = - 0.188, p = 0.000001). In other words, elderly people have lower levels of trust in online reviews and hence they hardly change their purchase decision based on such reviews as opposed to the younger generations. A similar outcome is obtained with monthly household income groups (τ_b = - 0.097, p = 0.010) and the number of times the decision is altered and insights of credibility (τ_b = - 0.122, p = 0.000161), indicating customers with higher monthly income have a lower level of trustworthiness on online reviews compared to those with lower family earnings. Hence, they also are not in favor of changing their opinion regarding buying or not buying a product or switching to other products based on online reviews only.

Table 5 : Correlation Result of Kendall's Tau-b Correlation

			Age Group	Household Monthly Income Group	Frequency of Altering Purchase Decisions Based on Online Review	The Credibility of Online Reviews
Kendall's Tau_b	Age group	Correlation Coefficient	1.000	.208**	-.122**	-.188**
		Sig. (2-tailed)	.	.000	.002	.000
	Household monthly income group	Correlation Coefficient	.208**	1.000	-.097**	-.142**
		Sig. (2-tailed)	.000	.	.010	.000
	Frequency of altering purchase decisions based on online review	Correlation Coefficient	-.122**	-.097**	1.000	.306**
		Sig. (2-tailed)	.002	.010	.	.000
	The credibility of online reviews	Correlation Coefficient	-.188**	-.142**	.306**	1.000
		Sig. (2-tailed)	.000	.000	.000	.

**. Correlation is significant at the 0.01 level (2-tailed).

Table 6 : Decision about Hypothesis on OR-based Purchase Decision and Credibility of OR

Hypothesis	Sig. (2-tailed)	Decision at α=5%
H_{011}	0.000	Reject the null

5. DISCUSSION AND IMPLICATIONS

This section discusses how our empirical findings relate to the existing literature and adds new perspectives to it to understand consumers' purchase decisions based on online reviews.

Our analysis shows that consumers read online reviews primarily for food, beverage, groceries, restaurants, and packaged food items (87.4%) followed by reviews for clothing and fashion accessories (76.3%). On one hand, these findings contradict the recent survey results based on the USA (Freddie, 2020) that consumers read online reviews most before they purchase technological products, while on the other hand, the findings support the argument by Vermeulen and Seegers (2008) that consumers read online review more for products whose utility can be evaluated after consumption. As with the survey, our study also found that a reasonable percentage of consumers seek information for electronic products (58.8%), accommodation (57.4%), and home appliances (48.1%), though not so significant in numbers like the USA. It reflects that a good number of consumers go through online reviews for high-involvement products and is consistent with the claim by some researchers (e.g., Elliot & Fowell, 2000). As such, our findings conform to the existing literature (e.g., Xiang et al., 2017) by clearly showing that the propensity to seek information on ORPs about a product varies across product categories.

While the existing literature (e.g., Zhang et al., 2020; Ma et al., 2022; König et al., 2022) focuses on platform designing, intervention strategies to encourage customers to review, and ORP management, our study expands the literature by finding out the preference of the consumers regarding their choice of ORPs for reading online reviews. Our study shows that the most preferred individual ORP for consumers in Bangladesh is social media (83%) followed by content community sites (69%) and retailer's sites (43%). However, we found that 85% of consumers look for multiple ORPs, i.e., before they take a decision to purchase any product, they search for reviews about the products on different online platforms. This finding indicates that most consumers lack in trust a single online review platform for which they try to validate the information they get about the product from multiple ORPs.

Researchers (e.g., Li et al., 2020; Chen et al., 2022) mostly consider that consumers review online platforms to make shopping decisions for shopping online. Counterintuitive to this usual approach of investigating usage of online reviews by consumers who shop online only, our study identified that online reviews are read by consumers for purchasing both from online and offline channels and explored how usage of those reviews varies for purchasing from various channels (online, offline, or both). We found consumers go through online reviews primarily for purchasing from online channels (56.2%). Since online reviews are read by consumers who purchase products or services physically as well (9% offline only and 34.8% both media), those organizations operating businesses only physically can, in no way, ignore online review platforms now. Again, the extant literature on online reviews barely focuses on the impact of demographic variables on the usage of such reviews. Our study contributes to this literature (e.g., Xiang et al., 2017; Rajani & Nakhat, 2019; Naujoks & Benkenstein, 2020; Zhang et al., 2020; Chen et al., 2022; Fang, 2022; Ma et al., 2022; Shen et al., 2022; Sikdar et al., 2022) by understanding the impact of demographic variables on this usage. Our study found a moderate to strong effect of gender, age, and income on the usage of online reviews for purchasing products through different shopping channels while education and occupation were found to have not so significant association. We found that females, in general, tend to check online review platforms more than males for purchasing products. We also found that younger consumers check online reviews mostly for online purchases, mid-aged consumers go through reviews before purchasing from both channels while elderly consumers mostly read online reviews for purchasing from the offline channel. Again, consumers of low income tend to check online reviews most for online purchases, consumers having an income of BDT 10,000 to BDT BDT 30,000 check online reviews for offline purchases and those, whose income range is between BDT 50,000 to BDT 70,000, go through the reviews for purchasing from both channels.

Our study also shows that more than 76% of the consumers are, to some extent, influenced by online reviews among which, around 54% change their decisions quite frequently based on online reviews. These findings are consistent with the current literature (e.g., Zhang et al., 2020; Chen et al., 2022; Fang, 2022; Ma et al., 2022) which shows that online reviews have an impact on the majority of consumers. Our study adds to this literature by investigating the impact of demographic variables on such decisions. We found that age and income have an influence on consumers in altering their decisions based on online reviews while gender, education, and occupation do not have such influence. It indicates, based on online reviews (either positive or negative), both male and female consumers alter their prior decisions at the same frequency. Similarly, for consumers of any age and of any education level, the frequency rate of changing their prior decision based on review is the same. On the other hand, the young generation (10-29 years old), senior citizens (>50 years old), and consumers of any income except high income (more than BDT 90,000) change their purchase decision frequently after going through online reviews. In this regard, our study shows there is a weak but statistically significant inverse association between age and income with the frequency of alternation of purchase decisions. As their age and income increase, they alter their decision less frequently indicating that credibility of online reviews decreases as they grow older and their income increases.

As can be seen from the preceding discussion, the article's findings added to the theory of consumer behavior (Micheal & Becker, 1973) by describing how demographic traits influence consumption behavior. The idea made suggestions about the potential influence of environmental or non-financial elements on consumer behavior. The results of our study open the door to understanding how such an impact arises. Accordingly, the findings of this research add to the body of knowledge on consumer behavior and offer rich insights for marketing professionals and policymakers. Given the upsurge of online users, e-commerce, and online marketing, organizations cannot ignore online review platforms, and understanding how demographic factors affect online purchasing decisions becomes increasingly important. Organizations can craft marketing strategies capitalizing on the insights gained related to how factors such as age, gender, income, education, and profession impact consumer decision-making based on online reviews. The study indicates that the management involved in businesses cannot ignore online reviews as consumers, irrespective of their purchasing channel, go through online reviews before they make their final decision. In addition, the identification of the preferences of ORPs by consumers and the products/services for which they look online reviews mostly would enable business managers to craft the appropriate strategies for their businesses. Similarly, as the credibility of online reviews depends on demographic variables, they would be able to adopt a segmented approach for their target markets. The findings of this study may also have implications for policy discussions related to online commerce and the need for consumer protection in the digital realm. This could be particularly relevant if certain demographics (certain age and income groups suggested by this study) are found to be more susceptible to deceptive or fraudulent online reviews.

Due to the inadequacy of the intended sample responses for some of the categories, the study was unable to adequately capture the impact of certain demographic factors, such as education, career, etc., even after selecting more participants than the necessary sample size. The problem might be resolved by using a larger sample size, however, that is questionable because the same event might occur again.

6. CONCLUSION

In addition to examining the product or service categories for which ORs are searched, this article also seeks to look at the platforms used for such searches and the impact of demographic characteristics on customers' purchasing behavior and buying decisions. The study produced several intriguing results, including the fact that most of the customers read the ORs for food, drink, and related services like restaurants. The need for ORs for clothing, accessories, beauty, and personal care products is also very high. The least popular, meanwhile, are online MOOC services. The majority of consumers do not rely on just one platform to find ORs; rather, they search for them through a variety of channels, including search engines, social media, content communities, review aggregators on merchants' websites, and so on.

Despite the widespread belief that ORs are exclusively used for internet buying, this research demonstrates that they are also useful for in-person purchases. Such behavior is also found to vary with consumers' demographic profiles like gender, age, and household monthly income. ORs can play a catalytic role in influencing consumers' choices and buying decisions and the frequency of such alteration is observed to vary with participants' age and household monthly income.

Trust in ORs might induce purchase decisions and buying behavior and hence the study investigated the association of the credibility of ORs with adjustments in a purchase decision. The study yielded that the extent to which customers alter purchase decisions is streamlined with the degree of faith they place in the ORs.

As a result, the study suggests business owners place more emphasis on assuring the quality of their goods and/or services, take ORs seriously, work on their products to cater to different demographic segments properly and, if necessary, make changes to their manufacturing processes, delivery systems, quality management, and supply chain management as a whole.

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APPENDIX

Table A1 : Products/Services Online Reviews Checked for

No.	Broad Category	Subcategory	% of online review checkers	Total (%)
1.	Food, Beverages & Groceries including Restaurants and Packaged Food Items	Restaurants	56.7	87.4
		Food	19.1	
		Beverages	4.2	
		Packaged food items	4	
		Grocery stores	3.4	
2.	Clothing & Fashion Accessories	Dress	51.4	76.3
		Jewelry	10.6	
		Shoes	8.1	
		Bags	5.6	
		Perfume	0.3	
		Watch	0.3	
3.	Beauty & Personal Care Products	Skincare	49.3	65.5
		Haircare	12.3	
		Makeup items	3.9	
4.	Electronic devices or gadgets	Smart Phones	26.4	58.8
		Laptops	14.3	
		Phone Accessories	7.8	
		Desktops	5.4	
		Laptop/desktop accessories	3.2	
		Other gadgets	1.3	
		Cameras	0.4	
5.	Accommodation	Hotel	29.4	57.4
		Resorts	20.3	
		Airbnb	7.7	
6.	Household Appliances	Refrigerators	22.1	48.1
		Air conditioners	12.3	
		Washing machines	11.4	
		Vacuum cleaners	2.3	

7.	Service Delivery Apps	Pathao parcel/food	8.8	42.6
		Daraz	7.8	
		Sheba XYZ	7.2	
		Foodpanda	6.7	
		HungryNaki	5.3	
		Shohoz	4.5	
		AjkerDeal	2.3	
8.	Ride Sharing Apps	Uber	19.6	37.3
		Pathao	15.2	
		OBHAI	2.1	
		DriveIn	0.4	
9.	Books & Stationeries	Books	26.3	29.1
		Stationery items	2.8	
10.	Financial Products/Services	-	18.4	18.4
11.	Consultancy (Business/ Financial/Legal/HR)	Business	6.8	15.6
		Financial	4.1	
		Legal	3.2	
		HR	1.5	
12.	Online MOOC Services	Coursera	4.6	12.7
		Udemy	3.6	
		Alison	3.3	
		Eshikhon.com	0.5	
		edX	0.4	
		FutureLearn	0.3	

Table A2 : Types of Purchases

Shopping Channels	**Frequency**	**Percent**
Online	255	56.2
Offline	41	9.0
Both	158	34.8
Total	454	100

Table A3 : Types of Purchases across Gender, Age, Education, Occupation, & Income

			Types of Purchases			
			Online	**Offline**	**Both**	**Total**
Gender	Male	Count	157	20	65	242
		% within Gender	64.9%	8.3%	26.9%	100.0%
	Female	Count	98	21	93	212
		% within Gender	46.2%	9.9%	43.9%	100.0%
Age Group (in years)	10-19	Count	11	0	10	21
		Expected Count	11.8	1.9	7.3	21.0
		% within Age Group (in years)	52.4%	0.0%	47.6%	100%
	20-29	Count	124	20	40	184
		Expected Count	103.3	16.6	64.0	184.0
		% within Age Group (in years)	67.4%	10.9%	21.7%	100%
	30-39	Count	48	9	43	100
		Expected Count	56.2	9.0	34.8	100.0
		% within Age Group (in years)	48.0%	9.0%	43.0%	100.0%
	40-49	Count	35	11	29	75
		Expected Count	42.1	6.8	26.1	75.0
		% within Age Group (in years)	46.7%	14.7%	38.7%	100.0%
	50-59	Count	24	1	36	61
		Expected Count	34.3	5.5	21.2	61.0
		% within Age Group (in years)	39.3%	1.6%	59.0%	100.0%
	>=60	Count	13	0	0	13
		Expected Count	7.3	1.2	4.5	13.0
		% within Age Group (in years)	100.0%	0.0%	0.0%	100.0%
Educational Qualification	Secondary level (SSC/ O-level)	Count	11	0	10	21
		Expected Count	11.8	1.9	7.3	21.0
		% within Educational Qualification	52.4%	0.0%	47.6%	100.0%
	Higher Secondary level (HSC/ A-level)	Count	36	9	14	59
		Expected Count	33.1	5.3	20.5	59.0
		% within Educational Qualification	61.0%	15.3%	23.7%	100.0%
	Bachelor	Count	111	17	62	190
		Expected Count	106.7	17.2	66.1	190.0
		% within Educational Qualification	58.4%	8.9%	32.6%	100.0%

	Masters	Count	90	13	72	175
		Expected Count	98.3	15.8	60.9	175.0
		% within Educational Qualification	51.4%	7.4%	41.1%	100.0%
	Other	Count	7	2	0	9
		Expected Count	5.1	.8	3.1	9.0
		% within Educational Qualification	77.8%	22.2%	0.0%	100.0%
Profession	Public Service	Count	25	2	23	50
		Expected Count	28.1	4.5	17.4	50.0
		% within Profession	50.0%	4.0%	46.0%	100.0%
	Private Service	Count	100	15	99	214
		Expected Count	120.2	19.3	74.5	214.0
		% within Profession	46.7%	7.0%	46.3%	100.0%
	Student	Count	67	1	28	96
		Expected Count	53.9	8.7	33.4	96.0
		% within Profession	69.8%	1.0%	29.2%	100.0%
	Business	Count	39	5	0	44
		Expected Count	24.7	4.0	15.3	44.0
		% within Profession	88.6%	11.4%	0.0%	100.0%
	Homemaker	Count	18	18	3	39
		Expected Count	21.9	3.5	13.6	39.0
		% within Profession	46.2%	46.2%	7.7%	100.0%
	Other	Count	6	0	5	11
		Expected Count	6.2	1.0	3.8	11.0
		% within Profession	54.5%	0.0%	45.5%	100.0%
Household Monthly Income (in BDT)	=<10000	Count	63	3	14	80
		Expected Count	44.9	7.2	27.8	80.0
		% within Income Group (in BDT)	78.8%	3.8%	17.5%	100.0%
	10001-30000	Count	51	14	19	84
		Expected Count	47.2	7.6	29.2	84.0
		% within Income Group (in BDT)	60.7%	16.7%	22.6%	100.0%
	30001-50000	Count	59	6	46	111
		Expected Count	62.3	10.0	38.6	111.0
		% within Income Group (in BDT)	53.2%	5.4%	41.4%	100.0%
	50001-70000	Count	27	5	44	76
		Expected Count	42.7	6.9	26.4	76.0
		% within Income Group (in BDT)	35.5%	6.6%	57.9%	100.0%

	70001-90000	Count	13	7	14	34
		Expected Count	19.1	3.1	11.8	34.0
		% within Income Group (in BDT)	38.2%	20.6%	41.2%	100.0%
	900001-110000	Count	27	4	17	48
		Expected Count	27.0	4.3	16.7	48.0
		% within Income Group (in BDT)	56.3%	8.3%	35.4%	100.0%
	>=110001	Count	15	2	4	21
		Expected Count	11.8	1.9	7.3	21.0
		% within Income Group (in BDT)	71.4%	9.5%	19.0%	100.0%

Table A4 : Types of Purchases across Age, Education, Occupation, & Income (reduced samples)

			Types of Purchases			
			Online	**Offline**	**Both**	**Total**
Age Group (in years)	20-29	Count	124	20	40	184
		% within Age Group	67.4%	10.9%	21.7%	100.0%
		% within types of purchases	59.9%	50.0%	35.7%	51.3%
	30-39	Count	48	9	43	100
		% within Age Group	48.0%	9.0%	43.0%	100.0%
		% within types of purchases	23.2%	22.5%	38.4%	27.9%
	40-49	Count	35	11	29	75
		% within Age Group	46.7%	14.7%	38.7%	100.0%
		% within types of purchases	16.9%	27.5%	25.9%	20.9%
Total		Count	207	40	112	359
		% within Age Group	57.7%	11.1%	31.2%	100.0%
		% within types of purchases	100.0%	100.0%	100.0%	100.0%
Educational Qualification	Higher Secondary level (HSC/ A-level)	Count	36	9	14	59
		% within Educational Qualification	61.0%	15.3%	23.7%	100.0%
		% within types of purchases	15.2%	23.1%	9.5%	13.9%
	Bachelor	Count	111	17	62	190
		% within Educational Qualification	58.4%	8.9%	32.6%	100.0%
		% within types of purchases	46.8%	43.6%	41.9%	44.8%
	Masters	Count	90	13	72	175
		% within Educational Qualification	51.4%	7.4%	41.1%	100.0%
		% within types of purchases	38.0%	33.3%	48.6%	41.3%
Total		Count	237	39	148	424
		% within Educational Qualification	55.9%	9.2%	34.9%	100.0%
		% within types of purchases	100.0%	100.0%	100.0%	100.0%

Household Monthly Income Group (in BDT)	=<10000	Count	63	3	14	80
		% within Household Monthly Income Group	78.8%	3.8%	17.5%	100.0%
		% within types of purchases	31.5%	10.7%	11.4%	22.8%
	10001-30000	Count	51	14	19	84
		% within Household Monthly Income Group	60.7%	16.7%	22.6%	100.0%
		% within types of purchases	25.5%	50.0%	15.4%	23.9%
	30001-50000	Count	59	6	46	111
		% within Household Monthly Income Group	53.2%	5.4%	41.4%	100.0%
		% within types of purchases	29.5%	21.4%	37.4%	31.6%
	50001-70000	Count	27	5	44	76
		% within Household Monthly Income Group	35.5%	6.6%	57.9%	100.0%
		% within types of purchases	13.5%	17.9%	35.8%	21.7%
Total		Count	200	28	123	351
		% within Household Monthly Income Group	57.0%	8.0%	35.0%	100.0%
		% within types of purchases	100.0%	100.0%	100.0%	100.0%

Table A5 : Frequency of Altering Purchase Decisions Based on Online Review

Responses	**Frequency**	**Percent**
Never	40	8.8
Rarely	68	15.0
Sometimes	101	22.2
Often	164	36.1
Always	81	17.8
Total	454	100.0

Figure A1 : Boxplot-Frequency of Altering Purchase Decision across Age Groups

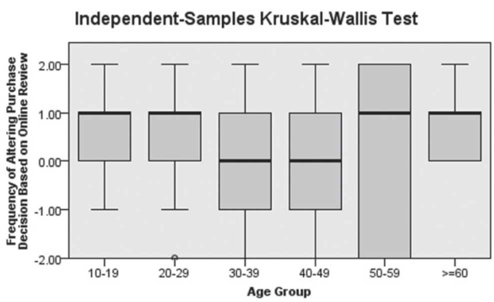


Figure A2 : Pairwise Comparisons of Age Group

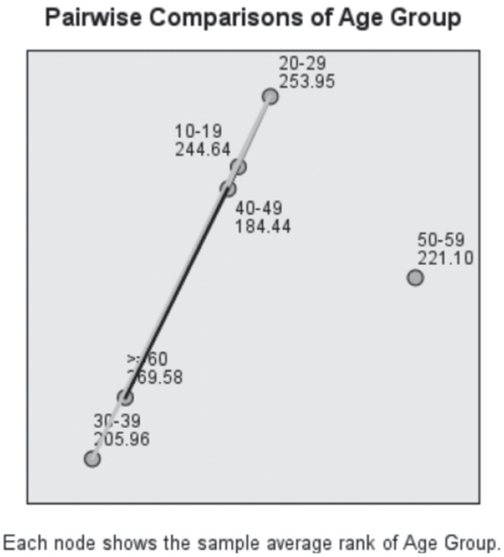


Table A6 : Results of Post Hoc Analysis of Pairwise Comparisons of Age Group

Sample1-Sample2	Test Statistic	Std. Error	Std. Test Statistic	Sig.	Adj.Sig.
40-49-30-39	21.515	19.350	1.112	.266	1.000
40-49-50-59	-36.658	21.840	-1.678	.093	1.000
40-49-10-19	60.203	31.274	1.925	.054	.813
40-49-20-29	69.514	17.354	4.006	.000	.001
40-49->=60	-85.137	38.056	-2.237	.025	.379
30-39-50-59	-15.143	20.579	-.736	.462	1.000
30-39-10-19	38.688	30.406	1.272	.203	1.000
30-39-20-29	47.999	15.737	3.050	.002	.034
30-39->=60	-63.622	37.346	-1.704	.088	1.000
50-59-10-19	23.544	32.049	.735	.463	1.000
50-59-20-29	32.855	18.715	1.756	.079	1.000
50-59->=60	-48.479	38.696	-1.253	.210	1.000
10-19-20-29	-9.311	29.177	-.319	.750	1.000
10-19->=60	-24.934	44.703	-.558	.577	1.000
20-29->=60	-15.623	36.353	-.430	.667	1.000

Figure A3 : Boxplot-Frequency of Altering Purchase Decision across Education Levels

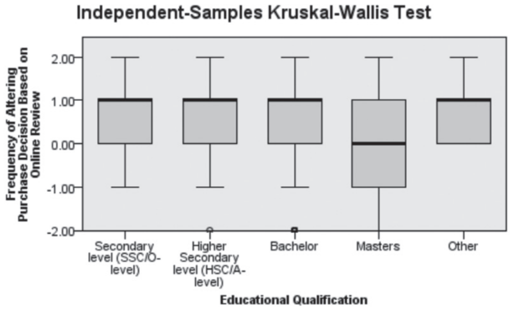


Figure A4 : Boxplot-Frequency of Altering Purchase Decision across Occupation

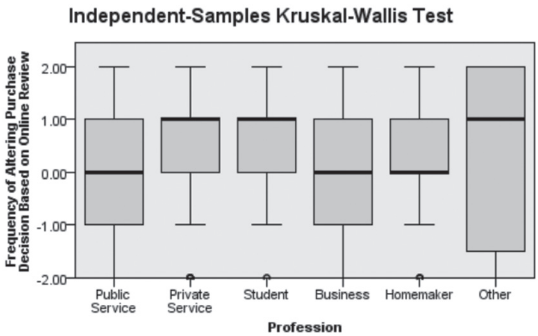


Figure A5 : Boxplot-Frequency of Altering Purchase Decision across Monthly Household Income

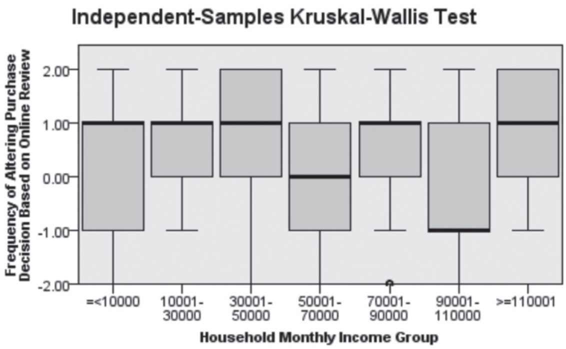
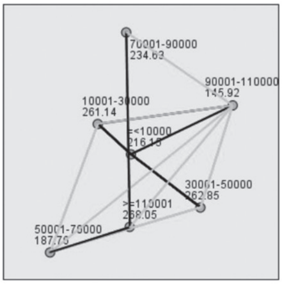


Figure A6 : Pairwise Comparisons of Income Group

Pairwise Comparisons of Household Monthly Income Group



Each node shows the sample average rank of Household Monthly Income Group.

Table A7 : Results of Post Hoc Analysis of Pairwise Comparisons of Income Group

Sample1-Sample2	Test Statistic	Std. Error	Std. Test Statistic	Sig.	Adj.Sig.
90001-110000-50001-70000	41.846	23.354	1.792	.073	1.000
90001-110000-<=10000	70.233	23.127	3.037	.002	.050
90001-110000-70001-90000	88.716	28.394	3.124	.002	.037
90001-110000-10001-30000	115.226	22.920	5.027	.000	.000
90001-110000-30001-50000	116.935	21.883	5.344	.000	.000
90001-110000->=110001	-122.131	33.142	-3.685	.000	.005
50001-70000-<=10000	28.387	20.290	1.399	.162	1.000
50001-70000-70001-90000	-46.869	26.136	-1.793	.073	1.000
50001-70000-10001-30000	73.380	20.054	3.659	.000	.005
50001-70000-30001-50000	75.088	18.860	3.981	.000	.001
50001-70000->=110001	-80.284	31.229	-2.571	.010	.213
<=10000-70001-90000	-18.482	25.933	-.713	.476	1.000
<=10000-10001-30000	-44.993	19.789	-2.274	.023	.483
<=10000-30001-50000	-46.701	18.578	-2.514	.012	.251
<=10000->=110001	-51.898	31.059	-1.671	.095	1.000
70001-90000-10001-30000	26.511	25.748	1.030	.303	1.000
70001-90000-30001-50000	28.219	24.829	1.137	.256	1.000
70001-90000->=110001	-33.415	35.157	-.950	.342	1.000
10001-30000-30001-50000	-1.708	18.319	-.093	.926	1.000
10001-30000->=110001	-6.905	30.905	-.223	.823	1.000
30001-50000->=110001	-5.196	30.144	-.172	.863	1.000