

**INFLUENCE OF ONLINE REVIEWS ON GEN Z
CONSUMERS**

WITH REFERENCE TO APPARELS

Thesis Submitted for the Award of the Degree of

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in

COMMERCE

By

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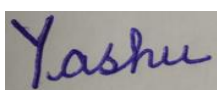


LOVELY PROFESSIONAL UNIVERSITY, PUNJAB

2026

DECLARATION

I, hereby declared that the presented work in the thesis entitled “**INFLUENCE OF ONLINE REVIEWS ON GEN Z CONSUMERS WITH REFERENCE TO APPARELS**” in fulfilment of degree of **Doctor of Philosophy (Ph. D.)** is outcome of research work carried out by me under the supervision of **Dr. Krishan Gopal**, working as **Associate Professor (Marketing)**, in the **Department of Commerce** of Lovely Professional University, Punjab, India. In keeping with general practice of reporting scientific observations, due acknowledgements have been made whenever work described here has been based on findings of other investigator. This work has not been submitted in part or full to any other University or Institute for the award of any degree.



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Name of the scholar: Yashu

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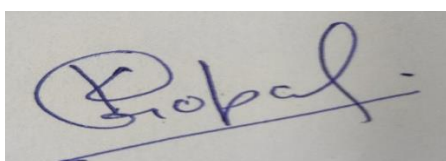
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Punjab, India

CERTIFICATE

This is to certify that the work reported in the Ph. D. thesis entitled “**INFLUENCE OF ONLINE REVIEWS ON GEN Z CONSUMERS WITH REFERENCE TO APPARELS**” submitted in fulfillment of the requirement for the award of degree of **Doctor of Philosophy (Ph.D.)** in the **Department of Commerce / Mittal School of Business**, is a research work carried out by **Yashu**, reg no-**12116752**, is bonafide record of his/her original work carried out under my supervision and that no part of thesis has been submitted for any other degree, diploma or equivalent course.



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Abstract

The research titled ‘Influence of Online Reviews on Gen Z Consumers with reference to Apparels’ investigates how online reviews impact the purchasing decisions of Generation Z consumers in Punjab, India, specifically within the apparel industry. This study was specifically initiated to focus on the apparel industry, as today's Gen Z consumers show a strong inclination toward the fashion sector. Internet penetration in India is steadily rising, making the country the second largest in terms of active users. This growing user base is driving technological advancements, enhancing digital literacy, and strengthening digital connectivity in the everyday lives of millions of Indians. The internet enables people to easily communicate, access entertainment, and pursue education. These advancements have created new opportunities for both consumers and businesses. E-commerce, in particular, has revolutionized the global business landscape, including in India. E-commerce allows consumers not only to buy and sell products but also to collaborate with business partners, while organizations can carry out electronic transactions internally. There are various e-commerce business models, including business-to-consumer (B2C), business-to-business (B2B), consumer-to-consumer (C2C), consumer-to-business (C2B), government-to-business (G2B), and government-to-citizen (G2C). In the business-to-consumer (B2C) model, a direct relationship is formed between companies and their customers. In contrast, the business-to-business (B2B) model involves transactions between two companies. This sector is experiencing faster growth compared to other industries. In the consumer-to-consumer (C2C) model, individuals sell products directly to other consumers through online platforms. The consumer-to-business (C2B) model reverses the traditional roles, with consumers offering goods or services to businesses. In the government-to-business (G2B) model, government bodies provide services and information to companies, while the government-to-citizen (G2C) model facilitates direct interaction between government agencies and citizens. E-commerce in India is expanding rapidly, with the market projected to reach \$350 billion by 2030. In 2022, it experienced a growth rate of 21.5%, reaching \$74.8 billion, and is expected to hit \$300 billion by 2030. Online shopping is increasingly becoming the preferred choice for consumers, as they now opt to purchase everything from groceries to clothing online. As consumer preferences shift, more people are embracing online shopping, finding it more convenient and time-efficient compared to traditional shopping.

methods. According to the IBEF India had the third-largest base of online shoppers, with 150 million in FY 2021, following China and the US, and this number is projected to grow to 350 million by FY 2026. Online shopping enables consumers to interact with vendors around the clock, easily access information, and place orders with minimal effort. Traditionally, consumers shared information verbally with friends, colleagues, and family. This word-of-mouth communication involves exchanging opinions about a company's products or services, which can be either positive or negative. Word-of-mouth is an informal exchange between a buyer and a sender, where they discuss products and services without any commercial intent. However, with the advent of the internet, the impact of word-of-mouth has dramatically evolved. Consumers can now share their experiences with others digitally. Advances in technology have led to the creation of social networks, enabling customers to access product and service information from companies without being limited by geography or time, significantly shaping consumer decision-making behavior. Consumers can now easily access information online and are increasingly influenced by interpersonal interactions due to the abundance of data available across various digital platforms. Online reviews, a type of electronic word-of-mouth, consist of peer evaluations of product quality, which are posted on company or third-party websites. These reviews are a crucial component of eWOM, typically generated by users but sometimes by experts as well. Customers often share their experiences and assessments of products purchased from specific companies or e-commerce platforms. Online customer reviews have become essential for offering personal recommendations to fellow consumers. They are increasingly valued by businesses, marketers, travellers, and researchers. This thesis focuses on online reviews within the apparel industry, specifically those posted by consumers on e-commerce platforms like Amazon, Flipkart, Meesho, Myntra, and Ajio. Generation Z, born between 1995 and 2012, is often characterized as a group of digital natives who are deeply engaged with technology. This generation is known for being highly educated, tech-savvy, and inherently creative, with a strong inclination towards self-expression, adventure, and personal fulfillment. Online reviews are increasingly impactful for Generation Z, as they actively share their experiences and engage in extensive research prior to making purchasing decisions. The clothing and fashion market has evolved into a flourishing sector, drawing significant investments from both established and emerging online apparel brands. According to Statista, revenue in India's apparel market is anticipated

to reach \$105.50 billion by 2024, with a projected annual growth rate of 3.81% (CAGR) from 2024 to 2028. The growing penetration of the internet and smartphones is enhancing access to online services and digital platforms, making online apparel shopping increasingly convenient. Shopping for clothing online has become akin to searching for product information prior to making a purchase. This study targets Generation Z in Punjab, India, specifically individuals aged 18 to 29 who engage in online apparel shopping. A multi-stage sampling method was used for this research, with data collected from the districts of Amritsar, Jalandhar, Ludhiana, Gurdaspur, Ferozepur and Hoshiarpur. Taking a quantitative approach, the study involved reaching out to respondents through personal contact, email, Telegram, WhatsApp, and mobile internet. From an initial distribution of 700 questionnaires, a final sample of 600 respondents was selected. To meet the study's objectives, factor analysis, SPSS and SEM-PLS were employed. The study examined the motivations behind reading online reviews on opinion platforms, revealing three key factors based on the literature review: Right Product Choice (Factor 1), Product Information (Factor 2), and Risk Reduction (Factor 3). Factor 1, Right Product Choice, emphasizes the importance of selecting the right product amid a multitude of options, where online reviews can provide significant assistance. Factor 2, Product Information, highlights that the information found in advertisements and product descriptions may not always present the complete picture, making accurate product information crucial for informed buying decisions. Factor 3, Risk Reduction, indicates that minimizing risk is essential for making knowledgeable purchases, with online reviews serving as an effective tool in this regard. Reading reviews before making a purchase enables consumers to benefit from the experiences of others. Confirmatory factor analysis indicated that all items aligned correctly with their respective factors. The findings regarding the impact of online reviews on Generation Z's purchase intentions revealed that factors such as quality of the reviews, quantity of the reviews, source credibility, review credibility, the usefulness of online reviews, and overall reviews positively and significantly influence their purchasing decisions. Online reviews serve as essential tools for consumers, providing practical insights and experiences that can help guide their buying choices. Online reviews offer extensive information regarding the quality, functionality, and satisfaction related to a product or service. The study examined the moderating effect of gender on the relationship between online reviews and the purchase intentions of Generation Z consumers using multigroup analysis.

This gender moderation analysis indicated that gender significantly influences the relationship between online reviews and purchase intentions. The results showed that in certain aspects of online reviews, males had a positive and significant impact, while in other aspects, females demonstrated a similar positive effect. Additionally, the study explored the impact of online reviews on the satisfaction of Gen Z consumers through the lens of Expectation Disconfirmation Theory (EDT). The findings revealed that online reviews positively and significantly affect consumer satisfaction. Positive disconfirmation occurs when a product's performance surpasses consumer expectations, often leading to high satisfaction levels. On the other hand, negative disconfirmation occurs when a product does not meet expectations, resulting in consumer dissatisfaction. Customers play a vital role in the success of any business, and today, companies are increasingly targeting Generation Z, who are significantly influenced by social media. This research is particularly valuable as it highlights the key ways in which online reviews impact purchase intentions, providing businesses with actionable insights to improve their utilization of online reviews. E-commerce platforms such as Amazon, Myntra, Flipkart, Meesho, and Ajio can leverage the findings of this study to better engage with Gen Z consumers in emerging markets by sharing high-quality, authentic content.

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LIST OF ABBREVIATIONS

IBEF	India Brand Equity Foundation
IAMAI	Internet and Mobile Association of India
CAGR	Compound Annual Growth Rate
TRAI	Telecom Regulatory Authority of India
OECD	Organization for Economic Co-operation and Development
WHO	World Health Organization
B2C	Business to Customer
B2B	Business to Business
C2C	Customer to Customer
C2B	Customer to Business
G2B	Government to Business
G2C	Government to Citizen
E-Commerce	Electronic Commerce
COD	Cash on Delivery
EMI	Instalment Payment Options
WOM	Word of Mouth
E-WOM	Electronic Word of Mouth
VR	Virtual Reality
OCRs	Online Consumer Reviews

RQn	Review Quantity
AR	Augmented Reality
CVR	Content Validity Ratio
CV	Content Validity
RQ	Review Quality
SC	Source Credibility
UOR	Usefulness of Online Reviews
RC	Review Credibility
PI	Purchase Intention
EP	Expectation
PP	Perceived Performance
DC	Disconfirmation
S	Satisfaction
EDT	Expectation Disconfirmation Theory
SPSS	Statistical Package for Social Science
EFA	Exploratory Factor Analysis
CFA	Confirmatory Factor Analysis
PLS-SEM	Partial Least Square- Structural Equation Modeling
IV	Independent Variable
DV	Dependent Variable
MGA	Multigroup Analysis

KMO	Kaiser- Meyer- Olkin
RPC	Right Product Choice
PIn	Product Information
RR	Risk Reduction
C.R.	Critical Ratio
S.E.	Standard error
GFI	Goodness of Fit Index
AGFI	Adjusted Goodness of Fit Index
NFI	Normal Fit Index
TLI	Tucker Lewis Index
CFI	Comparative Fit Index
RMR	Root Mean Square Residual
RMSEA	Root Mean Square Error of Approximation
DF	Degree of Freedom
MICOM	Measurement Invariance for Composite Model
R2	Coefficient of Determination
Q2	Predictive Relevance
SRMR	Standardized Root Mean Square Residual
HTMT	Heterotrait-Monotrait ratio
HOC	Higher Order Construct
LOC	Lower Order Construct

VIF	Variance Inflation Factor
AVE	Average Variance Explained
CV-PAT	Cross- Validated Predictive Ability Test
IA	Indicator Average
LM	Linear Model
M	Sample Mean
STDEV	Standard Deviation
O	Original Sample
CMV	Common Method Variance

Chapter 1

INTRODUCTION

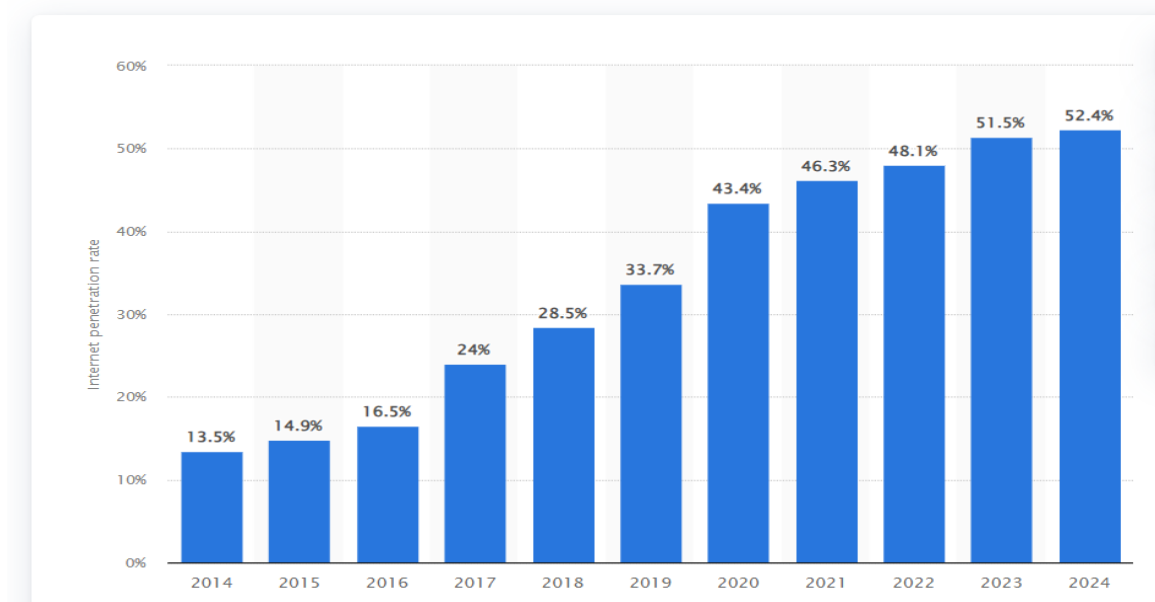
1.1 Internet users in India

India has witnessed a significant surge in internet and smartphone penetration in recent years. A Statista report (2024) in figure 1.1 highlights that the internet penetration rate in India increased to over 52 percent in 2024, a substantial rise from approximately 14 percent in 2014. While these percentages may appear modest, they represent a significant milestone, as more than half of the nation's 1.4 billion people had internet access that year. This achievement positioned India as the second-largest country globally in terms of active internet users. By 2021, the number of internet connections across the country had tripled, with urban areas exhibiting a higher concentration of connections compared to rural regions. According to the India Brand Equity Foundation (IBEF) report, as of June 2023, the total number of internet connections in India surged to 895 million, largely propelled by the 'Digital India' initiative. Of these connections, 55% were in urban areas, with an overwhelming 97% being wireless. The proliferation of smartphones has also been remarkable, with the smartphone user base projected to reach 1.1 billion by 2025. A report from IAMAI and Kantar Research anticipates that the number of internet users in India will climb to 900 million by 2025, up from around 622 million in 2020, marking a compound annual growth rate (CAGR) of 45% until 2025 reported by The Economic Times. Furthermore, the TRAI indicated that, as of 2023, internet penetration in India exceeded 954 million, and the number of telecom subscribers had risen to over 1.2 billion by May 2024. Despite the exceptionally low cost of internet services, there is still significant potential for further growth in internet usage across the country (Kalia et al., 2018; N. Kumar et al., 2018). With one of the largest populations of internet users globally, India is a hub of digital activity, with countless online interactions occurring every moment. The rapid increase in internet users and smartphone adoption, combined with rising incomes, has been a driving force behind the exponential growth of India's e-commerce sector (Das & Ara, 2015; Khosla & Kumar, 2017; Panigrahi et al., 2016). This growth is expected to continue as technological advancements and digital literacy improve, further integrating digital connectivity into the daily lives of millions of Indians. Growth in internet access is often driven by

advancements in technology, affordable data plans, and widespread use of smartphones (Angmo et al., 2024; Anuj et al., 2018; Balachandar & Devi, 2024; M. Singh et al., 2024). Increased internet penetration plays a crucial role in bridging the digital divide and promoting economic development by connecting more people to global opportunities. Additionally, government initiatives focused on expanding digital infrastructure and promoting online services are likely to accelerate this trend, making India a key player in the global digital economy (Ahmed & Joshi, 2024; Khandelwal, 2024; R. K. Singh, 2019).

Figure 1.1 Internet Penetration rate in India from 2014 to 2024

Internet penetration rate in India from 2014 to 2024



Source: Statista.com <https://www.statista.com/statistics/792074/india-internet-penetration-rate>

1.2 E-Commerce

The internet has long been recognized as a platform for communication, entertainment and education. In recent years, it has also emerged as a marketplace for the exchange of goods and services between buyers and sellers (Amit & Zott, 2017; Anvari & Norouzi, 2016; Menaka & Seethal, 2018). This development has opened up new opportunities for both consumers and businesses. E-commerce has brought about a significant transformation in the global business landscape, including in India. E-commerce and e-business have grown to be essential elements of business strategy in

today's global economy and are significant drivers of economic growth (Angmo et al., 2024; Asbari, 2023; Balachandar & Devi, 2024). The integration of ICT into business operations has transformed the way organizations and individuals within those organizations collaborate and form partnerships. Transforming into an e-business involves facilitating collaboration, information sharing, and electronic transactions among employees, business partners, suppliers, and customers (Balachandar & Devi, 2024). This approach enhances the organization's efficiency in delivering value. However, this definition leans heavily towards marketing, emphasizing employee empowerment and partnerships as if promoting a product or service. In 1998, the World Trade Organization described E-Commerce as, E-Commerce is the production, distribution, marketing, sales or delivery of goods and services by electronic means. In 1997, The OECD E-Commerce defines as “commercial transactions, involving both organizations and individuals, that are based upon the processing and transmission of digitized data, including text, sound and visuals images that are carried out over open networks (like, the internet) or closed networks (like, AOL or Mintel) that have gateway on to an open network.” According to Turban 2001 E-commerce is an emerging concept that describes the process of buying, selling, or exchanging products, services and information via computer networks, including the Internet. E-business refers to a broader definition of E-commerce, not just the buying and selling of goods and services, but also servicing customers, collaborating with business partners, and conducting electronic transactions within an organization. E-commerce is the process of buying, selling, or exchanging products, services and information via computer networks, including the Internet (Bhatti et al., 2020) E-Commerce is beneficial for both consumers and businesses. There are various types of models within Electronic Commerce, which are outlined below:

1.2.1 Business to Customer (B2C):

The B2C model relates to the retail sector of electronic commerce, focusing on the establishment of commercial electronic relationships between companies and individual consumers (Jiang et al., 2016; Mangiaracina et al., 2015). Essentially, it involves direct transactions between businesses and end customers. In this model, companies offer their goods and services online, which consumers purchase for personal use. Customers can gather information and buy physical products like electronics or digital items such as software, e-books etc. via the internet (S. S. Li &

Karahanna, 2015; Mangiaracina et al., 2019). A defining feature of the B2C e-commerce model is the open access customers have to online shops or business to consumer websites. The scope of B2C e-commerce covers areas such as online travel, financial services, digital downloads, and online retail services (Y. Choi & Mai, 2018; Giuffrida et al., 2017; K. H. Leung et al., 2018). B2C online shops often feature customer-specific pricing and discounts based on customer preferences (Jiang et al., 2016; Skare et al., 2023). This model also reduces transaction costs, particularly search costs, by enhancing consumer access to information and enabling them to find the best prices for products or services (Skare et al., 2023). Additionally, Business to Consumer e-commerce lowers market entry barriers, as setting up and maintaining a website is much more cost-effective.

1.2.2 Business to Business (B2B):

B2B e-commerce refers to electronic commerce conducted between businesses. This model focuses on the interactions and transactions between companies, accounting for approximately 80% of all e-commerce activities (Alsaad et al., 2021; Hamad et al., 2015; Skare et al., 2023). Experts anticipate that the B2B sector will continue to grow at a faster rate than the B2C segment. B2B e-commerce includes all electronic transactions between businesses, and in some cases, these transactions occur between virtual companies with no physical presence, conducted entirely online (Lahkani et al., 2020; Mohtaramzadeh et al., 2018; Ocloo et al., 2020; Prajapati et al., 2022; Qu et al., 2015). Notable examples of successful B2B models include companies like IBM, Amazon, Microsoft, and Adobe. Research in this field highlights three key areas of Business-to-Business e-commerce: E-Marketplace, E-Procurement, and E-Distribution (Hamad et al., 2015).

1.2.3 Customer to Customer (C2C):

C2C e-commerce refers to the process where individuals or customers sell goods directly to other consumers through online platforms, such as auction websites (Chandan & Gupta, 2018; Khosla & Kumar, 2017; R. K. Singh, 2019; Yadav & Singh, 2020). This segment of e-commerce is rapidly expanding and holds significant potential for developing new markets. Essentially, C2C involves trade between private individuals (Bhagat, 2020; Chandra, 2021). C2C e-commerce represents a growing

area characterized by the rise of electronic marketplaces, particularly within specific industries where businesses can bid on products from various suppliers (Kalia et al., 2018; Mahajan & Agarwal, 2015). This model can be divided into three categories: 1) Auctions, 2) Peer-to-Peer systems, and 3) Classified Ads.

1.2.4 Customer to Business (C2B):

The Consumer-to-Business (C2B) model refers to transactions where the roles of buyers and sellers are reversed compared to the traditional B2C model (Kumari, 2016). In this setup, the consumer acts as the seller, while the business organization becomes the buyer. Unlike the B2C model, where the business sets the price, in the C2B model, the consumer has control over pricing (Bhagat, 2020; Satheeshkumar et al., 2022). This model is particularly effective for scenarios where consumers offer services rather than physical goods. Consumers use online platforms to market their products or services to companies that might be interested in purchasing them. C2B includes activities like online comparison shopping, where users research products before making a purchase (Chandra, 2021; Prasanth & Jyothsna, 2018; Satheeshkumar et al., 2022). This model is gaining traction as businesses seek to tap into the individual talents and resources of consumers. Additionally, the flexibility of the C2B model allows consumers to negotiate prices, potentially leading to more personalized and mutually beneficial transactions (Bhagat, 2020; Chandra, 2021).

1.2.5 Government to Business (G2B):

Government-to-Business (G2B) e-commerce is a model where government entities provide information and services directly to business organizations. This exchange typically occurs through an extensive network of government websites, allowing businesses to access necessary data and services efficiently (Nandankar & Sachan, 2023; Raziei, 2020). The G2B model serves as a crucial link between the public sector and private enterprises, streamlining interactions such as regulatory compliance, tax filing and licensing. By offering a centralized platform for these services, governments can improve transparency and reduce the administrative burden on businesses (Ding, 2016; J. M. Joshi & Dumbre, 2017). This model also encourages greater efficiency in government operations, as digital platforms enable faster communication and processing of business-related requests (Taherdoost, 2023; Thakur et al., 2020). Additionally, G2B e-commerce supports economic growth by

providing businesses with up-to-date information on regulations, available incentives, and opportunities for collaboration on public projects. It also facilitates a smoother, more organized flow of transactions between the government and private sector, ultimately fostering a more favorable environment for business development (Satheeshkumar et al., 2022).

1.2.6 Government to Citizen (G2C):

The Government-to-Citizen (G2C) model was designed to establish a direct link between government agencies and citizens. This approach aims to minimize the time required to handle various requests related to different government departments. By using G2C platforms, citizens can access services such as marriage and birth registration, filing returns and tax payments more efficiently (Balaraman & Chandrasekar, 2016; Sohrabi & Khanlari, 2015). G2C websites are primarily focused on streamlining the process of servicing public requests, thereby reducing delays and improving overall user experience. These platforms facilitate quicker access to essential services and information, enhancing the convenience for citizens (Jabar & Ogunsola, 2022; Jedrzejczak-Gas et al., 2019; Rachbini et al., 2021). Moreover, the G2C model promotes greater transparency and accessibility, as individuals can perform various government-related tasks online without needing to visit physical offices. By leveraging digital technology, the G2C model helps to lower administrative costs for government agencies and provides a more responsive and user-friendly interface for the public (Balaraman & Chandrasekar, 2016; Jabar & Ogunsola, 2022). This efficiency not only benefits citizens but also contributes to better overall governance and service delivery.

1.3 E-Commerce in India

The initial phase of e-commerce in India faced numerous challenges, including low internet access, a limited number of online shoppers, sluggish internet speeds, low consumer trust in online shopping, and an underdeveloped logistics network (Asbari, 2023; Chandan & Gupta, 2018; Leung et al., 2018; Panigrahi et al., 2016; Prasanth & Jyothsna, 2018; Skare et al., 2023; Yadav & Singh, 2020). However, with the rapid expansion of e-commerce in the country, small businesses now have an unprecedented opportunity to engage in online shopping. E-commerce has become a critical tool for businesses today. Indian e-commerce companies offer some of the most effective and

secure e-commerce solutions, ensuring both the privacy and safety of their websites (Alsaad et al., 2018; Amit & Zott, 2017; Babenko et al., 2019; Bhatti et al., 2020). The swift rise of the Internet has significantly enhanced the potential of e-commerce, and it is widely acknowledged that the Internet and e-commerce will revolutionize traditional business practices and consumer behavior. India's e-commerce sector has dramatically altered the business landscape, opening up various commerce segments, including B2B, D2C, C2C, and C2B (Akter & Wamba, 2016; Alsaad et al., 2018; Chandan & Gupta, 2018; Hamad et al., 2015; K. H. Leung et al., 2018). Key segments like D2C and B2B have seen significant growth in recent years. According to the IBEF D2C market in India is projected to reach US\$ 60 billion by FY27. The overall e-commerce market is anticipated to reach US\$ 350 billion by 2030, with a growth rate of 21.5% in 2022, reaching US\$ 74.8 billion. Figure 1.2 shows that the Indian e-commerce industry is expected to grow significantly, potentially reaching US\$ 300 billion by 2030.

According to the Invest India the Quick E-Commerce market in India is set for rapid expansion, with projections indicating it could reach US\$ 19,932.5 million, driven by the increasing internet and smartphone usage, the convenience of quick deliveries, and accelerated adoption during the COVID-19 pandemic across various product categories and order value segments. According to Grant Thornton, India's e-commerce sector could be valued at US\$ 188 billion by 2025. Urban Indian consumers are experiencing increasing purchasing power, and branded goods across categories like apparel, cosmetics, footwear, watches, beverages, food, and jewellery are becoming increasingly popular. A Deloitte India Report suggests that as India moves toward becoming the third-largest consumer market globally, its online retail market could reach US\$ 325 billion by 2030, up from US\$ 70 billion in 2022, largely due to the rapid growth of e-commerce in tier-2 and tier-3 cities. The Indian e-commerce industry is thriving due to factors such as increased smartphone penetration, rising affluence, and low data costs, which are driving the growth of e-retail (Fusilier & Durlabhji, 2005; Panigrahi et al., 2016; Raport & Jaworski, 2001; V. Santos et al., 2023). With over 950 million users, India is the second-largest internet market globally, recording 131.16 lakh crore UPI transactions in FY 2023-24. According to the Statista Report expanding internet user base and favorable market conditions, India's e-commerce industry holds significant potential. The market value

of India's e-commerce sector grew rapidly, reaching 123 billion U.S. dollars in 2024, with projections estimating it could rise to 300 billion U.S. dollars by 2030.

Figure 1.2: Indian E-commerce Market

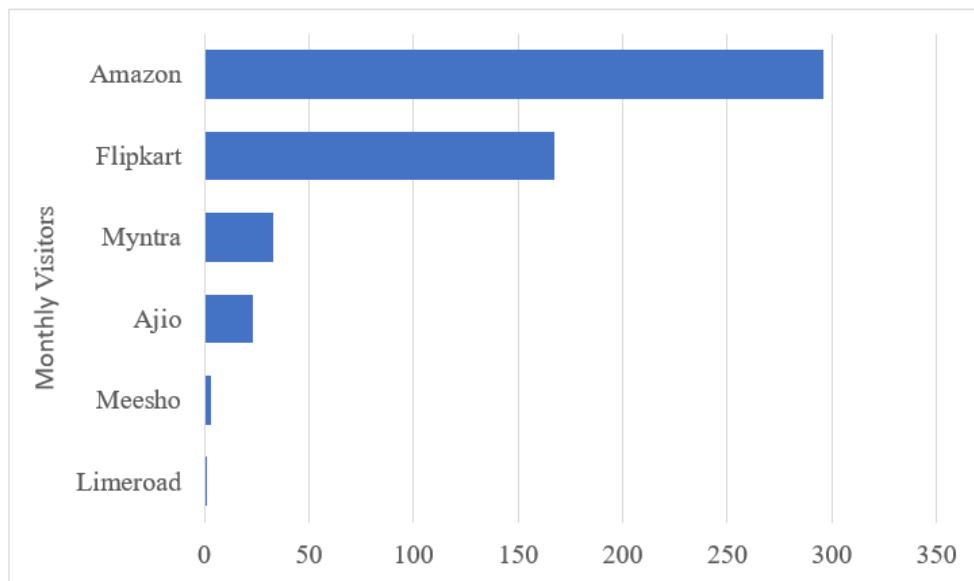


Source: IBEF <https://www.ibef.org/industry/ecommerce>

1.4 E-Commerce sites for online shopping in online apparel sector

Online shopping is steadily gaining momentum and influence in India, as more people opt to buy everything from groceries to clothing online. The nation has reached a stage where a significant number of consumers are purchasing apparel online and finding the experience satisfying. Certain e-commerce platforms have become particularly popular among shoppers for online purchases. According to a Statista report (2024) presented in Figure 1.3, Amazon, Flipkart, Myntra, Ajio, and Meesho emerged as the leading e-commerce platforms in India based on monthly visitor numbers. Amazon India dominated the market with over 295 million monthly visitors. Flipkart secured the second position with more than 167 million monthly visitors. Myntra attracting 32.9 million visitors, Ajio reaching 23.08 million, and Meesho drawing around 3.0 million visitors each month. Therefore, these five platforms were selected for the present study due to their leading positions in terms of monthly visitor traffic.

Figure 1.3: Monthly visits on leading marketplaces platform



Source:<https://www.statista.com/statistics/1239038/india-monthly-visits-on-leading-marketplace-platforms/>

1.4.1 Myntra

Myntra, a fashion e-commerce platform established in 2007, was founded by Mukesh Bansal along with co-founders Ashutosh Lawania and Vineet Saxena. In 2014, Flipkart acquired Myntra. The company originally started as an online marketplace for personalized gifts but later pivoted to focus on fashion and lifestyle retail. Myntra is now recognized as a prominent e-commerce site in India, offering a wide array of fashion and lifestyle products from both Indian and international brands. The platform offers an extensive collection of clothing, footwear, accessories, and personal care products for men and women. Myntra has partnered with leading brands like Nike, Puma, Adidas, H&M, among others, making it a comprehensive destination for fashion and lifestyle needs. With over 2,000 fashion brands and more than 5,00,000 styles available, Myntra is known for its diverse product range. The company has also introduced innovative features such as augmented reality, voice-enabled shopping, and personalized recommendations to elevate the customer shopping experience. Today, Myntra is one of India's top fashion e-commerce brands, serving millions of customers nationwide with its trendy and fashionable offerings.

1.4.2 Flipkart

Flipkart is considered one of the pioneers in the Indian e-commerce industry. It was the first India-based e-commerce platform, founded by two Indian entrepreneurs, Sachin Bansal and Binny Bansal. Initially, Flipkart's primary focus was to offer consumers the best-priced books. Over time, the platform expanded its product offerings to include electronics, cosmetics, groceries, fashion, footwear, daily essentials, and much more. Flipkart is also known for introducing several innovative features that have become standard in the industry, such as cash on delivery (COD), a 30-day replacement policy, and instalment payment options (EMI). Today, Flipkart stands as one of the largest and most influential names in the Indian e-commerce landscape.

1.4.3 Meesho

Meesho, established in 2015, has grown to become India's largest reselling platform, revolutionizing the way small businesses operate in the country. The Meesho app primarily serves as a bridge between manufacturers and resellers, enabling the latter to sell products directly to consumers through social media platforms such as WhatsApp, Facebook, and Instagram. Manufacturers from various industries, including clothing, accessories, furniture, kitchenware, and cosmetics, list their products on the Meesho app. Resellers, often individuals looking to start their own business with minimal investment, can browse these listings, select products, and then market them to their own network of customers via social channels. The resellers earn money by adding a profit margin to each transaction, while Meesho takes a commission of approximately 10-15%. Based in Bangalore, Meesho's mission is to create an ecosystem where anyone can start and grow a business without requiring significant financial resources. The platform has empowered over 2 million resellers, many of whom are women or first-time entrepreneurs, giving them the tools and opportunities to generate income and achieve financial independence. Additionally, Meesho has partnered with more than 20,000 suppliers from over 500 cities across India, offering a diverse range of products to its resellers. Meesho's business model is particularly appealing because it eliminates the need for resellers to maintain inventory, thus reducing risk. By leveraging the power of social networks, Meesho enables resellers to reach a vast audience with minimal upfront costs. The platform

also provides training and support to help new entrepreneurs succeed, making it a popular choice for those looking to enter the world of e-commerce without the barriers typically associated with starting a business. As Meesho continues to expand, it is playing a significant role in the growth of India's digital economy, empowering millions of small business owners and contributing to the rise of social commerce in the country.

1.4.4 Amazon

A significant number of people in India utilize Amazon's services, making it a major player in the country's e-commerce landscape. Amazon and Flipkart both offer a similar range of products and compete directly within the Indian market. Globally, Amazon holds the distinction of being the largest and one of the oldest online shopping platforms. Founded in 1994 by Jeff Bezos, with Mackenzie Scott as a key contributor in its early days, Amazon initially focused on online book sales before expanding its offerings. Amazon entered the Indian market in 2013, launching its Indian subsidiary as 'Amazon India' with the website Amazon.in. The company established its first headquarters in Bangalore, Karnataka. Over the years, Amazon India has grown exponentially, becoming a household name across the country. It now processes over 150,000 orders per day, solidifying its position as the highest-earning e-commerce platform not only in India but also on a global scale. Amazon's success in India can be attributed to its wide range of products, competitive pricing, and customer-centric services like fast delivery, easy returns, and a variety of payment options, including cash on delivery. Additionally, Amazon Prime has played a crucial role in attracting a loyal customer base by offering benefits like free and faster shipping, access to exclusive deals, and streaming services. The company's innovation, expansive product selection, and commitment to enhancing the customer experience have made it a dominant force in the Indian e-commerce market, competing fiercely with Flipkart and other local players. As Amazon continues to grow in India, it remains a key player not just in the e-commerce sector but also in the broader digital economy.

1.4.5 Ajio

AJIO, a relatively new player in the fashion e-commerce industry, is owned by Reliance Retail and serves as the digital fashion arm of the company, launched in

2016. Despite its recent entry, AJIO offers an extensive range of fashion products for both men and women, including apparel, footwear, accessories, and beauty items. AJIO's product lineup is notably diverse, encompassing everything from casual everyday wear to traditional ethnic attire and luxury fashion, thereby catering to a wide array of tastes and preferences. The brand sources its offerings from a mix of well-known Indian and international brands, alongside its own private label, which adds to the uniqueness of its catalog. One of the key factors behind AJIO's growing popularity is a distinct selection of fashion items, often featuring exclusive designer collaborations. This, combined with a user-friendly online shopping experience, has helped AJIO carve out a niche for itself in the competitive e-commerce landscape. The platform is especially noted for its innovative features, such as 3D virtual try-on rooms and a visual search option, both of which enhance the shopping experience by making it more personalized and engaging for users. AJIO.com has extended its reach beyond India, offering its products in over 200 countries worldwide, although its primary market remains India. The brand's private label, 'AJIO,' has become a significant part of its identity, known for delivering stylish and affordable fashion. In addition to its wide product range, AJIO is also recognized for its sustainable approach, incorporating eco-friendly practices into its operations and promoting ethical fashion choices. This commitment to sustainability, coupled with its customer-centric policies, has helped AJIO establish itself as a leading online fashion retailer in India. By continuously innovating and adapting to changing consumer demands, AJIO has positioned itself as a key player in the fashion e-commerce sector, offering a comprehensive and dynamic shopping experience.

1.5 Online shopping

Online shopping has seamlessly integrated into our everyday routines, encompassing both the intention to purchase and the actual purchasing behavior of consumers. It serves as a viable alternative to traditional shopping methods (Wang et al., 2006). As consumer preferences evolve, more individuals are turning to the internet for shopping, finding it more convenient and time-efficient than conventional shopping practices (Cova & Dalli, 2009). (Bhatti & Rehman, 2019) define online shopping as 'the means that allows the consumer to buy directly from the seller without any third person on an Internet browser.' According to the India Brand Equity Foundation, India's e-retail market is expected to exceed US\$ 160 billion by 2028. In 2023, the

market was estimated to be worth between US\$ 57-60 billion, reflecting a significant growth trajectory. After China and the US, India had the third-largest online shopper base of 150 million in FY21 and is expected to be 350 million by FY26. This growth equates to an annual addition of US\$ 8-12 billion since 2020. After China and the US, India had the third-largest online shopper base of 150 million in FY21 and is expected to be 350 million by FY26. This growth equates to an annual addition of US\$ 8-12 billion since 2020. The rise in use of online shopping websites like Amazon, Flipkart etc. and other very specific product-oriented websites like Myntra, Nykaa, Meesho and others has been a part of this process. Brands have rapidly adapted by making their websites more accessible, allowing customers to purchase directly online instead of visiting physical stores (Bhatti & Rehman, 2019; Jaiswal et al., 2024). The response to online shopping has been overwhelmingly positive, as it offers unparalleled convenience by bringing products directly to consumers' doorsteps (Agarwal & Bhati, 2016; K. Z. Zhang et al., 2014). This mode of shopping is particularly appealing to individuals who are busy and pressed for time. Online shopping encourages consumers to make purchases comfortably from their own homes while enjoying various benefits (Baidoun & Salem, 2024; Jaiswal et al., 2024). Privacy, authenticity, and quality are key factors influencing e-commerce (Baidoun & Salem, 2024). Through online shopping, consumers can easily connect with vendors worldwide, send emails 24/7, gather information, and place orders with minimal effort (Antwi & Amponsah, 2021; Wei et al., 2024). It also saves money on fuel costs and eliminates the hassle of standing in long lines. Additionally, online shopping allows consumers to compare products across different platforms with just a few clicks, enabling them to make informed and rational purchasing decisions (Antwi & Amponsah, 2021). To stay competitive, sellers must innovate and differentiate their products in a crowded marketplace (H. Shah et al., 2024). E-commerce retailers primarily aim to meet consumer demand and ensure buyer satisfaction. Social media has become a crucial tool for promoting online retail and shaping customer brand preferences (H. Shah et al., 2024; R. Wang, 2015; K. Z. Zhang et al., 2014). The context of the shopping experience significantly influences consumer behavior, particularly in the decision-making process (Antwi & Amponsah, 2021; Bhatti & Rehman, 2019; H. Shah et al., 2024; R. Wang, 2015). Research shows that female consumers are generally more inclined towards online shopping than males, largely due to the convenience it offers. However, online shopping is not without its risks and

uncertainties. The steady rise in internet users, growing interest in online shopping and transactions, favorable demographics, and the increasing availability of advanced internet-friendly devices are driving the expansion of e-commerce (Antwi & Amponsah, 2021; Baidoun & Salem, 2024; Bhatti & Rehman, 2019; Wei et al., 2024). According to the India Brand Equity Foundation (IBEF), as of December 2022, there were 7.8 billion daily e-commerce transactions globally. The number of online shoppers in India is projected to increase to approximately 500 million by 2030, up from 150 million in 2020.

1.6 WOM (Word of Mouth)

WOM has long been a focal point for marketers, leading to significant research across marketing, psychology, and sociology. WOM significantly influences consumer attitudes and behaviors (Ismagilova et al., 2020; X. Lu et al., 2014). Traditionally, WOM involves the exchange of information directly from one consumer to another (Dellarocas, 2003), a concept thoroughly explored in various studies. Quoted by Richins in 1984 “WOM is an interpersonal communication between consumers concentrating on evaluating the company’s product and services” (Brown & Beltramini, 1989). (Arndt., 1967) and (Litvin et al., 2008) offer additional definitions, suggesting word of mouth “a mode of communication between two people, between a communicator and a receiver who perceives information regarding a brand, product, or service as non-commercial”. (Harrison-Walker, 2001) defined WOM as “It is an informal peer-to-peer communication between non-commercial entities regarding a brand, service, product or even an organization.” Other academics have defined WOM as “the process which allows consumers to share their experiences about company’s offerings, it includes consumers' opinions or views which may be positive or negative” (Swarbrooke & Horner, 2007). According to Kotler, Philip - “The best advertising is done by satisfied customers.” Although positive word-of-mouth (WOM) significantly impacts consumer decision-making, research indicates that negative WOM can be even more influential. Dissatisfied customers tend to share their negative experiences more widely than satisfied or delighted customers do (Ismagilova et al., 2020). This type of communication affects various business outcomes, including customer acquisition, sales increases, and product usage decisions (Brown & Beltramini, 1989; E. Katz et al., 2017). Since the beginning of human society, WOM has been one of the most powerful means of information

dissemination (E. Katz et al., 2017). Before the Internet era, consumers relied on traditional WOM, such as conversations with friends and family, to share product-related experiences. According to Ogilvy (2014), 72% of customers consider their peers' opinions when making purchase decisions (Harrison-Walker, 2001). For decades, WOM has been a crucial form of interpersonal influence in the market, enabling consumers to share information and opinions that guide buyers toward specific products, services, and brands (Chevalier & Mayzlin, 2006). WOM refers to informal oral communication between a sender and receiver, typically discussing a product or service brand without any commercial intent (X. Lu et al., 2014). It involves transferring information about a brand or organization from one person to another and is considered a significant determinant of consumer behavior and purchase decisions. WOM is particularly influential for experience goods and is seen as a more credible medium because it is consumer-driven (Lau & Ng, 2001). Positive consumer experience with a brand can lead to favorable behaviors like recommending the company through WOM, while a negative experience can result in unfavourable behaviors like spreading negative WOM about the brand (Saag et al., 2018).

1.7 E-WOM (Electronic Word of Mouth)

The rise of the Internet has significantly revolutionized the power of Word of Mouth (WOM) (Chu & Kim, 2011). The advent of the digital age has provided WOM with a new platform for disseminating information and facilitating communication (Mishra & Satish, 2016). The internet offers a vast space for sharing an ever-growing number of customer opinions with peers (Mishra & Satish, 2016; C. Park & Lee, 2009). The digital era has also accelerated the spread of information across various online platforms such as discussion forums, review websites and social media (Awad & Ragowsky, 2008; Daugherty & Hoffman, 2017; J. Kim & Gupta, 2012). The technological advancement has created social networks, that allow customers to access company information about products and services without geographical or time constraints, significantly influencing consumer decision making behavior (Berger, 2014). It is defined “as positive or negative statement made by formed customer or actual consumers or potential buyer about a product or service which is available to read and reply by future customers present in the internet” (Hennig-Thurau, 2004). (Hennig-Thurau, 2004) were the pioneer in defining eWOM. They describe eWOM as “An informal positive or negative communication directed by former, actual, or

sometimes direct customers about the company's offerings, which is available to the magnitude of people on digital platforms." Additionally, (Sotiriadis & Van Zyl, 2013) highlighted the significance of the platform in eWOM communication, emphasizing It is a communication created and spread through varieties of digital platforms. One frequently cited definition of eWOM, derived from the traditional concept of WOM, describes it as "any informal messaging sent at consumers via Internet-based 29 technology regarding the use or quality of specific services, goods or their providers." (Litvin et al., 2008). eWOM can quickly spread information from one individual to many or from many individuals to many others on a global scale. Unlike other forms of digital communication such as advertisements and websites, eWOM is founded on customer evaluations, which generates higher levels of trust. Electronic word of mouth platforms has enabled internet users to share their opinions, thoughts, reactions, and recommendations on online platforms, which can be accessed easily without geographical limitations (M. Lee & Youn, 2009; Sotiriadis & Van Zyl, 2013). Typically, managers aim to understand consumer post-purchase behavior to enhance their services (Park & Lee, 2009). eWOM, which results from consumer purchases, has a significant potential to influence other consumers' purchasing decisions. Online consumer reviews about products offer free guidance to prospective buyers (Y. Chen & Xie, 2008). Researcher such as and (Yeh & Choi, 2011) have noted that eWOM continues to capture the interest of academics and marketers because it originates from traditional WOM, a subject extensively studied for many years. Moreover, eWOM supports customer-posted information in various formats, including pictures and videos, with addition to text. Consumers can now effortlessly access online information and are more influenced by interpersonal interactions due to the wealth of information available across multiple digital platforms (C. Park & Lee, 2009).

1.8 WOM v/s EWOM

Table 1.1: Difference between WOM and E-WOM

Characteristics	Word Of Mouth	Electronic Word of Mouth	References
Form and Communication Medium	WOM involves direct oral communication between a communicator and a receiver which can occur through various channels like letters, phone calls, meetings.	It is expressed in written or visual form on online platforms such as discussion forums and blogs.	(Amblee & Bui, 2008; Pan & Zhang, 2011; D. Verma & Dewani, 2021)
Context	It involves direct interpersonal communication conducted face to face.	It is communication that occurs via the internet.	(Meuter et al., 2013)
Privacy	Communication is private in nature since the sender knows the recipient.	The communication is generally public, taking place across various digital platforms.	(Gremier et al., 2001; Trenz & Berger, 2013)
Anonymity	The sender and receiver are closely known and familiar with each other.	The sender and receiver may or may not be known to each other, typically forming virtual social bonds and relationships.	(C. M. Cheung et al., 2008; Sundaram et al., 1998)
Diffusion Speed	The spread of the communication or information is synchronous, mostly occurring in	The communication or information spreads asynchronously, reaching a broad audience.	(Gupta & Harris, 2010)

	a one-to-one manner.		
Volume	There is no method to determine the quantity of reviews.	Reviews tend to be more abundant than traditional Word of Mouth (WOM).	(D.-H. Park & Kim, 2008; Vazquez-Casielles et al., 2013)
Audience	It primarily involves one-to-one communication	It is majorly consumed by multiple or large audiences on online platforms.	(Amblee & Bui, 2008; Hennig-Thurau et al., 2004)
Timing	It is asynchronous because production and consumption occur simultaneously.	Electronic word of mouth can be synchronous, it is primarily asynchronous.	(Dellarocas, 2003)
Credibility	The communication is highly credible because the recipient knows the sender well.	The communication has low credibility because the recipient may or may not be familiar with the sender.	(Fischer & Reuber, 2011; Steffes & Burgee, 2009; Trenz & Berger, 2013)
Network Size	The exchange of information among a select group or within communities without electronic platforms.	Sharing of information among people and societies globally via various electronic platforms.	(Gremmler et al., 2001; Sweeney et al., 2008; Vazquez-Casielles et al., 2013; D. Verma & Dewani, 2021)

1.9 Online Reviews

Online reviews, are form of ‘electronic word of mouth’, are evaluations of product quality created by peers and displayed on company or third-party website (Mudambi & Schuff, 2010). These Online Consumer Reviews (OCRs) are considered a type of eWOM (N. Hu et al., 2014). OCRs describe as "peer-generated product evaluations posted on company or third-party websites." Online reviews are a key element of eWOM, often generated by users and occasionally by experts. Customers frequently share their experiences and evaluations of products purchased from specific companies or e-commerce platforms (Kietzmann & Canhoto, 2013) The primary goal of online reviews is to provide information about products or services. Many individuals create, exchange, and share product information and usage experiences online, which then becomes accessible to others who may base their purchasing decisions on these reviews (Ye et al., 2009). There is a possibility that readers may perceive extremely positive reviews as promotional content written by companies or authors rather than genuine feedback from actual consumers (N. Hu et al., 2014). A survey by eMarketer in 2008 revealed that approximately 61% of consumers read online reviews and consider them in their purchasing decisions (Elwalda & Lu, 2016). According to product review (2020) 99.9% of online users regularly read product reviews before making purchase decisions. According to e-Marketers 75% of online consumers spend ten minutes or more reading these reviews. Online customer reviews have become a crucial tool for providing personal recommendations to other consumers. They are increasingly popular among businesses, marketers, tourists, and researchers. In the field of eWOM (electronic Word of Mouth), online reviews have gained significant importance (C. M.-Y. Cheung et al., 2012). Moreover, the influence of online reviews on buyers' actual behavior and future intentions has been empirically validated (N. Hu et al., 2014; E.-J. Lee & Shin, 2014; Mudambi & Schuff, 2010; Sheth, 1971; Ye et al., 2009). Review sites assist consumers even after they have used the products by offering a platform to post their opinions during the ‘post-purchase evaluation’ stage. Future consumers read these reviews, thereby completing the ‘decision-making process’ cycle (Mudambi & Schuff, 2010). It can be challenging for new consumers to find someone with firsthand product experience (P. Chatterjee, 2001; N. Hu et al., 2014; Lockie et al., 2015). Typically, satisfied customers leave positive reviews, while dissatisfied customers share their negative experiences (P.

Chatterjee, 2001). Online customer reviews play a crucial role in the purchasing decision process, whether they are negative or positive (Forman et al., 2008). It has been noted that while ratings are important during the information search stage, the sentiment analysis of review text is more crucial for decision-making and evaluation (N. Hu et al., 2014). By reading these reviews, customers can gather information about product quality and user experiences before making a purchase (Forman et al., 2008; E.-J. Lee & Shin, 2014). Thus, reviews are essential in the decision-making process and can help predict sales. The thesis concentrates on online reviews in the apparel industry that consumers have posted on e-commerce platforms such as Amazon, Flipkart, Meesho, Myntra and Ajio.

1.10 Role of online reviews among Generation Z Consumers

Generation Z, born between 1995 and 2012, is widely recognized as a generation of digital natives who are deeply immersed in technology. Members of Gen Z are often described as innovative, creative, open-minded, and entrepreneurial, with a strong belief in technology's role in their daily lives (Priporas, Stylos, & Fotiadis, 2017; L.-Y. Tseng et al., 2024). Technology is integral to their routine, and they devote a significant portion of their time to engaging with social media through their smartphones (M. L. Cheung et al., 2021; J. Lee & Kim, 2020). This generation is considered highly educated, tech-savvy, and naturally creative, with a strong desire for self-expression, adventure, and personal fulfillment. Born after 1994, they are seen as one of the most influential consumer groups (Cho & Workman, 2015). With constant internet access, Generation Z frequently shares their opinions, preferences, and information online (Aureliano-Silva et al., 2021). Gen Z consumers tend to rely on the internet for making purchases, sharing their experiences via social media, and using messaging apps. They are also more likely to leave online reviews compared to previous generations (Monaco, 2018; L.-Y. Tseng et al., 2024; Vizcaya-Moreno & Perez-Canaveras, 2020)). As a result, digital platforms and online recommendations play a crucial role in their purchasing decisions. In addition to their reliance on digital sources, Gen Z consumers highly value the opinions of family and friends during the pre-purchase phase, particularly when shopping for clothing (Devderea & Toader, 2018). However, unlike older generations, they spend less time discussing products with peers and instead focus on online reviews, videos, and detailed product information (Hall et al., 2017; SivaKumar & Gunasekaran, 2017; L. Y. Tseng et al.,

2022). Online reviews are becoming influential for this generation, as they actively share their experiences and conduct thorough research before making purchase decisions (Hall et al., 2017). 83% of Generation Z trust recommendations from friends and family, while 63% place trust in online consumer reviews. Their consumer behavior is shaped by these trusted sources, with eWOM playing a vital role in product and service purchases (Cho & Workman, 2015; Hussain et al., 2020; Priporas, Stylos, & Fotiadis, 2017). Furthermore, Gen Z is known for their keen interest in fashion, often using clothing as a means of self-expression and impression management. They are seen as trendsetters and are particularly concerned about the visibility of products like apparel (Kwak et al., 2023; P. Tiwari & Joshi, 2020). When it comes to fashion, they prioritize price, quality, and brand identity (Workman & Lee, 2017). Clothing is one of the top categories Gen Z spends money on, especially fashion apparel (Chetioui & El Bouzidi, 2023; Dorie & Loranger, 2024; D. Leung, 2021). In India, for example, the online fashion and lifestyle market is valued at \$16-17 billion, with fashion accounting for 75% of that total. This market is expected to grow to \$40-45 billion by 2028, driven by Gen Z's fashion choices, which are influenced by global trends, social media, and influencers. As a group, Gen Z is highly sensitive to price and motivated by savings in both time and money (Cho & Workman, 2015; P. Tiwari & Joshi, 2020). Reports indicate that they are less loyal to specific brands, posing a challenge for marketers as they are more open to trying new, innovative products (M. L. Cheung et al., 2021; Popa et al., 2023; Priporas, Stylos, Rahimi, et al., 2017).

1.11 Online Apparel Industry

The apparel industry is focused on the production and manufacturing of clothing for consumers. This includes various types of garments such as pants, sleepwear, jeans, jackets and other clothing items. Apparel encompasses men's, women's, and children's clothing. Some individuals purchase apparel to enhance their appearance and stay aligned with fashion trends, while others buy clothing regularly as a basic necessity (Hooda & Singh, 2018; E. Kim & Johnson, 2007; Shadrach et al., 2022). Apparel is often viewed as a reflection of class, personality, and culture, making it a fascinating area for studying consumer behavior (E. Kim & Johnson, 2007). The clothing and fashion market has grown into a thriving sector, attracting substantial investments from large firms in both established and emerging online apparel brands (S. Ha &

Stoel, 2012). Factors such as rapidly changing lifestyles, widespread availability of free online delivery, easy returns, the growing use of smartphones, and affordable internet access have significantly boosted the popularity of online clothing shopping (T.-M. J. Choi, 2016; Dasgupta & Kothari, 2018; Giri et al., 2019; S. Ha & Stoel, 2012; Hooda & Singh, 2018; Valaei & Nikhashemi, 2017; Zhenxiang & Lijie, 2011). In India, there is a noticeable shift towards organized and online retail, with almost all products and services accessible via the internet (S.-Y. Liu & Yuan, 2022). The global e-commerce apparel market was valued at USD 553.1 billion in 2021 and is projected to grow at a CAGR of 8.6% from 2022 to 2030. In India, the online fashion and lifestyle market is currently valued at \$11 billion and is expected to grow at a 25% CAGR, reaching \$35 billion by 2028, according to a report by consultancy Bain & Company and Aditya Birla Group's TMRW. As reported by Statista, the revenue in India's apparel market is expected to reach US\$105.50 billion in 2024. The market is projected to experience an annual growth rate of 3.81% (CAGR) from 2024 to 2028. Women's apparel is predicted to dominate the market, with an estimated value of US\$51.05 billion in 2024. This growth is attributed to evolving fashion trends, an increasing number of working women, a rising female population, and greater disposable income among consumers (Dasgupta & Kothari, 2018; Giri et al., 2019; Ha & Stoel, 2012; Hooda & Singh, 2018; F. Li et al., 2019). Additionally, ongoing product innovations and improving living standards are expected to further fuel demand. The increasing penetration of the internet and smartphones is expanding access to online services and digital platforms, making online apparel shopping more accessible. Online shopping for clothing has become similar to searching for product information online to make a purchase (E. Kim & Johnson, 2007). Apparel is one of the most significant categories driving online purchases. Virtual reality (VR) technology has played an essential role in the fashion industry, helping shoppers make informed decisions by viewing clothing from various angles. However, augmented reality (AR) is quickly surpassing VR in promoting online clothing sales (Anand & Kheterpal, 2014; Bastos Rudolph et al., 2023; F. Li et al., 2019; Nayak et al., 2015). Selling products and services online remains a significant challenge for e-retailers and marketers (Zhenxiang & Lijie, 2011).

Younger generations, particularly Gen Y and Gen Z, are known for their impulsive buying behavior and desire for instant gratification (Mazanec & Harantova, 2024;

Nanda, 2020). They often prioritize leisure activities such as recreation, grooming, socializing, and relaxation, leaving little time for in-store shopping. As a result, online shopping has become a highly convenient option for these generations (E. Kim & Johnson, 2007; Liang & Liu, 2019; Valaei & Nikhashemi, 2017). The growth of digital disruptors is largely driven by Gen Z, who have a strong preference for purchasing fashion items online. Consumer spending analysis shows that 24% of 18- to 24-year-olds buy from digital disruptor brands (McCoy et al., 2021). These brands cater to Gen Z by addressing their unique needs, such as confidence, fun, and well-being. Gen Z prefers online shopping due to the wide variety of choices and ease of returns, allowing them to save time—a valuable resource for young people—that can be spent on leisure activities (Anand & Kheterpal, 2014; Bastos Rudolph et al., 2023; Mazanec & Harantova, 2024; Nanda, 2020). According to a report by Boston Consulting Group and Snapchat, Gen Z consumers spend approximately \$45–50 billion on fashion. According to Technological advancements, such as the use of analytics, artificial intelligence, augmented reality, and qualitative analytics, have all contributed to the growing popularity of online clothing shopping (Anand & Kheterpal, 2014). Enhanced by real-time graphics, high-resolution images that provide a near-authentic sense of fabric, models showcasing the apparel, and 360-degree views, online shopping has become a truly immersive experience. Brands are now utilizing sizing data and other information to help customers find better-fitting clothing, made possible by these technological innovations (F. Li et al., 2019; Mazanec & Harantova, 2024; Nanda, 2020; Ngah et al., 2021). Furthermore, the emphasis on work-life balance and spending quality time with family has driven the growth of online shopping. Consumers can now compare various brands, prices, and other details before making a purchase, ensuring a more informed and satisfying shopping experience (S.-Y. Liu & Yuan, 2022).

1.12 Categories of Apparel

1.12.1 Western wear

Western wear is a unique clothing style that originates from the outfits worn by cowboys, ranchers, and pioneers in the American West during the 19th century. Denim jeans, a key piece of this style, were made from strong, durable fabric to handle the demands of outdoor work. Western shirts, often adorned with snap buttons,

embroidery, and yokes, combined practicality with a touch of style. The influence of Western fashion goes beyond these basic items, with accessories like turquoise jewellery becoming part of the look. Today, Western wear has spread worldwide, merging traditional elements with modern fashion trends. In India, Western wear has grown increasingly popular over the last few decades and is now a major part of the country's fashion scene. Clothing items such as denim jeans, t-shirts, and jackets have become staples in many Indian wardrobes. In professional settings, items like blazers, skirts, and dresses are commonly worn, showcasing a fusion of Western style with Indian tastes.

1.12.2 Woolen Clothes

Woolen wear is clothing made from wool, a natural fiber obtained from animals like sheep and goats. Wool is well-known for its ability to provide warmth, making it ideal for cold weather clothing. Common woolen items include sweaters, scarves, hats, gloves, and coats, all designed to keep you warm when the temperature drops. Although woolen clothing can be pricier than synthetic options, many people find it worth the investment due to its durability and high quality. During the colder months, people rely on woolen items such as shawls, sweaters, and blankets to stay warm. Woolen accessories like caps, mufflers, and gloves are also commonly used. India is known for producing a variety of woolen textiles, with cities like Ludhiana in Punjab being particularly famous for their woolen garments. These locally made woolen products are popular across the country and are also exported internationally. Woolen wear in India combines traditional craftsmanship with modern needs, providing both warmth and style during the winter months.

1.12.3 Ethnic Wear

Ethnic wear, deeply connected to cultural traditions and history, showcases the rich heritage of different regions and communities worldwide. Each ethnic group has its own unique clothing styles, patterns, and meanings. This type of attire goes beyond being just clothing; it serves as a way to express a community's history, values, and way of life. In India, ethnic wear includes a variety of garments like sarees, salwar kameez, lehengas, and kurta-pajamas, each representing different cultural values and occasions. Ethnic wear has also become a popular choice for special occasions like weddings, festivals, and cultural events, where people embrace their heritage with

pride. Designers worldwide have embraced ethnic elements, blending traditional patterns, fabrics, and techniques into modern styles. This approach not only preserves these ancient traditions but also gives them a fresh, contemporary appeal. As a result, ethnic wear continues to be cherished, not just for its beauty, but for the deep cultural connection it fosters among those who wear it.

1.12.4 Sports Wear

Sportswear is a type of clothing made specifically for physical activities, sports, and exercise. These outfits are designed to offer comfort, flexibility, and functionality, helping athletes and fitness enthusiasts perform their best while staying comfortable. Over time, sportswear has evolved to become a key part of not just athletic wear but also everyday fashion. In the sportswear industry, there's a growing emphasis on environmental sustainability, with many brands focusing on eco-friendly materials. Sportswear continues to advance with new technologies that improve performance, comfort, and style. In India, sportswear has experienced significant growth as more people focus on fitness, sports, and active lifestyles. Consumers are looking for sportswear that combines both style and performance, and many brands are responding by using sustainable, eco-friendly materials. Overall, sportswear in India reflects the country's dynamic culture, blending traditional values with modern, active lifestyles.

1.12.5 Formal Wear

Formal wear, also known as business or evening attire, refers to clothing typically worn for formal events, professional settings, or special occasions. Formal wear includes a variety of options such as dresses, skirts, and tailored pantsuits. It's often required for events like weddings, dinners, corporate meetings, and other occasions where a polished dress code is necessary. For evening events, especially those with a black-tie dress code, even more formal attire might be expected. The importance of formal wear goes beyond just looking good; it also communicates respect, professionalism, and careful attention to detail. In professional settings, dressing formally can leave a strong first impression, showing that the person is serious, capable, and mindful of the environment. This is particularly crucial in situations like job interviews and business meetings, where appearance can greatly impact how one is perceived. Additionally, formal wear is evolving to meet changing societal

expectations, with an increasing focus on inclusivity and comfort. There's a growing demand for formal clothing that caters to different body types, personal preferences, and cultural expressions. This trend mirrors a broader movement in fashion toward greater individuality and inclusiveness, even within the traditionally conservative space of formal attire. In the end, formal wear remains an essential part of fashion, blending tradition, professionalism, and style. Whether in a boardroom, at a wedding, or during any formal event, these garments continue to be key in how we present ourselves in important situations, combining practicality with a timeless elegance.

1.13 Summary of Chapter

This chapter delves into the exponential rise in internet users, with a particular emphasis on Generation Z, who are the most engaged demographic in the digital space. Unlike previous generations, Gen Z is deeply immersed in online activities, frequently interacting on social media platforms and utilizing e-commerce to a greater extent. The widespread use of the internet has substantially broadened the reach of e-commerce, creating new avenues for both consumers and businesses. E-commerce has introduced innovative features such as collaborations with celebrities and social media influencers, facilitated seamless information exchange, and enabled electronic transactions that have become a staple of modern commerce. This chapter also explores the variety of e-commerce models, including B2B, B2C, C2C, C2B and B2G, each offering unique opportunities for interaction and transaction. In India, the growth of e-commerce has been remarkable, but its early stages were marked by several challenges, such as slow internet speeds, limited awareness among consumers about online shopping, and concerns over product quality and security in payment methods. The convenience of e-commerce platforms like Myntra, Flipkart, Meesho, Amazon, and Ajio has revolutionized the shopping experience. Notably, India has emerged as the third-largest market for online shopping, illustrating the country's embrace of the digital economy. Gen Z's familiarity with technology and their entrepreneurial spirit makes them key players in the online shopping space. Moreover, their passion for fashion, which they often use as a medium for self-expression, drives significant traffic to online apparel platforms. This expansion is revolutionizing the fashion industry, with new trends emerging every day, making apparel one of the top-performing segments in the e-commerce world.

1.14 Structure of Thesis

Chapter 1 This chapter explains the growth of Internet users in India and the development of the e-commerce sector. It discusses online shopping platforms and e-commerce practices in India. The chapter also describes WOM and E-WOM and highlights the importance of online reviews in influencing consumer buying behavior. Special focus is given to how online reviews affect the purchase decisions of Generation Z consumers. In addition, this chapter discusses the online apparel industry and different categories of apparel to understand better fashion e-commerce market.

Chapter 2 This chapter presents a review of existing literature related to the research objectives. It discusses previous studies on the key variables used in the research and explains the reasons for selecting these variables. The chapter highlights the research gaps found through an in-depth review of past studies. In addition, this chapter covers the significance of the study, research questions, and the statement of the problem to provide a clear direction for the present research.

Chapter 3 This chapter explains the research design, population, variables, survey items, research instrument, sample size, sampling technique, survey tool, data collection methods, and data analysis techniques used in the study. It also describes the strategies and procedures followed to achieve the research objectives and test the hypotheses. In addition, the chapter outlines important aspects such as the sampling framework and data sources used for the research.

Chapter 4 This chapter focuses on examining the motives of Generation Z consumers for reading online reviews. An extensive review of existing literature was carried out to identify the key motives related to online review reading behavior among Gen Z consumers. In the first section, EFA was conducted using SPSS to examine the grouping of variables and their alignment with the identified factors in the context of this study. In the second section, these factors were further tested, validated, and confirmed through CFA using the CB-SEM approach.

Chapter 5 This chapter examines the influence of online reviews on the purchase intention of Generation Z consumers and the moderating effect of gender. It tests the proposed conceptual model by analyzing the relationship between online reviews and purchase intention, along with the role of gender as a moderating factor. Important

statistical tests, including the KMO measure and Bartlett's test, are applied to evaluate sampling adequacy and data reliability. The data analysis is carried out using Structural Equation Modelling (SEM) with the help of SMART-PLS 4 software.

Chapter 6 This chapter analyzes the effect of online reviews on the satisfaction of Generation Z consumers. It examines the relationship between online reviews and consumer satisfaction by testing the proposed research framework. Important statistical tests are applied to assess data reliability and validity. The data analysis is conducted using Structural Equation Modelling (SEM) with the help of SMART-PLS 4 software to ensure accurate and reliable results.

Chapter 7 This chapter presents the findings of the research study along with their analysis and interpretation. It summarizes the overall results and highlights the main conclusions of the study. The chapter also discusses the implications of the findings, identifies the limitations of the research, and provides recommendations based on the results. In addition, it outlines the contributions of the study and offers suggestions for future research to support further investigation in this area

Chapter 2

REVIEW OF LITERATURE

This chapter serves as the foundation for examining the existing research, studies, theories and findings related to the topic. The main objective of this chapter is to achieve a deeper comprehension of the topic by identifying key trends, research gap, and emerging insights that contribute to the current body of knowledge. Through the analysis of previous studies, this study helps to lay the groundwork for further investigation and provides a clearer direction for future research. Furthermore, it facilitates a critical evaluation of the existing literature, ensuring that the research makes a substantive contribution. By engaging in a comprehensive review, the research aligns itself with a broader academic context, highlighting its relevance and potential impact on both theoretical frameworks and practical applications. This process not only reinforces the study's academic foundation but also demonstrates its contribution to the advancement of knowledge in the field. The literature is divided into four sections as follows:

Studies on the motives for reading online reviews by Gen Z consumers

Studies on influence of online reviews on purchase intention of Gen Z consumers

Studies on moderation effect of Gender between online reviews and purchase intention

Studies on the effect of online reviews on Gen Z consumers satisfaction

2.1 STUDIES RELATED TO THE “MOTIVATION BEHIND TO READ ONLINE REVIEWS”

It is crucial to consider consumer motivations when studying behaviors like online word of mouth, as understanding the reasons behind these actions is essential for a comprehensive analysis. The motives that drive individuals to engage with online communication are closely tied to their behaviors, indicating that these motivations are strong predictors of how they respond to online feedback (Buchanan & Tullock, 1977). Typically, when consumers seek information about a product, they start by drawing from internal sources, such as their own past experiences or recollections. After utilizing these internal resources, they turn to external information like

advertisements, catalogs, or media articles (Bell et al., 2019; Olshavsky, 1979). Research suggests that services are often viewed as more risky than tangible products due to their intangible characteristics (Davis et al., 1979; Sparks & Browning, 2010). Price consciousness highlights the significance of getting the best value for money. Online reviews and opinions assist consumers in identifying products with the lowest prices or those of higher quality. The ease of use of the internet makes it simple for consumers to search for and compare products, as they can conveniently access this information from home, work, or other locations (Bell et al., 2019). Additionally, advertisements on television can motivate consumers to seek further information online. For some, searching for information on the internet is also considered fashionable or trendy. According to (Hennig-Thurau et al., 2007) Hennig-Thurau and Walsh, the motives behind reading online reviews plays a key role in shaping consumer behavior. Study found that many consumers turn to online reviews primarily to save time and make more informed purchasing choices (Hennig-Thurau et al., 2007; G. Walsh et al., 2010). To assess how virtual opinion platforms influence consumer choices, it is important to understand the motivations behind why consumers seek information from these resources. Motives are the "general drivers that direct a consumer's behavior toward attaining his or her needs". "Motives are needs or desires that cause a person to act and are a significant determinant of consumer behavior" (Ziegele & Weber, 2015). From an academic perspective, it is essential to address the questions: "Who writes online reviews?" and "What drives individuals to write, seek out, and share online reviews?" "Why consumers read others comments on virtual opinion platforms?" Consequently, consumer behavior is significantly influenced by these factors, providing insight into why individuals read reviews and feedback on online opinion platforms or websites. The study in question employed a deductive approach to explore the motivations behind consulting such platforms. In this (Shah & Unnithan, 2020) study deductive analysis began by examining relevant theories and concepts to better understand why users engage with customer reviews online, particularly on web-based opinion platforms. For instance, when consumers face dissatisfaction or frustration, they may express their negative emotions by sharing these experiences with others (D. M. Khammash, 2008). Seeking advice often becomes a priority when a consumer encounters an unfavourable consumption experience. In many cases, sharing negative experiences allows them to obtain useful suggestions or solutions from others. The study's (Schuckert et al.,

2015) findings suggest that when consumers experience superior product performance—such as high-quality, reliable, and durable items—and receive satisfying interactions with company employees, they are more likely to engage in positive word-of-mouth (D. M. Khammash, 2008). Conversely, unresolved issues tend to drive consumers to spread negative word of mouth. Consumers frequently post online comments about their experiences and may ask for advice from others to resolve their problems (Ziegele & Weber, 2015). When consumption is dissatisfying, it creates a sense of imbalance, which can stem from either highly positive or negative experiences. To examine the relationship between online reviews motives and consumer behavior, (Hennig-Thurau et al., 2007; G. Walsh et al., 2010) studied the impact of reading online reviews on changes in purchasing decisions and communication behavior. The rationale was that both buying and communication behaviors are likely influenced by engaging with online feedback (Sparks & Browning, 2010). Consumers are more inclined to purchase a product if the reviews are positive and tend to avoid products with negative feedback. Additionally, changes in communication behavior were analyzed by observing how likely consumers were to share information about the product after reading an online review.

In summary, (Hennig-Thurau et al., 2003; Sparks & Browning, 2010) studies found that consumers primarily read electronic word-of-mouth (eWOM) to save time and improve their purchasing decisions. (Oguta & Cezara, 2012) discovered that higher ratings and lower prices encourage customers to write reviews, and complaints about poor experiences also motivate customers to leave, typically negative, reviews. (Sparks & Browning, 2010) observed that customers who encounter service failures are likely to spread negative word-of-mouth, potentially impacting a brand or firm's reputation. Building on Dichter's motive typology for information providers, corresponding motives for information-seeking behavior are theoretically derived. (Schiffman et al., 1951) describe the reduction of risk in purchasing decisions and minimizing search time as "self-involvement motivations." The first motive stems from theories related to risk, where consumers seek reassurance from the experiences of others to make informed purchasing decisions (Wiedmann et al., 2001). This risk-reduction motive suggests that consumers look to the experiences of others to feel confident in their choices regarding a product or service. The second motive revolves around reducing the time spent obtaining a product, driven by the consumer's

perception of limited time availability (Schiffman et al., 1951; G. Walsh et al., 2010). As the marketplace becomes increasingly saturated with options and information, it becomes challenging for consumers to identify and evaluate all alternatives, making these motives highly relevant (Murray, 1991). The dissonance-reduction motive involves consumers seeking validation of their purchase by reviewing others' experiences with the same product or service after making a purchase. Another key motive, called the determination-of-social-position motive, refers to the desire to compare one's evaluation of a product or service with the opinions of others. (Schiffman et al., 1951) also identify a set of 'product-involvement motivations', where consumers seek to learn how to use a product and discover new products on the market. (Goldsmith & Horowitz, 2006) found that 20% of the customer comments in a news group were dedicated to discussing product usage, showing the significance of this motive in online articulations. These consumer discussions are often highly relevant to specific consumption situations, as opinion platforms allow for personalized information searches. Curiosity and the desire for novelty explain why consumers are drawn to discover new products (E. E. K. Kim et al., 2011). The need to learn how to use a product arises when consumers encounter issues or problems, prompting them to seek advice on opinion platforms. Consumers who enjoy engaging in platforms that share experiences demonstrate the "belonging-to-a-virtual-community" motive. If consumers are compensated for evaluating the input of others, this reflects the remuneration motive (Hennig-Thurau et al., 2007; G. Walsh et al., 2010). Additionally, consumers may visit opinion platforms to learn about new offerings in the market, motivated by the desire to stay updated on the latest products. The reduction-of-search-time motive occurs when consumers find it quicker and more convenient to access product or service quality information through opinion platforms rather than traditional methods (Engelbertink & Van Hullebusch, 2013). Lastly, consumers may also use these platforms to help others by warning them about negative experiences, or to alleviate their own anxiety by expressing dissatisfaction and venting frustration over poor purchase outcomes. Additionally, women are more inclined to read reviews for convenience, quality assurance, and risk reduction. The initial study on the motivations of WOM (word-of-mouth) opinion seekers identified three main motives: self-involvement, product-involvement, and other-involvement (Burton & Khammash, 2010). The self-involvement motive pertains to the consumer's desire to reduce perceived risk and ensure the correctness of their

purchase decision (Ziegele & Weber, 2015; Shah & Unnithan, 2020). This motive highlights the consumer's need for an efficient search process. The risk reduction aspect indicates that consumers seek validation from others' experiences with a product or service to make informed decisions (Zablocki, Makri, et al., 2019). Additionally, the dissonance-reduction aspect involves seeking post-purchase confirmation from others' experiences to validate their decision (Schiffman, 1972; C. S. Shah & Unnithan, 2020). The product-involvement motive is about the consumer's interest in learning how to use a product and staying informed about new or available products on the market. Lastly, the other-involvement motive, based on the social function of consumption (Parikh et al., 2015; Schiffman, 1972; Zablocki et al., 2019), explains the consumer's need for social acceptance and approval of their product choices, particularly those associated with social prestige. This motive also includes seeking reassurance by comparing one's evaluation of a product or service with others, referred to as the determination-of-social-position motive.

In study (Goldsmith & Horowitz, 2006) investigated the link between consumers' motivations for seeking electronic word-of-mouth (eWOM) and their purchasing behaviors. They applied two key criteria to assess buying activity: online purchasing behavior and the overall amount spent on online purchases (G. Walsh et al., 2010). To examine online buying behavior, they analyzed how likely consumers were to buy products or services over the internet. Meanwhile, the frequency of online purchases and the total expenditure on products were used to measure the amount of online purchasing (Hennig-Thurau et al., 2007). Consumers are often driven to participate in user-generated review platforms to gain both purposive and social value. Purposive value refers to the benefits derived from achieving a specific goal or purpose, such as sharing or acquiring useful information within an online community (Dholakia et al., 2004; Murray, 1991). For example, a user-generated review website might allow individuals to read others' experiences with restaurants, helping them make more informed decisions about where to dine. Social value, on the other hand, plays a significant role in motivating consumer engagement on these platforms (Hennig-Thurau et al., 2007). It offers users a social experience by allowing individuals with similar problems or experiences to interact with one another. These virtual communities foster interpersonal connections, where users can exchange advice, share experiences, and offer support, thereby enhancing the sense of belonging (Brennan &

Buchanan, 1977). User-generated restaurant review websites, in particular, expand the availability of detailed information about restaurant quality, which can be especially valuable for less well-known establishments. As more reviews are shared, traditional markers of reputation, such as chain affiliation, tend to become less influential (Schuckert et al., 2015). While chain affiliations usually imply a certain standard of service or quality, the growing volume of user reviews enables consumers to rely less on these assumptions and more on actual customer feedback. This shift allows them to assess restaurant quality based on diverse opinions and experiences rather than preconceived notions tied to brand associations. (Hennig-Thurau et al., 2003) further classified the motivations behind reading and contributing to user-generated reviews into four key categories: (a) risk reduction, (b) reduction of search time, (c) dissonance reduction, and (d) group influence. The risk-reduction motive emphasizes that consumers look to others' experiences to minimize uncertainty in their purchasing decisions (Engelbertink & Van Hullebusch, 2013). The reduction of search time reflects the desire to quickly gather information to make more efficient buying decisions. Dissonance reduction occurs when consumers seek reassurance by reading reviews after making a purchase, helping them feel more confident about their choices (Ziegele & Weber, 2015; G. Walsh et al., 2010). Lastly, group influence highlights the role of social interactions and shared experiences in shaping consumer behavior on these platforms. Together, these four categories provide a comprehensive framework for understanding why user-generated reviews are so widely utilized and valued by consumers (Burton & Khammash, 2010). By offering valuable insights, fostering social interactions, and reducing the uncertainty and effort associated with making purchasing decisions, these platforms play a pivotal role in modern consumer behavior (Hennig-Thurau et al., 2003). This framework demonstrates how user-generated content, such as online reviews, has become an essential tool for consumers navigating an increasingly complex and information-saturated marketplace (Ziegele & Weber, 2015; Bell et al., 2019).

2.2 STUDIES RELATED TO THE INFLUENCE OF ONLINE REVIEWS ON PURCHASE INTENTION OF GEN Z CONSUMERS

2.2.1 Generational Cohort

A generation or generational cohort refers to a “distinguishable group of people who share common birth years, experience similar life events, and grow up in environments with comparable resources, opportunities, and challenges.” The term "generation" identifies individuals “who are of the same age group and who have encountered specific social and historical events at similar stages in their lives. This commonality shapes their characteristics, beliefs, thought processes, attitudes, and experiences, influencing their behavior and work preferences” (Angeline, 2011; Duchscher & Cowin, 2004; Giancola, 2006; Kupperschmidt, 2000; Patalano, 2008; Weston, 2015). A generation is formed by individuals who are influenced by the same events, experiences, trends, fashion, music, idols, and education, which collectively shape their behaviors and skills, as well as their worldview (Agati, 2012; Costanza et al., 2012; Kupperschmidt, 2000; Westerman & Yamamura, 2007; Weston, 2015). A generation includes all people born within a span of approximately twenty years who experience similar life stages and historical events within that period (Costanza et al., 2012; Duchscher & Cowin, 2004;). Thus, the term "generation" encompasses a common historical context and a collective awareness shaped by the events of that era (Angeline, 2011; Duchscher & Cowin, 2004; Wey Smola & Sutton, 2002).

Each generational cohort exhibits unique behavioral traits and principles, leading to distinct motivations (Angeline, 2011; Costanza et al., 2012; Duchscher & Cowin, 2004; Giancola, 2006; Patalano, 2008; Westerman & Yamamura, 2007; Weston, 2015). These generational differences impact various aspects of life, including purchase behavior, work ethics, motivation, and socialization (Patalano, 2008; Weston, 2015). The values, beliefs, expectations, and behaviors developed by each generation tend to remain consistent throughout their lifetime, forming a generational identity. Research literature identifies the following generational cohorts: Baby Boomers, born between 1946 and 1960; Generation X, born between 1961 and 1980; and Generation Y, born between 1981 and 1995 (Agati, 2012; Angeline, 2011; Costanza et al., 2012; Giancola, 2006; Wey Smola & Sutton, 2002). Different researchers and historians have used various names and dates to define these cohorts.

In India, three generations are primarily active today: Generation X, Millennials (Gen Y), and Generation Z.

- **Generation X**

Generation X, defined as those born approximately between 1961 and 1980, were aged 63 to 44 in 2024 (Schroer, 2008). They grew up during the rise of the computer era, a time when computers were not very efficient. Studies indicate that Generation X experiences high levels of stress in various aspects of life (Satinover Nichols & Wehr Holt, 2023; Wolf et al., 2022). In India, this generation witnessed the technological evolution from basic landline phones to computers, mobile phones, and the early stages of the internet during their formative years (Heaney, 2007; Qader & Omar, 2013; Reisenwitz & Iyer, 2009). They were early adopters of these advancements, experiencing a mix of traditional values and modern influences that transformed their lifestyles, consumption habits, and entertainment preferences.

Despite the technological shift, Gen X tends to rely on traditional search and decision-making methods when making purchases (Heaney, 2007; Wolf et al., 2022). They value detailed explanations of product features and their necessity (Foris & Foris, 2018; Reisenwitz & Iyer, 2009), exhibit risk-averse behavior, and have a low tolerance for risk (Bailusy et al., 2022). The dynamic period of change experienced by Generation X in India has significantly influenced the development of modern Indian society. Known also as the 'Why Me' Generation and the 'Nonworkers' Generation, they reached adolescence and adulthood during economic crises (Bailusy et al., 2022; Qader & Omar, 2013; Schroer, 2011; Shaw et al., 2022). Consequently, they demand products and services tailored to their specific needs and lifestyles, responding positively to marketing communications that explain the necessity of particular product features (dos Santos Capelo, 2014). Generation X often disregards advertising directed at them and resists segmentation and marketing strategies. Due to having numerous needs and tighter financial constraints, they frequently shop at value-focused retailers. When shopping online, Gen X conducts extensive research, reading more reviews and visiting more opinion sites than other generations (Wolf et al., 2022). Overall characteristics of Generation X include: -

- (1) independence and resourcefulness
- (2) the ability to think concurrently
- (3) openness to change and diversity
- (4) a desire for balance between personal and professional life and
- (5) a commitment to lifelong learning.

- **Generation Y**

Generation Y, also known as Millennials, Digital Natives, Net Generation, Gen Y, Internet Generation, Echo Boomers, and Boomerang Generation, encompasses individuals born between 1981 and 1995 (Abrar et al., 2021; S. Kumar & Sadarangani, 2021; Muralidhar & Raja, 2019; Swarnakar et al., 2016). They matured during a time of economic growth and the rise of social media and reality television. The older members of this cohort entered adulthood around the year 2000 (Ang et al., 2011; Jain, 2020; N. Khan et al., 2021; Sakshi et al., 2024). This generation has grown alongside the development of computers and various technologies, which are integral to their work (Muralidhar & Raja, 2019; Sakshi et al., 2024). Highly individualistic, Gen Y is accustomed to the rapid, responsive nature of online social media, frequently using it to communicate and express themselves (Chakraborty & Balakrishnan, 2017; Chung et al., 2021; N. Khan et al., 2021). They are adept at using the Internet and are more open to adopting technological innovations (Balakrishnan et al., 2014; S. Kumar & Sadarangani, 2018). They represent the highest percentage of online shoppers, followed by Generation X and Baby Boomers. This generation is noted for its substantial purchasing power relative to other generations (Abrar et al., 2021; Farris et al., 2008; O'Cass & Choy, 2008; Swarnakar et al., 2016) and a strong inclination towards online shopping. For Gen Y, shopping is a serious activity that involves extensive online research, indulging in flash-sale promotions, following celebrity fashion trends, using, and keeping up with food and fashion blogs (Balakrishnan et al., 2014). Additionally, they are very comfortable with both online and mobile activities (Ang et al., 2011; Sakshi et al., 2024). Known for their confidence and optimism, Gen Y feels empowered to take action when things go wrong and possesses notable multitasking abilities due to their high energy and speed.

They prefer products that reflect their personality and lifestyle, often disregarding brand names in favor of price and product features (S. Kumar & Sadarangani, 2021). Their loyalty is influenced by fashion, trends, and brand popularity, with a focus on style and quality over price (Daowd et al., 2021; Xiao et al., 2018). Regarding branding, Millennials view reputable brands as symbols of status and are often willing to pay a premium for them (Xiao et al., 2018). Branding plays a crucial role for this generation as it helps them express their identity (Chakraborty & Balakrishnan, 2017). Despite having access to a wide range of options, Generation Y tends to show less brand loyalty compared to other generations (Abrar et al., 2021; Daowd et al., 2021; Jain, 2020; Swarnakar et al., 2016; Xiao et al., 2018). Additionally, Gen Y's lifestyle is shaped by factors such as increased job mobility, dual-income households, and higher education levels, which significantly impact their behavior. They are very conscious of others' opinions, which largely drives their consumption habits (Khan et al., 2021; Kumar & Sadarangani, 2021; Moslehpour et al., 2021).

- **Generation Z**

Generation Z, defined as individuals born in 1995 or later, represents a generation deeply immersed in digital technology from a young age (Agarwal & Teas, 2002; Bressolles et al., 2015; A. P. Singh & Dangmei, 2016; Utomo et al., 2023). According to (A. P. Singh & Dangmei, 2016), this generation, often called Gen Z, was born in the 1990s and came of age in the 2000s, a period marked by transformative technological advancements such as the internet, smartphones, laptops, and pervasive digital media (Bressolles et al., 2015; A. P. Singh & Dangmei, 2016). They have been labeled with various names, including The Founders, iGeneration, and post-millennials). As they move through their youth and into adulthood, there is a prevailing belief that Gen Z will experience an era of significant economic and social revival (Euajarusphan, 2021; Sudirjo et al., 2023; Sun & Xing, 2022). This cohort is highly proficient at sourcing and verifying information. Their upbringing amongst technological convenience has made them particularly tech-savvy (Chetioui & El Bouzidi, 2023). They have been surrounded by technology and raised by a generation equally comfortable with digital tools (A. P. Singh & Dangmei, 2016). Each generational cohort has distinct motivations and satisfaction when it comes to engaging with online social media (Agarwal & Teas, 2002; Agrawal, 2022; Utomo et al., 2023).

Generation Z stands out in their adept use of these platforms, having been born into an era where technological convenience is a given (Asih & Rubiyanti, 2022; Djafarova & Fouts, 2022). Their digital fluency poses a unique challenge for companies, as Gen Z consumers are meticulous in their search for the best products at the most competitive prices, often avoiding lesser-known brands (Koleva, 2023; K. C. Williams et al., 2010). They are acutely price-conscious and make purchasing decisions with a high level of awareness about product costs (A. P. Singh & Dangmei, 2016). For businesses, capturing the loyalty of Gen Z customers can address and mitigate issues such as efficiency, intense competition, globalization, and digital transformation (Asih & Rubiyanti, 2022). Despite their lower brand loyalty, Gen Z consumers have heightened expectations and place significant emphasis on the purchasing experience (Asih & Rubiyanti, 2022; Koleva, 2023; Sudirjo et al., 2023). Word of mouth attracts Generation Z to products and services since they frequently talk about the latest trends and market offers with their friends, peers, and loved ones (Agarwal & Teas, 2002; Koleva, 2023).

Studies indicate that this generation spends a considerable amount of time in the realm of social media, becoming increasingly engaged in the latest mobile and social media applications (Brand et al., 2022). Gen Z individuals not only consume internet content, but they also actively create and manage it. Ensuring high-quality e-service can provide Gen Z with a sense of benefit and an enhanced experience, thereby enabling companies to satisfy their needs and generate customer value (Agrawal, 2022; Chetoui & El Bouzidi, 2023; Copeland et al., 2023; White, 2019). The concept of online customer value is pivotal in determining the economic, social, and functional impacts, which are promoted through strong relationships between customers and service providers (Mude & Undale, 2023). These impacts reflect the value customers expect to receive after the effort they invest in acquiring a product (Copeland et al., 2023). Generation Z's unique characteristics and digital proficiency demand that companies innovate and adapt to meet their needs. By doing so, businesses can create lasting customer value and maintain a competitive edge in a rapidly evolving market (Sun & Xing, 2022; Thangavel et al., 2022).

- **Difference between Gen X, Gen Y and Gen Z**

When developing an online marketing campaign and strategy, it is essential for marketers to recognize that each generational cohort requires a unique approach to attract their attention (Atieq, 2019; Egerova et al., 2021; Kraus, 2017; Slootweg & Rowson, 2018). While the internet and online platforms play a significant role in the lives of all generations, their online behaviors differ in terms of activities, time spent, preferred platforms, chosen social media sites, and the impact of online content on their purchasing decisions (Francis & Hoefel, 2018). The readily available information on online platforms encourages individuals from all generations to remain active online at all times (Slootweg & Rowson, 2018). Table 2.1 presents the comparative analysis between Generation X, Generation Y and Generation Z.

Table 2.1: Difference between Gen X, Gen Y and Gen Z

	Generation X	Generation Y	Generation Z
Born Between	1961-1980	1981-1994	1995 to 2012
Current age	Around 63-44	Around 43-30	Around 29-12
General Values	Risk avoidance, Freedom, Autonomy	Diversity, Technology, Entrepreneurship, success	Innovativeness, highly self-esteem, Tolerance
Sources of Information	Media orientation	Strong Media orientation	Strongly influenced by social media
Technology	They learned technologies in school	This generation used computers, telephones easily communicate through SMS, email etc.	This generation is connected most important device mobile

2.2.2 Determinants of Online Reviews

- **Review Quality**

Review quality refers to the effectiveness of a review's content in terms of its information characteristics: relevance, understandability, sufficiency, and objectivity (H. S. Choi & Leon, 2020; Zinko et al., 2020). A high-quality review is noted for its logical structure, persuasiveness, and reliance on specific facts about the product. The adage quality is more important than quantity underscores the importance of review quality in influencing consumers' decision-making processes (S. Chatterjee, 2020; K. Li et al., 2020; Y. Lin et al., 2020; C. W. Park et al., 2021). Informational influence pertains to the degree to which individuals enhance their understanding of product knowledge by reading reviews. In reality, however, consumers also value the quantity of review comments (H. S. Choi & Leon, 2020). The volume of online reviews is often perceived as an indicator of a product's credibility and popularity (Nilashi et al., 2021). Consequently, an individual's interpretation of information can be influenced by the number of reviews available (Meng et al., 2020; Tian et al., 2021).

Reviews serve as a source of supplementary information, with those written by actual product purchasers being particularly valued (Mafe et al., 2020; Y. Wang & Kuchmaner, 2024). E-WOM plays a significant role in either deepening consumers' understanding of a product or enabling them to anticipate similar purchasing experiences as those described by reviewers (Bachleda & Berrada-Fathi, 2016; Xu et al., 2021). Social influence, therefore, enhances consumers' evaluation of online reviews usefulness and promotes the adoption of online reviews (Vana & Lambrecht, 2021). Online reviews can be either negative or positive. When a review contains critical feedback, it is referred to as negative word-of-mouth, whereas favorable opinions are termed positive word-of-mouth (S. Chatterjee, 2020). The concept of review valence captures the positivity in positive reviews and the negativity in negative reviews, acknowledging that no review is entirely positive or negative (Ruiz-Mafe et al., 2020; Tsai et al., 2020).

Positively framed online reviews highlights a product's strengths, while negatively framed online reviews focuses on its weaknesses or problems (Vana & Lambrecht, 2021; Wang & Kuchmaner, 2024). Positive online reviews involve the spread of positive consumer feedback following the use of a product or brand, whereas negative

online reviews involve the dissemination of negative information related to unpleasant consumption experiences (Bachleda & Berrada-Fathi, 2016; Xu et al., 2021; Zhu et al., 2020). Negative online reviews are often perceived as more reliable and impactful than positive online reviews, thereby increasing consumer trust, positive attitudes toward businesses, and purchase intentions (Y. Wu et al., 2020). The quality of information is also influenced by the visual presentation of the product (K. Li et al., 2020; C. W. Park et al., 2021). Consumer reviews that combine text and photos provide a richer context and are referred to as visual information (Filieri et al., 2021). The presence of visual elements in reviews can enhance the credibility and appeal of the information provided, making it more engaging and trustworthy for potential buyers (S. Chatterjee, 2020; Y. Wu et al., 2020; Zhu et al., 2020).

- **Review Quantity**

The vast availability of information significantly aids consumers in making informed purchasing decisions online (S. Park & Nicolau, 2015; Yang et al., 2012). The extensive amount of e-WOM information on online platforms encouraging customers to share their personal experiences with a company's products or services, thereby enhancing both favourable or unfavourable eWOM (Gonzalez-Rodriguez et al., 2016; Melian-Gonzalez et al., 2013). To measure review length, researchers have typically used the total word count in a review (Gao et al., 2017; X. Hu & Yang, 2021; S. Lee & Choeh, 2017; S. Park & Nicolau, 2015; Quaschnig et al., 2015; Tsai et al., 2020; Willemsen et al., 2011; Yang et al., 2012). Additionally, the quantity of reviews has been evaluated based on the number of words, sentences, and the overall length of reviews (S. Lee & Choeh, 2017). Detailed reviews enhance consumer confidence, assist in decision-making, and are considered valuable (Walsh, 2003; Y. Zhou & Yang, 2019). Concerning review length, many studies have concluded that longer reviews are more useful (H. Li et al., 2019; Z. Liu & Park, 2015; D.-H. Park et al., 2006; S. Park & Nicolau, 2015; Quaschnig et al., 2015; Siering et al., 2018; Spurling et al., 2010; Tsai et al., 2020; Walsh, 2003; Xiang et al., 2018; Yang et al., 2012; M. Zhang & Luo, 2023).

The volume of reviews on a given topic indicates the total number of reviews. It has been observed that online media generates a much higher volume of reviews compared to offline sources (Cheng & Ho, 2015; Xiang et al., 2018). Positive reviews

have a greater impact on repurchase intentions compared to the large number of reviews (Gao et al., 2017; Willemsen et al., 2011). In the realm of online shopping, when shoppers see a large number of reviews for a particular product, they often take a heuristic approach, exerting less cognitive effort (Asadi Damavandi & Ha, 2024; S. Lee & Choeh, 2017; Safitriani & Auliya, 2023; Siering et al., 2018; Willemsen et al., 2011; Xiang et al., 2018). This leads them to believe that a sufficient number of reviews are useful and valuable.

Thus, it is hypothesized that a higher number of reviews (Quaschnig et al., 2015; Safitriani & Auliya, 2023; Vazquez et al., 2023) improve shoppers' perceptions of the usefulness and value of online reviews (Gao et al., 2017; H. Li et al., 2019; V. Walsh, 2003; Yang et al., 2012; M. Zhang & Luo, 2023). Longer reviews tend to include more details about the products, attributes, and functionality (Mudambi & Schuff, 2010). However, information overload can result in dissatisfaction, lower confidence levels, and confusion about the products/services (Rajasa et al., 2023). Review length did not significantly affect review helpfulness (Asadi Damavandi & Ha, 2024; Hung et al., 2023; Safitriani & Auliya, 2023; Vazquez et al., 2023).

- **Review Credibility**

Online customer reviews, often written by peers who are mostly anonymous to the readers, raise questions about trust and credibility. Credibility is defined as the perceived believability of the message content (Assaker, 2020), and in its simplest form, it can be described as believability (D. Verma & Dewani, 2021). Within the context of electronic word-of-mouth (eWOM) eWOM credibility as the extent to which one perceives other consumers' recommendations or reviews as believable, true, or factual. (M. Y. Cheung et al., 2009; Levy & Gvili, 2015; Sotiriadis & Van Zyl, 2013). Review credibility, or the trust readers place in a review, significantly impacts their perception and trust in the e-commerce platform (C. A. Lin & Xu, 2017).

Online customer reviews are considered trustworthy sources of information on product quality (Sotiriadis & Van Zyl, 2013). Since these reviews are voluntarily provided by customers, they are often seen as highly reliable and trustworthy (Chevalier & Mayzlin, 2006; Chih et al., 2013). Electronic word of mouth significantly influences consumer purchasing behavior (Fogg & Tseng, 1999). Research has shown that respondents view online information as credible as that from

television, radio, and magazines, though less credible than newspapers (Levy & Gvili, 2015; Sotiriadis & Van Zyl, 2013). (Hsieh & Li, 2020; Pooja & Upadhyaya, 2024; D. Verma & Dewani, 2021) found eWOM to be less credible than traditional word-of-mouth. When consumers perceive positive online reviews as credible, they are more likely to rely on them for making purchase decisions (J.-K. Hsieh & Li, 2020).

- **Source Credibility**

The credibility of electronic Word of Mouth (eWOM) is determined by how believable, truthful, or factual a review is perceived to be (M. Y. Cheung et al., 2009; Ozboluk & Akdogan, 2022). Credibility can also be understood as an individual's perceived trust in the information or its source (Ludwig et al., 2013; Sussman & Siegal, 2003). Therefore, source credibility can be defined as “the belief in the message source's ability and motivation to generate accurate and factual information” (Zhu et al., 2014). Online reviews credibility refers to the degree to which the receiver finds online reviews information accurate and truthful (M. Y. Cheung et al., 2009). With the increase in fake reviews, issues of trust and credibility in online messages have become more prominent, and users have grown more aware of the validity and credibility of Online Customer Reviews (Aghakhani et al., 2023; Amarullah et al., 2022; Black & Kelley, 2009; M. Y. Cheung et al., 2009; Wathen & Burkell, 2002). Online reviews significantly influences consumer purchase behavior (Sussman & Siegal, 2003). The credibility of information is closely linked to the trustworthiness of those who post it. Research shows that respondents consider internet information to be as credible as that from television, radio, and magazines (C. M. Cheung & Thadani, 2012; J. Lee et al., 2008; Su et al., 2023).

Online reviews less credible than traditional word-of-mouth. When consumers perceive positive eWOM reviews as more credible, they are more likely to rely on these reviews for their purchase decisions (Amarullah et al., 2022). A study found that 49% of customers trust consumer reviews as much as statements from friends and family, while 37% trust recommendations from social media personalities they follow (Wathen & Burkell, 2002). Online buyers often browse through reviews and comments, using this information to inform their buying decisions. Existing literature suggests that information credibility is a critical element of a high-quality argument (Gonzalez-Rodriguez et al., 2022).

The credibility of online reviews is influenced by the information provided by reviewers (Chih et al., 2013). The trustworthiness of reviews is affected by the reviewers' past experiences examined the impact of reviewers providing detailed personal information (e.g., accurate profile pictures, real names, origins, lifestyles, etc.) (Sussman & Siegal, 2003; Wathen & Burkell, 2002). Source credibility affects the information's credibility, and the reviewer's credibility influences the perceived helpfulness of reviews (Chih et al., 2013; J. Li & Zhan, 2011). The trustworthiness of the source or reviewer explains the customer's level of confidence and acceptance (Su et al., 2023). Reviewer trustworthiness as “the extent to which the audience feels the reviewer intends to deliver valid assertions” (Aghakhani et al., 2023). Reviewer trustworthiness defines as “consumers' perceptions that a source of communication is reliable, unbiased, and honest” (Chevalier & Mayzlin, 2006; J. Lee et al., 2008). Reviewers who disclose personal information are considered more reliable than those who do not (C. M. Cheung & Thadani, 2012; Qiu et al., 2023; Su et al., 2023).

- **Usefulness of Online Reviews**

Online reviews play a crucial role in reducing the negative impact of information overload. Many websites that host reviews have implemented systems to identify the most useful reviews based on their content (D.Kaur & Kaur, 2023; Peng et al., 2014). These platforms often allow readers to vote on the helpfulness of a review by asking, Was this review helpful to you? (Mudambi & Schuff, 2010) Recent scholarly research has begun to investigate the factors that drive the perceived usefulness of reviews. Helpful reviews are those that offer evaluations of products and services from peers, which in turn influence potential consumers' decision-making processes (Joshi & Singh, 2017).

The helpfulness of a review is typically measured by the number of "Helpful" votes it receives. Research by (C. M. Cheung et al., 2008) has found that the perceived usefulness of a review significantly predicts consumers' willingness to follow the review's advice. Perceived usefulness can be understood as the perceived value of the review in the context of making a purchase decision (Donthu et al., 2021; S. Verma & Yadav, 2021). This highlights the importance of helpful online reviews when making purchasing decisions (Peng et al., 2014). To assess the quality and credibility of an online review, e-commerce platforms allow customers to read previous reviews and

rate them as "Helpful" or "Not helpful" (Baek et al., 2017; Peng et al., 2014; S. Verma & Yadav, 2021). Helpfulness serves as an indicator of the quality of online reviews and influences purchase decisions (Donthu et al., 2021; D. Kaur & Kaur, 2023). The helpfulness of an online review is measured as the percentage of "Helpful" votes it receives out of all votes (C. M. Cheung et al., 2008). This voting mechanism enables customers to easily evaluate the quality of each review (Joshi & Singh, 2017; K. Kaur & Singh, 2020).

- **Purchase intention**

Purchase intentions (PI) can be described as the possibility that consumers will plan or be willing to purchase a certain product or service in the future or may be referred as how likely it is that the individual would purchase the product (Purwianti & Niawati, 2022). Purchase intention can be described as the intention to purchase a reviewed item. It involves a decision-making process where consumers evaluate reasons to buy a particular brand (S. Khan et al., 2023; Zheng et al., 2022). (Montano & Kasprzyk, 2015) describe purchase intention as a situation where consumers are inclined to buy a specific product under certain conditions.

This intention is often assessed by asking consumers about their likelihood of purchasing, such as "considering purchasing," "desiring to purchase," and "likely to purchase" (Chang & Wildt, 1994; Spears & Singh, 2004). Purchase intention has been extensively studied in consumer behavior research as it is considered a primary predictor of actual purchase behavior (Dodds et al., 1991; S. Khan et al., 2023; Masuda et al., 2022). It manifests during the pre-purchase stage, capturing factors that drive consumer behavior (Apasrawirote & Yawised, 2022). (Vafaei-Zadeh et al., 2022; P. C. S. Wu et al., 2011) defines "online purchase intention as the degree to which a customer is willing to make a purchase from an online store." The decision to purchase is a complex process, influenced by consumer behavior, perceptions, and attitudes (S. Khan et al., 2023; Purwianti & Niawati, 2022). Evaluating and accessing a specific product often based on purchase behavior, which is viewed as the initial step toward actual buying behavior (Dodds et al., 1991; S. Khan et al., 2023; Zheng et al., 2022).

According to Utility Theory, the likelihood of purchase intention increases when consumers perceive more benefits than costs associated with a product (Montano &

Kasprzyk, 2015). (Limbu & Huhmann, 2024) also highlights perceived value as a critical antecedent influencing consumer purchase intention, encompassing both transaction and acquisition utility (Tiwari et al., 2024; Zheng et al., 2022). Purchase intention is a fundamental aspect of consumer behavior and serves as an indicator of a consumer's likelihood to buy a product (Dickson & Sawyer, 1990; Limbu & Huhmann, 2024; Montano & Kasprzyk, 2015). Generally, higher purchase intentions correlate with a greater willingness to purchase (Apasrawirote & Yawised, 2022; Dodds et al., 1991). (Masuda et al., 2022) define purchase intentions as an individual's conscious plan to make an effort to purchase a brand. Research has identified three consequences of purchase intention: willingness to consider buying, intention to purchase in the future, and the decision to repurchase (De Oliveira Lima et al., 2024; Soewandi, 2015; Song & Shin, 2024).

2.2.3 Impact of Online Reviews on Purchase Intention in Apparel Industry

Consumer buying decision process is a complex process experienced by consumer with evolves the stages from recognize the problem about the brand until select the product that solves the problem (L. Lu et al., 2014). There are five stages of consumer buying decision process which consist of problem recognition, information search, evaluation of alternatives, purchase decision, and post purchase evaluation. Purchase intention is a part of consumer buying decision process (Hajli et al., 2017; L. Lu et al., 2014; J. Park et al., 2021). This process appeals as the result of the way consumer search and evaluate the product information. Purchase intention can be defined as the probability of consumer will purchase particular product (D.-H. Park et al., 2007). Online purchase intention represents the willingness and intention of consumers toward a product to be purchased at a specific time or in a specific situation via online transaction platform (Ahmad & Zhang, 2020). In online shopping online reviews play a role in information search and has an influence in purchase intention. One of the studies found that all of the independent variables (source credibility, review quality, review quantity and review valence) has significant and positive relationship toward consumer purchase intention (Hajli & Lin, 2015; Purwianti & Niawati, 2022; Rausch & Kopplin, 2021). Review quality became the most influence variable that affects purchase intention, followed by review valence, source credibility, and review quantity. In addition, since the review quality have the biggest influence in consumer purchase intention, company could utilize the existing review which had good quality

and positive review as a part of company's business communication (L. Zhang et al., 2024). Found that the quality and quantity of online reviews affect consumers' purchasing intention (PI) but low-involvement consumers are affected by quantity rather than quality of online reviews and high-involvement consumers are affected mainly by review quantity when the review quality is high (Hajli & Lin, 2015; L. Lu et al., 2014; J. Park et al., 2021). Firstly, online reviews of a high quality had a positive effect on the purchasing intention of online shoppers. Reviews with strong argument quality supported with facts are perceived as being more objective (Purwianti & Niawati, 2022; Rausch & Kopplin, 2021; Ahmad & Zhang, 2020). Another previous study has showed that the popularity of product will be measured by the large quantity of positive reviews that are able to convince people to buy the product (Mutz & Reeves, 2005; J. Park et al., 2021). The result showed that one of the main reasons and critical role that enable shopping website to become more favorable and ultimately increase consumers purchase intention was number of reviews (Achrol & Kotler, 1999). Online reviews play an important role to cover the anonymity issue about the online reviews on shopping websites. Risk is recognized as a main barrier to online purchasing (Hajli & Lin, 2015). Trust is one of the most important factors in ecommerce as it helps to reduce perceived risk (Ahmad & Zhang, 2020; Hajli, 2015). Furthermore, trust has been found to influence in the consumer and enhances the intention to buy (J. Park et al., 2021; Rausch & Kopplin, 2021). Trust can be created through online reviews; according to (Achrol & Kotler, 1999) consumers consider online reviews as a more credible as other traditional sources of information. online consumer reviews provide a trusted source of product information for consumers (Hajli & Lin, 2015; L. Lu et al., 2014). A high number of reviews positively affects the purchasing intention of online consumers. Specifically, the attitudes of online consumers become more positive as the number of reviews increases (Ahmad & Zhang, 2020; Purwianti & Niawati, 2022). When there is a large number of reviews this is perceived as an indication of product popularity and hence the purchasing intention of consumers increases (Rausch & Kopplin, 2021). The ongoing growth of e-commerce leads to a continuous interest in understanding the principal factors that influence in the consumer's decision making (Mohd Sam & Tahir, 2009). Positive consumer reviews of products or companies are considered among the best predictors of business growth. Products with positive comments can promote online consumers' purchase intention more than those with negative comments and will bring more

profits to businesses (Ahmad & Zhang, 2020). Online reviews are one of the inexpensive online reviews which affect the purchase intention in social network sites (Mulyani et al., 2021).

2.3 STUDIES RELATED TO THE MODERATING ROLE OF GENDER

In various marketing strategies and consumer behavior research, demographic variables, with a particular focus on gender, have been explored across different scenarios. Gender stands out as one of the most critical demographic factors influencing decision-making processes (C. Chen et al., 2016; M. Zhou, 2014). In the realm of online reviews, gender functions as a key moderating variable, shaping how consumers interpret and react to feedback on products or services. Social role theory (Eagly et al., 1995; Venkatesh & Morris, 2000) suggests that men are generally more inclined to engage with new technologies, driven by their independent, competitive, and assertive nature (Venkatesh & Morris, 2000; N. Zhang, 2006). This often positions men as more technologically adept, goal-oriented, and likely to adopt technology to improve their online shopping experiences (N. Zhang, 2006). Conversely, women tend to exhibit higher levels of computer anxiety, which can impact their willingness to embrace new technology (Karavidas et al., 2005; M. Zhou, 2014). When it comes to online shopping, the shopping behaviors of men and women differ significantly (Arcand & Nantel, 2012; C. Chen et al., 2016). Women, in particular, are often more analytical, taking time to carefully evaluate situations before reaching a decision (Arcand & Nantel, 2012). Research has indicated that men and women process information differently, a pattern that extends to their interpretation of online reviews. Women are generally more attentive to detailed, emotionally rich content, often gravitating towards reviews that reflect personal experiences and feelings (Assaker et al., 2015; M. Zhou, 2014). They are more likely to be influenced by narratives that resonate with their own concerns, leading to a more thorough assessment of products. In contrast, men tend to focus on the factual and technical aspects of reviews. They often prioritize concise, clear information that emphasizes the functional benefits of a product (Setyarini et al., 2024). The emotional tone of a review may hold less sway over men, who prefer objective data and specific features that meet their practical needs (N. Zhang, 2006). These gender differences in how reviews are perceived can significantly impact purchasing decisions. For instance, a product with highly emotional and detailed positive reviews may appeal more to

female consumers, whereas male consumers might prefer a product with reviews that highlight clear, technical advantages. Furthermore, the perceived credibility of a review source can also be moderated by gender (Venkatesh & Morris, 2000; M. Zhou, 2014). Women are more likely to trust reviews from individuals they find relatable, while men may give more weight to reviews from experts or those with technical knowledge. These insights underscore the importance of considering gender as a moderating factor in the analysis of online reviews and their influence on consumer behavior (Prakash et al., 2022). Marketers should, therefore, tailor their review strategies to align with gender-based preferences, ensuring that their content addresses the distinct needs and expectations of different consumer segments (Tan et al., 2022; Tsihla et al., 2016). Additionally, recognizing these gender-driven nuances in review perception can help businesses craft more effective marketing messages, ultimately leading to higher consumer engagement and satisfaction (Setyarini et al., 2024; Tan et al., 2022). In today's digital landscape, consumers are not passive recipients of information but active participants who seek content that resonates with their personal values and expectations. By recognizing the gender-driven differences in review perception, businesses can tailor their messages more effectively. For example, ensuring that product descriptions, advertisements, and reviews are well-balanced, offering both emotional appeal and technical precision, can enhance consumer satisfaction and loyalty (Tan et al., 2022). This strategic approach allows companies to not only meet the expectations of diverse consumer segments but also foster long-term engagement by building trust through relatable, credible, and relevant content. Ultimately, these insights demonstrate that gender is not just a demographic variable but a pivotal factor that can shape the effectiveness of marketing strategies, particularly in the context of online reviews. Gender moderation is a critical factor in understanding how different consumer segments respond to online content, advertising, and digital interactions (N. Zhang, 2006). It reflects the influence of gender on how individuals process information, make decisions, and interact with technologies, which has a direct impact on their consumer behavior. In the context of online shopping and reviews, gender moderation plays a significant role in shaping preferences and responses. Men and women often differ in how they evaluate products and services based on their cognitive and emotional processing styles (C. Chen et al., 2016). For instance, while men tend to focus on the functional, practical, and technical aspects of a product, women may be more drawn to relational and

emotional elements, such as personal experiences shared in reviews. Gender moderation also impacts how consumers perceive the credibility and trustworthiness of online reviews (Arcand & Nantel, 2012). Women may give more importance to reviews written by peers who they find relatable, whereas men might value expert opinions or data-driven reviews. Moreover, the language used in online reviews can further moderate gender-based reactions. Reviews that contain emotional or detailed descriptions tend to resonate more with female shoppers, whereas more succinct, straightforward reviews may appeal to male consumers (Venkatesh & Morris, 2000). Understanding these gender-based differences allows businesses to tailor their online review strategies, improving targeting and personalization to enhance consumer trust and boost purchase intention across different demographics. Gender also moderates the influence of negative reviews on purchase intention. Women are more sensitive to negative feedback, as they may perceive it as a risk to their social standing or emotional satisfaction with a product (Arcand & Nantel, 2012). Conversely, men may treat negative reviews more analytically, assessing whether the issues raised are relevant to their specific needs. Additionally, the design and usability of digital platforms can influence gender-based engagement; platforms that reduce complexity and emphasize ease of use may alleviate some of the technological anxieties more commonly reported by female users (M. Zhou, 2014; Arcand & Nantel, 2012). Marketers and businesses must consider these gender-driven behaviors when developing strategies, ensuring that their messaging and content resonate with both male and female consumers. By understanding and leveraging gender moderation, businesses can create more personalized, effective marketing campaigns that cater to the unique needs of different demographics, enhancing consumer satisfaction and fostering brand loyalty (Setyarini et al., 2024).

2.4 STUDIES RELATED TO THE EFFECT OF ONLINE REVIEWS ON GEN Z CONSUMERS SATISFACTION

2.4.1 Expectation Disconfirmation Theory

This study examines the "Expectancy Disconfirmation Theory" (EDT), a prominent model for evaluating customer satisfaction. (E. Shin et al., 2022) argued that the expectation-disconfirmation framework is particularly suitable for analyzing consumer behavior within the e-commerce sector. The development of EDT illustrates

its effectiveness in assessing the quality of services and information provided by B2C e-commerce from the customer's perspective (Dabholkar et al., 2000; J.-U. Kim et al., 2004). Researchers across various domains—including marketing, tourism, psychology, information technology, repurchase behavior, customer retention, and the airline industry (Levesque & McDougall, 1996)—have utilized EDT to better comprehend customer expectations and how to meet them to enhance satisfaction (Spreng et al., 1996; Westbrook & Reilly, 1983). EDT is based on the Cognitive Dissonance Theory (CDT), introduced by (McKinney & Yoon, 2002), which explains the psychological discomfort that arises when there is a conflict between an individual's beliefs and reality. This discomfort, known as dissonance, motivates individuals to alter their perceptions to alleviate the psychological tension (Dabholkar et al., 2000). EDT extends this concept by measuring customer satisfaction as the difference between what customers expect and what they actually experience with a product or service (Oliver, 1997; P. G. Patterson et al., 1997). In this research, EDT is reviewed as a theory for assessing customer satisfaction by comparing pre-purchase expectations with post-purchase perceptions of product or service quality (P. G. Patterson et al., 1997). The theory revolves around key variables, such as expectation or desire, which are formed before the purchase based on anticipated performance. For instance, (McKinney & Yoon, 2002) applied the expectation-disconfirmation approach to evaluate web-customer satisfaction, while (Nevo & Chan, 2007) examined how user expectations and desires regarding knowledge management systems influence satisfaction.

Although ECT's predictive power has been proven in various contexts, including marketing, e-commerce, and information systems, it has also sparked debates (Bhattacharjee & Premkumar, 2004). Expectation Confirmation Theory is another theoretical approach used to explain the connection between consumer expectations, satisfaction, and their intention to repurchase (C. Schwarz & Zhu, 2015). This theory has been extensively applied in service marketing literature and the information systems field. It has been used by various researchers (Anderson & Sullivan, 1993) to explain how consumer satisfaction develops over time, covering both the pre-purchase and post-purchase stages. According to the expectation confirmation theory outlined by (J.-U. Kim et al., 2004; R. L. Oliver, 1993) consumers develop an initial set of expectations before making a purchase. These expectations represent what

consumers anticipate they should receive and will receive from the seller during the transaction. After they begin using the product or service, they develop perceptions of its actual performance (Anderson & Sullivan, 1993; Bhattacharjee, 2001). Consumers then compare these perceptions with their initial expectations to evaluate whether those expectations have been met, a process referred to as confirmation (Bhattacharjee, 2001). Their level of satisfaction is derived from the degree of confirmation in relation to their original expectations. If satisfied, the consumer is likely to develop an intention to repurchase. (Doong & Lai, 2008; Lankton & McKnight, 2012) utilized the expectation-disconfirmation approach to identify factors that influence continued use of e-negotiation systems. These studies suggest that the expectation-disconfirmation paradigm is applicable across various fields, especially when comparing customers' or users' perceived performance with their expectations is crucial for decision-making (C. Schwarz & Zhu, 2015; Lankton & McKnight, 2012). EDT outlines the consumer repurchasing process in five stages: (1) consumers form initial expectations before purchasing a product or service; (2) they develop perceptions based on their usage experience; (3) they compare perceived performance with initial expectations to determine whether expectations are met; (4) their satisfaction is shaped by this disconfirmation; and (5) satisfied consumers may have a repurchase intention, while dissatisfied ones may choose not to use the product or service again. Consumer reviews often reflect their pre-existing expectations (Roldan Bravo et al., 2017). In this context, confirmation refers to the alignment between expectations and actual product or service performance. This study and previous ones identified several themes related to perceived performance, including ease of use, fit accuracy, Be concerns (Roldan Bravo et al., 2017; J. Santos, 2003), delivery (N. Lankton & McKnight, 2006; D. Lee et al., 2015), and fit adjustment services. Apparel consumers consider factors like fit, care, fabric feel, quality, comfort, social feedback, usage situations, uniqueness, appearance, weight, color, price, and country of origin when reading reviews (J. Lee & Kim, 2020). In summary, EDT portrays a model of individual behavior where users develop initial expectations before using a product, experience its usage over time, and then form post-usage perceptions (W. Chen et al., 2022; Hossain, 2019). The disconfirmation construct captures the gap between original expectations and perceived performance. Disconfirmation can be positive (when actual performance exceeds expectations) or negative (when it falls short) (Roldan Bravo et al., 2017; Serrano et al., 2018). The EDT has been extensively

reported in consumer behavior literature within the marketing field, addressing areas such as consumer satisfaction, post-purchase behavior, and service marketing (Levesque & McDougall, 1996; Westbrook & Reilly, 1983). Numerous studies have validated EDT's predictive ability in various contexts, including product repurchase and service continuation, such as automobile repurchasing (R. L. Oliver, 1993), camcorder repurchasing (Spreng et al., 1996), and the use of professional business services (H. Li et al., 2013; Patterson et al., 1997).

- **Expectation**

Expectations shape what customers predict about the performance of products and services (Swan & Trawick, 1981). They are defined as a set of standards that forecast what customers anticipate regarding a specific product or service (Elkhani & Bakri, 2012). Expectations play a crucial role because satisfaction levels are often used to evaluate services and guide managerial decisions (Carraher-Wolverton & Hirschheim, 2023; Serrano et al., 2018). In social science literature, expectations are defined in various ways but are generally viewed as judgments of what individuals or groups believe will or should occur under certain circumstances (Venkatesh & Goyal, 2010). Expectations play a crucial role in shaping customer perceptions and satisfaction (Anderson & Sullivan, 1993; Bhattacharjee, 2001). They act as benchmarks that customers use to judge the quality and performance of products or services (Levesque & McDougall, 1996). The Expectation Disconfirmation Theory (EDT) can explain different customer behaviors during the purchasing process (Doong & Lai, 2008). First, customers who have previously interacted with a specific product or service tend to have expectations grounded in their past experiences, making these expectations more realistic (Franklin & Shemwell, 1995; J.-U. Kim et al., 2004). Second, new customers, who have no prior experience with a product or service, form their initial expectations based on feedback from other customers, advertisements, or mass media (I. Y. Choi et al., 2019; T. T. Kim et al., 2009; Kuo & Nakhata, 2019). When expectations align with or are exceeded by the actual experience, customer satisfaction is generally high (Picazo-Vela, 2009). However, when the experience falls short of these expectations, dissatisfaction can occur. Expectations are influenced by various factors, including previous experiences, word-of-mouth recommendations, marketing, and media portrayals (Carraher-Wolverton, 2022; Rekha et al., 2016; Sinha et al., 2020; Spreng et al., 1996). They are also dynamic and can evolve over

time as customers gain more experience or as market conditions change (Van Ryzin, 2013; Venkatesh & Goyal, 2010). There is extensive literature on how expectations are formed, the relationship between individual and collective expectations, and whether these expectations are rational, meaning they align with a particular model of social processes, especially when considered on average (Kokthi & Kruja, 2017; Roldan Bravo et al., 2017). The role of expectations in services has also been discussed as a potential factor influencing customer satisfaction (Tse & Wilton, 1988). Expectations are not static; they evolve over time as customers interact more with a product or service and as their needs and preferences change (Carraher-Wolverton & Hirschheim, 2023). This dynamic nature of expectations means that businesses must continuously monitor and manage them to stay aligned with customer perceptions (Venkatesh & Goyal, 2010; Nevo & Chan, 2007). Moreover, different segments of customers may have varying expectations based on their experience levels (Kuo & Nakhata, 2019). Understanding and managing customer expectations is essential for businesses to ensure positive customer experiences and long-term loyalty (C.-P. Lee et al., 2022).

- **Perceived Performance**

Perceived Performance indicates customer's experience after using products or services that can be better or worse than customer's expectation (J. Lee & Kim, 2020). Both kind of these customers who has first-hand experience or don't have first-hand experience will use purchased products or offered services for a while and can realize actual quality of presented products or services by the business (Kuo & Nakhata, 2019; Nam et al., 2020; E. Shin et al., 2022). Perceived performance refers to the customer's subjective evaluation of how well a product or service meets their expectations (McKinney & Yoon, 2002; Q.-A. Ha et al., 2021; Hien et al., 2024). Unlike objective measures of quality, which rely on specific metrics or standards, perceived performance is influenced by individual experiences, emotions, and personal benchmarks (Elkhani & Bakri, 2012; James, 2009). It plays a critical role in shaping customer satisfaction, as it directly impacts whether the customer's expectations are met, exceeded, or disappointed (I. Y. Choi et al., 2019; R. L. Oliver, 1993). Several factors contribute to perceived performance, including the quality of the product or service, the ease of use, the customer service experience, and the value for money (Rekha et al., 2016; Yu & Wang, 2017). However, perceived performance

is also highly contextual and can be influenced by external factors such as marketing messages, brand reputation, and peer reviews (Nam et al., 2020; Van Ryzin, 2013). For instance, if a product is heavily marketed as premium or high-quality, customers may set higher expectations, which in turn affects their perception of the product's performance (Qazi et al., 2017; Anderson & Sullivan, 1993). Additionally, perceived performance is not solely based on the tangible aspects of a product or service (Van Ryzin, 2013). Intangible elements, such as the emotional connection with the brand, the ambiance of a service environment, or the perceived status associated with a brand, can significantly influence how performance is perceived (P. G. Patterson et al., 1997). For example, two products with identical features might be perceived differently if one is associated with a prestigious brand. The gap between perceived performance and customer expectations can determine the overall satisfaction or dissatisfaction of the customer (H. Li et al., 2020; Nam et al., 2020). When perceived performance matches or exceeds expectations, customers are likely to be satisfied and even develop brand loyalty (Bollenbach et al., 2024; L. Fan & Suh, 2014). On the other hand, when there is a significant discrepancy between perceived performance and expectations, it can lead to dissatisfaction, negative word-of-mouth, and potential loss of business (N. Lankton & McKnight, 2006; Spreng et al., 1996). Understanding and managing perceived performance is crucial for businesses aiming to maintain customer satisfaction and loyalty (Qazi et al., 2017). By continuously monitoring customer feedback, addressing issues that affect perception, and ensuring that marketing messages align with the actual performance of the product or service, businesses can better manage customer expectations and enhance perceived performance, leading to a more positive customer experience (Carraher-Wolverton, 2022; N. Lankton et al., 2014; Nevo & Chan, 2007; Serrano et al., 2018).

- **Disconfirmation**

The concept of disconfirmation refers to the gap between a customer's initial expectations and the actual performance they observe (Swan & Trawick, 1981; Swan & Trawick, 1981). In the literature, disconfirmation is categorized into three types: positive disconfirmation, negative disconfirmation, and simple confirmation (W. Chen et al., 2022; Schwarz, 2011; Serrano et al., 2018; Van Ryzin, 2013; Venkatesh & Goyal, 2010). When a product or service fails to meet a customer's expectations, negative disconfirmation occurs, which typically results in customer dissatisfaction

(Qazi et al., 2017; Swan & Trawick, 1981; Serenko & Stach, 2009). On the other hand, positive disconfirmation happens when the actual performance of a product or service exceeds the customer's expectations, leading to customer satisfaction (N. Lankton & McKnight, 2006; Serenko & Stach, 2009). Simple confirmation occurs when the perceived performance aligns perfectly with what the customer initially expected, meaning there is no discrepancy between the expected and actual outcomes (Bollenbach et al., 2024; P. G. Patterson et al., 1997; Schwarz & Zhu, 2015). Within the expectation-disconfirmation framework, positive disconfirmation is observed when the perceived performance surpasses customer expectations, whereas negative disconfirmation arises when the performance falls short of these expectations (M. A. Hossain & Quaddus, 2012; H. Li et al., 2020; Yi, 1990). There is some debate in the literature regarding the definition of simple confirmation. While some scholars argue that simple confirmation leads to satisfaction, others suggest that it results in a state of neither satisfaction nor dissatisfaction, but rather a neutral experience (Qazi et al., 2017; C.-C. Hsieh, 2010). If customers perceive that a product or service meets or exceeds their initial expectations, positive disconfirmation occurs, resulting in their satisfaction (Levesque & McDougall, 1996; Anderson & Sullivan, 1993; Bhattacharjee & Premkumar, 2004). Conversely, if the perceived performance does not match the initial expectations, negative disconfirmation takes place, leading to dissatisfaction (Bollenbach et al., 2024; Carraher-Wolverton & Hirschheim, 2023; E. Shin et al., 2022; Sinha et al., 2020). The outcome of this disconfirmation—whether positive or negative—depends on whether the perceived quality of the product or service is better or worse than what was expected or desired by the customer (N. Lankton et al., 2014; Roldan Bravo et al., 2017). In essence, positive disconfirmation leads to customer satisfaction because the product or service outperforms expectations, while negative disconfirmation results in dissatisfaction due to underperformance (Dabholkar et al., 2000; Elkhani & Bakri, 2012; Q.-A. Ha et al., 2021; Hasan, 2019). These three theoretical constructs—expectations, positive or negative disconfirmation, and subsequent customer behavior in terms of satisfaction or dissatisfaction—are clearly outlined in a framework that distinguishes between these three types of disconfirmations and explains the relationships among them (M.J. Hossain, 2019; N. Lankton et al., 2014). This framework provides a transparent understanding of how customer expectations, perceived performance, and the

resulting satisfaction or dissatisfaction are interconnected (C.-P. Lee et al., 2022; Roldan Bravo et al., 2017; Serrano et al., 2018).

- **Satisfaction**

Customer satisfaction is a fundamental concept in marketing, emphasizing the importance of fulfilling customers' needs and desires. Although research on customer satisfaction, its measurement, and its implications has been ongoing for many years, it has gained significant momentum in recent decades (Miller & Miller, 1991; Parasuraman et al., 1988; Selnes, 1998; Van Ryzin, 2006; C.-C. Hsieh, 2010; H. Li et al., 2020; N. Lankton et al., 2014; E. Shin et al., 2022; Bollenbach et al., 2024; Carraher-Wolverton & Hirschheim, 2023). The concept of satisfaction is central and extensively discussed across various disciplines such as psychology, marketing, management, and information systems (Anderson & Sullivan, 1993; Cyr, 2008; Flavian et al., 2006; E.-J. Lee & Overby, 2004; C. Oliver, 1997; M. G. Patterson et al., 1997). Generally, satisfaction is understood as an evaluative response or attitude towards a specific object or experience. In the realm of consumer satisfaction research, the literature posits that perceived performance is a key precursor to satisfaction (Gardial et al., 1994; Mittal et al., 1999; R. L. Oliver, 1980; Van Ryzin, 2013; Venkatesh & Goyal, 2010; Westbrook & Reilly, 1983). Studies have examined the direct impact of perceived performance on satisfaction, as seen in the works of (Latour & Peat, 1979; Mittal et al., 1999; Selnes, 1998), while others have explored its indirect effects (Cadotte et al., 1987; Churchill & Surprenant, 1982; Qazi et al., 2017). The body of research on customer satisfaction is vast, encompassing individuals' satisfaction and dissatisfaction with private goods and services (Anderson & Sullivan, 1993; Cadotte et al., 1987; Carraher-Wolverton, 2022; Johnson et al., 1996; Kristensen et al., 1999; Parasuraman et al., 1988; Rekha et al., 2016; J. Santos, 2003; Westbrook & Reilly, 1983). Satisfaction is recognized as a crucial element in fostering successful, long-term relationships with customers (Garbarino & Johnson, 1999; W. G. Kim et al., 2009; Martensen et al., 2000; Moorman et al., 1993; Morgan & Hunt, 1994). Various scholars have proposed different definitions of customer satisfaction, but (R. L. Oliver, 1993) definition is widely accepted. According to Oliver, customer satisfaction is an attitude or evaluation formed by customers when they compare their pre-purchase expectations with the actual performance of a product or service they received (Anderson & Sullivan, 1993; Carraher-Wolverton &

Hirschheim, 2023; M. J. Hossain, 2019; Levesque & McDougall, 1996; H. Li et al., 2020; Qazi et al., 2017; J. Santos, 2003; E. Shin et al., 2022; Spreng et al., 1996). This concept is considered one of the most critical outcomes of all marketing activities within market-oriented companies (Kandampully & Suhartanto, 2000). When a service or product meets or exceeds customer expectations, it generally results in satisfaction. Conversely, if the service or product falls short of expectations, dissatisfaction usually ensues (Van Ryzin, 2013; Venkatesh & Goyal, 2010). Customer satisfaction is often viewed as a post-purchase attitude that emerges from a mental comparison between the quality of service and products that customers expected to receive and the actual quality they perceived after the exchange (Czepiel & Rosenberg, 1977; Kandampully & Suhartanto, 2000; J. Kim et al., 2009; LaTour & Peat, 1979; Levesque & McDougall, 1996; H. Li et al., 2020). To better understand and explain consumer satisfaction, various models and theories have been developed. One of the most prominent models in this field is the Expectation Confirmation Theory (ECT) (Kristensen et al., 1999). ECT suggests that customer satisfaction is derived from the comparison between a customer's post-purchase evaluation of a product or service and their initial pre-purchase expectations (H. Li et al., 2020; Qazi et al., 2017). This theory highlights the importance of managing customer expectations and delivering on promises to ensure satisfaction and foster long-term customer loyalty (Dabholkar et al., 2000; Doong & Lai, 2008; Q.-A. Ha et al., 2021).

2.5 Research Gap

The literature review played a crucial role in helping the researcher pinpoint specific gaps and overlooked areas that require further investigation for a more comprehensive understanding. The researcher examined a wide range of studies on social media usage in both Indian and Western contexts. Through this review, research gaps were identified and utilized to shape the current study. It is evident from previous research, journals, articles, and periodicals that a significant number of studies have been conducted in the broader field of social media usage, electronic word of mouth, and online reviews (Hai Ming et al., 2022; Mahmud et al., 2024). Despite the extensive body of literature, there remains a gap in examining the purchase intentions of Gen Z consumers, especially within the apparel industry (Hirst & Omar, 2007). A comprehensive literature review revealed that while there is an abundance of research on the influence of online reviews on both online and offline purchases, the majority

of these studies have focused on a single platform of online reviews. Research specific to the North Indian context, particularly in regions like Punjab, is relatively scarce. Additionally, there is a noticeable lack of empirical research that takes a holistic approach, covering various online review platforms within the online apparel industry, as referenced by Gen Z consumers in India (Kautish & Rai, 2019; Lim et al., 2016). Existing studies have primarily targeted academic populations and general residents, often including respondents from various age groups and countries, including India. This highlights a limitation in previous studies and underscores the need for future research that focuses on specific generational categories within India. Moreover, there is a scarcity of research on the purchase intentions of Gen Z consumers in relation to services like online shopping for apparel (Mukhopadhyay et al., 2023). As a result, the present study focuses on the Indian Gen Z population as a representative sample, recognizing that they are a highly tech-savvy generation who actively engage with online review platforms and various digital activities (Euajarusphan, 2021; Koleva, 2023; Lina et al., 2022). This generation, particularly the younger members, constitutes one of the largest consumer groups and is instrumental in the adoption of new technologies, influencing a wide range of industries, including business, services, and beyond (Koleva, 2023; NGO et al., 2022; Puiu et al., 2022). Previous studies have also delved into various domains such as the travel and hospitality industries (M. Y. P. Peng et al., 2023). While some research has touched upon the apparel segment, there remains a need for a more in-depth exploration of this industry specifically. Traditionally, clothing has been purchased from physical stores where customers can touch, feel, and try on items before making a purchase (Lina et al., 2022; Mude & Undale, 2023). However, Gen Z consumers, who have ample time and financial resources, view online clothing shopping as an attractive option, largely due to the convenience provided by the internet. Research has shown that young people place a high value on their appearance, and clothing plays a significant role in shaping their self-perception. They invest considerable money in their attire as a means of expressing their identity. Therefore, it is crucial to study the online shopping behavior of young consumers concerning garment purchases. There is a notable lack of research focused on Generation Z, especially as they transition into the workforce (Thangavel et al., 2022). Understanding this generation is essential to integrating them into the online apparel purchasing landscape. The acceptance of online review information varies across different

demographics of Indian online review users. However, no study has thoroughly explored the moderating role of demographic variable, such as gender, in the relationship between online reviews and the purchase intentions of Gen Z consumers. Furthermore, the application of Expectation Disconfirmation Theory in the context of online reviews and purchase intentions of Gen Z consumers remains underexplored. This theory is valuable for understanding whether the information Gen Z consumers receive from online reviews meets their expectations when purchasing apparel. Notably, the connection between higher-order variables like online reviews and first-order variables such as expectation, disconfirmation, perceived performance, and satisfaction has received little attention in previous researches. This study aims to address these gaps comprehensively, providing a deep exploration of these under-researched areas.

2.6 Research Questions

RQ 1 What are the motives for reading online reviews by Gen Z consumers?

RQ 2 How online reviews influence the purchase intention of Gen Z consumers?

RQ 3 Does gender moderates between the online reviews and purchase intention of Gen Z consumers?

RQ 4 How online reviews effect the Gen Z consumers satisfaction?

2.7 Statement of the Problem

In the apparel industry, it is essential for marketers to understand the influence of online reviews on Generation Z consumers while purchasing. India's retail sector is rapidly evolving, shifting from unorganized to organized segments. Notably, about 50% of the population is between 18 to 29 years old (Harari et al., 2023; R. Katz et al., 2022), making Gen Z a significant and influential consumer group. Gaining insights into their preferences, shopping habits, and decision-making processes enables businesses to effectively tailor their strategies to meet this demographic's unique needs (Tabassum et al., 2020; N. Zhang et al., 2022). Understanding the factors that drive Gen Z to shop online is crucial for satisfying their demands (Priporas et al., 2017; Thangavel et al., 2022). Beyond these influencing factors, it is equally important to consider the demographic profile of online shoppers, including age, gender, income, and education, to develop targeted strategies (Sudirjo et al.,

2023; Sun & Xing, 2022). The widespread availability of the Internet and easy access to online information have empowered consumers to rely on digital resources during their decision-making process (Angmo et al., 2024; Anvari & Norouzi, 2016; Grover et al., 2010). Today, everyone from small-scale entrepreneurs to large organizations depends on social media for business growth. The shopping landscape is shifting from traditional in-store visits to smarter, online methods. Online reviews are generally perceived as more credible than marketer-generated content (Qin et al., 2023; Sethna et al., 2017), making them a powerful tool for influencing consumer decisions. These reviews function as free, online sales assistants, helping consumers, especially those less familiar with products, to identify items that meet their needs (R. K. Singh, 2019; H.-R. Shin & Choi, 2021). In recent years, online shopping has significantly penetrated Tier-II and Tier-III cities. As companies increasingly focus on mobile commerce (m-commerce), online shopping is poised for substantial growth in the near future (H. Shah et al., 2024). However, online shopping presents consumers with uncertainties due to the abundance of information, as well as the intangibility and impersonality of the online environment. As a result, consumers actively seek out online information before making purchases (E. T. G. Wang et al., 2006, R. Wang, 2015). Peer-based online reviews are the most influential information source for online shoppers, and after making a purchase, many consumers are eager to share their experiences online, which can create a ripple effect on consumer behavior. Given the significant impact of online reviews on shopping behavior, this topic has acquired attention from both marketing practitioners and researchers worldwide (C. Li et al., 2024). This study investigates the factors that motivate Gen Z consumers to engage with online reviews on e-commerce platforms and whether they are satisfied with their purchases after using these reviews. The study aims to assess the influence of online reviews on the purchase intention of Gen Z consumers in the apparel industry. A survey was conducted in the districts Jalandhar, Amritsar, Ludhiana, Gurdaspur, Ferozepur and Hoshiarpur of Punjab to explore the impact on Gen Z consumers who purchased apparel online. The research reveals that there has been limited study on online apparel shopping and Gen Z consumers in emerging markets like India. Therefore, understanding the online purchase intentions and behavior of Gen Z consumers in the apparel industry has been identified as a critical research problem for this study.

2.8 Significance of Study

India is a vast and multifaceted society, with a large population characterized by immense diversity in language, customs, ethnicity, habitat, and lifestyle. Even among India's major cities, consumer behavior varies significantly (Ruiz-Mafe & Veloutsou, 2017). In recent years, e-commerce has emerged as a significant force in Indian society, with online shopping becoming a crucial part of daily life (Khosla & Kumar, 2017; Thakur et al., 2020). This rapid expansion of e-commerce is largely attributed to the government's focus on enhancing digital infrastructure, widespread Internet access, a growing number of smartphone users, and increased consumer confidence in shopping online (C. M. Cheung & Thadani, 2012). Generation Z, in particular, stands out for their extensive internet use compared to other generations (R. Katz et al., 2022; Sudirjo et al., 2023). This demographic share common needs and traits with their global counterparts. For marketers, understanding the behavior of Gen Z consumers is essential, especially regarding their likelihood of reading online reviews when purchasing apparel from e-commerce platforms (Guo & Luo, 2023; Handayani et al., 2021). Generation Z is predicted to become the largest online consumer segment. Globally, they place high value on maintaining social connections and actively engaging with each other. Interaction and engagement are key motivators for sharing online reviews (Alanko, 2018; Duffett, 2017; A. Fan et al., 2023). Many consumers express their brand loyalty on social media through online reviews (Alcaniz et al., 2019; Duffett, 2017). Gen Z consumers value the authenticity and honesty found in online reviews and rely on them when making purchasing decisions. The focus on the apparel industry is particularly relevant, as Gen Z consumers frequently purchase clothing online from various e-commerce platforms like Myntra, Ajio, Meesho etc. In the highly competitive e-commerce landscape, online reviews play a critical role in shaping consumer attitudes and behaviors (Vasan, 2023; C. M. Cheung & Thadani, 2012). Consumers often depend on the opinions of others shared online to reduce the risks associated with online purchases. After completing a purchase, they are also eager to share their experiences on online platforms (Azhar et al., 2023; Szymkowiak et al., 2021). Online reviews often emerge from exchanges between friends and acquaintances on social media, where they discuss products or services they've used (Chu & Kim, 2011; Erkan & Evans, 2016) These reviews help alleviate the uncertainties associated with challenging online purchases (C. M.

Cheung & Thadani, 2012; Erkan & Evans, 2016). The widespread availability of the Internet and the proliferation of social media platforms, consumer review sites, and blogs empower consumers to engage in active information searches during online purchases (Chetioui & El Bouzidi, 2023; Guo & Luo, 2023). In the digital age, online reviews are essential, serving as a key source of product-related information. Online reviews have become one of the most crucial marketing communications tools, accessible to customers at any time. Both the type and number of reviews can significantly impact product adoption (D.-H. Park & Kim, 2008). This study aims to explore various aspects of online reviews that influence the online consumer decision-making process. The findings of this study will be of great importance to both marketers and academics. Understanding the motivations behind to read the online reviews can help marketers to understand the consumers easily (Ismagilova et al., 2020). Recognizing the reasons why consumers seek out online reviews during their shopping journey can enable companies to address those needs, such as focusing on elements that reduce uncertainty and perceived risks associated with online shopping in apparel. Since risk reduction is a primary motivation for seeking online reviews, understanding this can help marketers better meet consumer expectations (Guo & Luo, 2023). The quality of apparel and the overall shopping experience are significant factors influencing consumers' purchase decisions. This study will provide marketers with insights into consumer behavior during the apparel purchase decision-making process (Djafarova & Bowes, 2021; Sudirjo et al., 2023). Academically, this research will contribute to understanding the impact of online reviews on Gen Z consumers' purchase intention in the apparel industry within the Punjab context. Despite numerous studies examining the influence of online reviews on online shoppers' behavioral intentions (C. M. Cheung & Lee, 2012; Erkan & Evans, 2016) there remains a need to investigate how online reviews affect apparel purchases in the emerging Indian e-commerce market. Furthermore, it's essential to assess whether Gen Z consumers are satisfied with their purchases after using online reviews. Lastly, understanding the purchase intentions of Gen Z, who spend a significant amount of time on social media, is crucial.

2.9 Summary of Chapter

This chapter is divided into four key sections. The first focuses on identifying the reasons why consumers read online reviews before making a purchase, with an

emphasis on the influence of OR's on Generation Z's PI. Additionally, it examines the moderating role of gender in the relationship between online reviews and purchase intentions, as well as how online reviews impact Gen Z consumers' satisfaction levels. A major area of exploration is the motivations that drive consumers to consult online reviews. Research has highlighted several key motivators such as saving time and money, learning about new products in the market, reducing dissonance, managing risks, and cutting down on search time. For marketers, understanding these motivations is essential as it provides insight into consumer behavior and the specific product attributes that resonate with their audience.

The chapter also delves into the generational differences in consumer behavior, particularly focusing on Generation Z. Each generational cohort has distinct lifestyles, work cultures, beliefs, and mindsets. Through literature review, it was noted that Generation Z is the most digitally native generation, having grown up in a world dominated by technology. Unlike earlier generations, Generation Z has found it relatively easy to adapt to digital tools and platforms. They are also more inclined toward fashion, often seeking trendy apparel and spending more on stylish items. Before making any online purchase, their first step is to check online reviews to gauge the experiences of other consumers. Online reviews, which consist of feedback from previous buyers, hold several key dimensions like review quality, quantity, credibility, and usefulness. Positive reviews significantly shape Gen Z's purchase intentions, making online reviews an inexpensive yet highly valuable tool for marketers to understand consumer preferences.

Another significant section of this chapter is dedicated to exploring the moderating effect of gender on the relationship between online reviews and purchase decisions. Gender, as a critical demographic variable, influences decision-making processes in distinct ways. Studies have shown that while women were initially hesitant to adopt online shopping due to technological anxiety, they are now more inclined toward e-commerce, often spending more time on online platforms. Moreover, women tend to read online reviews more frequently than men, which makes understanding these gender-based preferences essential for businesses seeking to engage both male and female consumers effectively.

Lastly, the chapter examines consumer satisfaction through the lens of the Expectation Disconfirmation Theory, a widely used framework across disciplines. This theory suggests that consumers form expectations about a product based on online reviews and then compare those expectations with the product's actual performance after purchase. If the product meets or exceeds their expectations, positive disconfirmation occurs, leading to higher satisfaction. On the other hand, if the product falls short of expectations, negative disconfirmation results in dissatisfaction.

CHAPTER 3

RESEARCH METHODOLOGY

3.1 Introduction:

This chapter delineates the research methodology employed to fulfil the objectives of this study. It includes the necessity and scope of the research, elaborates the research process, provides detailed information of data collection methods, outlines the sampling design, and provides justification for the sample size. Additionally, it discusses the design of the questionnaire and the pilot study conducted. The chapter concludes with a discussion on the statistical tools utilized and the interpretation methodologies adopted in the research.

The structure of the chapter is as follows:

- Need of study
- Objectives of study
- Conceptual framework model
- Research hypothesis
- Research design
- Sample size and design
- Data Collection
- Validity and Reliability of Questionnaire

3.2 Need and Scope of Study

The advent of e-commerce in Indian society has made online shopping a vital aspect of our everyday lives. The rapid expansion of e-commerce has led to greater internet penetration, a surge in smartphone users, and increased consumer confidence in online shopping. Numerous online retailers offer a wide range of products and brands on their websites. Consumers are regarded as the central figures in the market, playing a crucial role in business growth. Despite the variety of marketing strategies available, each one must prioritize consumer needs and satisfaction. This study aims to evaluate the impact of Online Consumer Reviews (OCR) on shopping websites, focusing on how consumers benefit from these reviews. Given the significant rise in online shopping in India, this is an opportune moment to explore the effects of electronic

Word of Mouth, particularly OCR. Surveys indicate that consumer electronics are frequently purchased online. While there is an abundance of product reviews available, reading all of them can be tedious and time-consuming for customers, leading most to read reviews selectively. Online customer reviews have significantly influenced purchase decisions in the realm of online shopping, adding a modern dimension to the concept of word-of-mouth. Numerous studies have examined the impact of online reviews on electronic goods, tourism, and the hospitality industry. However, the influence of online reviews in the online apparel e-commerce sector, including platforms like Amazon, Meesho, Myntra, Ajio, and Flipkart, requires more in-depth research in India particularly focusing on Gen Z consumers. In the current generation, Gen Z is known for their tech-savviness, spending a significant amount of time on social media. They possess extensive knowledge about online shopping and actively seek out online reviews to understand other consumers' experiences. The present study attempts to assess the influence of online reviews on Gen Z consumers in apparel industry. It examined how Gen Z consumers are influenced by online reviews. The scope of this study is focused on identifying the motivations behind reading online reviews, specifically among Generation Z online consumers in Punjab. With the rapid increase in online purchasing in India, this is an opportune moment to examine the impact of online reviews. Various surveys indicate that consumer electronics are frequently bought through online shopping. This study will offer practical insights to e-commerce platforms and consumers by identifying the factors that influence the choice of websites for purchasing apparel and the aspects of online reviews that affect purchasing decisions. The research aims to explore the influence of online consumer reviews on the purchasing decisions for apparel in Punjab, India. The data collected and the conclusions drawn from this study could help redesign websites to boost online apparel sales, making them more relevant and effective, and inform future development strategies. The study analyzed various factors related to online reviews, including review quantity, review quality, source credibility, the usefulness of online reviews, review credibility, and purchase intention. Additionally, the satisfaction of Gen Z consumers with products, based on online reviews, was examined using the expectation disconfirmation theory. Factors related to this theory expectation, perceived performance, disconfirmation ad satisfaction were analyzed.

3.3 Objectives of the study

This study adds to the growing body of research on online reviews and their impact on the purchase intentions of Gen Z consumers in Punjab. The study has been designed with the following objectives:

Objective 1: To identify the motives for reading online reviews by Gen Z consumers.

Objective 2: To study the influence of online reviews on purchase intention of Gen Z consumers.

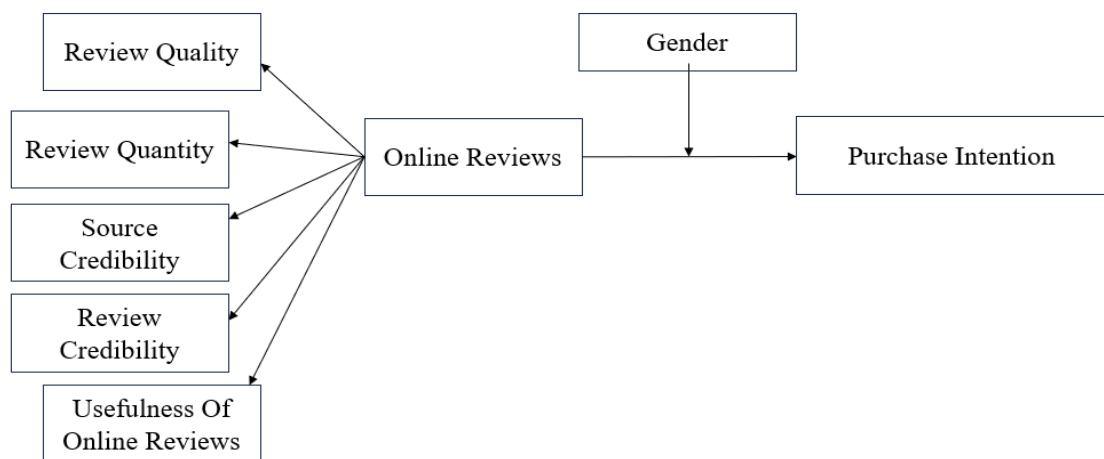
Objective 3: To analyze the moderating effect of gender between online reviews and purchase intention of Gen Z consumers.

Objective 4: To analyze the effect of online reviews on Gen Z consumers satisfaction.

3.4 Conceptual Framework

- a) To achieve the objective second i.e. to study the influence of online reviews purchase intention of Gen Z consumers and objective third i.e. moderating effect of gender between online reviews and purchase intention of Gen Z consumers.

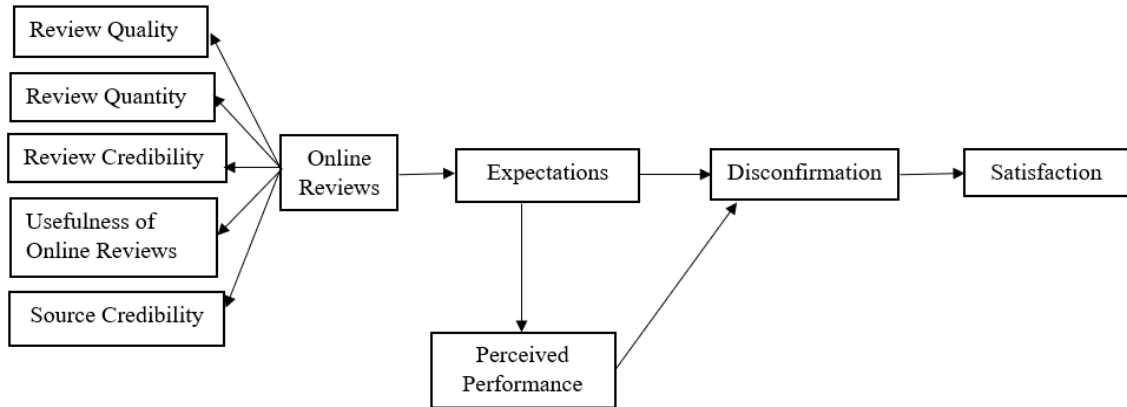
Figure 3.1: Conceptual Framework (a)



Source: Author's own creation

- b) To achieve the objective fourth i.e. to analyze the effect of online reviews on Gen Z consumers satisfaction following framework was utilized:

Figure 3.2: Conceptual Framework (b)



Source: Author's own creation

3.5 Research Hypothesis:

Main Hypothesis

Ha1- There is a positive relationship between online reviews and purchase intention of Gen Z consumers.

Sub Hypothesis

Ha 1.1- There is a positive relationship between Review Quality of online reviews and purchase intention of Gen Z consumers.

Ha 1.2- There is a positive relationship between Review Quantity of online reviews and purchase intention of Gen Z consumers.

Ha 1.3- There is a positive relationship between Source Credibility of online reviews and purchase intention of Gen Z consumers.

Ha 1.4- There is a positive relationship between Review credibility of online reviews and purchase intention of Gen Z consumers.

Ha 1.5- There is a positive relationship between usefulness of online reviews of online reviews and purchase intention of Gen Z consumers.

Main Hypothesis

H_{a2}- Gender moderates the relationship between Online Reviews and Purchase Intention of Gen Z consumers.

Sub Hypothesis

H_{a 2.1}- Gender moderates the relationship between Review Quality of online reviews and purchase intention of Gen Z consumers.

H_{a 2.2}- Gender moderates the relationship between Review Quantity of online reviews and purchase intention of Gen Z consumers.

H_{a 2.3}- Gender moderates the relationship between Source Credibility of online reviews and purchase intention of Gen Z consumers.

H_{a 2.4}- Gender moderates the relationship between Review Credibility of online reviews and purchase intention of Gen Z consumers.

H_{a 2.5}- Gender moderates the relationship between Usefulness of online reviews of online reviews and purchase intention of Gen Z consumers.

H_{a 3}- Online Reviews have a positive impact on Gen Z consumers Expectations.

H_{a 4}- There is a positive relationship between Gen Z consumers Expectations and Perceived Performance.

H_{a 5}- Gen Z consumers expectations have a positive influence on disconfirmation

H_{a 6}- There is a positive relationship between Perceived Performance and Disconfirmation.

H_{a 7}- There is a significant relationship between disconfirmation and Gen Z consumers satisfaction.

3.6 Research Design

The research design serves as a blueprint encompassing all methods and procedures or the conceptual framework within which the research is carried out. A thorough review of the literature has facilitated an understanding of the relevant concepts and theories for this study. However, there is a scarcity of similar studies focusing on online reviews in the apparel industry in India, particularly in the state of Punjab. According

to (Bickman, 2000), research design is a systematic and controlled method of inquiry that aids in planning the process for collecting and analyzing necessary information. (Creswell & Creswell, 2017) describes research design as a roadmap for the research process, ensuring it is conducted in a controlled and manageable manner by validating facts and figures. (Mishra et al., 2015) view research design as the blueprint for research work, outlining the methodology for data collection, sampling methods, research instruments, and data analysis. (Pelzang & Hutchinson, 2018) identify various types of research design, including exploratory, descriptive, explanatory, and experimental. In the current research, both exploratory and descriptive approaches were employed for examination. Consequently, a quantitative research design was implemented to test the hypothesis. Descriptive research design, a quantitative technique, aims to collect measurable data for statistical analysis of the population sample. On the other hand, exploratory research design is a methodological approach used to investigate research questions that have not been studied extensively before. Descriptive research design involves the natural observation of the behavior, characteristics, and attitudes of the population under study without deliberately manipulating the variables. The research design for the present study includes the following steps:

3.7 Sample size and design

Sampling is a crucial aspect of research. When choosing sample items, the researcher must use a careful selection technique to ensure the sample is reliable and suitable for further study.

3.7.1 Sample Frame

A sample is a smaller, more manageable segment of a larger population. This subgroup represents the characteristics of the entire population. Samples are used in statistical testing when the population size is too large to include all possible participants or observations. In North region, Punjab has been selected due to its high level of digital connectivity and substantial population base. According to the Telecom Regulatory Authority of India Punjab has approx. 25.51million subscribers which indicates Punjab has a strong potential for digital engagement. Furthermore, as per the Census 2011, in North region Punjab has more population. The target population for this study is Generation Z in Punjab, India, aged 18 to 29, who were

doing online shopping of apparels. Below age 18 respondents were not picked according to the privacy policies of e-commerce sites because they don't allow to create account below age 18. Multi-stage sampling was employed in this investigation. This method ensured a comprehensive approach to selecting participants.

3.7.2 Sampling Technique

The sample was selected using a multistage sampling technique. Punjab was divided into three regions: Majha, Malwa, and Doaba. In the first stage, the two most populated districts in these regions—Amritsar, Gurdaspur, Ludhiana, Ferozepur, Hoshiarpur and Jalandhar, —were chosen based on the Statistical Abstract of Punjab (<https://punjab.gov.in/state-profile>), with populations of 24,90,656, 16,21,725, 34,98,739, 10,02,874, 15,86,625 and 21,93,590 respectively. From each selected district, 100 respondents were taken. In the second stage, the three most populated tehsils from each district were selected: Amritsar I, Amritsar II and Ajnala from Amritsar; Gurdaspur, Dera Baba Nanak and Batala from Gurdaspur; Ludhiana (East), Jagraon and Ludhiana (West) from Ludhiana; Ferozepur, Zira and Guru Har Sahai from Ferozepur; Hoshiarpur, Dasuya and Mukeria from Hoshiarpur and Jalandhar II, Jalandhar I and Phillaur from Jalandhar.

In the third stage, samples were selected from each tehsil proportionate to their population as shown in table 3.1: Ludhiana East (73), Ludhiana West (14), Jagraon (13), Ferozepur (56), Zira (26), Guru Har Sahai (18), Amritsar II (65), Ajnala (20), Amritsar I (15), Gurdaspur (51), Batala (41), Dera Baba Nanak (8), Jalandhar I (63), Phillaur (21), Jalandhar II (16), Hoshiarpur (44), Dasuya (29) and Mukeria (27). Respondents were then chosen using purposive sampling. Given the infinite and diverse population widely dispersed, reaching Gen Z consumers engaged in online apparel shopping was challenging using traditional methods. Consequently, both online surveys and hard copies of questionnaires were distributed to these consumers. This approach ensured targeting respondents who could provide the specific information needed for the study.

Table 3.1: Sample Size and Selection

Regions	Most Populated Districts from Each Region	Top Four Populated Tehsils from Each District	Population Of Tehsils	Sample Size by Proportionate Sampling
Malwa	Ludhiana (100)	Ludhiana (East)	19,34,225	73
		Ludhiana (West)	3,62,602	14
		Jagraon	3,41,234	13
	Ferozepur (100)	Ferozepur	5,67,191	56
		Zira	2,58,438	26
		Guru Har Sahai	1,77,245	18
Majha	Amritsar (100)	Amritsar II	14,15,214	65
		Ajnala	4,42,711	20
		Amritsar I	3,12,240	15
	Gurdaspur (100)	Gurdaspur	8,21,539	51
		Batala	6,75,891	41
		Dera Baba Nanak	1,24,295	8
Doaba	Jalandhar (100)	Jalandhar I	11,45,692	63
		Phillaur	3,81,732	21
		Jalandhar II	2,91,477	16
	Hoshiarpur (100)	Hoshiarpur	5,60,346	44
		Dasuya	3,60,505	29
		Mukeria	3,35,063	27

3.7.3 Sample size

To accurately represent the target population and minimize sampling error, this study uses Cochran's (1977) sample size calculation formula for an infinite population. The parameters for this study are set with a confidence interval of ± 5 percentage points and a 95% confidence level, corresponding to a z-value of 1.96. The population proportion is assumed to be 50% (0.5). Populations exceeding fifty thousand individuals are considered infinite. The formula applied is as follows:

$$\text{Using the formula; } n_o = \frac{Z^2 pq}{d^2}$$

Where: n_o = required sample size

Z^2 = 1.96 - is the value of standard variant at 95% confidence level.

$p = 0.5$ - estimated characteristic of target population

$q = 1 - 0.5$

$d^2 = 0.05$ = acceptable margin of error for proportion being estimated = 0.05

SS = Sample Size

$$\begin{aligned} SS &= \frac{(1.96)^2 * (0.5) (0.5)}{(0.05)^2} \\ &= \frac{3.8416 * 0.25}{0.0025} \\ &= \frac{0.9604}{0.0025} \\ &= 384 \text{ (Minimum required Sample)} \end{aligned}$$

3.8 Data Collection

The success of any research hinges on effective data collection. The chosen research methodology is heavily influenced by the data collected by the researcher. Data can be obtained through two main techniques: primary and secondary data collection.

3.8.1 Secondary Source

Secondary data provides the theoretical framework necessary for constructing a conceptual model, serving as a guide for empirical observations. Researchers gather secondary data from previous studies conducted by others, which have been statistically validated or evaluated. This includes the review of literature, development of conceptual models, hypothesis formulation, questionnaire design, pilot testing, distribution of questionnaires, data collection, data analysis, and deriving conclusions and recommendations. The data can be published or unpublished and is typically gathered for purposes other than the current research problem. For the present study, secondary data was collected from a variety of sources such as articles, research papers, review papers, magazines, journals, books, and statistical reports that are directly or indirectly related to the study's main topic. This secondary data was instrumental in identifying all relevant dimensions of online reviews, including review quantity, quality, source credibility, the usefulness of online reviews, review credibility, and purchase intention. These insights were then used to obtain primary data from sample respondents for the research.

3.8.2 Primary Source

Primary data collection is a crucial method for obtaining necessary information, as it allows for the gathering of both quantitative and qualitative data. This study relied heavily on primary data collected from online shoppers in Punjab through a widely recognized sample survey technique. Specifically, a questionnaire survey was employed to gather relevant data. Adopting a quantitative approach, the study involved contacting respondents personally, via mail, telegram, whatsapp and mobile internet. A sample of 600 respondents was finalized from an initial distribution of 700 questionnaires. 35 questionnaires were excluded due to age criteria, as the respondents did not belong to the Generation Z category. 12 respondents were below 18 while 23 were above 29. As some respondents either did not complete the questionnaire or provided incomplete answers. The questionnaire designed for online shoppers was divided into five sections. One section focused on collecting demographic details such as age, gender, educational qualifications, occupation, district and tehsil, and monthly income.

3.9 Development of Instrument

The most popular method for data collection involves using a structured questionnaire, which consists of a pre-defined series of questions designed to gather information from respondents. Developing a logical and reliable questionnaire requires several stages. This instrument was created following an extensive review of relevant literature and secondary data sources. The initial step involved clearly defining the construct domain, determining what should be included and excluded. To make these decisions, a thorough review of major conceptual literature on review quantity, review quality, source credibility, the usefulness of online reviews, review credibility, and purchase intention was conducted. This instrument serves as the foundation for the study. The questionnaire aimed to collect data from Generation Z respondents, focusing on their demographic profiles, online shopping attitudes, and perceptions regarding the influence of online reviews on their purchase intentions in the online apparel industry. Various questions addressed aspects such as the devices used for online shopping, frequency of online apparel purchases, monthly expenditure on online apparel shopping, preferred online shopping websites, and favored categories of apparel for online purchase. The questionnaire is divided into two sections. The first section captures demographic details, while the second section addresses the variables studied. Each construct is measured using a set of items rated on a 5-point Likert scale, Strongly Disagree- 1', 'Disagree- 2', 'Neutral- 3', 'Agree- 4', 'Strongly Agree- 5'. The questions developed for this study were found to have high reliability and good validity.

3.10 Validation of the Questionnaire

To ensure the instrument's validity, the study adapted its instrument from previous research and assessed content validity. Content validity, or CV, measures how well an instrument's items represent the entire content domain. The Content Validity Ratio (CVR), developed by Lawshe in 1975, quantifies this validity based on expert evaluations and indicates whether an item should be retained. To determine the CVR, the researcher consulted a panel of subject matter experts for feedback on the items developed for the study's constructs. The CVR method helps decide whether to keep, modify, or discard questionnaire items based on expert judgments. This evaluation involved experts with a deep understanding of the instrument's content domain. The

questionnaire was distributed via Google Forms and hard copies, leveraging LinkedIn connections for wider reach. Validation was sought from industry experts, specifically managers from online apparel e-commerce websites, and academicians, including professors. The table 3.2 below provides details about the experts involved in the validation process:

The formula for computation of Content Validity Ratio

$$CVR = \frac{ne - \frac{N}{2}}{N/2}$$

- Ne= is the number of panellists identifying as an item ‘keep’
- N= is the total of number of panellists
- If all the panel members marked any item as ‘keep’ - CVR is 1.
- If none of the panel member marked any item as ‘discard- CVR is 0
- When the number of panellists rating an item as ‘modify’ is more than half, but less than all, CVR is between 0- 0.99.

Table 3.2: Details of Experts

Experts		Designation	Affiliation
Industry Experts	Expert 1	Product Manager	Myntra
	Expert 2	Product Manager-3	Myntra
	Expert 3	Product Manager	Ajio
	Expert 4	Product Manager-1	Meesho
	Expert 5	Assistant Manager	Flipkart
Academicians	Expert 6	Assistant Professor	Central University of Jammu
	Expert 7	Assistant Professor	Karnavati University, Gujarat
	Expert 8	Professor	IIM Visakhapatnam
	Expert 9	Associate Professor	Lovely Professional University, Jalandhar
	Expert 10	Professor	Lovely Professional University, Jalandhar

Source: Compiled from survey

Table 3.3: Minimum values for CVR

S. No	No. of panellists	Minimum values of CVR
1	5	.99
2	6	.99
3	7	.99
4	8	.75
5	9	.78
6	10	.62
7	11	.59
8	12	.56

Source: Lawshe, 1975

Table 3.4: Computation of CVR (Motives to read online reviews while online shopping)

S.NO.	CVR	Less than 0.62 CVR not acceptable
M1	0.8	Y
M2	1	Y
M3	0.4	N
M4	0.8	Y
M5	0.8	Y
M6	0.6	N
M7	0.8	Y
M8	0.8	Y
M9	0.8	Y
M10	1	Y
M11	0.8	Y
M12	0.8	Y
M13	0.8	Y
M14	0.8	Y
M15	0.8	Y
M16	1	Y
M17	0.8	Y
M18	0.8	Y
M19	0.2	N
M20	0.4	N

Source: Computed from threshold value (CVR is less than 0.62- statements not accepted)

Note: **Content Validity Ratio** = $\{(ne-N/2) \div N/2\}$

$$= (10- 10/2)/ (10/2) = (10-5)/ (5) = 1$$

$$= (9- 10/2)/ (10/2) = (9-5)/ (5) = 0.8$$

$$= (8- 10/2)/ (10/2) = (8-5)/ (5) = 0.6$$

$$= (5- 10/2)/ (10/2) = (5-5)/ (5) = 0$$

Table 3.5: Computation of CVR (Dimensions of Online Reviews)

S.NO.	CVR	Less than 0.62 CVR not acceptable
RQn 1	0.8	Y
RQn 2	0.8	Y
RQn 3	1	Y
RQn 4	0.8	Y
RQn 5	1	Y
RQ 1	0.8	Y
RQ 2	0.8	Y
RQ 3	0.8	Y
RQ 4	0.8	Y
RQ 5	1	Y
RQ 6	0.8	Y
SC 1	0.8	Y
SC 2	0.8	Y
SC 3	0.8	Y
SC 4	0.8	Y
SC 5	0.8	Y
SC 6	0.8	Y
SC 7	1	Y
UOR 1	1	Y
UOR 2	0.4	N
UOR 3	1	Y

UOR 4	0.8	Y
UOR 5	0.8	Y
RC 1	0.8	Y
RC 2	0.8	Y
RC 3	1	Y
RC 4	1	Y
RC 5	0.8	Y
PI 1	1	Y
PI 2	1	Y
PI 3	0.8	Y
PI 4	0.8	Y

Source: *Computed from threshold value (CVR is less than 0.62- statements not accepted)*

Note: Content Validity Ratio = $\{(ne-N/2) \div N/2\}$

$$= (10- 10/2)/ (10/2) = (10-5)/ (5) = 1$$

$$= (9- 10/2)/ (10/2) = (9-5)/ (5) = 0.8$$

$$= (8- 10/2)/ (10/2) = (8-5)/ (5) = 0.6$$

$$= (5- 10/2)/ (10/2) = (5-5)/ (5) = 0$$

Table 3.6: Computation of CVR (Dimensions that effects the satisfaction)

S.NO.	CVR	Less than 0.62 CVR not acceptable
EP1	0.8	Y
EP2	1	Y
EP3	0.8	Y
EP4	0.8	Y
EP5	0.6	N
PP1	0.8	Y
PP2	0.8	Y
PP3	0.8	Y
PP4	1	Y
PP5	0.4	N
DC1	0.8	Y

DC2	0.8	Y
DC3	0.8	Y
DC4	1	Y
DC5	0.8	Y
S1	0.8	Y
S2	1	Y
S3	1	Y
S4	0.8	Y
S5	0.6	N

Source: Computed from threshold value (CVR is less than 0.62- statements not accepted)

Note: **Content Validity Ratio** = $\{(ne-N/2) \div N/2\}$

$$= (10- 10/2)/ (10/2) = (10-5)/ (5) = 1$$

$$= (9- 10/2)/ (10/2) = (9-5)/ (5) = 0.8$$

$$= (8- 10/2)/ (10/2) = (8-5)/ (5) = 0.6$$

$$= (5- 10/2)/ (10/2) = (5-5)/ (5) = 0$$

In this study, the research questionnaire was validated by the 10 experts. Based on the criteria shown in the table 3.3, statements with a CVR (Content Validity Ratio) below 0.62 are not accepted. According to Lawshe's guidelines (referenced in table 3.3), any statement with a CVR value under 0.62 will be removed from the questionnaire. Out of the original 72 statements, 64 were retained as their CVR values met or exceeded the 0.62 threshold.

Items M3 (read online reviews to know about the value of the product), M6 (read online reviews to buy products at cheaper price), M19 (read online reviews to know about the delivery speed of the product), M20 (read online reviews to get information about any issues experienced by customers while delivering the product) as these statements are considered as repetitive statements and not practical.

Items UOR2 (online reviews enhance my online shopping effectiveness) this statement is not related with the concept or construct.

Items EP5 (I was able to expect the trend of product by using online reviews), PP5 (Product performance was adequate in terms of design and style), S5 (I feel satisfied

with the design and style of product) as these statements were discarded because of non-contributory and not practical.

Table 3.7: Final Questionnaire

S. No.	Coding	Construct	Items	Measurement	Source
1.	M1	I read online reviews to avoid mistakes while choosing a product		1=Strongly Disagree 2= Disagree	Hennig-Thurau et al., 2007; D. M. Khammash, 2008; Sparks & Browning, 2010; Ziegele & Weber, 2015; Bell et al., 2019; Shah & Unnithan, 2020
2.	M2	I read online reviews to evaluate the quality of product		3= Neutral 4=Agree 5=Strongly Agree	
3.	M3	I read online reviews to know about the experiences of other consumers.			
4	M4	I read online reviews to know about durability of the product			
5.	M5	I read online reviews to reduce the time taken while choosing the product			
6.	M6	I read online reviews to get information about the product			
7.	M7	I read online reviews to make my purchases confidently			
8.	M8	I read online reviews to evaluate the overall satisfaction of consumers			
9.	M9	I read online reviews in order to avoid wrong			

		choice of product with bad performance.			
10.	M10	I read online reviews to reduce anxiety caused by not-seeing or touching product.			
11.	M11	I read online reviews to avoid financial loss caused by wrong decision.			
12.	M12	I read online reviews to learn how a product is to be consumed			
13.	M13	I read online reviews to get information about the new products			
14.	M14	I read online reviews to compare the products and services			
15.	M15	I read online reviews to ensure that product meets with my specific requirements			
16.	M16	I read online reviews to protect myself from fraudulent schemes			
17.	RQn1	Review Quantity	Number of online reviews available about a product is important to me		
				1=Strongly Disagree 2= Disagree 3= Neutral 4=Agree 5=Strongly Agree	M. Y. Cheung et al., 2009; P. C. S. Wu et al., 2011; Yang et al., 2012; Sotiriadis & Van Zyl, 2013; Quaschning et

18.	RQn2		More Number of online reviews about a product gets my attention		al., 2015; Bachleda & Berrada-Fathi, 2016; Gao et al., 2017; Joshi & Singh, 2017; S. Chatterjee, 2020; K. Li et al., 2020; Y. Lin et al., 2020; C. W. Park et al., 2021; Y. Wang & Kuchmaner, 2024; Asadi Damavandi & Ha, 2024; S. Khan et al., 2023; Zheng et al., 2022
19.	RQn3		Number of online reviews are helpful in decision making		
20.	RQn4		Number of online reviews provide more information about product if they are more in number		
21.	RQn5		Number of online reviews denotes the popularity of the product/brand		
22.	RQ1	Review Quality	Online reviews are useful in my purchasing decision if content of the reviews is understandable	1=Strongly Disagree 2= Disagree 3= Neutral 4=Agree 5=Strongly Agree	
23.	RQ2		Online		

			reviews are useful in my information need if content of the online reviews is relevant		
24.	RQ3		Online reviews are more useful in my purchasing decision if they are factual and elaborate		
25.	RQ4		Online Reviews are useful if they present both the pros and cons of a product/brand rather than one sided review		
26.	RQ5		Online reviews with visual presentation of product help in my online purchase decision.		

27.	RQ6		Online reviews are useful if they are current		
28.	SC1	Source Credibility	I feel that if the reviewer's identity is disclosed reviews are more credible.	1=Strongly Disagree 2= Disagree 3= Neutral 4=Agree 5=Strongly Agree	
29.	SC2		I feel that reviewer who post online reviews are trustworthy		
30.	SC3		I feel that reviewer who post online reviews are reliable.		
31.	SC4		I feel that reviewer should be experienced about the product being reviewed		
32.	SC5		I feel that reviewer should be an expert in evaluating the product being reviewed.		

33.	SC6		I feel that knowledge level of usage of the product by reviewer is important to me.		
34.	SC7		I feel that person who posted the online reviews should be verified users		
35.	UOR1	Usefulness of Online Reviews	Online reviews improve the quality of my online shopping.	1=Strongly Disagree 2= Disagree 3= Neutral 4=Agree 5=Strongly Agree	
36.	UOR2		Online reviews make it easier for me to shop online		
37.	UOR3		Online reviews are quite helpful in my online purchase decision making process.		

38.	UOR4		Online reviews helps me to accomplish my purchasing task more quickly		
39.	RC1	Review Credibility	Online reviews are accurate	1=Strongly Disagree 2= Disagree 3= Neutral 4=Agree 5=Strongly Agree	
40.	RC2		Online reviews are credible if it is unbiased		
41.	RC3		Online reviews are credible if it is authentic		
42.	RC4		Online reviews are credible if it is believable		
43.	RC5		The online reviews are trustworthy		
44.	PI1	Purchase Intention	I am quite likely to buy the product that is recommended by the reviewer	1=Strongly Disagree 2= Disagree 3= Neutral 4=Agree 5=Strongly Agree	

45.	PI2		Based on online reviews I intend to purchase the product online.		
46.	PI3		I would make a special effort to buy the product/ brand recommended by the reviewers		
47.	PI4		I would like to recommend the product to my friends based on online reviews		
48.	EP1	Expectation	I expected the accuracy of information by reading online reviews	1=Strongly Disagree 2= Disagree 3= Neutral 4=Agree 5=Strongly Agree	E. Shin et al., 2022; Dabholkar et al., 2000; J.-U. Kim et al., 2004; McKinney & Yoon, 2002; C. Schwarz & Zhu, 2015; J.-U. Kim et al., 2004; R. L. Oliver, 1993; Bhattacharjee,
49.	EP2		I expected that online reviews have ability to meet my personal needs		
50.	EP3		I expected the quality of product by reading online		

			reviews		2001; Lankton & McKnight, 2012; Roldan Bravo et al., 2017; W. Chen et al., 2022; Hossain, 2019
51.	EP4		I expected reviewers provide the detailed information about product		
52.	PP1	Perceived Performance	Online reviews improve my learning	1=Strongly Disagree 2= Disagree 3= Neutral	
53.	PP2		Online reviews improve my skill of decision making	4=Agree 5=Strongly Agree	
54.	PP3		Online reviews enable me to access a lot of useful information		
55.	PP4		Online reviews are worth using as it easily accessible		
56.	DC1	Disconfirmation	My experience to use the product was better than what I had expected	1=Strongly Disagree 2= Disagree 3= Neutral 4=Agree 5=Strongly	

				Agree	
57.	DC2		The information provided by online reviews was better than what I had expected.		
58.	DC3		Overall, most of my expectations from the online reviews were matched		
59.	DC4		Expectations based on online reviews were met after using it		
60.	DC5		The extent of help provided by online reviews was better than expected		
61.	S1	Satisfacti on	The information provided by reviewers makes me feel satisfied	1=Strongly Disagree 2= Disagree 3= Neutral 4=Agree 5=Strongly Agree	
				Agree	

62.	S2		Using the online reviews makes me feel very connected with others		
63.	S3		Using the online reviews makes me feel very pleased		
64.	S4		I feel contented by using online reviews		

3.11 Pre-Testing

The initial draft of the questionnaire was pilot tested to assess the clarity of its language, layout, and wording. A pilot study, which is a small-scale survey conducted before the main investigation, helps to determine the feasibility of a larger study. In this case, the pilot study involved administering the questionnaire to a small sample, comprising 10% of the intended respondents (Bajpai, 2011; Cann et al., 2008). This step was crucial to ensure that the questions were comprehensible to the target audience. Participants were asked to thoroughly read and respond to the items, helping to identify and eliminate any potential ambiguities or difficulties. Based on their feedback and suggestions, further refinements were made to the presentation and language of the questions.

3.12 Reliability and Validity of Questionnaire

It is essential for researchers to evaluate the accuracy of the instruments used in their studies to ensure reliable and consistent results. In the current study, the validity and reliability of the instrument were assessed to confirm the consistency of its items. Validity is defined as "the attribute of an instrument wherein it truly measures what it

was intended to measure” (Cronbach, 1971). Initially, face and content validity were established through an extensive review of relevant literature. The items were then reviewed by experts with comprehensive knowledge of the subject area, who rated each item's relevance and consistency. Items that demonstrated high consistency with the study's objectives were included in the instrument. Reliability means ‘consistency of the instrument to get the same results if it will be measured more than once’ (Malhotra & Dash, 2013). The Cronbach’s Alpha test was conducted on data from sixty respondents. The instrument's reliability was evaluated using data collected from ten percent of the sample, analyzed with the Statistical Package for Social Sciences (SPSS). The reliability scores for all items exceeded .85. As a result, the instrument was deemed reliable and valid for data collection from the respondents. As table 3.8 shows the reliability of all constructs:

Figure 3.3: Lee Cronbach in 1951

Cronbach’ Alpha	Internal consistency
$\alpha \geq 0.9$	Excellent
$0.9 > \alpha \geq 0.8$	Good
$0.8 > \alpha \geq 0.7$	Good and Acceptable
$0.7 > \alpha \geq 0.6$	Acceptable
$0.6 > \alpha \geq 0.5$	Unacceptable
$0.5 \geq \alpha$	Poor

The formula for Cronbach’s alpha is:
$$\alpha = \frac{N \cdot \bar{c}}{\bar{v} + (N-1) \cdot \bar{c}}$$

Where:

- N = the number of items
- $\bar{c}$ = average covariance between item-pairs
- $\bar{v}$ = average variance

Table 3.8: Reliability of the research instrument

Sr. No.	Constructs	Items included	Cronbach's Alpha	Consistency
1.	Reliability of Expectation	4	.928	Excellent
2.	Reliability of Perceived Performance	4	.922	Excellent
3.	Reliability of Disconfirmation	5	.941	Excellent
4.	Reliability of Satisfaction	4	.948	Excellent
5.	Reliability of Review Quantity	5	.950	Excellent
6.	Reliability of Review Quality	6	.971	Excellent
7.	Reliability of Source Credibility	7	.960	Excellent
8.	Reliability of Usefulness of Online Reviews	4	.932	Excellent
9.	Reliability of Review Credibility	5	.917	Excellent
10.	Reliability of Purchase Intention	4	.959	Excellent

Source: Overall reliability of all variable from SPSS software

3.13 Demographic Profile and Online Buying Pattern of Gen Z consumers

The buying behavior and decisions of consumers, along with their subsequent actions, can influence them at different stages of the purchasing process. The purchase intentions of Generation Z consumers vary based on their demographic characteristics. There are notable differences in purchasing patterns between men and women, especially regarding their decision-making processes. Additionally, online shopping habits can be influenced by the demographic profiles of the participants. The study considered various demographic factors, including gender, educational background, districts, tehsils, occupation, and monthly income. The demographic

profile of the 600 respondents is detailed in terms of frequency and percentage in the accompanying table 3.10

Table 3.9 shows males constituted 39% of the respondents, while females represented 61% of the sample. In education qualification 3 respondents (0.5%) were Below Matriculation/10th, 6 respondents (1.0%) were 10th/Matriculation, 23 respondents (3.8%) were 10+2, 306 respondents (50.9%) were Undergraduate, 250 respondents (41.6%) were Postgraduate, 12 respondents (2.0%) were any other consider 7 Diploma or 3 Ph.D or 2 some professional courses. 100 respondents (16.6%) were taken from each district (Amritsar, Jalandhar, Ludhiana, Ferozepur, Gurdaspur and Hoshiarpur). From tehsils Amritsar2 65 respondents (10.8%), Ajnala 20 respondents (3.3%), Amritsar1 15 respondents (2.5%), Jalandhar1 63 respondents (10.5%), Jalandhar2 21 respondents (3.5%), Phillaur 16 respondents (2.7%), Ludhiana (East) 73 respondents (12.1%), Ludhiana (West) 14 respondents (2.3%), Jagraon 13 respondents (2.2%), Ferozepur 56 respondents (9.3%), Zira 26 respondents (4.3%), Guru Har Sahai 18 respondents (3.0%), Gurdaspur 51 respondents (8.5%), Batala 41 respondents (6.8%), Dera Baba Nanak (1.3%) were responded. 421 respondents (70.0%) were students, 101 respondents (16.8%) were private employee, 40 respondents (6.7%) were government employee, 26 respondents (4.3%) were Business/ Self-employed and 12 respondents (2.0%) were unemployed. Monthly income of 330 respondents (54.9%) had less than 10000, 62 respondents (10.3%) had income between 10001-20000, 113 respondents (18.8%) had income between 20001-40000, 59 respondents (9.8%) had income between 40001-60000, 36 respondents (6.0%) had income more than above 60001. In online buying pattern all the respondents were do online shopping. 5 respondents (0.8%) use desktop for online shopping, 61 respondents (10.2%) use laptop, 499 respondents use (83.2%) use smartphone, 34 respondents (5.7%) use tablet. 209 Gen Z consumers (34.8%) purchase apparels online less than once a month, 158 respondents (26.3%) purchase once in a month, 155 respondents (25.8%) purchase two times a month, 35 respondents (5.8%) purchase three times a month, 43 respondents (7.2%) purchase more than three times a month. 277 respondents (46.1%) spend less than 2000 on apparels in a month, 202 respondents (33.6%) spend between 2001- 4000, 76 respondents (12.6%) spend between 4001- 6000 and 45 respondents (7.7%) spend more than 6001. 78 respondents (13.0%) favourite website was Meesho from where

they purchase apparel, 198 respondents (32.9%) were preferred Myntra, 119 respondents (19.8%) were preferred Amazon, 109 respondents (18.1%) were preferred Ajio and 96 respondents (16.0%) were preferred Flipkart. 244 respondents (40.6%) were preferred to purchase western wear, 54 respondents (9.0%) were preferred to purchase woolen clothes, 118 respondents (19.6%) were preferred to purchase ethnic wear, 101 respondents (16.8%) were preferred to purchase sport wear and 83 respondents (13.8%) were preferred to purchase formal wear.

Table 3.9: Demographic Profile and Online buying pattern of Gen Z consumers

Demographic	Statement	Frequency	Percent %
Gender	Male	233	39%
	Female	367	61%
Educational Qualification	Below Matriculation/10th	3	0.5%
	10 th /Matriculation	6	1.0%
	10+2	23	3.8%
	Under Graduate	306	50.9%
	Post Graduate	250	41.6%
	Any Other	12	2%
Districts	Amritsar	100	16.6%
	Jalandhar	100	16.6%
	Ludhiana	100	16.6%
	Ferozepur	100	16.6%
	Gurdaspur	100	16.6%
	Hoshiarpur	100	16.6%
Tehsils	Amritsar 2	65	10.8%
	Ajnala	20	3.3%
	Amritsar 1	15	2.5%
	Jalandhar 1	63	10.5%
	Jalandhar 2	21	3.5%
	Phillaur	16	2.7%
	Ludhiana (East)	73	12.1%

	Ludhiana (West)	14	2.3%
	Jagraon	13	2.2%
	Ferozepur	56	9.3%
	Zira	26	4.3%
	Guru Har Sahai	18	3.0%
	Gurdaspur	51	8.5%
	Batala	41	6.8%
	Dera Baba Nanak	8	1.3%
	Hoshiarpur	44	7.3%
	Dasuya	29	4.8%
	Mukeria	27	4.5%
Occupation	Student	421	70.0%
	Private Employee	101	16.8%
	Government Employee	40	6.7%
	Business/Self Employed	26	4.3%
	Unemployed	12	2.0%
Monthly Income	Less than 10000	330	54.9%
	10001-20000	62	10.3%
	20001-40000	113	18.8%
	40001-60000	59	9.8%
	Above 60001	36	6.0%
Do you shop online? If Yes Kindly Proceed Further	Yes	600	100%
Which device do you mostly use for online shopping?	Desktop	5	0.8%
	Laptop	61	10.2%
	Smartphone	499	83.2%
	Tablet	34	5.7%
How often Gen Z purchase apparels online?	Less than once a month	209	34.8%
	Once in a month	158	26.3%
	Two times a month	155	25.8%
	Three times a month	35	5.8%

	More than three times a month	43	7.2%
How much you spend in a month on apparels while online shopping?	Less than 2000	277	46.1%
	2001- 4000	202	33.6%
	4001-6000	76	12.6%
	More than 6001	45	7.7%
Favourite online shopping website from you purchase apparel	Meesho	78	13.0%
	Myntra	198	32.9%
	Amazon	119	19.8%
	Ajio	109	18.1%
	Flipkart	96	16.0%
Select the category of apparel that you prefer to purchase online	Western Wear	244	40.6%
	Woolen Clothes	54	9.0%
	Ethnic Wear	118	19.6%
	Sports Wear	101	16.8%
	Formal Wear	83	13.8%

Source: SPSS software

3.14 Data Analysis Tools

Table 3.10: Statistical Tools used with research objectives

Objective	Statistical Technique
To identify the motives for reading online reviews by Gen Z consumers.	Exploratory factor Analysis Confirmatory factor analysis Sparks, B. A., & Browning, V. (2010), Khammash, M. (2005), Parikh et al., 2015 Hussain, S., Song, X., & Niu, B. (2020)
To study the influence of online reviews on purchase intention of Gen Z consumers.	Structural Equation Modeling Abdul-Rahamon, O. A., & Adejare, A. T. (2014), (Sethna et al., 2017) Kumar, R. (2018), (Tabassum et al., 2020), (H.-R. Shin

	& Choi, 2021), (Ngo et al., 2024)
To analyze the moderating effect of gender between online reviews and purchase intention of Gen Z consumers.	Structural Equation Modeling (Sethna et al., 2017), (Zhu et al., 2020), (H.-R. Shin & Choi, 2021), (N. Zhang et al., 2022), (Al-Abbadi et al., 2022)
To analyze the effect of online reviews on Gen Z consumers satisfaction.	Structural Equation Modeling (Picazo-Vela, 2009), (Qazi et al., 2017), (Ranchi et al., 2018), (Kuo & Nakhata, 2019), (J. Lee & Kim, 2020), (E. Shin et al., 2022)

3.14.1 SPSS

SPSS (Statistical Package for the Social Sciences) is a powerful statistical software suite widely used for data management, advanced analytics, multivariate analysis and business intelligence. Developed by IBM, SPSS is known for its user-friendly interface, making it accessible to both experienced users. It offers robust statistical procedures to analyze and visualize data effectively. Researchers and analysts appreciate its comprehensive range of statistical tests and data handling capabilities. SPSS also integrates well with other software and platforms, enhancing its functionality and versatility in various fields. SPSS 26 version was used in this study. The software allows for the calculation of Cronbach's alpha to assess internal consistency, and supports performing factor analysis, correlation, and regression analysis.

3.14.2 Smart PLS (SEM)

SEM is a statistical technique, which is often used in the marketing research, because marketers can examine the relationship between dependent variables and independent variables, in order to serve the better services to the customers (Wong, 2013). SEM is a versatile analytical method that integrates regression, correlation, and factor analyses concurrently, making it valuable for tackling significant questions across the

social sciences, biological sciences, and humanities. PLS, a variant of SEM, is especially effective for intricate predictive models, emphasizing the maximization of the explained variance in dependent variables (Dilalla, 2000). PLS-SEM is the most fully developed and general system and it is also called a “silver bullet” (Al-Emran et al., 2019; Hair, Risher, et al., 2019). It is divided into two main models, ‘measurement model and structural model’. Measurement model also known as “outer model” it measures the relationship between constructs and its relevant items and structural model refers as the “inner model”, it measures the relationship between the constructs themselves.

3.14.3 Factor Analysis

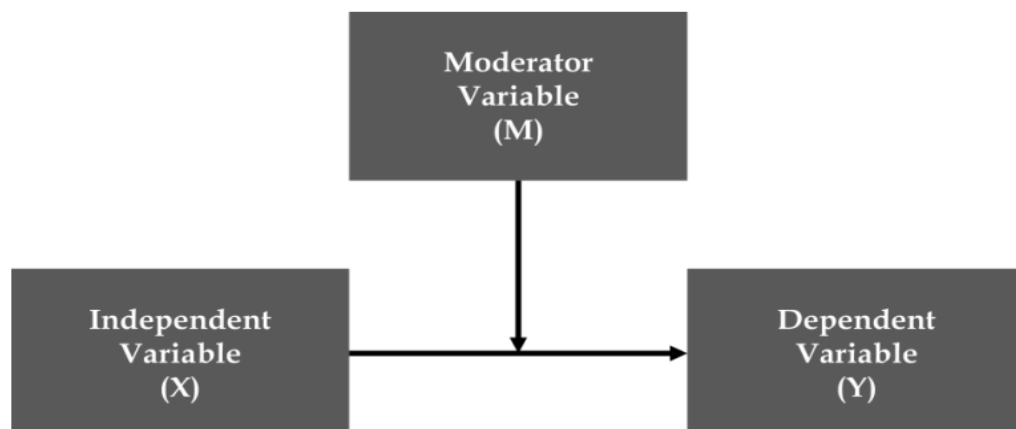
Factor analysis is a versatile statistical method used across various fields for multiple purposes. It is primarily employed for data reduction, simplifying large datasets by identifying underlying factors and reducing the number of variables while preserving essential information. This technique also detects the structure of relationships between variables, helping researchers understand the data's underlying dimensions. In scale development, factor analysis assists in creating and validating measurement scales by identifying items that group together. By addressing multicollinearity issues in regression analysis, factor analysis combines correlated variables into single factors. Factor analysis have two types of factors i.e. Exploratory factor analysis and confirmatory factor analysis. Exploratory Factor Analysis (EFA) is generally more effective with large samples and aims to uncover latent factors. Both EFA and CFA serve this purpose, but EFA takes a more exploratory approach compared to CFA (Osborne & Banjanovic, 2016). CFA, on the other hand, focuses on confirming the fit of a proposed model to the data using a different statistical method, specifically SEM or a Measurement Model, and relies on covariation matrices. EFA is useful for determining the factor structure or model and explains the maximum amount of variance, while CFA is used to validate the number of factors and analyze which items load onto each factor (M. D. Cooper & Phillips, 2004).

3.14.4 Structural Equation Modelling (Moderation analysis)

Moderation in statistical analysis refers to a scenario where the relationship between an independent variable (IV) and a dependent variable (DV) changes based on the value of a third variable, known as the moderator (Dawson, 2014; J. J. Wang et al.,

2019). The moderating variable influences the strength or direction of the relationship between the IV and DV. Essentially, the impact of the IV on the DV varies depending on the level of the moderator. Moderators are crucial in determining if the relationship between two variables remains consistent across different groups. Moderation describes a situation where the connection between two variables is not stable but instead depends on the value of a third variable, known as the moderator (Dawson, 2014; Hair, Ringle, et al., 2019; Hayes, 2018). Understanding moderation is key to comprehending the mechanisms within social science theories (Frazier et al., 2004; Hayes, 2018; Maes et al., 2014; Srisathan et al., 2023). In summary, a moderation model addresses the question of "when" or "for whom" a variable significantly influences an outcome (Frazier et al., 2004). In a typical moderation model as figure shows 3.3 there is a dependent variable (Y), an independent variable (X), and a moderator (M). The moderator is depicted as influencing the relationship between X and Y. However, the statistical representation of moderation differs slightly from the conceptual model, as it includes an interaction term, represented as $X*M$ (Z). Moderators can take on different forms: they may be categorical variables when using nominal or ordinal scales (e.g., male vs. female; public vs. private bank) or continuous variables when using interval scales (e.g., high vs. low levels of organizational support) (Memon et al., 2019; Pico-Saltos et al., 2022) .

Figure 3.4: Moderation Analysis



Source: Memon, M. A., Cheah, J. H., Ramayah, T., Ting, H., Chuah, F., & Cham, T. H. (2019). *Moderation analysis: issues and guidelines*.

3.14.5 MGA (Multigroup Analysis)

Multigroup analysis (MGA) within partial least squares structural equation modeling (PLS-SEM) has seen significant growth in application across various research disciplines, particularly within the business sector, over recent years. Multigroup analysis is especially advantageous for conducting moderation analysis when the moderator is a categorical variable or when a continuous variable has been transformed into a categorical one (Carranza et al., 2020; Hult et al., 2018). The core idea behind Multigroup analysis is to compare effects across different groups by considering a categorical moderator variable. According to (Bergh et al., 2016; Bernerth & Aguinis, 2016) such a moderator influences the direction and/or strength of the relationship between an independent (predictor) variable and a dependent (criterion) variable. The primary purpose of Multigroup analysis is to identify whether there are statistically significant differences among various groups (Ghazali et al., 2020; Hult et al., 2018; Jr. et al., 2017; MacKinnon, 2011). While many researchers often concentrate on the impact of a moderator on the overall model relationships when employing MGA (Alomari et al., 2022; Carranza et al., 2020; Hult et al., 2018; Matthews et al., 2018), it is important to recognize that MGA in Smart PLS can also be used to assess the significance of moderating effects on specific individual relationships. Through PLS-MGA, researchers can analyze the structural path differences among multiple groups (Aggarwal & Kapoor, 2021; Alomari et al., 2022; Carranza et al., 2020; Cheah et al., 2023). MGA is a well-established method for comparing groups and has become a preferred choice for investigating differences between categorical variables, such as gender or geographical regions (Alomari et al., 2022; Carranza et al., 2020; Cheah et al., 2023; Chmura Kraemer et al., 2008; Tran et al., 2019). In this particular study, the demographic variable gender was employed as the moderator. Multigroup analysis facilitates a comprehensive understanding of how various groups may show differing patterns in their relationships within the model, thus offering deeper insights into the dynamics involved.

3.14.6 Kaiser-Meyer-Olkin (KMO)

The KMO test is used to evaluate the adequacy of the sample size for analysis. KMO test has been used to assess the suitability of data for factor analysis. It measures the sufficiency of each construct in the model as well as for the whole model. The values

should be varied from 0 to 1. If the value of KMO comes between 0.8 to 1.0, indicates the adequate sampling. If the value falling between 0.7 to 0.79 indicates the mediocre sampling, while a value below 0.6 indicates the inadequate sampling and serious action should be taken (Shrestha, 2021; B. Williams et al., 2010).

3.14.7 Bartlett's Test of Sphericity

This statistical test is utilized to assess whether the hypothesis that variables are uncorrelated holds true. Essentially, this means that each variable in the population correlation matrix has a perfect correlation with itself ($r=1$), while showing no correlation with any other variables ($r=0$). Bartlett's test of sphericity assesses the substantial correlation among the variables. A highly significant result, typically ($p < 0.001$) which indicates the significant correlation among variables. Moreover, when the significant value is below than 0.05 indicates the factor analysis is relevant for the dataset (Shrestha, 2021; B. Williams et al., 2010).

3.15 Measurement Scale

Measurement scales are categorized into four types: nominal, ordinal, interval, and ratio scales. Researchers often use ordinal and interval scales when organizing responses to questionnaires in a specific order.

3.15.1 Nominal Scale:

The nominal scale is the most basic level of measurement, where numbers and letters assigned to objects function merely as labels for identification or classification purposes. This type of data is frequently utilized in surveys to categorize major subgroups within a population (D. R. Cooper & Schindler, 2014; Zigmund et al., 2012). Examples of nominal data classifications include marital status, gender, nationality, and similar factors. The nominal scale is solely for classification, without involving any order, distance, or absolute zero point (e.g., gender) (Dalati, 2018).

3.15.2 Ordinal Scale:

An ordinal scale organizes and categorizes objects based on their relative standing in an ordered relationship. Using an ordinal scale indicates a greater-than or less-than comparison without specifying the exact amount of difference (Cruz Lopez, 2021).

This level involves both classification and order, such as ranking service quality from excellent to poor (Dalati, 2018).

3.15.3 Interval Scale:

An interval scale includes the concept of fixed distances between values, ensuring that the gap between 1 and 2 is the same as between 2 and 3. Many attitude scales, such as intelligence scores, semantic differential scales, and other graphical scales, are considered interval scales (D. R. Cooper & Schindler, 2014; Zigmund et al., 2012). The interval scale represents the third level of measurement, where classification, order, and equal distances are applied, but there is no absolute zero point (e.g., temperature) (Dalati, 2018).

3.15.4 Ratio Scale:

The ratio scale represents the highest level of measurement, encompassing all characteristics: classification, order, equal distances, and a true zero point (Cruz Lopez, 2021). Examples include income, weight, and height. At the ratio level, zero holds an absolute meaning, signifying the complete absence of the quantity being measured (Dalati, 2018).

3.16 Summary of Chapter

This chapter delves into the research methodology employed to achieve the objectives of the study. The research design serves as the foundational framework, guiding the choice of methods used to explore the relevant theories and concepts associated with the study. It was conducted in the Punjab region and targeted Gen Z, specifically individuals aged 18 to 29. A descriptive research design, utilizing a quantitative approach, was adopted to gather measurable data for statistical analysis of the population. Six major districts in Punjab—Ludhiana, Ferozepur, Gurdaspur, Jalandhar, Amritsar and Hoshiarpur—were selected for data collection. The target sample size, calculated using a standard formula, indicated that 385 respondents would be sufficient. However, to enhance the study's generalizability the sample size was increased to 600. Data collection was facilitated through questionnaires, distributed both in hard copy and electronically via platforms such as email, Telegram, WhatsApp etc. The questionnaire was validated from academic and industry experts. During this process, certain statements were removed or modified to

improve clarity and relevance. Once finalized, the reliability and validity of the questionnaire were assessed using SPSS software. In this chapter, an in-depth analysis of the respondents' demographics is provided, covering factors such as gender, educational qualifications, occupation, and monthly income. These demographic details offer a clearer understanding of the characteristics of the participants, contributing to a more comprehensive interpretation of the data. A variety of advanced statistical techniques and software tools were employed to meet the research objectives. These included SPSS, PLS for path analysis, EFA, CFA, SEM, and moderation analysis to examine the interaction effects. These tools and techniques not only supported the analysis of the data but also ensured that the study's findings were robust and reliable. By integrating these methodologies, this chapter lays the groundwork for understanding the factors of online reviews which affect their purchasing decisions.

CHAPTER 4

MOTIVES TO READ ONLINE REVIEWS BY GEN Z CONSUMERS

4.1 Introduction:

This chapter examines the reasons why Generation Z consumers read online reviews. It investigates the motivations behind reading customer reviews on opinion platforms and highlights additional factors related to these motivations. Identifying the reasons that drive consumers to seek information from these sources is crucial. The more marketers understand consumer involvement in electronic word of mouth, the better they can manage its impact on buying behavior. Motives are defined as the "general drivers that direct a consumer's behavior toward fulfilling their needs" and are the primary reasons behind behaviors (Hennig-Thurau et al., 2003). This is theoretically significant because any study of consumer behavior, such as reading online reviews, would be incomplete without considering the underlying motivations (M. Khammash, 2005). Through a literature review, 16 items were identified.

This chapter have two sections. First section presented the KMO and Bartlett's test of Sphericity of constructs. Second section presented the Factor Analysis. Further second section was divided into two parts i.e. EFA and CFA Third section presented the content and face validity (Reliability statistics). EFA presented the exploratory factor extraction, rotated component matrix and extracted common factors. The EFA was conducted using the SPSS software suite, utilizing the principal component analysis as the extraction method and the varimax rotation method was employed. The confirmatory factor analysis was conducted by using the Smart PLS (CB-SEM) software, utilizing the model fit indices, chi-square, degree of freedom, probability value.

The present study explored the reasons to read online reviews by GEN Z consumers. To accomplish the objective 1, data was collected from Gen Z consumers who were engaged in online shopping from Sub Tehsils (Amritsar 1, Amritsar 2, Ajnala, Jalandhar 1, Jalandhar 2, Phillaur, Ludhiana East, Ludhiana West, Jagraon, Ferozepur, Zira, Guru Har Sahai, Gurdaspur, Batala, Dera Baba Nanak, Hoshiarpur, Dasuya and Mukeria) of six districts of Punjab (Amritsar, Jalandhar, Ludhiana, Ferozepur, Gurdaspur and Hoshiarpur). The study utilized an adapted scale comprising 16

statements related to motives for reading online reviews. To categorize the identified variables, a factor analysis was conducted. There are two primary techniques for factor analysis: EFA and CFA. Both methods aim to identify underlying factors, but EFA is inherently more exploratory, while CFA is used to confirm the extent to which the proposed model fits the data (Osborne & Banjanovic, 2016). The results of the factor analysis are presented in tables 4.4 and 4.7. All the Items like to avoid mistakes while choosing a product, to evaluate the quality of product, to know about the experiences of other consumers, durability of product, reduce time taken, get information about the product, make purchases confidently, overall satisfaction of consumers, avoid wrong choice of product, reduce anxiety caused by not seeing or touching product, avoid financial loss, learn how a product is consumed, get information about new products, compare products and services, product meets the specific requirement, protect from fraudulent schemes carried from the (Burton & Khammash, 2010; Hennig-Thurau et al., 2003; D. M. Khammash, 2008; M. Khammash, 2005; Kim et al., 2011; Parikh et al., 2015)

4.2 Factor Analysis:

Factor analysis has been utilized to identify the key drivers behind Gen Z consumer's motives for reading online reviews. This statistical method helps eliminate redundant variables and condense the data into a manageable number of factors. To group the identified variables, factor analysis was conducted. There are two main techniques for analyzing factors: EFA and CFA (Polit & Beck, 2008). EFA is generally more effective with large samples and aims to uncover latent factors. Both EFA and CFA serve this purpose, but EFA takes a more exploratory approach compared to CFA (Osborne & Banjanovic, 2016). CFA, on the other hand, focuses on confirming the fit of a proposed model to the data using a different statistical method, specifically SEM or a Measurement Model, and relies on covariation matrices. EFA is useful for determining the factor structure or model and explains the maximum amount of variance, while CFA is used to validate the number of factors and analyze which items load onto each factor (M. D. Cooper & Phillips, 2004). Therefore, EFA was applied in this study to identify factors, and these factors were then validated using CFA. The factor analysis in this study was conducted using the principal component extraction method with varimax rotation.

4.3 Bartlett's test of Sphericity and Kaiser- Meyer- Olkin

KMO test has been used to assess the suitability of data for factor analysis. It measures the sufficiency of each construct in the model as well as for the whole model. The values should be varied from 0 to 1. If the value of KMO comes between 0.8 to 1.0, indicates the adequate sampling. If the value falling between 0.7 to 0.79 indicates the mediocre sampling, while a value below 0.6 indicates the inadequate sampling and serious action should be taken (Shrestha, 2021; B. Williams et al., 2010). Bartlett's test of sphericity assesses the substantial correlation among the variables. A highly significant result, typically ($p < 0.001$) which indicates the significant correlation among variables. Moreover, when the significant value is below than 0.05 indicates the factor analysis is relevant for the dataset (Shrestha, 2021; B. Williams et al., 2010). Table 4.1 reveals the KMO value with more than 0.5, and Barlett's test highlights the significant correlation with the value below from 0.05, which indicates the values are adequate to proceed for factor analysis.

Table 4.1: KMO and Bartlett' Test

KMO and Bartlett's Test		
Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.952
Bartlett's Test of Sphericity	Approx. Chi-Square	1938.699
	df	120
	Sig.	.000

Source: SPSS Software

4.4 Exploratory Factor Analysis:

EFA is a statistical method designed to examine the underlying structure of datasets. Developed in the early 20th century to explore whether intelligence is composed of multiple dimensions or a single entity, EFA has since evolved into a widely used method for reducing the dimensionality in diverse fields (M. D. Cooper & Phillips, 2004). EFA is a statistical technique used to analyze correlations among measured data variables. It helps summarize data by extracting essential information using a smaller number of factors to represent the original data, thereby clarifying complex relationships between variables. EFA is particularly useful for identifying data patterns in questionnaires, reorganizing data as needed, and reducing the measured variables into an optimum number of extracted factors (Thompson, 2004). Exploratory Factor Analysis (EFA) typically generates variables for more precise

modeling of structural equations. It is based on the principle that only non-nominal items that may belong to reflective latent factors should be included. Nominal or categorical variables, such as gender or marital status, and formative measures are excluded (Osborne & Banjanovic, 2016). The primary goal of EFA is to identify potential latent factors or unobserved variables that depend on the measured variables. It ensures sample size adequacy and validates the content of questionnaire items. EFA is particularly valuable because it aims to identify groups of items that, when combined, explain the maximum amount of observed covariance. These groups of observed variables are referred to as factors or latent factors (Thompson, 2004).

4.4.1 Exploratory Factor Extraction

Exploratory factor analysis (EFA) consolidates variables that have high factor loadings into distinct latent factors. Factor loadings represent the correlation coefficient between individual variables and their corresponding common factors (Thompson, 2004). The analysis was performed using the principal component factor analysis extraction method. Table 4.2 presents the total variance derived from the factor analysis, including the components, initial eigenvalues, extraction sums of squared loadings, and rotated sums of squared loadings. The percentage of variance column indicates the proportion of the total variance explained by each component expressed as a percentage. The Cumulative% column shows the cumulative percentage of variance explained by the first n components (Polit & Beck, 2008). For instance, the cumulative percentage for the second component is the sum of the percentages of variance accounted for by both the first and second components (M. D. Cooper & Phillips, 2004). In table 4.2 three latent factors was extracted, which showed a total variance of 69.025%. The latent factors with eigen value greater than 1 were extracted through EFA

Table 4.2: Total Variance Explained

Total Variance Explained									
Component	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	4.468	27.924	27.924	4.468	27.924	27.924	4.335	27.093	27.093
2	3.812	23.827	51.751	3.812	23.827	51.751	3.874	24.211	51.304
3	2.764	17.274	69.025	2.764	17.274	69.025	2.835	17.720	69.025
4	.960	5.997	75.022						
5	.669	4.183	79.205						
6	.511	3.196	82.401						
7	.473	2.957	85.358						
8	.434	2.714	88.072						
9	.375	2.343	90.415						
10	.305	1.908	92.323						
11	.300	1.878	94.201						
12	.252	1.575	95.775						
13	.217	1.358	97.133						
14	.189	1.181	98.314						
15	.164	1.025	99.339						
16	.106	.661	100.000						
Extraction Method: Principal Component Analysis.									

Source: SPSS Software

The rotated component matrix was utilized to categorize the items. From this matrix, a total of three factors were identified. Only factor loadings with a minimum value of 0.50 or higher were considered (Osborne & Banjanovic, 2016; Polit & Beck, 2008). Based on the factor analysis results, the variables were grouped into three dimensions. The table 4.3 presents the three extracted latent factors along with their respective factor loadings after the rotation of the correlation matrix. Each extracted common factor was labeled to reflect its shared and potential characteristics for easier comprehension. Here one very important item M16 (online reviews protect myself from fraudulent schemes) was omitted by EFA as its factor loading was less than 0.50.

Table 4.3: Rotated Component Matrix

Component Matrix			
	Component		
	1	2	3
M1	.796		
M2	.812		
M3	.713		
M4	.839		
M5		.903	
M6	.852		
M7		.803	
M8	.865		
M9			.832
M10			.789
M11			.838
M12		.903	
M13		.768	
M14	.865		
M15		.837	
M16			
Extraction Method: Principal Component Analysis.			
Rotated Method: Varimax with Kaiser Normalization.			
a. 3 components extracted.			

Table 4.4: Extraction Factors

Extracted Common Factors	Observed Items	Component		
		1	2	3
Right Product Choice	I read online reviews to avoid mistakes while choosing a product	.796		
	I read online reviews to evaluate the quality of product	.812		
	I read online reviews to know about the experiences of other consumers	.713		
	I read online reviews to know about the durability of the product	.839		
	I read online reviews to get information about the product	.852		
	I read online reviews to evaluate the overall satisfaction of consumers	.865		
	I read online reviews to compare the products and services	.865		
Product Information	I read online reviews to reduce the time taken while choosing the product		.903	
	I read online reviews to make my purchases confidently		.803	
	I read online reviews to learn how a product is to be consumed		.903	
	I read online reviews to get information about the new products		.768	
	I read online reviews to ensure that product meets with my specific requirements		.837	

Risk Reduction	I read online reviews in order to avoid wrong choice of product with bad performance			.832
	I read online reviews to reduce anxiety caused by not seeing or touching product			.789
	I read online reviews to avoid financial loss caused by wrong decision			.838
	Extraction Method: Principal Component Analysis. Rotated Method: Varimax with Kaiser Normalization.			
	a. 3 components extracted.			

Source: SPSS Software

4.4.2 Explanation of the Extracted Factors:

Factor-1 (RPC) Right Product Choice: Factor 1 accounted for total 27.93% of the total variance as shown in table 4.4 with seven items i.e. avoid mistakes while choosing a product (M1), evaluate the quality of product (M2), know about the experiences of other consumers (M3), Know about the durability of product (M4), to get information about the product (M6), to evaluate the overall satisfaction of consumers (M8). All these items are related to the motives to read online reviews, hence named as “Right Product Choice”.

Factor-2 (PIIn) Product Information: Factor 2 accounted for total 23.83% of the total variance as shown in table 4.4 with five items i.e. to reduce the time taken while choosing the product (M5), to make my purchases confidently (M7), to learn how a product is to be consumed (M12), to get information about the new products (M13), to ensure that product meets with my specific requirements (M15). All these items are related to the motives to read online reviews, hence named as “Product Information”.

Factor-3 (RR) Risk Reduction: Factor 3 accounted for total 17.27% of the total variance as shown in table 4.4 with three items i.e. to avoid wrong choice of product with bad performance (M9), to reduce anxiety caused by not seeing or touching product (M10), to avoid financial loss caused by wrong decision (M11). All these

items are related to the motives to read online reviews, hence named as “Risk Reduction”.

4.5 Confirmatory Factor Analysis

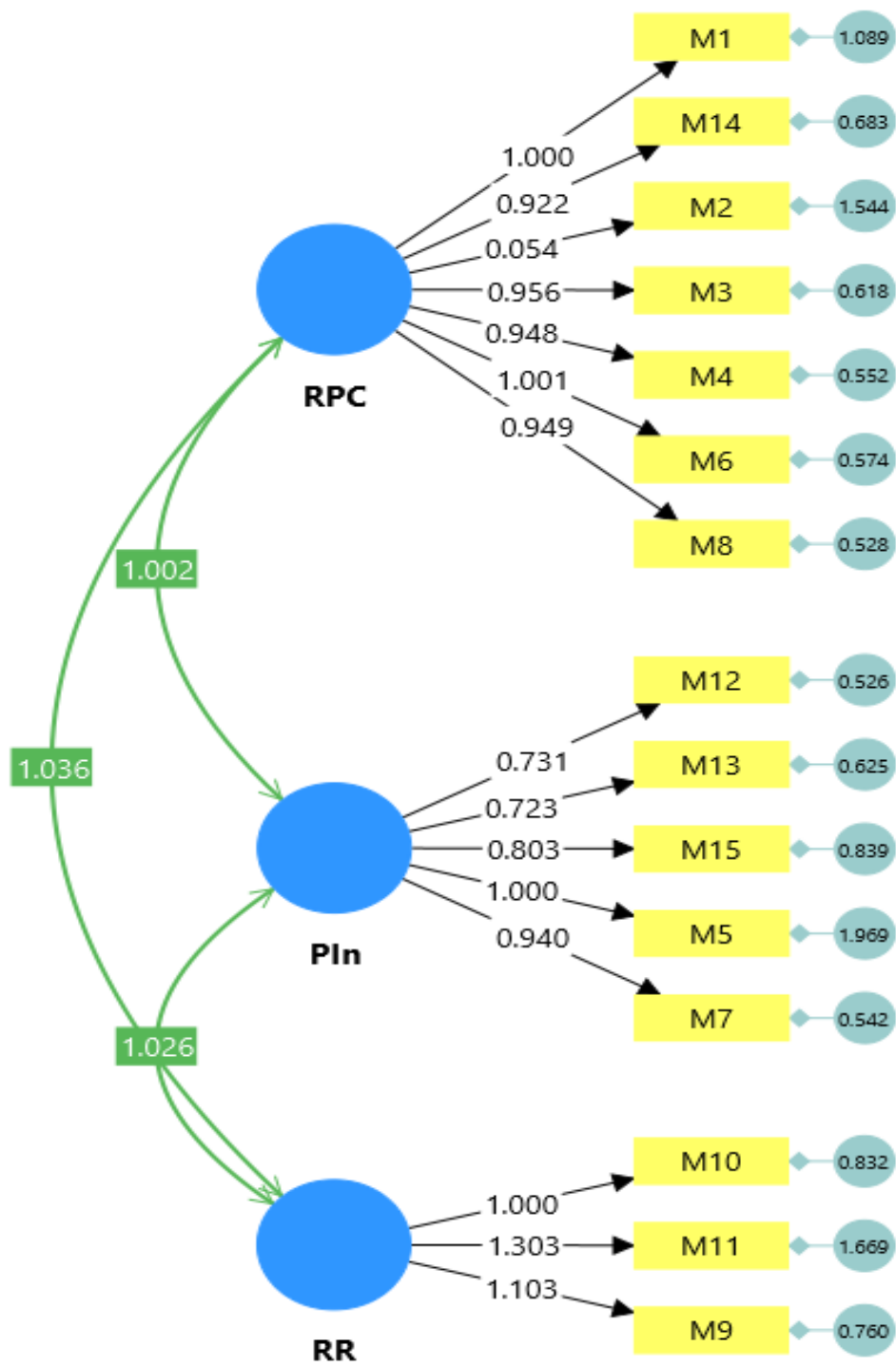
Confirmatory Factor Analysis was utilized in this study for construct validation to investigate the relationships between variables associated with the motives for reading online reviews. In this section confirmatory factor analysis performed with the CB-SEM. It is often considered more user-friendly compared to other programs like AMOS, LISREL and Mplus. Confirmatory Factor Analysis (CFA) offers straightforward, step-by-step guidance. It is a specific application within Structural Equation Modeling (SEM) (Millsap & Yun-Tein, 2004). The fit of individual parameters in the model can be assessed based on three criteria: (1) whether the parameter estimates have the correct sign and appropriate magnitude, as incorrect signs or sizes might suggest a flawed model or insufficient information in the input matrix; (2) whether the standard errors are excessively large or small, which could signal a poor model fit; and (3) whether the parameter estimates are statistically significant. (Shek & Yu, 2014). The ‘p’ value is significant at the 1% level. Seven items load onto the factor of right product choice, five items onto the factor of product information, and three items onto the factor of risk reduction. The table 4.5 displays the estimates, standard errors, and probabilities. Standard error (S.E.), is considered relevant if it exceeds 1.9. The probability level should be below 0.05. In table 4.5 all the values of S.E. was acceptable according to the threshold limits (Thompson, 2004). Table 4.5 shows the correlation between three factors i.e. factor1 (Right Product Choice) factor 2 (Product Information), factor 3 (Risk Reduction) with the interconnection with each other. The table 4.6 displays the variable coding after assigning the items to their respective factors: Right Product Choice (RPC), Product Information (PIn), and Risk Reduction (RR).

Table 4.5: Factor Loadings

	Parameter estimates	Standard errors	T values	P values
M1 <- RPC	1.001	0.068	11.782	0.000
M10 <- RR	1.000	0.075	13.185	0.000
M11 <- RR	1.303	0.100	13.031	0.000
M12 <- PIn	0.731	0.059	12.317	0.000
M13 <- PIn	0.723	0.061	11.906	0.000
M14 <- RPC	0.922	0.067	13.775	0.000
M15 <- PIn	0.803	0.068	11.769	0.000
M2 <- RPC	0.054	0.065	0.827	0.409
M3 <- RPC	0.956	0.066	14.403	0.000
M4 <- RPC	0.948	0.065	14.543	0.000
M5 <- PIn	1.000	0.069	11.782	0.000
M6 <- RPC	1.001	0.068	14.671	0.000
M7 <- PIn	0.940	0.071	13.198	0.000
M8 <- RPC	0.949	0.064	14.723	0.000
M9 <- RR	1.103	0.076	14.555	0.000

Source: Computed from Smart Pls

Figure 4.1: Confirmatory Factor Analysis



Source: Computed from Smart PLS

Table 4.6: Factors Name

Factor Name	Observed Items	Variable Code
Right Product Choice	avoid mistakes while choosing a product	RPC1
	evaluate the quality of product	RPC2
	know about the experiences of other consumers	RPC3
	know about the durability of the product	RPC4
	get information about the product	RPC5
	evaluate the overall satisfaction of consumers	RPC6
	compare the products and services	RPC7
Product Information	reduce the time taken while choosing the product	PIn1
	make my purchases confidently	PIn2
	learn how a product is to be consumed	PIn3
	get information about the new products	PIn4
	ensure that product meets with my specific requirements	PIn5
Risk Reduction	avoid wrong choice of product with bad performance	RR1
	reduce anxiety caused by not seeing or touching product	RR2
	avoid financial loss caused by wrong decision	RR3

CFA model is evaluated using various model fit indices, including Chi-square, Goodness of Fit Index, Adjusted Goodness of Fit Index, Normal Fit Index, Tucker Lewis Index, Comparative Fit Index, Root Mean Square Residual, and Root Mean Square Error of Approximation. According to (L.-T. Hu & Bentler, 1995), a satisfactory model fit is indicated by Comparative Fit Index (CFI), Tucker Lewis Index (TLI), and (Normal Fit Index) NFI values of 0.90 or higher, with values near 1 representing an excellent fit. For the Root Mean Square Error of Approximation

(RMSEA), a value below 0.08 suggests a reasonable fit, while a value below 0.05 indicates a good fit considering the degrees of freedom. The results of the Confirmatory Factor Analysis, as shown in the table 4.7, indicate the following values: chi-square = 258.228, degrees of freedom = 87, p-value = 0.055, chi-square/DF = 2.967, GFI = 0.927, AGFI = 0.962, NFI = 0.928, TLI = 0.941, CFI = 0.951, RMR = 0.066, and RMSEA = 0.068. All these values fall within acceptable limits, suggesting that the model fits the data well.

Table 4.7: Threshold Limits

Indicators	Value	Recommended Value
Chi-Square Value	258.228	-
DF	87	-
P Value	0.055	>0.05 (Hair et al, 1998)
Chi-square value/DF	2.967	<5.00 (Hair et al, 1998)
GFI	0.927	>0.90 (L.-T. Hu & Bentler, 1995)
AGFI	0.962	>0.90 (Hair et al, 1998)
NFI	0.928	>0.90 (L.-T. Hu & Bentler, 1995)
TLI	0.941	>0.90 (L.-T. Hu & Bentler, 1995)
CFI	0.951	>0.90 (Daire et al., 2008)
RMR	0.066	<0.08 (Daire et al., 2008)
RMSEA	0.068	<0.08 (Hair et al. 2006)

4.6 Summary of Chapter:

In table 4.4 according to the exploratory factor analysis results, three distinct factors were identified, highlighting the motivations for Gen Z consumers to read online reviews. Furthermore, in table 4.7 the confirmatory factor analysis results indicate that the proposed model fits the data exceptionally well. Results of new findings on the motives to read online reviews by Gen Z consumers reflect the earlier research outcomes, while incorporating the novel insights through detailed analysis. In their earlier studies, authors utilized readers' stories and interviews to identify themes related to reading other consumers' reviews. This research aids marketers in understanding how to influence and encourage consumers to read about their products and services, as well as determining the type of information that should be provided

(Burton & Khammash, 2010). Another study examined the motivations behind consumers' behavior in reading online reviews. A quantitative approach was used to assess the relevance of these motivations and their impact on consumer purchasing behavior. The key managerial implication is to develop strategies that enable organizations to effectively leverage online consumer opinions (Khammash, 2008). Another author revealed that the motivations behind customers' online interactions are significant predictors of behavioral responses in online communities. Consequently, opinion portal providers should thoroughly examine the motive structures of their communities to effectively manage key interaction elements. This research adopts a qualitative narrative approach to gain a deeper understanding of consumer motivations for reading on online opinion portals (M. Khammash, 2005). Furthermore, the author revealed that consumers primarily read online reviews to save time in decision-making and to make more informed purchasing decisions. A large-scale empirical study tested the relevance of these motivations and their impact on consumer buying and communication behavior (Hennig-Thurau et al., 2003). Another study investigated the factors that motivate consumers to seek eWOM, identifying convenience and quality, risk reduction, and social reassurance as key drivers. The analysis showed notable gender differences in these motivating factors, with women being more inclined to read reviews for convenience, quality assurance, and minimizing risk. In contrast, men's reliance on online reviews differed depending on their level of expertise (Kim et al., 2011). Understanding these motivations is crucial for marketers, as it enables them to better manage how eWOM influences consumers' purchasing decisions (Shah & Unnithan, 2020). In the age of technological advancement and the booming of e-commerce industry, online shopping is on the rise, consequently elevating the significance of online reviews. Consumers now prefer to read online reviews over seeking opinions from peers and relatives while making the purchasing decisions. Within the apparel industry, online reviews serve as essential resources for consumers seeking insights into various aspects such as quality, color, size, fit, comfort and fabric of clothing items. Managers also value online reviews as they provide insights into consumer preferences and sentiments towards the products.

CHAPTER 5

INFLUENCE OF ONLINE REVIEWS ON PURCHASE INTENTION OF GEN Z CONSUMERS AND EFFECT OF GENDER MODERATION

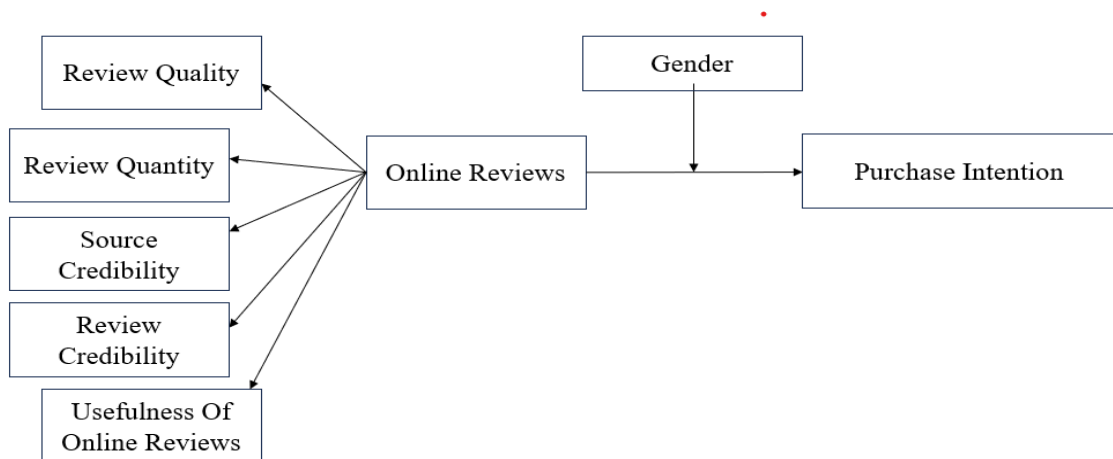
5.1 Introduction:

This chapter has been divided into two parts which deals with the influence of ORs on Gen Z consumers purchase intention within the apparel industry and also check the relationship between online reviews and PI if gender is a moderator. Dimensions of online reviews (review credibility, review quality, review quantity, source credibility, usefulness of online reviews) have its influence on PI. In contemporary society, it is notable that Gen Z is the most familiar generation with the smart technology and extensive engagement with social media (Tabassum et al., 2020). In earlier studies it was found that millennials were hesitated to purchase the products online but today current trends demonstrates that Gen Z purchase the most of things from online (Sethna et al., 2017). While purchasing the product they read the online reviews to gain the knowledge of products and services. In this chapter we also analyzed that Gen Z males or Gen Z females have any association between ORs and PI by using the multigroup analysis technique (H.-R. Shin & Choi, 2021).

This chapter have six sections. First section presented the KMO and Bartlett's test of Sphericity of constructs. Second section presented the Common Method Variance. Third section presented the content and face validity (Reliability statistics). Fourth section presented the Structure equation modeling (SEM) which performed two-step process, "Measurement Model" and "Structural Model". Measurement model presented the Reflective indicator loadings, Construct reliability, Cronbach's Alpha, Composite Reliability, Convergent validity and Discriminant validity. Structural Model presented the Collinearity among constructs, significance and relevance of the path coefficients, predictive relevance (R Square, Q square, PLS Predict) and goodness of fit / SRMR. Fifth section presented the Measurement invariance for composite model (MICOM) and last section sixth presented the Multigroup analysis technique.

The present study explored the determinants to check the effect of online reviews on GEN Z consumers purchase intention and analyze the relationship between ORs and PI if gender is a moderator. To accomplish the objective 2 and 3, data was collected from Gen Z consumers who were engaged in online shopping from Sub Tehsils (Amritsar 1, Amritsar 2, Ajnala, Jalandhar 1, Jalandhar 2, Phillaur, Ludhiana East, Ludhiana West, Jagraon, Ferozepur, Zira, Guru Har Sahai, Gurdaspur, Batala, Dera Baba Nanak, Hoshiarpur, Dasuya and Mukeria) of six districts of Punjab (Amritsar, Jalandhar, Ludhiana, Ferozepur, Gurdaspur and Hoshiarpur). The study used an adapted scale, which include 5 items of (RQn), 6 items of (RQ), 7 items of (SC), 4 items of (UOR), 5 items of (RC) and 4 items of (PI). The reliability and validity of constructs have been checked through Cronbach alpha values 0.950 (RQn), 0.971 (RQ), 0.960 (SC), 0.917 (RC), 0.932 (UOR) and 0.959 (PI) which were met with the threshold limit. Conceptual framework and hypothesis were proposed on to analyze the influence of ORs on Gen Z consumers PI in Apparel Industry as shown in figure 5.1.

Figure 5.1 Conceptual Framework



Source: Author's own creation

Objective 2: To study the influence of online reviews on purchase intention of Gen Z consumers.

Main Hypothesis

Ha1- There is a positive relationship between online reviews and purchase intention of Gen Z consumers.

Sub Hypothesis

Ha 1.1- There is a positive relationship between Review Quality of online reviews and purchase intention of Gen Z consumers.

Ha 1.2- There is a positive relationship between Review Quantity of online reviews and purchase intention of Gen Z consumers.

Ha 1.3- There is a positive relationship between Source Credibility of online reviews and purchase intention of Gen Z consumers.

Ha 1.4- There is a positive relationship between Review credibility of online reviews and purchase intention of Gen Z consumers.

Ha 1.5- There is a positive relationship between usefulness of online reviews of online reviews and purchase intention of Gen Z consumers.

5.2 Bartlett's test of Sphericity and Kaiser- Meyer- Olkin

KMO test has been used to assess the suitability of data for factor analysis. It measures the sufficiency of each construct in the model as well as for the whole model. The values should be varied from 0 to 1. If the value of KMO comes between 0.8 to 1.0, indicates the adequate sampling. If the value falling between 0.7 to 0.79 indicates the mediocre sampling, while a value below 0.6 indicates the inadequate sampling and serious action should be taken (Shrestha, 2021; B. Williams et al., 2010). Bartlett's test of sphericity assesses the substantial correlation among the variables. A highly significant result, typically ($p < 0.001$) which indicates the significant correlation among variables. Moreover, when the significant value is below than 0.05 indicates the factor analysis is relevant for the dataset (Shrestha, 2021; B. Williams et al., 2010). Tables (5.1), (5.2), (5.3), (5.4), (5.5) and (5.6) reveals the KMO value of RQn, RQ, SC, UOR, RC and PI more than 0.5, and Barlett's test

highlights the significant correlation with the value below from 0.05, which indicates the values are adequate to proceed for factor analysis.

Table 5.1: Review Quantity

KMO and Bartlett's Test		
Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		0.874
Bartlett's Test of Sphericity	Approx. Chi-Square	1781.369
	df	10
	Sig.	0.000

Source: Computed from SPSS

Table 5.2: Review Quality

KMO and Bartlett's Test		
Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		0.916
Bartlett's Test of Sphericity	Approx. Chi-Square	2399.603
	df	15
	Sig.	0.000

Source: Computed from SPSS

Table 5.3: Source Credibility

KMO and Bartlett's Test		
Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		0.908
Bartlett's Test of Sphericity	Approx. Chi-Square	2375.992
	df	21
	Sig.	0.000

Source: Computed from SPSS

Table 5.4: Usefulness of online reviews

KMO and Bartlett's Test		
Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		0.866
Bartlett's Test of Sphericity	Approx. Chi-Square	1224.652
	df	10
	Sig.	0.000

*Source: Computed from SPSS***Table 5.5: Review Credibility**

KMO and Bartlett's Test		
Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		0.803
Bartlett's Test of Sphericity	Approx. Chi-Square	910.446
	df	6
	Sig.	0.000

*Source: Computed from SPSS***Table 5.6: Purchase Intention**

KMO and Bartlett's Test		
Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		0.822
Bartlett's Test of Sphericity	Approx. Chi-Square	1407.141
	df	6
	Sig.	0.000

Source: Computed from SPSS

5.3 Common Method Variance

In social science research, questionnaire surveys are frequently used to analyze the respondent's personalities, behaviors and perceptions on various issues. In data analysis survey gives the information about the dependent and independent variables (Eichhorn, 2014; Tehseen et al., 2017). However, Common method variance arises when same respondents were used in a study to collect the data of dependent variable and independent variable in the same context and characteristics. Harman's Single-

Factor Test has been used to analyze the CMV in the study, it is conducted post data collection. If a common latent factor explains over the 50% (Harman, 1976) of the variance, then it might be suggesting that common method biasness is present (Eichhorn, 2014). As shown in table 5.7 factor explained 47.61% of the total variance, which is below the threshold limit of 50%. The result indicates that there is no common method variance in this study.

Table 5.7: Common Method Variance

Factors	Extraction Sum of Square loadings		
	Total	%age of Variance explained	% Cumulative
	22.583	47.610	47.610

Source: Computed from SPSS Software

5.4 Content and Face Validity (Reliability Statistics)

In this section content and face validity of questionnaire items were measured. To evaluate the internal consistency of this study Cronbach Alpha was used. Cronbach alpha and composite reliability tests are applied on the 10% of the sample size (Connelly, 2008). SPSS software was used to check the values of Cronbach alpha. If the values lie between 0.7 to 0.9, it indicates that there is an internal consistency in scale, and if value comes above the 0.9, it indicates that there is a high internal consistency in scale (Surucu & Maslakci, 2020). As table depicts 5.8 the values of Cronbach alpha of constructs come above the 0.9, which shows that there is a high internal consistency.

Table 5.8: Reliability Statistics of the research study

Sr. No.	Constructs	Items included	Cronbach's Alpha	Consistency
1.	Reliability of Review Quantity	5	.950	Excellent
2.	Reliability of Review Quality	6	.971	Excellent
3.	Reliability of Source Credibility	7	.960	Excellent
4.	Reliability of Usefulness of Online Reviews	4	.932	Excellent
5.	Reliability of Review Credibility	5	.917	Excellent
6.	Reliability of Purchase Intention	4	.959	Excellent

Source: Computed from SPSS Software

5.5 Structural Equation Modelling

SEM is a statistical technique, which is often used in the marketing research, because marketers can examine the association between ‘independent variables and dependent variables’, in order to serve the better services to the customers (Wong, 2013). PLS-SEM is the most fully developed and general system and it was also called a “silver bullet”(Al-Emran et al., 2019; Hair, Risher, et al., 2019). It is divided into two main models, ‘measurement model and structural model’. Measurement model also known as ‘outer model’ it measures the relationship between constructs and its relevant items and structural model refers as the “inner model”, it measures the relationship between the constructs themselves. In figure 5.2 the measurement model shows the reliability and content validity between the blue circles and yellow boxes. The arrows between the blue circles shows the structural model or inner model, which indicates whether the one variable have the direct effect on another variable. Here, expectation disconfirmation theory is used to check the effect of online reviews on satisfaction.

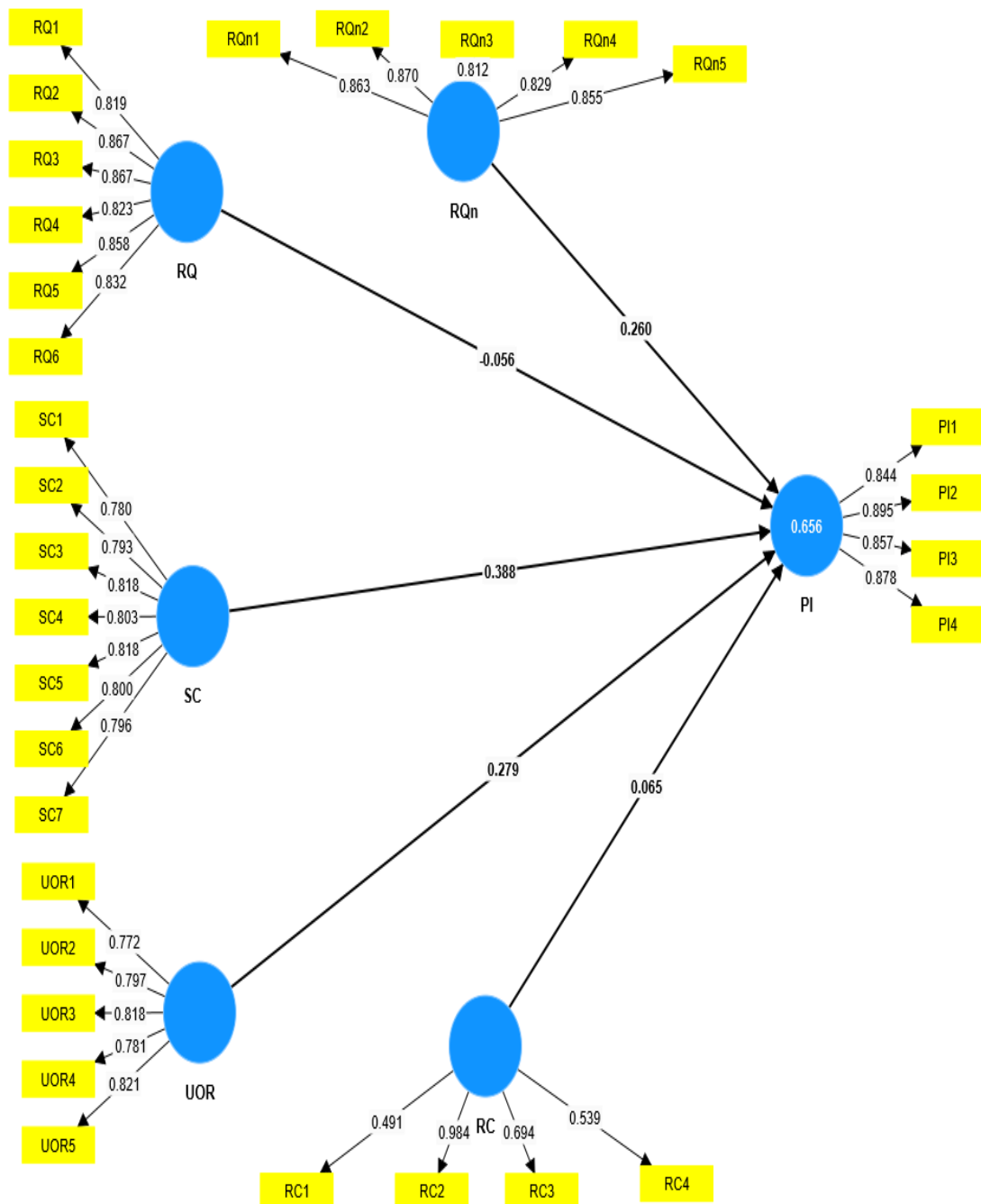
Further, measurement model measures the both ‘reflective and formative models’ (Al-Emran et al., 2019). In measurement reflective model measures the ‘Reflective indicator loadings, Construct reliability, Cronbach’s Alpha, Composite Reliability,

Convergent validity through Average Variance Extracted and Discriminant validity through HTMT', cross loadings and Fornell and Larcker. Structural model measures the Collinearity among constructs, significance and relevance of the path coefficients, predictive relevance (R Square, Q square, PLS Predict) and goodness of fit / SRMR (Hair, Risher, et al., 2019). Figure (5.2) shows the lower order construct of online reviews and figure (5.3) shows the online review in higher order construct. online reviews measured with both lower order construct. Measurement model measures the reliability and validity. After the assessment of reliability and validity in measurement model, further researcher can proceed to the structural model. Steps to calculate the measurement model in PLS-SEM are: Firstly, import the data file in PLS software (CSV format) > Create model > Click on calculate > Select PLS-SEM algorithm > Select Factor > Start Calculation > Assess the PLS-SEM output.

5.6 Lower-Order Construct (LOC) to Higher Order Construct (HOC)

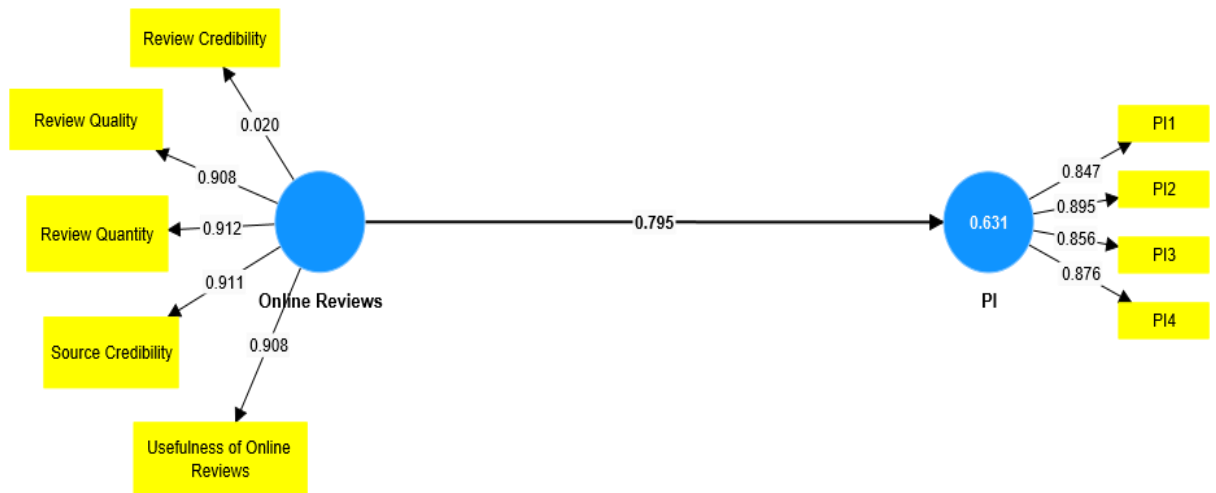
In this study, the exogenous variable (Online Reviews) having various lower order constructs (Review Quantity, Review Quality, Review Credibility, Source credibility, Usefulness of online reviews) which may become complicated to analyse as the LOC. Instead of analyzing the sub constructs of online reviews as a single construct layer we converted it into the HOC. Within the realm of PLS-SEM higher order constructs are “also referred as the hierarchical component models” (HCM) (Sarstedt et al., 2019; Wong, 2016). There are some advantageous features of HOC. For instance, firstly, it helps to reduce the number of relationships in the path model. Secondly, it addresses the bandwidth-fidelity dilemma. Thirdly, higher order constructs mitigate collinearity among the indicators (Sarstedt et al., 2019). In this study, higher order construct was used for its ability to simplify the analysis of complex model into a simple model (Ciavolino & Nitti, 2010).

Figure 5.2: PLS-SEM Algorithm for Measurement Model and Path Coefficients of Lower Order Constructs:



Source: Computed from Smart PLS Software

Figure 5.3: PLS-SEM Algorithm for Measurement Model and Path Coefficients of Higher Order Construct:



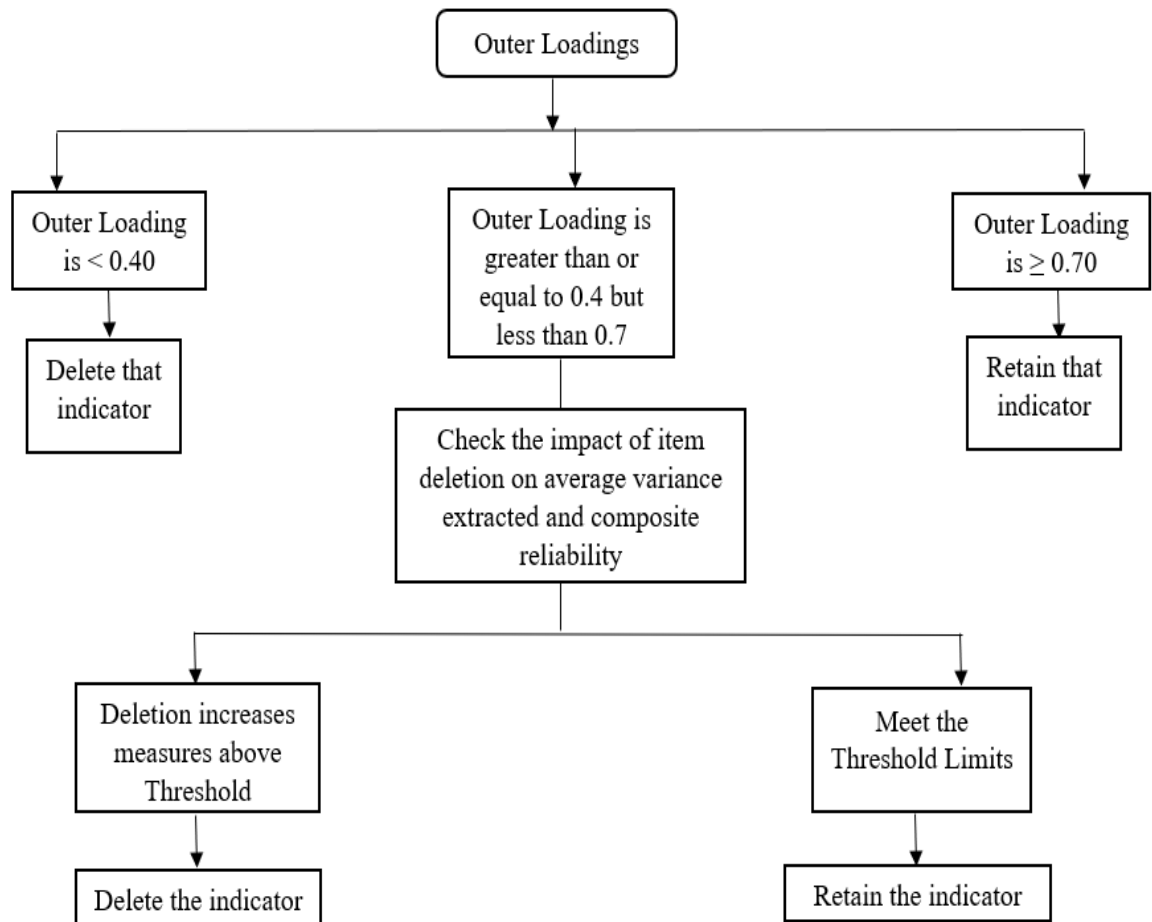
Source: Computed from Smart PLS Software

5.7 Internal Consistency Reliability

5.7.1 Indicator Reliability (Outer Loadings):

In a reflective measurement model first step is to examine the indicator loadings. In this study, one endogenous construct and five exogenous constructs are used to measure the model. For each latent variable item reliability is measured based on the outer loadings (Hair, Risher, et al., 2019). As figure 5.4 depicts that if the value of outer loadings is less than 0.40, it is recommended to delete that item. If the outer loadings having value between 0.4 to 0.7, firstly check the impact of deleted item on Average Variance Extracted and Composite reliability, if it meets the threshold limit retain that item but if it doesn't meet the threshold limit delete that item. If the outer loadings having value greater than 0.7 it is considered as acceptable and retain that indicator (Al-Emran et al., 2019; Hair, Risher, et al., 2019; Jr, 2017). In our study, the factor loadings of each indicator of their latent variable having values greater than the 0.7 which is considered as all the items are acceptable. As table 5.9 shows the factor loadings of Purchase Intention, Review Credibility, Review Quality, Review Quantity, Source Credibility, Usefulness of online reviews and online reviews ranged between 0.84-0.89, 0.83-0.98, 0.82-0.88, 0.81-0.87, 0.78-0.82, 0.77-0.82 and 0.80-0.91 respectively. All the factor loadings are acceptable and fits to the model.

Figure 5.4: Threshold limits for outer loadings



Source: Hair, J. F., Risher, J. J., Sarstedt, M., & Ringle, C. M. (2019). When to use and how to report the results of PLS-SEM. *European Business Review*, 31(1), 2–24.

Table 5.9: Indicator Reliability (Outer loadings and VIF)

Constructs	Indicators	PI	RC	RQ	RQn	SC	UOR	Online Reviews	VIF
Purchase Intention	PI1	0.844							2.281
	PI2	0.895							2.885
	PI3	0.857							2.321
	PI4	0.878							2.540
Review Credibility	RC1		0.891						1.846
	RC2		0.984						1.898
	RC3		0.794						2.030
	RC4		0.839						1.590
Review Quality	RQ1			0.819					2.285
	RQ2			0.867					2.886
	RQ3			0.877					2.843
	RQ4			0.823					2.298
	RQ5			0.858					2.711
	RQ6			0.832					2.357
Review Quantity	RQn1				0.863				2.657
	RQn2				0.870				2.746
	RQn3				0.812				2.053
	RQn4				0.829				2.202
	RQn5				0.855				2.445
Source Credibility	SC1					0.780			2.045
	SC2					0.793			2.123
	SC3					0.818			2.274
	SC4					0.803			2.319
	SC5					0.818			2.282
	SC6					0.800			2.394
	SC7					0.796			2.190
Usefulness	UOR1						0.772		1.727

of Online Reviews	UOR2						0.797		1.789
	UOR3						0.818		2.001
	UOR4						0.781		1.778
	UOR5						0.821		1.971
Online Reviews	RC							0.801	1.007
	RQ							0.908	2.856
	RQn							0.912	2.876
	SC							0.911	2.484
	UOR							0.908	2.420

Source: Computed from Smart PLS software

5.7.2 Construct Reliability (Cronbach Alpha)

Construct reliability can be measured with two methods (Cronbach Alpha and composite reliability). If the values of Cronbach alpha should not be less than 0.60 and be greater than 0.95. It indicates that if values are less than the 0.60 it is the early stage of research, if values are greater than 0.95 that are also not desirable in research (Hair, Risher, et al., 2019). Cronbach alpha have some limitations, if the items are unweighted it is the less precise to measure the reliability. It is also too conservative. As compared to the cronbach alpha composite reliability is recommended more appropriate because it includes the indicators differential weights and it is also liberal (Hair, Risher, et al., 2019; Jr, 2017). Both the values are ranged between the “0 and 1” (Al-Emran et al., 2019). Higher the value indicates the higher reliability. In exploratory research values of 0.60 to 0.70 considered as acceptable but in more advanced research, values of 0.70 to 0.90 are considered as satisfactory (Fornell & Larcker, 1981, 1981; Hair, Risher, et al., 2019; Jr, 2017). In table 5.10 the values of composite reliability of all the constructs PI (0.892), RC (0.923), RQ (0.920), RQn (0.902), SC (0.908), UOR (0.860) and online reviews (0.932) are met with their threshold limits which indicates that there is a reliability in constructs.

5.8 Construct Validity

5.8.1 Convergent Validity (Average Variance Explained)

Convergent validity refers to “the extent to which a measure correlates positively with alternative measures of the same construct” (Hair, Risher, et al., 2019). It is assessed

by looking at how strongly the indicators relate with their respective construct, which helps to calculate the AVE from each construct (Henseler et al., 2015). AVE refers to the grand mean value of the squared loadings of the indicators associated with the construct (i.e the sum of the squared loadings divided by the number of indicators) (Hair, Risher, et al., 2019). The acceptable values of outer loadings should be greater than or equal to 0.70. To ensure the convergent validity, the outer loadings of the indicators should exceed the 0.50, which signifies that construct score includes at least 50% of the variable variance (Hair, Risher, et al., 2019; Henseler et al., 2015). In table 5.10 the AVE values are more than 0.50 RQn (0.716), RQ (0.713), SC (0.643), RC (0.701), UOR (0.637) and online reviews (0.814), which signifies that all the constructs used in study are strongly reliable.

Table 5.10: Construct Reliability and convergent validity

Constructs	Cronbach's alpha	rho_a	rho_c	AVE
PI	0.891	0.892	0.925	0.755
RC	0.834	0.923	0.784	0.796
RQ	0.919	0.920	0.937	0.713
RQn	0.901	0.902	0.926	0.716
SC	0.907	0.908	0.926	0.642
UOR	0.857	0.860	0.898	0.637
Online Reviews	0.811	0.932	0.888	0.662

Source: Computed from Smart PLS software

Table 5.11: Construct Reliability and convergent validity of HOC

Constructs	Cronbach's alpha	rho_a	rho_c	AVE
Online Reviews	0.811	0.932	0.888	0.662
PI	0.891	0.892	0.925	0.755

Source: Computed from Smart PLS software

5.8.2 Discriminant Validity (HTMT)

Discriminant validity refers to “the extent to which a construct is truly distinct from other constructs by empirical standards” (Henseler et al., 2015). In structural model discriminant validity shows that a construct is empirically different from another construct (Hair, Risher, et al., 2019). Discriminant validity means that each construct of model represent the different phenomenon not represented by the other construct (Hair, Risher, et al., 2019; Jr, 2017). It can be measured by Cross loadings, Fornell and Larcker and HTMT. Cross loadings, an indicator should show a stronger correlation with its own constructs compared to any other constructs. In terms of Fornell and Larcker criterion, it compared the square root of the AVE with the correlations among variables (Al-Emran et al., 2019). The values of square root of AVE should be greater than its highest correlation among other constructs. A recent study has been introduced a novel criterion to evaluate the discriminant validity known as the ‘Heterotrait-Monotrait ratio; of correlations. HTMT is defined as the “mean value of the item correlations across constructs relative to the mean of the average correlations for the items measuring the same construct” (Henseler et al., 2015). The threshold limit of HTMT value for (Clark & Watson, 2016) should be less than 0.85 and for (Gold et al., 2001) should be less than 0.90. In table 5.12 the values of constructs (RC, RQ, RQn, SC, UOR), purchase intention and online reviews met the threshold limit, which signifies that there is a proper discriminant validity. From all the findings (Outer loadings, Cronbach alpha, AVE and HTMT), it is confirmed that this study has good internal consistency and the convergent validity of the measurement model.

Table 5.12: Discriminant Validity of lower order constructs (HTMT)

Constructs	PI	RC	RQ	RQn	SC	UOR
PI						
RC	0.868					
RQ	0.728	0.732				
RQn	0.795	0.067	0.847			
SC	0.847	0.612	0.817	0.85		
UOR	0.848	0.452	0.837	0.846	0.907	

Source: Computed from Smart PLS software

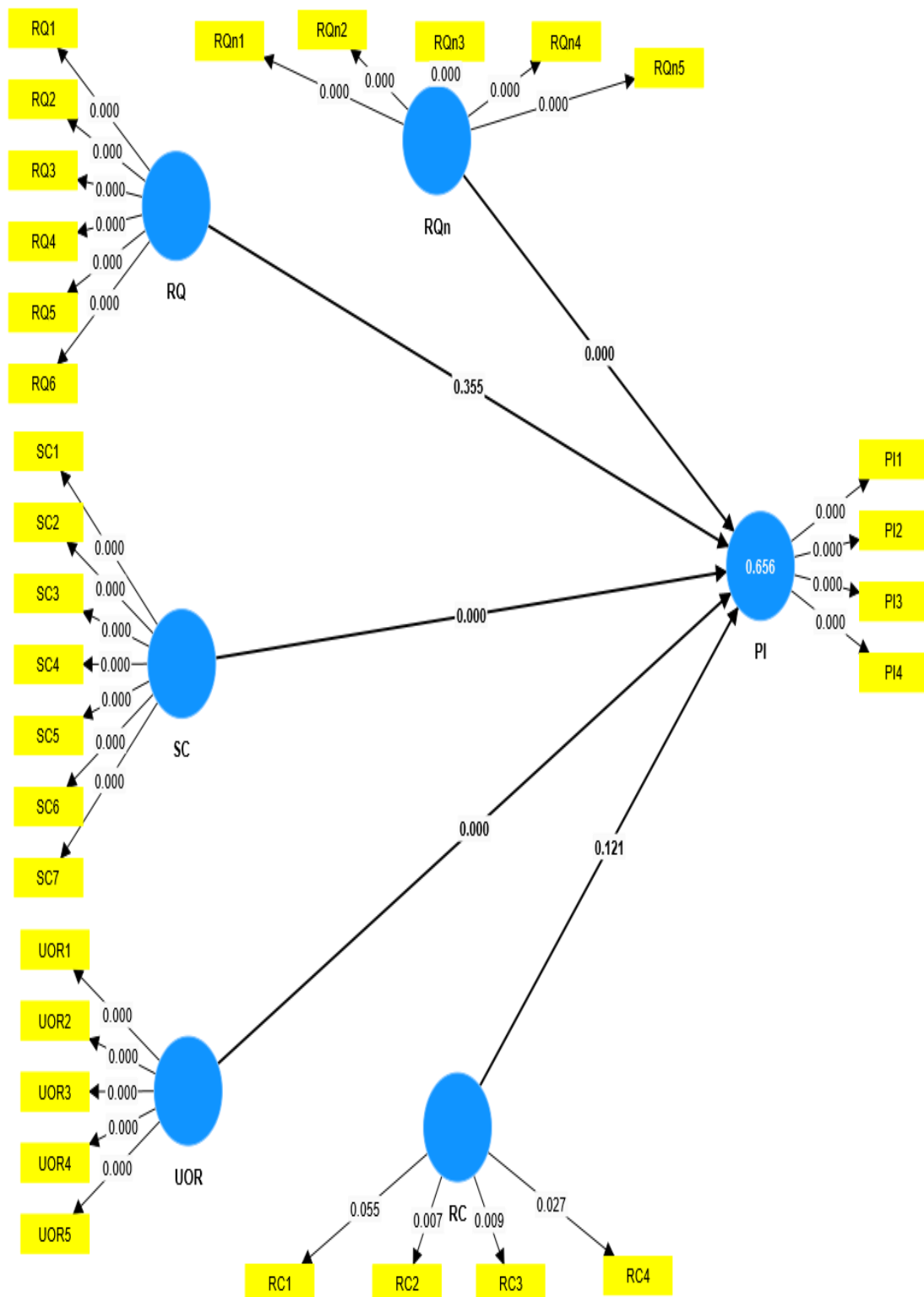
5.9 Variance Inflation Factor

VIF is used to check the collinearity among the indicators. As a rule of thumb, ideally the values of VIF should be less than 3 (Hair, Risher, et al., 2019) but if values are more than three and less than five it also suggests that there is no collinearity among indicators. If VIF having values more than five researcher should not considered that in study (Al-Emran et al., 2019; Hair, Risher, et al., 2019). Table (5.9) demonstrates that the VIF values of all the indicators (Purchase Intention, Review Credibility, Review Quality, Review Quantity, Usefulness of Online Reviews and Online Reviews) have less than 3 which indicates that indicators have no collinearity issues.

5.10. ASSESSMENT OF STRUCTURAL MODEL)

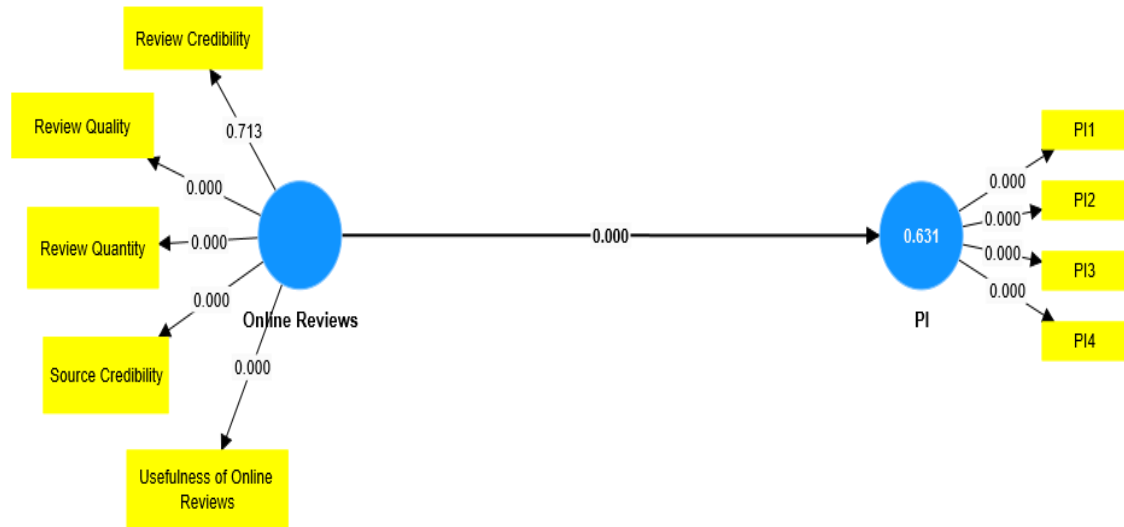
In PLS structural equation modelling after assessing the measurement model, next step is to measure the structural model. In structural model both the predictive ability of model and the connections between the constructs are measured. Assessment criterion of structural model includes, R square, Q square and Path coefficients. Additionally, predictive power has been analyzed by PLS-PREDICT in structural model. Hypothesis were tested by bootstrapping procedure with a re-sample of 5000 (Al-Emran et al., 2019; Hair, Risher, et al., 2019). The structural model presents the evaluation in figure 5.5 of lower constructs of online reviews (RQn, RQ, RC, SC, UOR) and figure 5.6 presents the structural model with higher order construct (online reviews) and purchase intention.

Figure 5.5: Bootstrapping Model of First Order constructs in Structural assessment



Source: Computed from Smart PLS software

Figure 5.6: Bootstrapping Model of Second Order constructs in Structural assessment



Source: Computed from Smart PLS software

5.11 Coefficient of Determination (R square)

In structural model after the assessment of collinearity issues, measure the predictive power through coefficient of determination. R square measured the endogenous variables and f square measured the exogeneous variables. The values ranged between R square from 0 to 1, indicates that higher values have a stronger explanatory power (Al-Emran et al., 2019). The rule of thumb, ‘ R^2 values 0.75, 0.50 and 0.25 considered as substantial, moderate and weak respectively’ (Hair, Risher, et al., 2019) but R^2 values are also depend on the discipline of the study. In table 5.13 the R square having value of Purchase Intention is 0.631, which means there is a substantial predictive power and 61% of variance in purchase intention is occurred by online reviews.

Table 5.13: R Square

R-square	R-square adjusted
0.631	0.633

Source: Computed from Smart PLS Software

5.12: Effect Size (F Square)

The effect size for each path in a structural model can be assessed using Cohen’s f^2 statistic. This metric helps in evaluating the contribution of an exogenous construct to

an endogenous construct within the model. According to Cohen (1988), f^2 values of 0.02, 0.15, and 0.35 are typically interpreted as small, medium, and large effect sizes, respectively. The f^2 value indicates the extent to which an independent variable contributes to the variance explained in the dependent variable. Table 5.14 shows f^2 value is 1.713, which significantly exceeds the threshold for a large effect. This exceptionally high value suggests a very strong influence of the construct on the corresponding endogenous variable which emphasizes the robustness and practical significance of the relationship.

Table 5.14: F Square

	Online Reviews	PI
Online Reviews		1.713
PI		

Source: Computed from Smart PLS Software

5.13 PLS-PREDICT

Q Square is another method to assess the predictive accuracy in PLS path model (Geisser, 1974). Q^2 is not only reflect the out of sample prediction accuracy, but it combines both the aspects (out-of-sample prediction and in- sample explanatory power) (Geisser, 1974; Hair, Risher, et al., 2019). Q square is measured only for endogenous variables. Minor variances between the ‘predicted and original values’ result into a higher value of q square, which indicates a higher predictive accuracy (Shmueli et al., 2019). In structural model the value of q square should be larger than zero for endogenous variables. If Q^2 having the value 0.25 it depicts small predictive relevance in path model, but if Q^2 having values between 0.25-0.50 and more than 0.50, it depicts there is a medium and large predictive relevance in path model (Geisser, 1974; Hair, Risher, et al., 2019; Shmueli et al., 2019). In table 5.14 Q^2 of endogenous variables (Items of Purchase Intention) having values more than zero, which indicates the high predictive power in this model.

Table 5.15: Q Square Predict

Indicators	Q ² predict
PI 1	0.459
PI 2	0.491
PI 3	0.466
PI 4	0.485

Source: Computed from Smart PLS Software

5.14 CV-PAT (Indicator Average & Linear Model)

Cross- validated predictive ability test offers a statistical test to compare the predictive accuracy of a recognized model against that of an alternative model (Sharma et al., 2023). If PLS Loss have values lower than the indicator average (IA) loss and average loss difference comes in negative, it depicts that high predictive power. If PLS Loss also have values lower than linear model (LM) loss than there is a strong predictive power, but if values come higher of PLS loss with LM loss than there is a predictive power but not strong predictive power (Hair, Risher, et al., 2019; Shmueli et al., 2019). In table 5.15 Pls Loss have higher values than IA loss, which means there is a predictive power but in table 5.16 when we compared the pls loss with LM than average loss difference comes not significant, which means there is a predictive power but not strong predictive power in this model.

Table 5.16: CV/PAT (PLS-SEM V/S Indicator Average)

Constructs	PLS loss	IA loss	Average loss difference	t value	p value
PI	0.637	1.212	-0.575	9.521	0.000
Overall	0.637	1.212	-0.575	9.521	0.000

Source: Computed from Smart PLS Software

Table 5.17: CV/PAT (PLS-SEM V/s Linear Model)

Constructs	PLS loss	LM loss	Average loss difference	t value	p value
PI	0.637	0.618	0.019	1.818	0.000
Overall	0.637	0.618	0.019	1.818	0.000

Source: Computed from Smart PLS Software

5.15 Statistical Significance and Path Coefficient Relevance

The path coefficients illustrate the hypothesized links between the constructs, ranging from -1 to +1, where values close to +1 indicate robust positive relationships. Significance of these relationships is often determined using p-values, with the significant threshold < 0.05 . Hence, the outcomes of the path model examining the significance of all structural relationships through t-values, p-values, and confidence intervals (Al-Emran et al., 2019; Fornell & Larcker, 1981; Hair, Risher, et al., 2019). In table 5.17 the results revealed that relationship between online reviews and purchase intention is significant, as indicated by Ha1 ($\beta = 0.795$, $t = 32.35$, $p < 0.05$). The hypothesis in first order Ha 1.1 ($\beta = 0.066$, $t = 0.289$, $p < 0.05$) signifies that review quality have also a positive relationship with purchase intention. The hypothesis Ha 1.2 ($\beta = 0.260$, $t = 4.419$, $p < 0.05$), signifies that review quantity have a positive and significant relationship with purchase intention. Hypothesis Ha 1.3 is also accepted because p value is significant ($\beta = 0.388$, $t = 6.268$, $p < 0.05$) which signifies that source credibility has a positive and significant relationship with purchase intention. The hypothesis Ha 1.4 ($\beta = 0.065$, $t = 1.552$, $p < 0.05$) shows that review credibility has a positive relationship with purchase intention. The hypothesis Ha 1.5 ($\beta = 0.279$, $t = 4.438$, $p < 0.05$) shows that usefulness of online reviews has a positive relationship with purchase intention. All the hypotheses are accepted summary of hypothesis is presented in the table 5.18.

Table 5.18: Path Coefficients of Inner Model

Hypothesis	Path Co-efficient	(O)	(M)	STDEV	(O/STDEV)	P values
Ha1	Online Reviews -> PI	0.795	0.795	0.025	32.35	0.000
Ha 1.1	RQ -> PI	0.066	0.289	0.060	0.925	0.000
Ha 1.2	RQn -> PI	0.260	0.258	0.059	4.419	0.000
Ha 1.3	SC -> PI	0.388	0.394	0.062	6.268	0.000
Ha 1.4	RC -> PI	0.065	0.070	0.042	1.552	0.000
Ha 1.5	UOR -> PI	0.279	0.281	0.063	4.438	0.000

Source: Computed from Smart PLS Software

Table 5.19: Summary of Hypothesis Testing

Hypothesis Studied		P Value	Accepted/ Rejected
Ha 1	There is a positive relationship between online reviews and purchase intention of Gen Z consumers.	0.000	Accepted
Ha 1.1	There is a positive relationship between Review Quality of online reviews and purchase intention of Gen Z consumers.	0.000	Accepted
Ha 1.2	There is a positive relationship between Review Quantity of online reviews and purchase intention of Gen Z consumers.	0.000	Accepted
Ha 1.3	There is a positive relationship between Source Credibility of online reviews and purchase intention of Gen Z consumers.	0.000	Accepted
Ha 1.4	There is a positive relationship between Review credibility of online reviews and purchase intention of Gen Z consumers.	0.000	Accepted
Ha 1.5	There is a positive relationship between usefulness of online reviews of online reviews and purchase intention of Gen Z consumers.	0.000	Accepted

5.16 Goodness of Fit/ SRMR:

Moreover, this study also undergoes a model fit test, where the SRMR value is calculated as 0.053. To test the whole model (reject or support) goodness of fit is measured. It assessed the quality of the whole model jointly (outer and the inner model) (Hair, Risher, et al., 2019). To report the SRMR should be less than 0.08 (or 0.10) (Al-Emran et al., 2019; Hair, Risher, et al., 2019; Henseler et al., 2015). SRMR is squared discrepancy between the observed correlations and the model implied indicator correlations (Hair, Risher, et al., 2019). In this study, the model has the SRMR value 0.052 as shown in table 5.19, which is less than the 0.08, it indicates that model have a goodness of fit.

Table 5.20: Goodness Of Fit

Model Fit	Saturated model	Estimated model
SRMR	0.052	0.052
d_ULS	1.317	1.317
d_G	0.688	0.688
Chi-square	2272.873	2272.873
NFI	0.84	0.84

Source: Computed from Smart PLS Software

Objective 3: To analyze the moderating effect of gender between online reviews and purchase intention of Gen Z consumers.

Ha2: Gender moderates the relationship between Online Reviews and Purchase Intention of Gen Z consumers.

Ha 2.1: Gender moderates the relationship between Review Quality of online reviews and purchase intention of Gen Z consumers.

Ha 2.2: Gender moderates the relationship between Review Quantity of online reviews and purchase intention of Gen Z consumers.

Ha 2.3: Gender moderates the relationship between Source Credibility of online reviews and purchase intention of Gen Z consumers.

Ha 2.4: Gender moderates the relationship between Review Credibility of online reviews and purchase intention of Gen Z consumers.

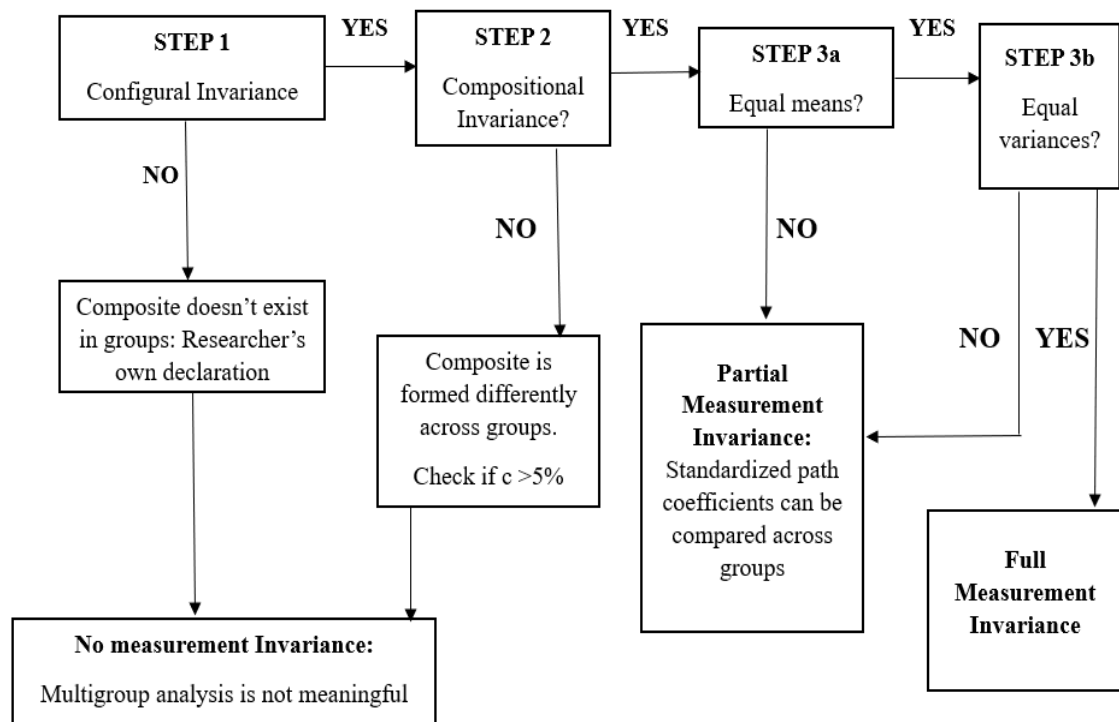
Ha 2.5: Gender moderates the relationship between Usefulness of online reviews of online reviews and purchase intention of Gen Z consumers.

5.17 Measurement invariance for composite model (MICOM) (Gender Moderator)

MICOM was utilized in the research to determine the heterogeneity. As shown in figure 5.7 the measurement of invariance in the data three step process was used in MICOM i.e ‘Configural Invariance, Compositional invariance and the equality of composite mean values and variances’ (Henseler et al., 2016; D. Kaur & Kaur, 2022). Additionally, it is advisable to evaluate the stability of invariance through the application of the MICOM procedure (Cuevas-Vargas et al., 2022). The MICOM method is necessary to understand the two groups (female and male) have similar understanding of the measurements (Azila et al., 2021). First step is to analyze the

configural invariance, results presented in table 5.20 demonstrates that both groups (male and female) have the identical fundamental factor structures such as equivalent indicators within each measurement model, equal treatment of the data and also uniform algorithm settings or optimization criteria (Azila et al., 2021; Henseler et al., 2016; D. Kaur & Kaur, 2022). Hence, the present study confirms the establishment of configural invariance. In the second step, compositional invariance was examined, to check the original correlation which is should be greater than or equal to the 5% quantile values, achieving this criterion indicates the attainment of compositional invariance. In table 5.21 the values obtained from group 1 (male) and group 2 (female) are greater than the 5% quantile, which indicates that compositional invariance is also presented in this study. Till now both the compositional invariance and configural invariance were achieved, it demonstrates that this study includes the partial invariance. Step three was achieved in two parts 3(a) and 3(b) to compare the variances and mean values (D. Kaur & Kaur, 2022). In tables 5.22 and 5.33 the findings indicate that original differences for both the means and variances fall within the confidence intervals bounds, which confirmed that there is a full measurement invariance (Cuevas-Vargas et al., 2022; Henseler et al., 2016).

Figure 5.7: Three step process of MICOM



Source: *Henseler, J., Ringle, C. M., & Sarstedt, M. (2016). Testing measurement invariance of composites using partial least squares. International Marketing Review, 33(3), 405–431.*

Table 5.21: Configural Invariance (Step1)

Constructs	Configural Invariance
PI	YES
RC	YES
RQ	YES
RQn	YES
SC	YES
UOR	YES

Table 5.22: Compositional Invariance (Step 2)

Constructs	Original correlation	Correlation permutation mean	5.00% Quantile	Permutation p value	Compositional Invariance
PI	1.000	1.000	0.970	0.276	YES
RC	0.918	0.967	0.908	0.209	YES
RQ	1.000	1.000	1.000	0.563	YES
RQn	1.000	1.000	1.000	0.711	YES
SC	0.954	1.000	0.839	0.569	YES
UOR	0.962	1.000	0.878	0.608	YES
Online Reviews	0.998	0.999	0.997	0.251	YES

Source: Computed from Smart PLS Software

Table 5.23: Equal means (Step 3(a))

Constructs	Original difference	Permutation mean difference	2.50%	97.50%	Permutation p value	Equal mean
PI	0.101	-0.004	-0.154	0.154	0.231	YES
RC	-0.116	0.001	-0.156	0.152	0.162	YES
RQ	0.078	0.000	-0.160	0.156	0.358	YES
RQn	0.127	0.000	-0.158	0.152	0.542	YES
SC	0.038	0.001	-0.163	0.162	0.712	YES
UOR	0.151	0.002	-0.162	0.153	0.390	YES
Online Reviews	0.163	0.000	-0.164	0.161	0.417	YES

Source: Computed from Smart PLS Software

Table 5.24: Equal variances (Step 3 (b))

Constructs	Original difference	Permutation mean difference	2.50%	97.50%	Permutation p value	Equal Variances	Measurement Invariance
PI	0.298	0.005	-0.290	0.302	0.501	YES	FULL
RC	0.272	0.009	-0.271	0.275	0.678	YES	FULL
RQ	0.144	0.004	-0.356	0.371	0.419	YES	FULL
RQn	0.109	0.000	-0.373	0.388	0.567	YES	FULL
SC	0.203	-0.002	-0.371	0.405	0.279	YES	FULL
UOR	0.083	0.001	-0.367	0.385	0.651	YES	FULL
Online Reviews	0.183	0.001	-0.440	0.460	0.380	YES	FULL

Source: Computed from Smart PLS Software

5.18 Multigroup Analysis (MGA) (Gender Moderation)

Multigroup analysis was conducted to assess the significant distinctions between the groups (male and female). To moderating effect of gender was assessed through multigroup analysis technique using bias-corrected bootstrapping with 5000

subsamples (D. Kaur & Kaur, 2022). The sample was segmented into male and female groups to conduct the MGA. MGA is a nonparametric technique proposed by (Henseler et al., 2016) was employed to exploring the differences between females and males. This method directly assess the “path coefficients between two groups using bootstrapping, and the p value indicating differences between path coefficients should be below 0.05 to show the significant variations in the path coefficient” (Henseler et al., 2016; Owusu-Bempah et al., 2022; Malaysia et al., 2020).

As table 5.24 shows that the results of this study support a significant difference between male and female for relationships review quality and purchase intention ($p=0.002$) (Ha 2.1), source credibility and purchase intention ($p=0.012$) (Ha 2.3) and usefulness of online reviews and purchase intention ($p=0.052$) (Ha 2.5) females were more influenced as compared to males. This should also be notified that there was not a significant difference between male and female for relationships between review credibility and purchase intention ($p=0.986$) (Ha 2.4), review quantity and purchase intention ($p=0.138$) (Ha 2.2) which means influence of RC and RQn on PI is similar in both groups. The relationship between online reviews and purchase intention was also significant ($p= 0.000$) (Ha 2). The differences in path coefficients revealed that impact of online reviews on purchase intention was stronger in females in comparison to males.

Table 5.25: PATH COEFFICIENT

Path Co-efficient	Difference (Male - Female)	1-tailed (Male vs Female) p value	2-tailed (Male vs Female) p value
RQ -> PI	-0.342	0.999	0.002*
RQn -> PI	-0.173	0.069	0.138**
SC -> PI	-0.305	0.006	0.012*
RC -> PI	-0.005	0.507	0.986**
UOR -> PI	-0.233	0.974	0.005*
Online Reviews -> PI	-0.048	0.867	0.000*

Source: Computed from Smart PLS Software

*Note: *Significant $p<0.05$,*

***Not Significant $p>0.05$*

5.19 BOOTSTRAPPING RESULTS

In bootstrapping results table 5.25 shows the different results of female and male. In both females and males, relationship between RC, RQn to PI is not significant ($p=0.194$, $p=0.091$), ($p=0.101$, $p=0.081$) respectively. Relationship between RQ, UOR and source credibility to purchase intention in both females and males are significant ($p=0.032$, $p=0.024$, $p=0.000$, $p=0.001$ and $p=0.000$, $p=0.000$) respectively. In higher order as shown in tables 5.25 and 5.26 relationship between online reviews and purchase intention is significant in both females and males ($p=0.000$ and $p=0.000$) respectively.

Table 5.26: Bootstrapping results of female

Path Co-efficient	Original Female (β)	Mean (Female)	STDEV (Female)	t value (Female)	p value (Female)
RC -> PI	0.098	0.049	0.075	1.299	0.194
RQ -> PI	0.166	0.164	0.077	2.147	0.032
RQn -> PI	0.120	0.124	0.074	1.638	0.101
SC -> PI	0.242	0.238	0.067	3.639	0.000
UOR -> PI	0.394	0.395	0.079	4.963	0.000
Online Reviews -> PI	0.828	0.827	0.028	29.766	0.000

Source: Computed from Smart PLS Software

Table 5.27: Bootstrapping results of male

Path Co-efficient	Original (Male) (β)	Mean (Male)	STDEV (Male)	t value (Male)	p value (Male)
RC -> PI	0.103	0.09	0.061	1.69	0.091
RQ -> PI	-0.176	-0.173	0.078	2.259	0.024
RQn -> PI	0.294	0.288	0.091	3.23	0.081
SC -> PI	0.547	0.55	0.105	5.23	0.000
UOR -> PI	0.161	0.16	0.092	1.747	0.001
Online Reviews -> PI	0.779	0.780	0.034	22.846	0.000

Source: Computed from Smart PLS Software

Table 5.28: Summary of Hypothesis Testing

Hypothesis Studied		P Value	Accepted/ Rejected
Ha2:	Gender moderates the relationship between online reviews and purchase intention of Gen Z consumers.	0.000	Accepted
Ha 2.1:	Gender moderates the relationship between Review Quality of online reviews and purchase intention of Gen Z consumers.	0.002	Accepted
Ha 2.2:	Gender moderates the relationship between Review Quantity of online reviews and purchase intention of Gen Z consumers.	0.138	Rejected
Ha 2.3:	Gender moderates the relationship between Source Credibility of online reviews and purchase intention of Gen Z consumers.	0.012	Accepted
Ha 2.4:	Gender moderates the relationship between Review Credibility of online reviews and purchase intention of Gen Z consumers.	0.986	Rejected
Ha 2.5:	Gender moderates the relationship between Usefulness of online reviews of online reviews and purchase intention of Gen Z consumers.	0.005	Accepted

5.20 Summary of Chapter

According to the findings, presented in the table 5.18 all the hypothesis of objective second are accepted, which indicated that online reviews have influence on Gen Z consumers purchase intention. However, in table 5.27 some hypothesis shows the positive significance, others do not have significant effects. In higher order construct, objective three, moderation effect of gender is positively significant between the ORs and PI. Results of new findings on the influence of ORs on the Gen Z consumers PI and moderation effect of gender reflect the earlier research outcomes, while incorporating the novel insights through detailed analysis. The differences in path coefficients revealed that impact of online reviews on purchase intention was stronger in females in comparison to males. Authors in their earlier studies, emphasize the results that characteristics of electronic word of mouth (information quality, quantity, credibility, need of information and attitude towards information) have a positively significance impact on the PI of consumers through the two mediations information usefulness and information adoption (Ngo et al., 2024). This study explores the five determinants of online reviews on the PI of generation z consumers in online apparel

industry with gender as a moderator between the ORs and PI. As another author revealed the effect of ORs and live streaming on the PI of consumers by using the different variables. In e-commerce user's participation in buying, selling and to share the information about products and services has become essential (Qin et al., 2023). Another research paper explored the consumers purchase intention of cell phones based on online reviews and this paper suggested to the enterprises, to use the online reviews in a better way for the promotion of products and also to attract the consumers. Online reviews are the communication between who posted the online reviews and who want to purchase the product (N. Zhang et al., 2022). As another research revealed the relationship of source credibility and hotel brand image with purchase intention as generation (millennials and earlier generation) is a moderator. In source credibility two constructs were used expertise and trustworthiness. The research article revealed that millennials are strongly affected by user generated content rather than the earlier generations (H.-R. Shin & Choi, 2021). Another study explored the influence of UGC on purchasing behaviour, trust and the purchase intention. It is also refers as to the online reviews and study explored that there is no gender differences between the UGC and purchase intention but trust in females is more significant rather than in males (Sethna et al., 2017). Additionally, researchers explored the impact of Ewom on the PI of consumers by using three variables (electronic word of mouth quality, quantity and credibility), this study found that quality and quantity have a significant impact on the PI but e-WOM credibility have no significant impact on the consumers PI (Mehyar et al., 2005). In this study review credibility also have a significant influence on GEN Z consumers PI. In another research influence of online reviews and packaging design on the brand awareness and brand awareness impact on the PI. Here, brand awareness used as a mediator between the ORs and PI. It was explored that direct or indirect online reviews have a significant impact on the consumers purchase intention in skin care products (Akbar et al., 2023). Another study explored that effect of online reviews (image of product) on the purchase intention of consumers by using the different variables (Review timing, Size, Product Knowledge, Source Credibility, Social impact and benefit gaining). Product image as a mediation between ORs and PI. Findings shows that there is no any other strategy to influence the electronic consumers purchase intention. Online reviews has a significant effect on purchase intention of electronic consumers (Al-Abbadi et al., 2022). In one study it was explored that how online

reviews can affect the purchase intention by using the stimulus-organism-response framework. Here information quality of online reviews measured with (completeness, accuracy, adequacy objectivity, relevance, timeliness and many more), results found that hypothesis of impact of ORs on PI is positively significant with the variables trust and satisfaction (Zhu et al., 2020). The present study offers an examination and a lot of studies conducted related to the ORs and PI. In conclusion, online reviews play a pivotal role to enhance the purchase intention of Gen Z consumers in the online apparel industry. As we have explored throughout the study, the connection between ORs and PI is essential for the long-term success of apparel industry. In e-commerce ORs are important for selling products easily because consumers liked to see the online reviews and ratings before purchasing the product. Specially, in the online apparel industry consumers want to know the quality of clothes, color is matched what they see online and long-term durability. Experiences of other consumers helps them to feel more confident about their purchases. So, for online clothing stores, having lots of honest reviews is a key to attract the consumers making sales. Online reviews help to reduce the risk of consumers and increase the trust among customers. If consumers are satisfied with the product, they often share positive online reviews. E-Commerce sites paid more attention to online reviews.

CHAPTER 6

ANALYZE THE EFFECT OF ONLINE REVIEWS ON GEN Z CONSUMERS SATISFACTION

6.1 Introduction:

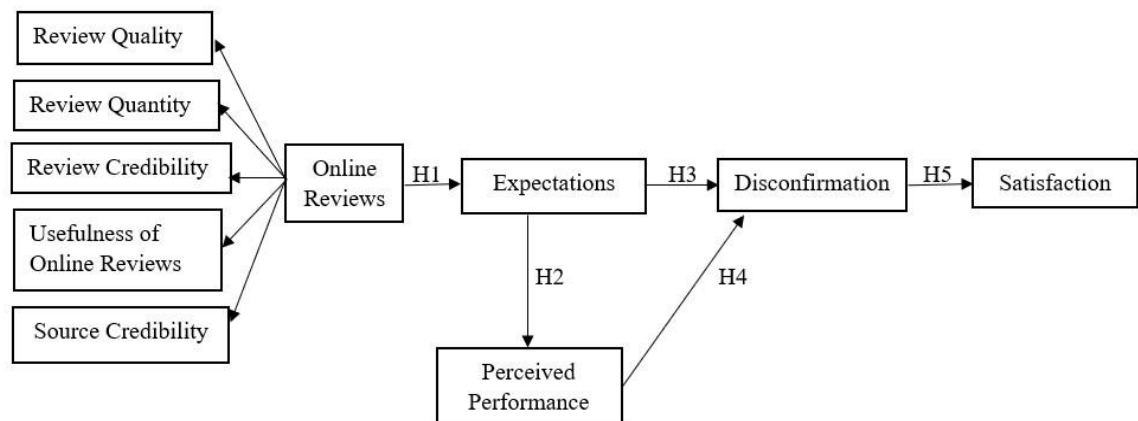
This chapter deals with the effect of online reviews on GEN Z consumers satisfaction with in the apparel industry. Determinants of online reviews (review credibility, review quality, review quantity, source credibility, usefulness of online reviews) have influence on satisfaction through expectation disconfirmation theory. When consumers read the online reviews, they formulate the perceptions or expectations regarding the product. When they received the product, they compared their expectations with the actual performance of the product. If their expectations were matched with the actual performance of product it leads to the positive disconfirmation and if their expectations were not matched with the actual performance of product then it leads to the negative disconfirmation (R. L. Oliver, 1980).

This chapter have four sections. First section presented the KMO and Bartlett's test of Sphericity of constructs. Second section presented the Common Method Variance. Third section presented the content and face validity (Reliability statistics). Fourth section presented the Structure equation modeling (SEM) which performed two-step process, "Measurement Model" and "Structural Model". Measurement model presented the Reflective indicator loadings, Construct reliability, Cronbach's Alpha, Composite Reliability, Convergent validity and Discriminant validity. Structural Model presented the Collinearity among constructs, significance and relevance of the path coefficients, predictive relevance (R Square, Q square, PLS Predict) and goodness of fit / SRMR.

The present study explored the determinants to check the effect of online reviews on GEN Z consumers satisfaction in apparel industry. To accomplish the objective 4, data was collected from Gen Z consumers who were engaged in online shopping from Sub Tehsils (Amritsar 1, Amritsar 2, Ajnala, Jalandhar 1, Jalandhar 2, Phillaur, Ludhiana East, Ludhiana West, Jagraon, Ferozepur, Zira, Guru Har Sahai, Gurdaspur, Batala, Dera Baba Nanak, Hoshiarpur, Dasuya and Mukeria) of six districts of Punjab (Amritsar, Jalandhar, Ludhiana, Ferozepur, Gurdaspur and Hoshiarpur). The study

used an adapted scale, which include 5 items of (RQn), 6 items of (RQ), 7 items of (SC), 4 items of (UOR), 5 items of (RC), 4 items of (EP), 4 items of (PP), 5 items of (DC), 4 items of (S). The reliability and validity of constructs have been checked through Cronbach alpha values 0.950 (RQn), 0.971 (RQ), 0.960 (SC), 0.917 (RC), 0.932 (UOR), 0.928 (EP), 0.922 (PP), 0.941 (DC), 0.948 (S) which were met with the threshold limit. Conceptual framework and hypothesis were proposed on to analyze the effect of online reviews on GEN Z consumers satisfaction in Apparel Industry as shown in figure 6.1.

Figure 6.1 Conceptual Framework



Source: Author's own creation

Objective 4: To analyze the effect of online reviews on Gen Z consumers satisfaction.

Ha 3- Online Reviews have a positive impact on Gen Z consumers Expectations.

Ha 4- There is a positive relationship between Gen Z consumers Expectations and Perceived Performance.

Ha 5- Gen Z consumers expectations have a positive influence on disconfirmation

Ha 6- There is a positive relationship between Perceived Performance and Disconfirmation.

Ha 7- There is a significant relationship between disconfirmation and Gen Z consumers satisfaction.

6.2 Bartlett's test of Sphericity and Kaiser- Meyer- Olkin

KMO test has been used to assess the suitability of data for factor analysis. It measures the sufficiency of each construct in the model as well as for the whole model. The values should be varied from 0 to 1. If the value of KMO comes between 0.8 to 1.0, indicates the adequate sampling. If the value falling between 0.7 to 0.79 indicates the mediocre sampling, while a value below 0.6 indicates the inadequate sampling and serious action should be taken (Shrestha, 2021; B. Williams et al., 2010). Bartlett's test of sphericity assesses the substantial correlation among the variables. A highly significant result, typically ($p < 0.001$) which indicates the significant correlation among variables. Moreover, when the significant value is below than 0.05 indicates the factor analysis is relevant for the dataset (Shrestha, 2021; B. Williams et al., 2010). Table 6.1, 6.2, 6.3, 6.4 and 6.5 reveals the KMO value with more than 0.5, and Barlett's test highlights the significant correlation with the value below from 0.05, which indicates the values are adequate to proceed for factor analysis.

Table 6.1: Expectation

KMO and Bartlett's Test			
Kaiser-Meyer-Olkin Measure of Sampling Adequacy.			0.802
Bartlett's Test of Sphericity	Approx. Chi-Square		971.126
	Df		6
	Sig.		0.000

Source: Computed from SPSS

Table 6.2: Perceived Performance

KMO and Bartlett's Test			
Kaiser-Meyer-Olkin Measure of Sampling Adequacy.			0.818
Bartlett's Test of Sphericity	Approx. Chi-Square		1134.380
	df		6
	Sig.		0.000

Source: Computed from SPSS

Table 6.3: Satisfaction

KMO and Bartlett's Test			
Kaiser-Meyer-Olkin Measure of Sampling Adequacy.			0.837
Bartlett's Test of Sphericity	Approx. Chi-Square		1231.919
	df		6
	Sig.		0.000

*Source: Computed from SPSS***Table 6.4: Disconfirmation**

KMO and Bartlett's Test			
Kaiser-Meyer-Olkin Measure of Sampling Adequacy.			0.882
Bartlett's Test of Sphericity	Approx. Chi-Square		1654.930
	df		10
	Sig.		0.000

*Source: Computed from SPSS***Table 6.5: Online Reviews**

KMO and Bartlett's Test			
Kaiser-Meyer-Olkin Measure of Sampling Adequacy.			0.883
Bartlett's Test of Sphericity	Approx. Chi-Square		2835.559
	df		10
	Sig.		0.000

*Source: Computed from SPSS***6.3 Common Method Variance**

In social science research, questionnaire surveys are frequently used to analyze the respondent's personalities, behaviors and perceptions on various issues. In data analysis survey gives the information about the dependent and independent variables (Eichhorn, 2014; Tehseen et al., 2017). However, Common method variance arises when same respondents were used in a study to collect the data of dependent variable and independent variable in the same context and characteristics. Harman's Single-

Factor Test has been used to analyze the CMV in the study, it is conducted post data collection. If a common latent factor explains over the 50% (Harman, 1976) of the variance, then it might be suggesting that common method biasness is present (Eichhorn, 2014). As shown in table 6.6 factor explained 47.61% of the total variance, which is below the threshold limit of 50%. The result indicates that there is no common method variance in this study.

Table 6.6: Common Method Variance

Factors	Extraction Sum of Square loadings		
	Total	%age of Variance explained	% Cumulative
	22.583	47.610	47.610

Source: Computed from SPSS Software

6.4 Content and Face Validity (Reliability Statistics)

In this section content and face validity of questionnaire items were measured. To evaluate the internal consistency of this study Cronbach Alpha was used. Cronbach alpha and composite reliability tests are applied on the 10% of the sample size (Connelly, 2008). SPSS software was used to check the values of Cronbach alpha. If the values lie between 0.7 to 0.9, it indicates that there is a internal consistency in scale, and if value comes above the 0.9, it indicates that there is a high internal consistency in scale (Sürücü & Maslakçı, 2020). As table depicts 6.7 the values of Cronbach alpha of constructs come above the 0.9, which shows that there is a high internal consistency.

Table 6.7: Reliability Statistics of the research study

Sr. No.	Constructs	Items included	Cronbach's Alpha	Consistency
1.	Reliability of Expectation	4	.928	Excellent
2.	Reliability of Perceived Performance	4	.922	Excellent
3.	Reliability of Disconfirmation	5	.941	Excellent
4.	Reliability of Satisfaction	4	.948	Excellent
5.	Reliability of Review Quantity	5	.950	Excellent
6.	Reliability of Review Quality	6	.971	Excellent
7.	Reliability of Source Credibility	7	.960	Excellent
8.	Reliability of Usefulness of Online Reviews	4	.932	Excellent
9.	Reliability of Review Credibility	5	.917	Excellent

Source: Computed from SPSS Software

6.5 Structural Equation Modelling (Measurement Model)

SEM is a statistical technique, which is often used in the marketing research, because marketers can examine the relationship between dependent variables and independent variables, in order to serve the better services to the customers (Wong, 2013). PLS-SEM is “the most fully developed and general system” and it is also called a “silver bullet” (Al-Emran et al., 2019; Hair, Risher, et al., 2019). It is divided into two main models, measurement model and structural model. Measurement model also known as “outer model” it measures the relationship between constructs and its relevant items and structural model refers as the “inner model”, it measures the relationship between the constructs themselves. In figure 6.2 the measurement model shows the reliability and content validity between the blue circles and yellow boxes. The arrows between

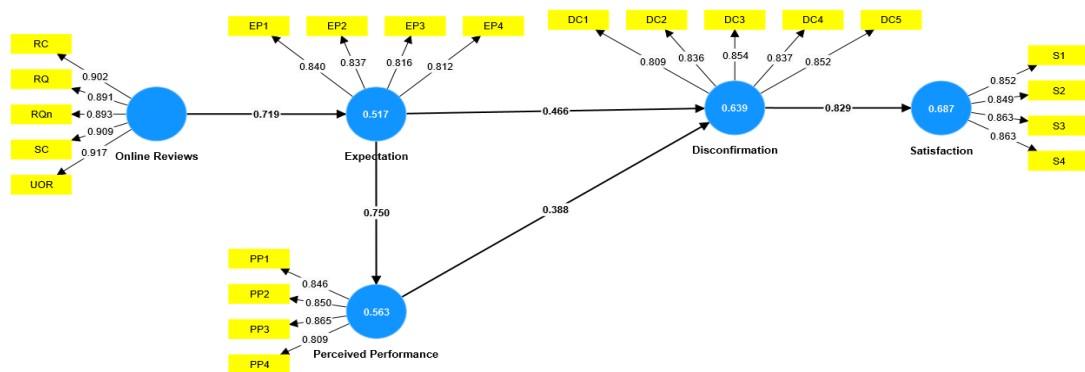
the blue circles shows the structural model or inner model, which indicates whether the one variable have the direct effect on another variable. Here, expectation disconfirmation theory is used to check the effect of online reviews on satisfaction.

Further, measurement model measures the both reflective and formative models (Al-Emran et al., 2019). In measurement reflective model measures the Reflective indicator loadings, Construct reliability, Cronbach's Alpha, Composite Reliability, Convergent validity through Average Variance Extracted and Discriminant validity through HTMT, cross loadings and Fornell and Larcker. Structural model measures the Collinearity among constructs, significance and relevance of the path coefficients, predictive relevance (R Square, Q square, PLS Predict) and goodness of fit / SRMR (Hair, Risher, et al., 2019). In figure 6.2 construct online review is in higher order construct while other constructs (expectation, perceived performance disconfirmation and satisfaction) are in the lower order construct. Measurement model measures the reliability and validity. After the assessment of reliability and validity in measurement model, further researcher can proceed to the structural model. Steps to calculate the measurement model in PLS-SEM are: Firstly, import the data file in PLS software (CSV format) > Create model > Click on calculate > Select PLS-SEM algorithm > Select Factor > Start Calculation > Assess the PLS-SEM output.

6.6 Lower-Order Construct (LOC) to Higher Order Construct (HOC)

In this study, the exogenous variable (Online Reviews) having various lower order constructs (Review Quantity, Review Quality, Review Credibility, Source credibility, Usefulness of online reviews) which may become complicated to analyse as the lower order construct (LOC). Instead of analyzing the sub constructs of online reviews as a single construct layer we converted it into the higher order construct (HOC). Within the realm of PLS-SEM higher order constructs are “also referred as the hierarchical component models” (HCM) (Sarstedt et al., 2019; Wong, 2016). There are some advantageous features of higher order construct (HOC). For instance, firstly, it helps to reduce the number of relationships in the path model. Secondly, it addresses the bandwidth-fidelity dilemma. Thirdly, higher order constructs mitigate collinearity among the indicators (Sarstedt et al., 2019). In this study, higher order construct was used for its ability to simplify the analysis of complex model into a simple model (Ciavolino & Nitti, 2010).

Figure 6.2: PLS-SEM Algorithm for Measurement Model and Path Coefficients:



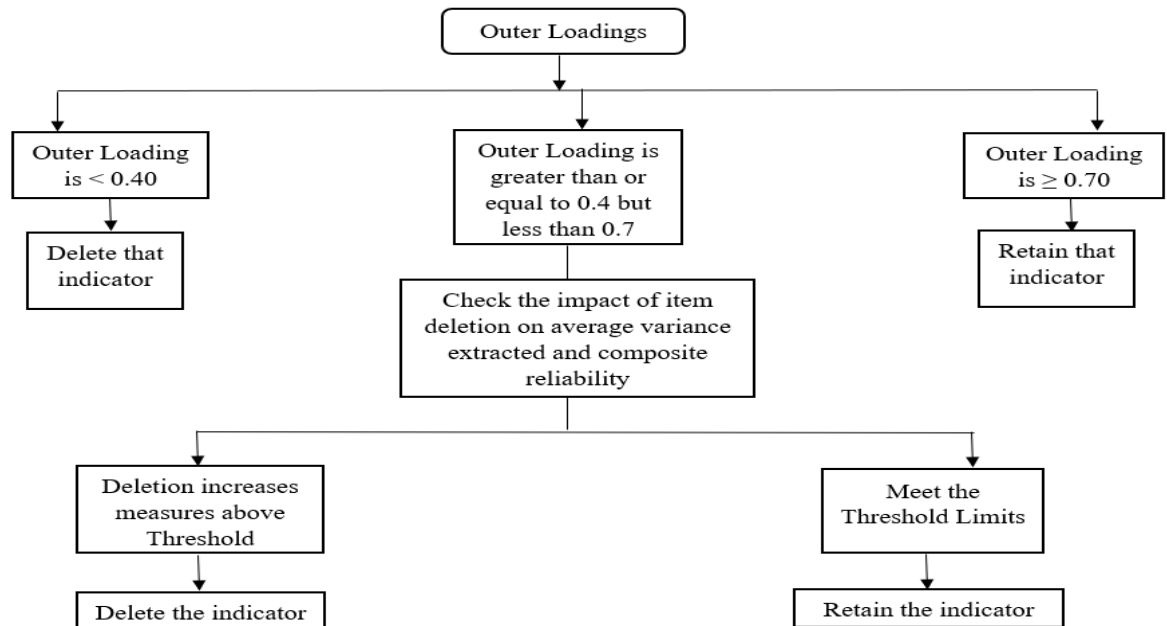
Source: Computed from Smart PLS Software

6.7 Internal Consistency Reliability

6.7.1 Indicator Reliability (Outer Loadings):

In a reflective measurement model first step is to examine the indicator loadings. In this study, five exogeneous constructs and four endogenous constructs are used to measure the model. For each latent variable item reliability is measured based on the outer loadings (Hair, Risher, et al., 2019). As figure 6.3 depicts that if the value of outer loadings is less than 0.40, it is recommended to delete that item. If the outer loadings having value between 0.4 to 0.7, firstly check the impact of deleted item on Average Variance Extracted and Composite reliability, if it meets the threshold limit retain that item but if it doesn't meet the threshold limit delete that item. If the outer loadings having value greater than 0.7 it is considered as acceptable and retain that indicator (Al-Emran et al., 2019; Hair, Risher, et al., 2019; Jr, 2017). In our study, the factor loadings of each indicator of their latent variable having values greater than the 0.7 which is considered as all the items are acceptable. As table 6.8 shows the factor loadings of Review Quantity, Review Quality, Source credibility, Usefulness of online reviews, Review credibility, Expectation, Perceived Performance, Disconfirmation and Satisfaction ranged between 0.82-0.86, 0.81-0.87, 0.73-0.81, 0.77-0.81, 0.78-0.87, 0.81-0.84, 0.80-0.86, 0.80-0.85, 0.84-0.86. Indicator loadings in higher order construct of online reviews also having values more than 0.7 which are acceptable. All the factor loadings are acceptable and fits to the model.

Figure 6.3: Threshold limits for outer loadings



Source: Hair, J. F., Risher, J. J., Sarstedt, M., & Ringle, C. M. (2019). When to use and how to report the results of PLS-SEM. *European Business Review*, 31(1), 2–24.

Table 6.8: Internal Consistency Reliability and Indicator Consistency Reliability (Outer loadings, VIF, Cronbach Alpha, Rho_a, AVE and Composite Reliability)

Constructs	Indicators	Indicator Loadings	VIF	Cronbach Alpha	Rho_a	AVE	Composite Reliability
Review Quantity	RQn1	0.864	2.657	0.901	0.905	0.716	0.926
	RQn2	0.864	2.746				
	RQn3	0.805	2.053				
	RQn4	0.839	2.202				
	RQn5	0.857	2.445				
Review Quality	RQ1	0.819	2.285	0.919	0.920	0.713	0.937
	RQ2	0.863	2.886				
	RQ3	0.870	2.843				
	RQ4	0.824	2.298				
	RQ5	0.857	2.711				
	RQ6	0.833	2.357				
Source	SC1	0.733	2.044	0.907	0.908	0.642	0.926

Credibility	SC2	0.787	2.123				
	SC3	0.811	2.274				
	SC4	0.814	2.320				
	SC5	0.818	2.282				
	SC6	0.807	2.393				
	SC7	0.797	2.190				
Usefulness of Online Reviews	UOR1	0.782	1.727	0.857	0.859	0.637	0.898
	UOR2	0.797	1.789				
	UOR3	0.816	2.001				
	UOR4	0.775	1.778				
	UOR5	0.819	1.971				
Review Credibility	RC1	0.851	2.162	0.857	0.860	0.701	0.904
	RC2	0.833	2.015				
	RC3	0.876	2.461				
	RC4	0.787	1.679				
Expectation	EP1	0.840	1.982	0.845	0.846	0.682	0.896
	EP2	0.837	1.947				
	EP3	0.815	1.832				
	EP4	0.812	1.871				
Perceived Performance	PP1	0.846	2.035	0.864	0.864	0.710	0.907
	PP2	0.850	2.295				
	PP3	0.865	2.446				
	PP4	0.809	1.720				
Disconfirmation	DC1	0.809	2.000	0.894	0.894	0.702	0.922
	DC2	0.836	2.178				
	DC3	0.854	2.450				
	DC4	0.837	2.220				
	DC5	0.852	2.462				
Satisfaction	S1	0.852	2.157	0.879	0.880	0.734	0.917
	S2	0.849	2.105				
	S3	0.863	2.266				
	S4	0.863	2.331				

Online Reviews	RQn	0.893	3.904	0.943	0.944	0.814	0.956
	RQ	0.891	2.664				
	SC	0.909	3.800				
	UOR	0.917	3.266				
	RC	0.902	2.818				

Source: Computed from Smart PLS software

6.7.2 Construct Reliability (Cronbach Alpha)

Construct reliability can be measured with two methods (Cronbach Alpha and composite reliability). If the values of Cronbach alpha should not be less than 0.60 and be greater than 0.95. It indicates that if values are less than the 0.60 it is the early stage of research, if values are greater than 0.95 that are also not desirable in research (Hair, Risher, et al., 2019). Cronbach alpha have some limitations, if the items are unweighted it is the less precise to measure the reliability. It is also too conservative. As compared to the cronbach alpha composite reliability is recommended more appropriate because it includes the indicators differential weights and it is also liberal (Hair, Risher, et al., 2019; Jr, 2017). Cronbach's alpha and composite reliability values are ranged between the "0 and 1" (Al-Emran et al., 2019). Higher the value indicates the higher reliability. In exploratory research values of 0.60 to 0.70 considered as acceptable but in more advanced research, values of 0.70 to 0.90 are considered as satisfactory (Fornell & Larcker, 1981, 1981; Hair, Risher, et al., 2019; Jr, 2017). In table 6.8 the values of composite reliability of all the constructs are met with their threshold limits which indicates that there is a reliability in constructs. Smart pls was used to calculate the values of cronbach's alpha and composite reliability for the constructs.

6.8 Construct Validity

6.8.1 Convergent Validity (Average Variance Explained)

Convergent validity refers to "the extent to which a measure correlates positively with alternative measures of the same construct" (Hair, Risher, et al., 2019). Convergent validity is assessed by looking at how strongly the indicators relate with their respective construct, which helps to calculate the average variance extracted from each construct (Henseler et al., 2015). AVE refers to "the grand mean value of

the squared loadings of the indicators associated with the construct (i.e the sum of the squared loadings divided by the number of indicators)” (Hair, Risher, et al., 2019). The acceptable values of outer loadings should be greater than or equal to 0.70. To ensure the convergent validity, the outer loadings of the indicators should exceed the 0.50, which signifies that construct score includes at least 50% of the variable variance (Hair, Risher, et al., 2019; Henseler et al., 2015). In table 6.8 the AVE values are more than 0.50 RQn (0.716), RQ (0.713), SC (0.643), RC (0.701), UOR (0.637), EP (0.682), PP (0.710), DC (0.702), S (0.734) and online reviews (0.814), which signifies that all the constructs used in study are strongly reliable.

6.8.2. Discriminant Validity (HTMT)

Discriminant validity refers to “the extent to which a construct is truly distinct from other constructs by empirical standards” (Henseler et al., 2015). In structural model discriminant validity shows that a construct is empirically different from another construct (Hair, Risher, et al., 2019). Discriminant validity means that each construct of model represent the different phenomenon not represented by the other construct (Hair, Risher, et al., 2019; Jr, 2017). It can be measured by Cross loadings, Fornell and Larcker and HTMT. Cross loadings, an indicator should show a stronger correlation with its own constructs compared to any other constructs. In terms of Fornell and Larcker criterion, it compared the square root of the average variance extracted values with the correlations among variables (Al-Emran et al., 2019). The values of square root of AVE must be greater than its highest correlation among other constructs. A recent study has been introduced a novel criterion to evaluate the discriminant validity known as the Heterotrait-Monotrait ratio (HTMT) of correlations. HTMT is defined as the “mean value of the item correlations across constructs relative to the mean of the average correlations for the items measuring the same construct” (Henseler et al., 2015). The threshold limit of HTMT value for (Clark & Watson, 2016) should be less than 0.85 and for (Gold et al., 2001) should be less than 0.90. In table 6.9 the values of online reviews, expectation, perceived performance, disconfirmation and satisfaction met the threshold limit, which signifies that there is a proper discriminant validity. From all the findings (Outer loadings, Cronbach alpha, AVE and HTMT), it is confirmed that this study has good internal consistency and the convergent validity of the measurement model.

Table 6.9: Discriminant Validity (HTMT)

Online Reviews	Disconfirmation	Expectation	Online Reviews	Perceived Performance	Satisfaction
Disconfirmation					
Expectation	0.871				
Online Reviews	0.862	0.884			
Perceived Performance	0.836	0.877	0.835		
Satisfaction	0.864	0.830	0.827	0.898	

Source: Computed from Smart PLS Software

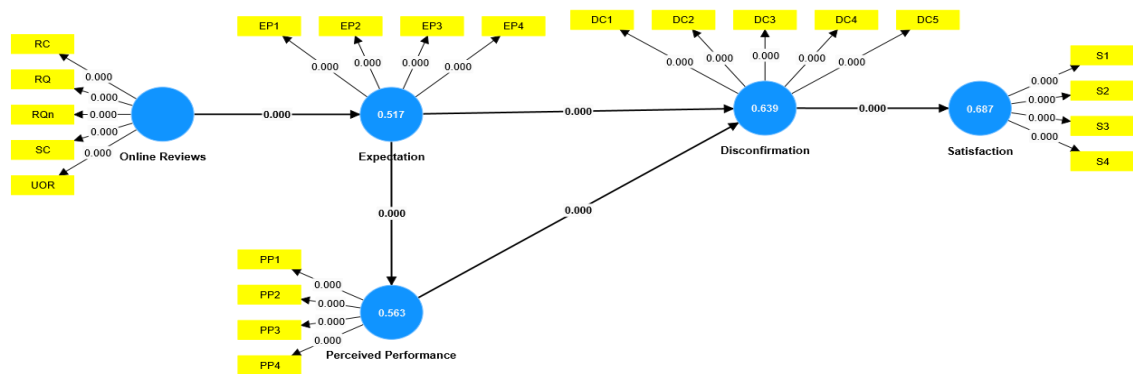
6.9 VIF (Variance Inflation Factor)

VIF is used to check the collinearity among the indicators. As a rule of thumb, ideally the values of VIF should be less than 3 (Hair, Risher, et al., 2019) but if values are more than three and less than five it also suggests that there is no collinearity among indicators. If VIF having values more than five researcher should not considered that in study (Al-Emran et al., 2019; Hair, Risher, et al., 2019). Table 6.8 demonstrates that the VIF values of all the indicators (online reviews, expectation, perceived performance, disconfirmation and satisfaction) have less than 3 which indicates that indicators have no collinearity issues.

6.10 ASSESSMENT OF STRUCTURAL MODEL (INNER MODEL)

In PLS structural equation modelling after assessing the measurement model, next step is to measure the structural model. In structural model both the predictive ability of model and the connections between the constructs are measured. Assessment criterion of structural model includes, R square, Q square and Path coefficients. Additionally, predictive power has been analyzed by PLS-PREDICT in structural model. Hypothesis were tested by bootstrapping procedure with a re-sample of 5000 (Al-Emran et al., 2019; Hair, Risher, et al., 2019). The structural model presents the evaluation in figure 6.4 of online reviews (RQn, RQ, RC, SC, UOR), Expectation, Perceived Performance, Disconfirmation and Satisfaction.

Figure 6.4: Bootstrapping Model in Structural assessment



Source: Computed from Smart PLS Software

6.11 Coefficient of Determination (R square)

In structural model after the assessment of collinearity issues, measure the predictive power through coefficient of determination. R square measured the endogenous variables and f square measured the exogeneous variables. The values ranged between R square from 0 to 1, indicates that higher values have a stronger explanatory power (Al-Emran et al., 2019). The rule of thumb, R^2 values 0.75, 0.50 and 0.25 considered as substantial, moderate and weak respectively (Hair, Risher, et al., 2019) but R^2 values are also depend on the discipline of the study. In table 6.10 the R square having values of (Disconfirmation, expectation, perceived performance and satisfaction) ranged between 0.52 - 0.69, which means there is a moderate predictive power.

Table 6.10: R Square

Constructs	R-square	R-square adjusted
Disconfirmation	0.639	0.638
Expectation	0.517	0.516
Perceived Performance	0.563	0.562
Satisfaction	0.687	0.687

Source: Computed from Smart PLS Software

6.12 PLS-PREDICT

Q Square is another method to assess the predictive accuracy in PLS path model (Geisser, 1974). Q^2 is not only reflect the out of sample prediction accuracy, but it combines both the aspects (out-of-sample prediction and in- sample explanatory power) (Geisser, 1974; Hair, Risher, et al., 2019). Q square is measured only for

endogenous variables. Minor variances between the predicted and original values result into a higher value of q square, which indicates a higher predictive accuracy (Shmueli et al., 2019). In structural model the value of q square should be larger than zero for endogenous variables. If Q^2 having the value 0.25 it depicts small predictive relevance in path model, but if Q^2 having values between 0.25-0.50 and more than 0.50, it depicts there is a medium and large predictive relevance in path model (Geisser, 1974; Hair, Risher, et al., 2019; Shmueli et al., 2019). In table 6.11 Q^2 of endogenous variables (Expectation, Disconfirmation, Perceived Performance and Satisfaction) having values more than zero, which indicates the high predictive power in this model.

Table 6.11: Q Square Predict

Indicators	Q^2 predict
DC1	0.361
DC2	0.397
DC3	0.406
DC4	0.405
DC5	0.403
EP1	0.326
EP2	0.405
EP3	0.346
EP4	0.312
PP1	0.419
PP2	0.339
PP3	0.362
PP4	0.352
S1	0.351
S2	0.354
S3	0.341
S4	0.349

Source: Computed from Smart PLS Software

6.13 CV-PAT (Indicator Average & Linear Model)

Cross- validated predictive ability test offers a statistical test to compare the predictive accuracy of a recognized model against that of an alternative model (Sharma et al., 2023). If PLS Loss have values lower than the indicator average (IA) loss and average loss difference comes in negative, it depicts that high predictive power. If PLS Loss also have values lower than linear model (LM) loss than there is a strong predictive power, but if values come higher of PLS loss with LM loss than there is a predictive power but not strong predictive power (Hair, Risher, et al., 2019; Shmueli et al., 2019). In table 6.12 Pls Loss have higher values than IA loss, which means there is a predictive power but in table 6.13 when we compared the pls loss with LM than average loss difference comes not significant, which means there is a predictive power but not strong predictive power in this model.

Table 6.12: CV-PAT (PLS-SEM V/S Indicator Average)

Constructs	PLS loss	IA loss	Average loss difference	t value	p value
Disconfirmation	0.604	0.996	-0.392	8.904	0.000
Expectation	0.674	1.030	-0.356	5.25	0.000
Perceived Performance	0.596	0.944	-0.348	7.441	0.000
Satisfaction	0.594	0.912	-0.318	9.056	0.000
Overall	0.616	0.972	-0.356	7.913	0.000

Source: Computed from Smart PLS Software

Table 6.13: CV-PAT (PLS-SEM V/S Linear Model)

Constructs	PLS loss	LM loss	Average loss difference	t value	p value
Disconfirmation	0.604	0.556	0.048	4.036	0.000
Expectation	0.674	0.668	0.005	1.114	0.000
Perceived Performance	0.596	0.551	0.045	3.335	0.001
Satisfaction	0.594	0.516	0.078	5.187	0.000
Overall	0.616	0.572	0.044	4.937	0.000

Source: Computed from Smart PLS Software

6.14 Statistical Significance and Path Coefficient Relevance

The path coefficients illustrate the hypothesized links between the constructs, ranging from -1 to +1, where values close to +1 indicate robust positive relationships. Significance of these relationships is often determined using p-values, with the significant threshold < 0.05 . Hence, the outcomes of the path model examining the significance of all structural relationships through t-values, p-values, and confidence intervals (Al-Emran et al., 2019; Fornell & Larcker, 1981; Hair, Risher, et al., 2019; Henseler et al., 2015). In table 6.14 the results revealed that relationship between online reviews and expectation is significant, as indicated by Ha 3 ($\beta = 0.719$, $t = 16.202$, $p < 0.05$). The hypothesis Ha 4 and Ha 5 ($\beta = 0.750$, $t = 27.128$, $p < 0.05$) ($\beta = 0.466$, $t = 8.892$, $p < 0.05$), signifies that expectation have also a positive relationship with both perceived performance and disconfirmation. The hypothesis Ha 6 ($\beta = 0.388$, $t = 6.729$, $p < 0.05$), signifies that perceived performance have a positive and significant relationship with disconfirmation. So, hypothesis Ha 6 is also accepted. The hypothesis Ha 7 ($\beta = 0.829$, $t = 40.307$, $p < 0.05$) shows that disconfirmation have a positive relationship with satisfaction. All the five hypotheses are accepted summary of hypothesis is presented in the table 6.15.

Table 6.14: Path Coefficients of Inner Model

Path Co-efficient	Original sample (β)	Sample mean (M)	Standard deviation (STDEV)	T statistics (O/STDEV)	P values
Online reviews -> Expectation	0.719	0.719	0.044	16.202	0.000
Expectation -> Perceived Performance	0.750	0.749	0.028	27.128	0.000
Expectation -> Disconfirmation	0.466	0.464	0.052	8.892	0.000
Perceived Performance -> Disconfirmation	0.388	0.390	0.058	6.729	0.000
Disconfirmation -> Satisfaction	0.829	0.829	0.021	40.307	0.000

Source: Computed from Smart PLS Software

Table 6.15: Summary of Hypothesis Testing

Hypothesis Studied		P Value	Accepted/ Rejected
Ha 3:	Online Reviews have a positive impact on Gen Z consumers Expectations.	0.000	Accepted
Ha 4:	There is a positive relationship between Gen Z consumers Expectations and Perceived Performance.	0.000	Accepted
Ha 5:	Gen Z consumers expectations have a positive influence on disconfirmation	0.000	Accepted
Ha 6:	There is a positive relationship between Perceived Performance and Disconfirmation.	0.000	Accepted
Ha 7:	There is a significant relationship between disconfirmation and Gen Z consumers satisfaction.	0.000	Accepted

6.15 Goodness of Fit/ SRMR

Moreover, this study also undergoes a model fit test, where the Standardized Root Mean Square Residual (SRMR) value is calculated as 0.053. To test the whole model (reject or support) goodness of fit is measured. It assessed the quality of the whole model jointly (outer and the inner model) (Hair, Risher, et al., 2019). To report the standardized root mean square residual (SRMR) should be less than 0.08 (or 0.10) (Al-Emran et al., 2019; Hair, Risher, et al., 2019; Henseler et al., 2015). SRMR is squared discrepancy between the observed correlations and the model implied indicator correlations (Hair, Risher, et al., 2019). In this study, the model has the SRMR value 0.053 as shown in table 6.16, which is less than the 0.08, it indicates that model have a goodness of fit.

Table 6.16: Goodness of Fit

Model Fit	Saturated model	Estimated model
SRMR	0.053	0.115
d_ULS	0.707	3.331
d_G	0.476	0.613
Chi-square	1688.695	1968.565
NFI	0.853	0.828

Source: Computed from Smart PLS Software

6.16 Summary of Chapter

According to the findings, presented in the table 6.15, all the hypothesis are accepted, indicating that online reviews have influence on satisfaction of Gen Z consumers in apparel industry through expectation disconfirmation theory. Results of new findings on the effect of online reviews on the satisfaction of Gen Z consumers reflect the earlier research outcomes, while incorporating the novel insights through detailed analysis. Authors in their earlier studies, emphasize the results that online opinion types (regular, comparative and suggestive opinions) have a positive effect on consumers expectations. Moreover, the authors include the sentiment words as the full mediator to forecast the consumers satisfaction and additionally, their research revealed a strong relationship between the expectation, perceived performance and disconfirmation (Qazi et al., 2017). As another author revealed that, how electronic word-of-mouth (eWOM) influences the relationship between consumers and retailers by analyzing consumer satisfaction. They explored before purchasing the product how positive and negative electronic word of mouth increased or decreased the consumer satisfaction and how e-WOM helps to make the decision making process (Kuo & Nakhata, 2019). Another study has evaluated the effect of online reviews on customer satisfaction, which founds that firstly, online reviews shape the expectations and later on the impact of satisfaction of consumers when disconfirmation played the role of mediated variable. Author did the experiment method on the online reviews of books (Picazo-Vela, 2009). In another study authors used the constructs (Review quality, Review timeliness, Visual Image Quality, Review rating, Review adoption, Confirmation, Positive review Intentions, Negative review intentions), which indicates that review quality, timeliness, image, rating have a significant and positive impact on review adoption. Further review adoption has a positive impact on confirmation both (positive and negative) (J. Lee & Kim, 2020). In their study expectation confirmation theory was used with different variables. With the expectation confirmation theory, they framed the model which was linked between the pre purchase stage and the post purchase stage to select the restaurant. After reading the online reviews consumers choose the restaurant and the expectation of restaurant after reading online reviews leads to the decision of review adoption (J. Lee & Kim, 2020). One of study used influence of online reviews in apparel products by applying the expectation disconfirmation theory. In their study authors found that,

consumers made some expectations regarding apparel products and services were using like virtual try on in the pre stage process, but after that in post purchase stage disconfirmation has occurred between the expectations and the perceived performance of the product. Consumers write the online reviews in the recommendation form, complaint form, regret form, repurchase intention form, return intention form and many more in online apparel sector (E. Shin et al., 2022). (Ban & Kim, 2019) explored the use of online reviews and satisfaction of consumers in the airplane passengers. In this study they take the main types of online reviews (seat comfort, food and beverage, entertainment, value for money, ground services staff) which were written by consumers regarding the different-different airplane companies. One of study used the same theory expectation confirmation theory, but they studied in a different context, how consumers are influenced to write the positive and negative electronic word of mouth (Nam et al., 2020). Additionally, (Ranchi et al., 2018) also used the expectation confirmation theory with different variables (site usefulness, product usefulness, enjoyment, review involvement word of mouth intent and intention to write online reviews). Their study analyze the behaviour of consumers behind to write the online reviews, which reveals that if consumers feel the negative confirmation then they preferred to post the online reviews (Ranchi et al., 2018). Customer satisfaction and experiences in the hotel (Disneyland) were examined by the online customer's review. Regarding the hotel industry seven factors were found from the online reviews "(transportation, food quality, value, dining, employee attitude, pool, family empathy)" which are influence to book the hotel (X. Zhang & Kim, 2021).

In the age of technological advancement and the booming of e-commerce industry, online shopping is on the rise, consequently elevating the significance of online reviews. Consumers now prefer to read online reviews over seeking opinions from peers and relatives while making the purchasing decisions. Within the apparel industry, online reviews serve as essential resources for consumers seeking insights into various aspects such as quality, color, size, fit, comfort and fabric of clothing items. Managers also value online reviews as they provide insights into consumer preferences and sentiments towards the products. Online reviews are extensively utilized across various sectors including tourism, hospitality and apparel. In the apparel industry, managers preferred to enhance the product ratings as consumers

often prioritize items with higher ratings. These online reviews shape the consumers expectation, which they compared with the actual performance of the product. If the expectations are less than the actual performance of the product, it leads to the satisfaction. It is evident that the significance of online reviews will continue to grow as consumers increasingly rely on the online reviews. With everything accessible online, both consumers and managers benefit from a deeper understanding of products through online reviews.

Chapter 7

FINDINGS, MANAGERIAL IMPLICATIONS, CONCLUSION AND LIMITATIONS

7.1 Introduction

This study was conducted to explore the impact of online reviews on Generation Z consumers in Punjab, specifically within the apparel industry.

Chapter 1 begins by highlighting the rapid internet penetration in India, positioning the country as the second largest in terms of active internet users. According to reports from the India Brand Equity Foundation and the Telecom Regulatory Authority of India, internet connections are surging, driven by government initiatives like “Digital India”. The chapter also delves into the concept of e-commerce, noting that today's generation prefers online shopping due to its time-saving and convenience advantages over traditional markets. E-commerce operates through various models, including Business-to-Customer (B2C), Business-to-Business (B2B), Customer-to-Customer (C2C), Customer-to-Business (C2B), Government-to-Business (G2B), and Government-to-Citizen (G2C). The use of e-commerce in India is on the rise, with the industry projected to grow significantly, potentially reaching US\$300 billion by 2030. In the apparel sector, the top five e-commerce platforms preferred by customers are Myntra, Flipkart, Meesho, Amazon, and Ajio. Furthermore, the chapter discusses online shopping, defined as "a means that allows the consumer to buy directly from the seller without any intermediary through an Internet browser." India's retail market is expanding, with expectations of surpassing US\$160 billion by 2028. Studies show that India ranks third globally in terms of online shoppers, following China and the US. The online apparel market, in particular, is anticipated to reach US\$105.50 billion by 2024. The study covered various apparel categories, including Western wear, woolen clothes, ethnic wear, sportswear, and formal wear. It was found that online shopping is continuously growing, with apparel being the most preferred category among customers.

Chapter 2 offers an extensive review of existing literature that reinforces the relevance and validity of the research topic. The review encompasses over a thousand research papers from reputable international journals, along with related articles from websites

and books on the subject. The studies were organized into three main sections: the reasons people read online reviews, the influence of these reviews on Gen Z consumers' purchase intentions, and how gender affects the relationship between online reviews and the purchase intentions of Gen Z consumers. Additionally, the chapter explores how online reviews impact the satisfaction of Gen Z consumers, using the Expectation Disconfirmation Theory (EDT) as a framework. The review first discusses the concept of word-of-mouth communication, how it evolved into electronic word-of-mouth (eWOM), and the differences between the two. Traditionally, when consumers bought products, they would rely on verbal feedback from others to learn about their experiences. However, with the increasing use of the internet, consumers now look for online reviews, photos uploaded by other customers, and product ratings before making a purchase. These online reviews serve as a new form of word-of-mouth, providing essential information that influences buying decisions. Consumers are motivated to read online reviews mainly to gather information about products, save time, and improve their purchasing decisions. Generation Z, the first generation to grow up in the digital age, is particularly active online and more accustomed to using the internet compared to previous generations. Unlike Generations X and Y, each of which has its own unique characteristics, Gen Z is known for its heavy reliance on digital platforms for information and decision-making. Online reviews significantly influence the purchase intentions of Gen Z consumers, with purchase intention being a key predictor of actual buying behavior in consumer research. Several factors determine the impact of online reviews, including the quality of the reviews, the number of reviews, the credibility of both the reviews and their sources, and the overall usefulness of the reviews. Young consumers, particularly those in Gen Z, frequently buy apparel from e-commerce platforms like Amazon, Flipkart, Meesho, Myntra, and Ajio. In this context, online reviews play a crucial role in helping consumers understand the experiences of others, especially through photos that give insights into aspects like fabric quality and color. The chapter also examines the role of gender as a moderating factor in online shopping. Numerous studies have shown that women are generally more drawn to online shopping than men. Women tend to be more analytical and take more time to evaluate products and situations before making a decision. This finding suggests that gender plays an essential role in how online reviews influence purchase intentions. In the final section, the chapter delves into the Expectation Disconfirmation Theory (EDT). This theory

explains the consumer purchasing process, where consumers first form initial expectations before buying a product or service. After using the product, they develop perceptions based on their experience and compare this perceived performance with their initial expectations. If the product meets or exceeds these expectations, the consumer is satisfied; if not, they are dissatisfied. This satisfaction or dissatisfaction influences whether the consumer will repurchase the product or avoid it in the future. The review of the literature highlights the need for a comprehensive study focused on Gen Z consumers in Punjab, particularly in the context of the online apparel industry. The study should explore how online reviews contribute to consumer satisfaction after a purchase, as well as the broader impact of these reviews on the buying behavior of young consumers. The growing importance of online reviews in shaping both purchase intentions and post-purchase satisfaction underscores the need for further research in this area, especially given the unique characteristics of Gen Z.

Chapter 3 detailed the research methodology employed to accomplish the objectives of the current study. This chapter encompasses an overview of the necessity and scope of the study, the research design, sampling methods, objectives, and key hypotheses, as well as data collection procedures, a description of the sample, and the research instruments used to measure the study's variables. A multi-stage sampling technique was employed to select a predetermined number of respondents from specific districts. Participants were chosen from Jalandhar, Amritsar, Ludhiana, Ferozepur, Hoshiarpur and Gurdaspur as these districts have the highest population in Punjab. The sample comprised 600 Generation Z consumers from the aforementioned districts. The research instrument for data collection included three scales: (1) a 16-item scale assessing motives for reading online reviews adapted from (Ziegele & Weber, 2015; G. Walsh et al., 2010; Engelbertink & Van Hullebusch, 2013; Shah & Unnithan, 2020) (2) a 31-item scale evaluating the influence of online reviews on purchase intentions adapted from (H. S. Choi & Leon, 2020; C. W. Park et al., 2021; M. Zhang & Luo, 2023; Safitriani & Auliya, 2023; Su et al., 2023; Amarullah et al., 2022; Donthu et al., 2021; S. Verma & Yadav, 2021) and (3) a 17-item scale measuring the satisfaction of Generation Z consumers adapted from (Roldan Bravo et al., 2017; Serrano et al., 2018; Carraher-Wolverton & Hirschheim, 2023; Hien et al., 2024; W. Chen et al., 2022; E. Shin et al., 2022). The analysis in this chapter employs various statistical techniques, including Descriptive Statistics, Exploratory Factor

Analysis (EFA), Confirmatory Factor Analysis (CFA), ANOVA, and Structural Equation Modeling using Partial Least Squares (SEM-PLS), to examine the research objectives in detail.

7.2 Objective wise Findings are as follows:

7.2.1 Motives for reading online reviews by Gen Z consumers

The factors motive to read online reviews by Gen Z consumers identified through factor analysis (Exploratory Factor Analysis and Confirmatory Factor Analysis). Findings suggest that there are many factors which motives to read online reviews. Major findings are:

- Using EFA three latent factors were identified. These factors were extracted based on an eigen value greater than 1. The combined total variance explained by these three latent factors was found to be 69.025%.
- The Rotated Component Matrix organized the items into three distinct latent factors, including those with factor loadings of 0.5 or higher. Motive 16 was excluded from the analysis due to its loading being below 0.5. The results showed that M1, M2, M3, M4, M6, M8, and M14 were grouped under the first factor; M5, M7, M12, M13, and M15 were grouped under the second factor; and M9, M10, and M11 were grouped under the third factor.
- Based on the literature review, the three factors identified were named as follows: Right Product Choice (Factor 1), Product Information (Factor 2) and Risk Reduction (Factor 3).
- Factor 1 Right Product Choice found choosing the right product is really important, especially with so many options available today. It can be easy to get overwhelmed, but online reviews can be a big help. These reviews come from real people who have used the product, so they can help you avoid making a bad purchase. By reading them, you can learn about both the good and bad sides of a product—things that might not be obvious from the manufacturer's description. It's like having a friend share their experience and advice, helping you decide what works best for you. Instead of guessing, let others' experiences guide you to the best choice.
- Factor 2 Product Information founds product information is key to making smart buying decisions, we see in advertisements and product descriptions

often isn't the full story. Online reviews can fill in the gaps, offering real-world insights from people who have already used the product. These reviews provide a deeper understanding of how a product actually performs, revealing details that official sources might overlook or omit. By reading them, you gain access to honest feedback on quality, durability, and value. Think of it as having access to the experiences of thousands of users, helping you see beyond the marketing and make a choice that truly fits your needs.

- Factor 3 Risk Reduction finds that reducing risk is a critical aspect of making informed purchases, and online reviews are best option in this process. Before purchasing a product, reading reviews allows to learn from the experiences of others. These reviews often reveal potential issues, hidden defects, or shortcomings that aren't obvious from the product description alone. It can significantly lower the chances of making a regrettable purchase. Online reviews protect from wasting time, money, and effort on products and make choice both smart and safe.
- In confirmatory factor analysis it has been found that all items were appropriately with their respective factors. In CFA model is evaluated by using the various model fits indices including Chi-square, GFI, AGFI, NFI, TLI, CFI, RMR, and RMSEA. In results found that chi-square = 258.228, degrees of freedom = 87, p-value = 0.055, chi-square/DF = 2.967, GFI = 0.927, AGFI = 0.962, NFI = 0.928, TLI = 0.941, CFI = 0.951, RMR = 0.066, and RMSEA = 0.068. All these values fall within acceptable limits.

7.2.2 Influence of online reviews on purchase intention of Gen Z consumers

The factors of online reviews and its influence on purchase intention of Gen Z consumers identified through Partial Least Square by Structural Equation Modelling. Findings suggest that the determinants of online reviews were significantly influence the purchase intention of Gen Z consumers. The results of the SEM confirmed the acceptable fit of the hypothesised structural model with the observed data. Six hypotheses related to online reviews were developed and tested. Major findings are:

- It has been found that Hypothesis Ha 1.1 test the influence of RQ of online reviews on purchase intention of Gen Z consumers. This hypothesis was accepted confirming that the RQ had positively and significantly affects the PI

of Gen Z consumers ($\beta = 0.066$, $t = 0.289$, $p < 0.05$). In RQ found that the accuracy and reliability of ORs is important while online shopping of apparels. RQ often based on firsthand experience offering a balanced perspective that includes both positive and negative aspects (K. Li et al., 2020; C. W. Park et al., 2021). Good reviews also consider the needs of the audience, ensuring that the information provided is relevant and helpful for making informed decisions.

- It has been found that Hypothesis Ha 1.2 test the influence of RQn of online reviews on PI of Gen Z consumers. This hypothesis was accepted confirming that the RQn had positively and significantly affects the PI of Gen Z consumers ($\beta = 0.260$, $t = 4.419$, $p < 0.05$). In RQn found that longer reviews that are well-supported with sufficient arguments tend to be more persuasive and useful than shorter ones because the added details can influence purchasing decisions. The extra content provides deeper insights, making it easier for potential buyers to make informed choices. However, it is essential to balance quantity with quality to ensure that the information is both plentiful and reliable (Tsai et al., 2020; M. Zhang & Luo, 2023).
- It has been found that Hypothesis Ha 1.3 test the influence of SC of online reviews on PI of Gen Z consumers ($\beta = 0.388$, $t = 6.268$, $p < 0.05$). This hypothesis was accepted confirming that the source credibility had positively and significantly affects the purchase intention of Gen Z consumers. In SC found that trustworthiness and reliability of information is important. Reviewers should provide accurate, unbiased or transparent information. Relying on credible sources is crucial for making well informed decisions and forming valid options (Qiu et al., 2023; Su et al., 2023).
- It has been found that Hypothesis Ha 1.4 test the influence of RC of online reviews on PI of Gen Z consumers. This hypothesis was accepted confirming that the review credibility had positively and significantly affects the PI of Gen Z consumers ($\beta = 0.065$, $t = 1.552$, $p < 0.05$). Consumers found that review credibility is important in their purchasing decisions. In RC found that reviews were written by verified users or experts who provide honest, unbiased opinions based on their actual experiences. The credibility of a review can be influenced by the reviewer's transparency and whether the review is free from

external influence or manipulation. Reliable reviews help potential buyers make informed decisions by offering genuine insights (Hsieh & Li, 2020; Pooja & Upadhyaya, 2024; D. Verma & Dewani, 2021).

- It has been found that Hypothesis Ha 1.5 test the influence of usefulness of online reviews of online reviews on purchase intention of Gen Z consumers. This hypothesis was accepted confirming that the usefulness of online reviews had positively and significantly affects the purchase intention of Gen Z consumers ($\beta = 0.279$, $t = 4.438$, $p < 0.05$). The usefulness of online reviews lies in their ability to highlight both the strengths and weaknesses of an item, helping potential buyers to evaluate their options more effectively (K. Kaur & Singh, 2020). Additionally, online reviews can reveal trends or recurring issues that might not be evident from the product description alone, making them essential for informed decision-making.
- It has been found that Hypothesis Ha1 test the influence of online reviews on purchase intention of Gen Z consumers. This hypothesis was accepted confirming that the online reviews had positively and significantly affects the purchase intention of Gen Z consumers ($\beta = 0.795$, $t = 32.35$, $p < 0.05$). R square having value of Purchase Intention is 0.61, which means there is a substantial predictive power and 61% of variance in purchase intention is occurred by online reviews. Online reviews are invaluable tools for consumers, offering real-world insights and experiences that can guide purchasing decisions (Ahmad & Zhang, 2020). They provide a wealth of information about the quality, functionality, and satisfaction associated with a product or service. Additionally, reviews often include practical tips and advice that can enhance the user experience. Overall, they serve as a crucial tool for making informed choices in the digital marketplace (Purwianti & Niawati, 2022).

7.2.3 Moderating effect of gender between online reviews and purchase intention of Gen Z consumers.

Moderating effect of gender between online reviews and purchase intention of Gen Z consumers identified through PLS by SEM. Findings suggest that the Moderating effect of gender was significantly influence the PI of Gen Z consumers. The results of

the SEM confirmed the acceptable fit of the hypothesised structural model with the observed data. Six hypotheses related to moderating effect of gender between online reviews and PI of Gen Z consumers were developed and tested. Major findings are:

- Before proceeding with the Multigroup Analysis (MGA), MICOM was conducted to determine whether MGA could be appropriately applied. In the first step of MICOM, it was confirmed that configural invariance was established. This indicates that both male and female groups share identical fundamental factor structures. Specifically, the indicators within each measurement model are equivalent, the data are treated consistently across both groups, and the algorithm settings or optimization criteria are applied uniformly.
- In the second step it has been found that in compositional invariance original correlation value was greater than 5% quantile value which was indicate that compositional invariance was occurred. It has been found that both the compositional invariance and configural invariance were achieved, which shows that partial invariance was included.
- In the third step it has been found that original differences for both the means and variances fall within the confidence intervals bounds, which confirmed that there is a full measurement invariance.
- After completing the MICOM analysis, the Multigroup Analysis (MGA) was conducted to test the hypotheses related to moderation effect of gender between online reviews and purchase intention of Gen Z consumers.
- It has been found that Hypothesis Ha 2.1 gender positively and significantly moderates the relationship between RQ and PI with the p value 0.002. In bootstrapping result, it has been found that both male and female relationship between review quality and purchase intention is significant ($p=0.032$, $p=0.024$).
- It has been found that Hypothesis Ha 2.2 gender not positively and significantly moderates the relationship between review quantity and purchase intention with the p value 0.138. In bootstrapping result, it has been found that both male and female relationship between review quantity to purchase intention is insignificant ($p=0.101$, $p=0.081$).

- It has been found that Hypothesis Ha 2.3 gender positively and significantly moderates the relationship between source credibility and purchase intention with the p value 0.012. In bootstrapping result, it has been found that both male and female relationship between source credibility and purchase intention is significant ($p=0.000$, $p=0.000$).
- It has been found that Hypothesis Ha 2.4 gender positively and significantly moderates the relationship between review credibility and purchase intention with the p value 0.986. In bootstrapping result, it has been found that both male and female relationship between review credibility and purchase intention is not significant ($p=0.091$, $p=0.194$).
- It has been found that Hypothesis Ha 2.5 gender positively and significantly moderates the relationship between usefulness of online reviews and purchase intention with the p value 0.005. In bootstrapping result, it has been found that both male and female relationship between usefulness of online reviews and purchase intention is significant ($p=0.000$, $p=0.001$).
- It has been found that Hypothesis Ha 2 gender positively and significantly moderates the relationship between ORs and purchase intention with the p value 0.000. In bootstrapping result, it has been found that both male and female relationship between online reviews and purchase intention is significant ($p=0.000$, $p=0.000$).
- The differences in path coefficients revealed that impact of online reviews on purchase intention was stronger in females in comparison to males.

7.2.4 Effect of Online Reviews on Gen Z Consumers Satisfaction

Effect of online reviews on Gen Z consumers satisfaction identified through Partial Least Square by Structural Equation Modelling. Findings suggest that there is a positive relationship between online reviews and Gen Z consumers satisfaction. The results of the SEM confirmed the acceptable fit of the hypothesised structural model with the observed data. Six hypotheses related to effect of ORs on Gen Z consumers satisfaction were developed and tested. Major findings are:

- It has been found that Hypothesis Ha 3 test the online reviews have a positive impact on Gen Z consumers expectations. This hypothesis was accepted

confirming that the online reviews had a positively and significantly affects the Gen Z consumers satisfaction ($\beta = 0.719$, $t = 16.202$, $p < 0.05$). R square having value of expectation is 0.57, which means there is a substantial predictive power and 52% variance in expectation is occurred by online reviews.

- It has been found that Hypothesis Ha 4 test the positive relationship between Gen Z consumers Expectations and Perceived Performance. This hypothesis was accepted confirming that the expectations had a positively and significantly affects the perceived performance ($\beta = 0.750$, $t = 27.128$, $p < 0.05$). R square having value of perceived performance is 0.563, which means there is a substantial predictive power and 57% variance in perceived performance is occurred by expectation.
- It has been found that Hypothesis Ha 5 test the Gen Z consumers expectations have a positive influence on disconfirmation. This hypothesis was accepted confirming that the expectations had a positively and significantly affects the disconfirmation ($\beta = 0.466$, $t = 8.892$, $p < 0.05$). R square having value of disconfirmation is 0.639, which means there is a substantial predictive power and 64% variance in disconfirmation is occurred by perceived performance.
- It has been found that Hypothesis Ha 6 test the positive relationship between Perceived Performance and Disconfirmation. This hypothesis was accepted confirming that the there is a positive relationship between Perceived Performance and Disconfirmation. ($\beta = 0.388$, $t = 6.729$, $p < 0.05$). R square having value of disconfirmation is 0.639, which means there is a substantial predictive power and 64% variance in disconfirmation is also occurred by perceived performance.
- It has been found that Hypothesis Ha 7 test the relationship between disconfirmation and Gen Z consumers satisfaction. This hypothesis was accepted confirming that the there is a positive relationship between disconfirmation and Gen Z consumers satisfaction. ($\beta = 0.829$, $t = 40.307$, $p < 0.05$). R square having value of satisfaction is 0.687, which means there is a substantial predictive power and 69% variance in satisfaction is occurred by disconfirmation.

- EDT provides valuable insights into how consumer expectations and perceptions influence satisfaction and subsequent behaviors. According to this theory, consumers form expectations before making a purchase, influenced by various factors such as online reviews, previous experiences, and marketing efforts (E. Shin et al., 2022). These expectations establish a benchmark against which the product or service's performance is evaluated. Once the consumer receives the product, they compare its actual performance with their initial expectations (Hossain, 2019). This comparison leads to disconfirmation, which can be either positive or negative. Positive disconfirmation occurs when the product's perceived performance exceeds the consumer's expectations, often resulting in high levels of satisfaction. Conversely, negative disconfirmation arises when the product falls short of expectations, leading to dissatisfaction (Roldan Bravo et al., 2017; Serrano et al., 2018). In some cases, if the product performs exactly as expected, neutral disconfirmation occurs, resulting in moderate satisfaction. The level of satisfaction is directly linked to the degree of disconfirmation experienced. Positive disconfirmation tends to enhance satisfaction, encouraging repeat purchases and positive word-of-mouth, while negative disconfirmation can decrease future purchases and prompt consumers to explore alternatives (J. Lee & Kim, 2020). The theory also highlights that cultural and contextual factor, such as the type of industry or product category, play a significant role in shaping the expectation-disconfirmation process. These factors can lead to varied outcomes in terms of consumer satisfaction and behavioral intentions (Carraher-Wolverton & Hirschheim, 2023). The implications of these findings emphasize the importance for businesses to manage customer expectations effectively and to deliver consistently high-quality experiences. By doing so, companies can foster positive disconfirmation, thereby enhancing customer satisfaction and loyalty.

7.3 Key Recommendations/ Managerial Implications

Few studies have delved into examining the impact of ORs on the purchase intentions of Generation Z consumers, particularly in the context of online apparel shopping. This research distinguishes itself by incorporating multiple dimensions of online reviews, including Review Quality, Review Quantity, Review Usefulness, Source

Credibility, and Review Credibility. Additionally, it explores the moderating effect of gender on the relationship between online reviews and the purchase decisions of Gen Z consumers. The managerial implications support existing literature and provide a foundation for future research on online reviews, Generation Z, and online apparel. Moreover, offer recommendations and guidelines for online review platforms, digital marketers, and suppliers to create and improve content that better appeals to younger audiences.

Based on previous research findings and the results of the current study, the following key recommendations are proposed:

- This study identified three key factors that motivate consumers to read online reviews first was the risk reduction. To address this, marketers have taken steps such as showing reviews from verified buyers to build trust and provide more reliable information to consumers. However, to further reduce the risk, they should also consider some demographic details of the reviewers such as age, weight, and height as this additional context can help consumers make more informed and confident purchasing decisions (Shin et al. 2021).
- The second factor identified was the product information. Consumers often share insights about a product's quality, fit, size, and usage, which proves helpful to others during their purchase decisions. E-commerce platforms have introduced feature-based rating system for the younger generations such as separate ratings for comfort, fabric quality, value for money, stitching quality, lightweight feel, and how accurately the product matches its photos. To further enhance the depth of information available to buyers, marketers should also highlight review factors such as hassle-free return and refund policies, which can significantly influence purchase decisions.
- The third key factor was the right product choice. By reading multiple reviews, buyers can compare specific features, understand what differentiates one product from another, and select options that align more closely with their personal needs and preferences. For better decision-making, marketers should consider implementing post-purchase surveys that gather customer feedback regarding overall satisfaction. These follow-ups should be conducted one or

two months after the purchase to provide valuable long-term insights for future buyers, especially regarding the product's durability.

- This study examined the impact of online review quality on Gen Z consumers' purchase intention. The study evaluated the quality of online consumer reviews based on factors such as relevance, reliability, clarity, and sufficiency. To support Gen Z consumers in making better purchase decisions, marketers and e-commerce platforms are improving the transparency of reviews and encouraging them to upload the photos or videos, as this generation prefers clear, visual, and trustworthy information. Marketers should provide quick summary of online reviews with pros and cons of product, which will help the consumers in saving time and making confident decisions.
- The purchase intention of consumers tends to increase with a higher number of online reviews. Therefore, the quantity of online reviews plays a significant role in influencing Gen Z consumers' purchasing decisions, especially when it comes to apparel. A large volume of reviews is often seen as a sign of a product's popularity and trustworthiness, which can strengthen potential buyers' intent to purchase. To encourage more reviews, marketers should offer small incentives such as discount coupons or reward points and send timely polite follow-up reminders prompting customers to share their feedback. Additionally, recognizing frequent reviewers through ranks or badges which can further motivate participation and help build a vibrant review community.
- This study identified the review credibility is a key dimension which significantly influence the consumers' purchase intention. To enhance source credibility, e-commerce platforms should display basic reviewer information, such as location or review history to help build trust among potential buyers. Marketers are already providing credibility by showing verified buyers who purchase the product in reality. Moreover, to further strengthen reviewer credibility, it's important to verify actual product usage under relevant conditions, such as wearing the product in real-life situations and indicating the duration of use, which can provide a more accurate picture for future buyers.
- Review credibility is a key factor that directly impacts consumer purchasing behavior. In the digital landscape, where user-generated content plays a

dominant role, the trustworthiness of online reviews has become more critical than ever. Consumers tend to rely on reviews that appear authentic, unbiased, and well-detailed, as these help them make informed decisions. To enhance the transparency and build consumer trust, marketers should encourage the consumers to provide authentic reviews and proactively responding to the negative reviews (Rachmiani et al. 2024).

- Marketers should treat review sections not just as feedback tools but as interactive platforms where consumers can engage, ask questions, and share detailed experiences. Features like Q&A forums can provide real insights. This approach not only enhances the value of online reviews but also helps potential buyers make informed choices, reducing the risk of dissatisfaction.
- Study reveals that gender acts as a moderating factor in the relationship between online reviews and purchase intention, with female consumers being more influenced by reviews than male consumers. For female consumers, reviews that focus on fabric texture, fit, color accuracy, and style preferences can be highly valuable. Females are often more influenced by visual content when shopping for apparel online. Marketers are already promoting photo and video reviews from verified female buyers to help others visualize the product's look, fit, and quality. On the other hand, male consumers may prefer concise, straightforward reviews that quickly convey the product's core benefits and value. To encourage more contributions from female users, e-commerce platforms can introduce storytelling-based review formats that invite users to describe why they purchased the product, how they used it, and how it met their expectations, with top storytellers receiving rewards or recognition. For male users, platforms can implement gamified review systems that offer incentives through points, badges, or ranks to motivate regular participation (Vinerean et al. 2025).
- Expectation Disconfirmation Theory allows marketers to assess how well their products or services meet consumer expectations. When a product meets or exceeds expectations, it leads to positive disconfirmation, increasing customer satisfaction and brand loyalty. Marketers can use online reviews to identify common expectations and should adjust product features, descriptions, or services to better align with consumer needs, reducing negative feedback. To

further bridge the gap between expectations and actual experiences, marketers should implement a “Real vs. Expectations Tracker.” Encourage the reviewers to answer questions like “What surprised you most?” or “What was not as expected?” can provide valuable expectation gap feedback. This targeted insight helps future buyers better understand potential differences between their expectations and the product’s actual performance.

- Some e-commerce platforms currently lack features such as reviewer profile activity, filter options like “reviews with photos” and “verified purchase,” and AI-generated summaries of online reviews. Incorporating these elements can enhance the overall review experience and significantly boost purchase intention among Gen Z consumers.

7.4 Conclusion

- The increasing popularity of online shopping has brought about new challenges for marketers, particularly in understanding the unique needs and purchasing behaviors of Generation Z consumers. Marketers now face the challenge of understanding the factors that affect Gen Z's online shopping choices and making strategic changes to better serve this tech-savvy group. The digital shopping landscape presents a set of unique challenges for consumers, characterized by its intangible nature and the overwhelming amount of information available, which can often lead to heightened uncertainty.
- In this context, the study titled "Influence of Online Reviews on Gen Z Consumers Purchase Intention with Reference to Apparels" is especially relevant. This research explores the significant impact of digital transformation on the apparel industry, focusing on how online reviews shape the purchasing intentions of Gen Z consumers. This study, carried out with Generation Z shoppers in Punjab, explores the reasons why these young consumers rely on online reviews when buying apparel. A survey method was employed, gathering data from 600 respondents through a structured questionnaire, and multistage sampling was utilized to select participants from various regions of Punjab.

- The study employed advanced statistical tools, including factor analysis with SPSS and SEM using PLS, to identify the key reasons Gen Z consumers read online reviews. The research reveals that Gen Z consumers are driven to consult online reviews for several reasons: to mitigate the risks associated with online purchases, to rely on the experiences of other consumers, or due to the lack of sufficient product information. Interestingly, it was found that online reviews play a crucial role during the evaluation stage of the purchase decision-making process, significantly influencing the purchase intentions of Gen Z shoppers.
- Moreover, the study highlights the moderating effect of gender on the relationship between online reviews and purchase intentions, with multigroup analysis employed to examine this aspect. Through EFA and CFA, three key factors were identified that explain why Gen Z consumers engage with online reviews. The study also applied the Expectation Disconfirmation Theory to assess how satisfied Gen Z consumers are, showing that they typically feel pleased with the information they get from online reviews.
- Given that Generation Z is characterized by assertiveness, a willingness to take risks, and an openness to new experiences, understanding this demographic is crucial for businesses, particularly in the apparel industry. As Gen Z begins to enter the workforce and gain purchasing power, they are set to become a significant consumer base. Therefore, it is imperative for marketers to delve deeper into the aspirations, motivations, and behaviors of Gen Z. By doing so, businesses can tailor their strategies and offerings to meet the unique preferences of this generation, ensuring long-term success in a rapidly evolving digital marketplace.

7.5 Limitations

- The current research examines the purchase intention of Gen Z consumers specifically within the context of online apparel shopping. The study concentrated on this age cohort, recognizing that while other age groups also contribute significantly to the online apparel market, they were not included in this particular research.

- Additionally, the study is geographically limited, as it focuses exclusively on Generation Z consumers in Punjab, India. Therefore, the results may not be applicable to other regions or countries, and replication of the study in different locations is recommended to assess its broader applicability.
- The study's sample consisted of 600 respondents, which, although adequate for this investigation, could be expanded in future studies to enhance the generalizability of the findings. Despite all respondents completing the questionnaire in full, the data underwent rigorous cleaning, and appropriate analytical tools were employed to ensure accuracy. However, there remains a potential limitation due to unintentional inaccuracies from respondents, which could affect the reliability of certain variables.
- The limitations identified in the previous section open several promising avenues for future research and offer numerous extension themes that could be explored using this study as a foundation. While the current study employed a quantitative approach to investigate the relationship between the variables, a method commonly used in social science research, future studies might consider adopting a more qualitative approach. This would provide a deeper and more sophisticated insight into Generation Z's perspectives on online reviews. Additionally, shifting the focus to examine how companies leverage online reviews to influence Generation Z's purchase intentions could provide valuable insights and new perspectives.
- This study primarily concentrated on the relationship between ORs, customer satisfaction, purchase intentions, and Gen Z consumers. However, it did not distinguish between different product categories when analyzing the impact of online reviews. Future research could delve into how shopping behaviors vary across specific product categories such as footwear, cosmetics, and consumables within the e-commerce landscape. Incorporating advanced technological constructs like the influence of artificial intelligence, machine learning, and social media data mining could further enrich future studies.
- Moreover, comparative research analyzing the use of online reviews in urban versus rural settings would be a meaningful addition to the field. Investigations could also extend to various forms of online reviews—such as text, images, videos, and ratings—to assess their distinct impacts. Future

studies could explore cross-national and cross-cultural differences in consumer behavior, as these factors could significantly affect the relationship between purchase intention and online reviews. The literature review suggests that using moderators can enhance the understanding of this relationship, pointing to the need for further research to identify which moderators are most significant.

- As social media continues to penetrate everyday life, conducting thorough and comprehensive research into eWOM on these platforms could yield valuable insights. Such research would enable marketers to craft more effective social media marketing strategies, thereby strengthening consumer relationships and enhancing brand loyalty.
- Furthermore, the study was confined to a specific set of e-commerce platforms, including Amazon, Myntra, Meesho, Ajio, and Flipkart, which may not represent the entire online apparel industry. The research also exclusively targets the online apparel sector, suggesting a need for future studies to explore other industries for a more comprehensive understanding of Generation Z's purchase intention in the digital marketplace.

7.6 Scope for Future Research

- The limitations identified in the previous section open several promising avenues for future research and offer numerous extension themes that could be explored using this study as a foundation. While the current study employed a quantitative approach to investigate the relationship between the variables, a method commonly used in social science research, future studies might consider adopting a more qualitative approach. This would allow for a richer, more nuanced understanding of Generation Z's perceptions of online reviews. Additionally, shifting the focus to examine how companies leverage online reviews to influence Generation Z's purchase intentions could provide valuable insights and new perspectives.
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- As social media continues to pervade everyday life, conducting thorough and comprehensive research into eWOM on these platforms could yield valuable insights. Such research would enable marketers to craft more effective social media marketing strategies, thereby strengthening consumer relationships and enhancing brand loyalty.

REFERENCES

- Oliver, R. L. (1980). *A Cognitive Model of the Antecedents and Consequences of Satisfaction Decisions*. 17, 460–469.
- Abrar, M., Sibtain, M. M., & Shabbir, R. (2021a). Understanding purchase intention towards eco-friendly clothing for generation Y & Z. *Cogent Business & Management*, 8(1), 1997247. <https://doi.org/10.1080/23311975.2021.1997247>
- Achrol, R. S., & Kotler, P. (1999). Marketing in the Network Economy. *Journal of Marketing*, 63(4_suppl1), 146–163. <https://doi.org/10.1177/00222429990634s114>
- Agarwal, S., & Bhati, N. S. (2016). Customer's perceived e-service quality: Role of gender differences in online shopping. *Ictact Journal on Management Studies*, 2(3), 349–356.
- Agarwal, S., & Teas, R. K. (2002). Cross-national applicability of a perceived quality model. *Journal of Product & Brand Management*, 11(4), 213–236.
- Agati, H. A. (2012). *The millennial generation: Howe and Strauss disputed*. The College of William and Mary.
- Aggarwal, V. S., & Kapoor, M. (2021). Multigroup analysis of higher-order model of knowledge variables in the context of global ventures through PLS-SEM. *South Asian Journal of Business Studies*, 10(1), 128–146.
- Aghakhani, N., Oh, O., Gregg, D., & Jain, H. (2023). How review quality and source credibility interacts to affect review usefulness: An expansion of the elaboration likelihood model. *Information Systems Frontiers*, 25(4), 1513–1531.
- Agrawal, D. K. (2022). Determining behavioural differences of Y and Z generational cohorts in online shopping. *International Journal of Retail & Distribution Management*, 50(7), 880–895.
- Ahmad, W., & Zhang, Q. (2020). Green purchase intention: Effects of electronic service quality and customer green psychology. *Journal of Cleaner Production*, 267, 122053.
- Ahmed, K., & Joshi, V. (2024). E-Commerce expansion in Indian retail: A strategic analysis of market penetration and competitive dynamics. *Frontiers in Management Science*, 3(1), 12–20.
- Akbar, A. R., Kalis, M. C. I., Afifah, N., Purmono, B. B., & Yakin, I. (2023). The Influence of Product Packaging Design and Online Customer Review on

- Brand Awareness and Their Impact on Online Purchase Intention. *South Asian Research Journal of Business and Management*, 5(1), 10–18.
<https://doi.org/10.36346/sarjbm.2023.v05i01.002>
- Akter, S., & Wamba, S. F. (2016). Big data analytics in E-commerce: A systematic review and agenda for future research. *Electronic Markets*, 26(2), 173–194.
<https://doi.org/10.1007/s12525-016-0219-0>
- Al-Abbadi, L. H., Bader, D. M. K., Mohammad, A., Al-Quran, A. Z., Aldaihani, F. M. F., Al-Hawary, S. I. S., & Alathamneh, F. F. (2022). The effect of online consumer reviews on purchasing intention through product mental image. *International Journal of Data and Network Science*, 6(4), 1519–
- Alanko, P. J. (2018). *Mapping eWOM effectiveness for Generation Z consumers: An integrative approach*
<https://helda.helsinki.fi/bitstream/123456789/189234/1/Alanko.pdf>
- Alcaniz, M., Bigné, E., & Guixeres, J. (2019). Virtual reality in marketing: A framework, review, and research agenda. *Frontiers in Psychology*, 10, 1530.
- Al-Emran, M., Mezhuyev, V., & Kamaludin, A. (2019). PLS-SEM in Information Systems Research: A Comprehensive Methodological Reference., *Proceedings of the International Conference on Advanced Intelligent Systems and Informatics 2018* (Vol. 845, pp. 644–653). Springer International Publishing.
https://doi.org/10.1007/978-3-319-99010-1_59
- Alomari, M. M., Hania, E.-K., Topal, A., & Alshdaifat, N. I. (2022). Energy conservation behavior of university occupants in Kuwait: A multigroup analysis. *Sustainable Energy Technologies and Assessments*, 52, 102198.
- Alsaad, A., Mohamad, R., Taamneh, A., & Ismail, N. A. (2018). What drives global B2B e-commerce usage: An analysis of the effect of the complexity of trading system and competition pressure. *Technology Analysis & Strategic Management*, 30(8), 980–992.
<https://doi.org/10.1080/09537325.2018.1432853>
- Alsaad, A., Taamneh, A., Sila, I., & Elrehail, H. (2021). Understanding the global diffusion of B2B E-commerce (B2B EC): An integrated model. *Journal of Information Technology*, 36(3), 258–274.
<https://doi.org/10.1177/0268396220961396>
- Amarullah, D., Handriana, T., & Maharudin, A. (2022). Ewom credibility, trust, perceived risk, and purchase intention in the context of e-commerce:

- Moderating role of online shopping experience. *Jurnal Ekonomi Bisnis Dan Kewirausahaan*, 11(1), 61–83.
- Amblee, N., & Bui, T. (2008). Can Brand Reputation Improve the Odds of Being Reviewed On-Line? *International Journal of Electronic Commerce*, 12(3), 11–28. <https://doi.org/10.2753/JEC1086-4415120302>
- Amit, R., & Zott, C. (2017). Value Drivers of e-Commerce Business Models. In M. A. Hitt, R. Amit, C. E. Lucrier, & R. D. Nixon (Eds.), *Creating Value: Winners in the New Business Environment* (1st ed., pp. 13–43). Wiley. <https://doi.org/10.1002/9781405164092.ch2>
- Anand, N., & Kheterpal, V. (2014). Growth of apparel industry in India: Present and future aspects. *Scholars World*, 11.
- Anderson, E. W., & Sullivan, M. W. (1993). The antecedents and consequences of customer satisfaction for firms. *Marketing Science*, 12(2), 125–143.
- Ang, R. P., Lowe, P. A., & Yusof, N. (2011). An examination of the RCMAS-2 scores across gender, ethnic background, and age in a large Asian school sample. *Psychological Assessment*, 23(4), 899.
- Angeline, T. (2011). Managing generational diversity at the workplace: Expectations and perceptions of different generations of employees. *African Journal of Business Management*, 5(2), 249.
- Angmo, D., Aithal, R. K., & Jaiswal, A. K. (2024). Reducing market separation through e-commerce: Cases of Bottom of the Pyramid (BoP) firms in India. *Information Technology for Development*, 30(1), 93–113. <https://doi.org/10.1080/02681102.2023.2285484>
- Antwi, S., & Amponsah, R. K. (2021). Repurchase Intention among Ghanaian Online Consumers: Perceived Shopping Value Approach. *European Journal of Business and Management*, 13(8), 1–10.
- Anuj, K., Fayaz, F., & Kapoor, N. (2018). Impact of e-commerce in Indian economy. *Journal of Business and Management*, 20(5), 59–71.
- Anvari, R. D., & Norouzi, D. (2016). The impact of e-commerce and R&D on economic development in some selected countries. *Procedia-Social and Behavioral Sciences*, 229, 354–362.
- Apasrawirote, D., & Yawised, K. (2022). Factors influencing the behavioral and purchase intention on live-streaming shopping. *Asian Journal of Business Research*, 12(1), 39–56.

- Arcand, M., & Nantel, J. (2012). Uncovering the nature of information processing of men and women online: The comparison of two models using the think-aloud method. *Journal of Theoretical and Applied Electronic Commerce Research*, 7(2), 106–120.
- Asadi Damavandi, A., & Ha, L. (2024). e–WOM and app stores in Iran: How online reviews influence purchase intention of paid mobile apps. *Journal of Islamic Marketing*.
- Asbari, M. (2023). Scope of e-business & e-commerce to business and modern life. *Journal of Information Systems and Management (JISMA)*, 2(1), 33–38.
- Asih, T. S., & Rubiyanti, N. (2022). Factors Influencing Consumer Online Shopping Behavior During National Online Shopping Day: Perspective of Indonesian Generation Z. *Proc. 3rd Asia Pacific Int. Conf. Ind. Eng. Oper. Manag*, 13(15).
- Assaker, G. (2020). Age and gender differences in online travel reviews and user-generated-content (UGC) adoption: Extending the technology acceptance model (TAM) with credibility theory. *Journal of Hospitality Marketing & Management*, 29(4), 428–449.
<https://doi.org/10.1080/19368623.2019.1653807>
- Assaker, G., Hallak, R., Assaf, A. G., & Assad, T. (2015). Validating a structural model of destination image, satisfaction, and loyalty across gender and age: Multigroup analysis with PLS-SEM. *Tourism Analysis*, 20(6), 577–591.
- Atieq, M. Q. (2019). Comparative analysis of employee engagement in employees Generation X, Y, and Z. *Al-Amwal: Jurnal Ekonomi Dan Perbankan Syariah*, 11(2), 285–299.
- Aureliano-Silva, L., Leung, X., & Spers, E. E. (2021). The effect of online reviews on restaurant visit intentions: Applying signaling and involvement theories. *Journal of Hospitality and Tourism Technology*, 12(4), 672–688.
- Awad, N. F., & Ragowsky, A. (2008). Establishing Trust in Electronic Commerce Through Online Word of Mouth: An Examination Across Genders. *Journal of Management Information Systems*, 24(4), 101–121.
<https://doi.org/10.2753/MIS0742-1222240404>
- Azhar, M., Akhtar, M. J., Rahman, M. N., & Khan, F. A. (2023). Measuring buying intention of generation Z on social networking sites: An application of social commerce adoption model. *Journal of Economic and Administrative Sciences*.

- Azila, J., Farha, W. W., Munirah, M. J., & Mohammad, I. (2021). Who exhibits environmental awareness more? a multi-group analysis of gender differences. *International Journal of Social Science Research*, 3(1), 146–160.
- Babenko, V., Kulczyk, Z., Perevosova, I., Syniavska, O., & Davydova, O. (2019). Factors of the development of international e-commerce under the conditions of globalization. *SHS Web of Conferences*, 65, 04016.
- Bachleda, C., & Berrada-Fathi, B. (2016). Is negative eWOM more influential than negative pWOM? *Journal of Service Theory and Practice*, 26(1), 109–132.
- Baek, H., Oh, S., Yang, H.-D., & Ahn, J. (2017). Electronic word-of-mouth, box office revenue and social media. *Electronic Commerce Research and Applications*, 22, 13–23.
- Baidoun, S. D., & Salem, M. Z. (2024). Factors affecting consumer post COVID-19 online shopping behavior: The moderating role of commitment – evidence from Palestine. *Journal of Strategic Marketing*, 32(3), 358–373. <https://doi.org/10.1080/0965254X.2023.2229329>
- Bailusy, M. N., Buamonabot, I., Fahri, J., & Arilaha, M. A. (2022). Online Shopping Indonesia: Customer Perception. *International Journal of Applied Business and International Management (IJABIM)*, 7(2), 82–104.
- Bajpai, N. (2011). *Business research methods*. Pearson Education India.
- Balachandar, A., & Devi, A. J. (2024). The Impact of Internet Marketing in E-Commerce: A Case Study. *International Journal of Case Studies in Business, IT and Education (IJCSBE)*, 8(1), 326–339.
- Balakrishnan, B. K., Dahnil, M. I., & Yi, W. J. (2014). The impact of social media marketing medium toward purchase intention and brand loyalty among generation Y. *Procedia-Social and Behavioral Sciences*, 148, 177–185.
- Balaraman, P., & Chandrasekar, S. (2016). E-commerce trends and future analytics tools. *Indian Journal of Science and Technology*, 9(32), 1–9.
- Ban, H.-J., & Kim, H.-S. (2019). Understanding Customer Experience and Satisfaction through Airline Passengers' Online Review. *Sustainability*, 11(15), 4066. <https://doi.org/10.3390/su11154066>
- Bastos Rudolph, L. T., Bassi Suter, M., & Barakat, S. R. (2023). The Emergence of a New Business Approach in the Fashion and Apparel Industry: The Ethical Retailer. *Journal of Macromarketing*, 43(3), 367–383. <https://doi.org/10.1177/02761467231180456>

- Bell, C., Clark, V., & Mack, E. (2019). Influential Article Review-Using an Online Approach to Help End-users to Overcome Information Surplus. *Journal of Marketing Development and Competitiveness*, 13(6).
- Berger, J. (2014). Word of mouth and interpersonal communication: A review and directions for future research. *Journal of Consumer Psychology*, 24(4), 586–607.
- Bergh, D. D., Aguinis, H., Heavey, C., Ketchen, D. J., Boyd, B. K., Su, P., Lau, C. L. L., & Joo, H. (2016). Using meta-analytic structural equation modeling to advance strategic management research: Guidelines and an empirical illustration via the strategic leadership-performance relationship. *Strategic Management Journal*, 37(3), 477–497. <https://doi.org/10.1002/smj.2338>
- Bernerth, J. B., & Aguinis, H. (2016). A Critical Review and Best-Practice Recommendations for Control Variable Usage. *Personnel Psychology*, 69(1), 229–283. <https://doi.org/10.1111/peps.12103>
- Bhagat, A. K. (2020). E-Commerce in India: Growth, future, and barriers. *International Journal of Marketing and Technology*, 10(6), 1–7.
- Bhattacharjee, A. (2001). *UNDERSTANDING INFORMATION SYSTEMS CONTINUANCE: AN EXPECTATION- CONFIRMATION*.
- Bhattacharjee, A., & Premkumar, G. (2004). Understanding changes in belief and attitude toward information technology usage: A theoretical model and longitudinal test. *MIS Quarterly*, 229–254.
- Bhatti, A., Akram, H., Basit, H. M., Khan, A. U., Raza, S. M., & Naqvi, M. B. (2020). E-commerce trends during COVID-19 Pandemic. *International Journal of Future Generation Communication and Networking*, 13(2), 1449–1452.
- Bhatti, A., & Rehman, S. U. (2019). Perceived benefits and perceived risks effect on online shopping behavior with the mediating role of consumer purchase intention in Pakistan. *International Journal of Management Studies*, 26(1), 33–54.
- Bickman, L. (2000). *Research Design: Donald Campbell' s Legacy*. Sage Publications.
- Black, H. G., & Kelley, S. W. (2009). A STORYTELLING PERSPECTIVE ON ONLINE CUSTOMER REVIEWS REPORTING SERVICE FAILURE AND RECOVERY. *Journal of Travel & Tourism Marketing*, 26(2), 169–179. <https://doi.org/10.1080/10548400902864768>

- Bollenbach, J., Halbrügge, S., Wederhake, L., Weibelzahl, M., & Wolf, L. (2024). Customer satisfaction at large charging parks: Expectation-disconfirmation theory for fast charging. *Applied Energy*, 365, 122735.
- Brand, B. M., Rausch, T. M., & Brandel, J. (2022). The importance of sustainability aspects when purchasing online: Comparing generation X and generation Z. *Sustainability*, 14(9), 5689.
- Brennan, G., & Buchanan, J. M. (1977). Towards a tax constitution for Leviathan. *Journal of Public Economics*, 8(3), 255–273.
- Bressolles, G., Durrieu, F., & Deans, K. R. (2015). An examination of the online service-profit chain. *International Journal of Retail & Distribution Management*, 43(8), 727–751. <https://doi.org/10.1108/IJRDM-11-2013-0214>
- Brown, S. P., & Beltramini, R. F. (1989). Consumer complaining and word of mouth activities: Field evidence. *Advances in Consumer Research*, 16(1).
- Buchanan, J. M., & Tullock, G. (1977). The expanding public sector: Wagner squared. *Public Choice*, 147–150.
- Burt, S., & Sparks, L. (2003). E-commerce and the retail process: A review. *Journal of Retailing and Consumer Services*, 10(5), 275–286.
- Burton, J., & Khammash, M. (2010). Why do people read reviews posted on consumer-opinion portals? *Journal of Marketing Management*, 26(3–4), 230–255. <https://doi.org/10.1080/02672570903566268>
- Cadotte, E. R., Woodruff, R. B., & Jenkins, R. L. (1987). Expectations and Norms in Models of Consumer Satisfaction. *Journal of Marketing Research*, 24(3), 305–314. <https://doi.org/10.1177/002224378702400307>
- Cann, A. P., Connolly, M., Ruuska, R., MacNeil, M., Birmingham, T. B., Vandervoort, A. A., & Callaghan, J. P. (2008). Inter-rater reliability of output measures for a posture matching assessment approach: A pilot study with food service workers. *Ergonomics*, 51(4), 556–572. <https://doi.org/10.1080/00140130701711455>
- Cao, X.-Y., Li, B.-H., Wang, Y., Fu, Y., Yin, H.-L., & Chen, Z.-B. (2024). Experimental quantum e-commerce. *Science Advances*, 10(2), eadk3258. <https://doi.org/10.1126/sciadv.adk3258>
- Carraher-Wolverton, C. (2022). The co-evolution of remote work and expectations in a COVID-19 world utilizing an expectation disconfirmation theory lens. *Journal of Systems and Information Technology*, 24(1), 55–69.

- Carraher-Wolverton, C., & Hirschheim, R. (2023). Utilizing expectation disconfirmation theory to develop a higher-order model of outsourcing success factors. *Journal of Systems and Information Technology*, 25(1), 1–29.
- Carranza, R., Diaz, E., Martín-Consuegra, D., & Fernandez-Ferrin, P. (2020). PLS–SEM in business promotion strategies. A multigroup analysis of mobile coupon users using MICOM. *Industrial Management & Data Systems*, 120(12), 2349–2374.
- Chakraborty, T., & Balakrishnan, J. (2017). Exploratory tendencies in consumer behaviour in online buying across gen X, gen Y and baby boomers. *International Journal of Value Chain Management*, 8(2), 135. <https://doi.org/10.1504/IJVC.2017.085483>
- Chandan, C. L., & Gupta, N. (2018). B2C E-Commerce in India: Evolution, Prospects and Challenges. *Asian Journal of Management*, 9(1), 197–202.
- Chandra, A. (2021). The Future of e-Commerce in India. *International Journal of Accounting*.
- Chang, T.-Z., & Wildt, A. R. (1994). Price, Product Information, and Purchase Intention: An Empirical Study. *Journal of the Academy of Marketing Science*, 22(1), 16–27. <https://doi.org/10.1177/0092070394221002>
- Chatterjee, P. (2001). *Online reviews: Do consumers use them?*
- Chatterjee, S. (2020). Drivers of helpfulness of online hotel reviews: A sentiment and emotion mining approach. *International Journal of Hospitality Management*, 85, 102356.
- Cheah, J.-H., Amaro, S., & Roldan, J. L. (2023). Multigroup analysis of more than two groups in PLS-SEM: A review, illustration, and recommendations. *Journal of Business Research*, 156, 113539.
- Chen, C., Velasquez Tuliao, K., Cullen, J. B., & Chang, Y. (2016). Does gender influence managers' ethics? A cross-cultural analysis. *Business Ethics: A European Review*, 25(4), 345–362. <https://doi.org/10.1111/beer.12122>
- Chen, W., Dong, B., Hsieh, C.-W., Lee, M. J., Liu, N., Walker, R. M., Wang, Y., Wen, B., Wen, W., & Wu, P. (2022). A replication of “an experimental test of the expectancy-disconfirmation theory of citizen satisfaction.” *Public Administration*, 100(3), 778–791.

- Chen, Y., & Xie, J. (2008). Online Consumer Review: Word-of-Mouth as a New Element of Marketing Communication Mix. *Management Science*, 54(3), 477–491. <https://doi.org/10.1287/mnsc.1070.0810>
- Cheng, Y.-H., & Ho, H.-Y. (2015). Social influence's impact on reader perceptions of online reviews. *Journal of Business Research*, 68(4), 883–887.
- Chetioui, Y., & El Bouzidi, L. (2023). An investigation of the nexus between online impulsive buying and cognitive dissonance among gen Z shoppers: Are female shoppers different? *Young Consumers*, 24(4), 406–426.
- Cheung, C. M., & Lee, M. K. (2012). What drives consumers to spread electronic word of mouth in online consumer-opinion platforms. *Decision Support Systems*, 53(1), 218–225.
- Cheung, C. M., Lee, M. K., & Rabjohn, N. (2008). The impact of electronic word-of-mouth: The adoption of online opinions in online customer communities. *Internet Research*, 18(3), 229–247.
- Cheung, C. M., & Thadani, D. R. (2012). The impact of electronic word-of-mouth communication: A literature analysis and integrative model. *Decision Support Systems*, 54(1), 461–470.
- Cheung, C. M.-Y., Sia, C.-L., & Kuan, K. K. (2012). Is this review believable? A study of factors affecting the credibility of online consumer reviews from an ELM perspective. *Journal of the Association for Information Systems*, 13(8), 2.
- Cheung, M. L., Leung, W. K., & Chan, H. (2021). Driving healthcare wearable technology adoption for Generation Z consumers in Hong Kong. *Young Consumers*, 22(1), 10–27.
- Cheung, M. Y., Luo, C., Sia, C. L., & Chen, H. (2009). Credibility of Electronic Word-of-Mouth: Informational and Normative Determinants of On-line Consumer Recommendations. *International Journal of Electronic Commerce*, 13(4), 9–38. <https://doi.org/10.2753/JEC1086-4415130402>
- Chevalier, J. A., & Mayzlin, D. (2006). The Effect of Word of Mouth on Sales: Online Book Reviews. *Journal of Marketing Research*, 43(3), 345–354. <https://doi.org/10.1509/jmkr.43.3.345>
- Chih, W.-H., Wang, K.-Y., Hsu, L.-C., & Huang, S.-C. (2013). Investigating Electronic Word-of-Mouth Effects on Online Discussion Forums: The Role of Perceived Positive Electronic Word-of-Mouth Review Credibility.

- Cyberpsychology, Behavior, and Social Networking*, 16(9), 658–668.
<https://doi.org/10.1089/cyber.2012.0364>
- Chmura Kraemer, H., Kiernan, M., Essex, M., & Kupfer, D. J. (2008). How and why criteria defining moderators and mediators differ between the Baron & Kenny and MacArthur approaches. *Health Psychology*, 27(2S), S101.
- Cho, S., & Workman, J. E. (2015). College students' frequency of use of information sources by fashion leadership and style of information processing. *Fashion and Textiles*, 2(1), 25. <https://doi.org/10.1186/s40691-015-0049-2>
- Choi, H. S., & Leon, S. (2020). An empirical investigation of online review helpfulness: A big data perspective. *Decision Support Systems*, 139, 113403.
- Choi, I. Y., Moon, H. S., & Kim, J. K. (2019). Assessing personalized recommendation services using expectancy disconfirmation theory. *Asia Pacific Journal of Information Systems*, 29(2), 203–216.
- Choi, T.-M. J. (2016). *Information systems for the fashion and apparel industry*. Woodhead Publishing.
- Choi, Y., & Mai, D. Q. (2018). The sustainable role of the e-trust in the B2C e-commerce of Vietnam. *Sustainability*, 10(1), 291.
- Chu, S.-C., & Kim, Y. (2011). Determinants of consumer engagement in electronic word-of-mouth (eWOM) in social networking sites. *International Journal of Advertising*, 30(1), 47–75. <https://doi.org/10.2501/IJA-30-1-047-075>
- Chung, J. F., Abdulraqueb, A., & Khaled, S. (2021). Factors affecting online purchase intention of gen Y in Klang Valley, Malaysia. *International Journal of Academy Research in Business and Social Science*, 11(4), 983–1034.
- Churchill, G. A., & Surprenant, C. (1982). An Investigation into the Determinants of Customer Satisfaction. *Journal of Marketing Research*, 19(4), 491–504.
<https://doi.org/10.1177/002224378201900410>
- Ciavolino, E., & Nitti, M. (2010). *HIGH-ORDER CONSTRUCTS FOR THE STRUCTURAL EQUATION MODEL*.
- Clark, L. A., & Watson, D. (2016). *Constructing validity: Basic issues in objective scale development*.
- Connelly, L. M. (2008). Pilot studies. *Medsurg Nursing*, 17(6), 411.
- Cooper, D. R., & Schindler, P. (2014). *Business research methods*. McGraw-hill.
- Cooper, M. D., & Phillips, R. A. (2004). Exploratory analysis of the safety climate and safety behavior relationship. *Journal of Safety Research*, 35(5), 497–512.

- Copeland, L. R., Bhaduri, G., & Huang, O. (2023). Understanding Chinese Gen Z and their online shopping intentions through TAM. *Asia Pacific Journal of Marketing and Logistics*, 35(10), 2361–2376.
- Costanza, D. P., Badger, J. M., Fraser, R. L., Severt, J. B., & Gade, P. A. (2012). Generational differences in work-related attitudes: A meta-analysis. *Journal of Business and Psychology*, 27, 375–394.
- Cova, B., & Dalli, D. (2009). Working consumers: The next step in marketing theory? *Marketing Theory*, 9(3), 315–339. <https://doi.org/10.1177/1470593109338144>
- Creswell, J. W., & Creswell, J. D. (2017). *Research design: Qualitative, quantitative, and mixed methods approaches*. Sage publications.
- Cronbach, L. J. (1971). Test validation. *Educational Measurement*.
- Cruz Lopez, D. E. (2021). Organizational Behavior And Leadership. *Available at SSRN*.
- Cuevas-Vargas, H., Velázquez-Espinoza, N., & Colín-Salgado, M. (2022). Technological Innovation in Colombian Small Firms: A Gender Multi-Group Analysis. *Business Systems Research Journal*, 13(1), 46–65. <https://doi.org/10.2478/bsrj-2022-0004>
- Cyr, D. (2008). Modeling Web Site Design Across Cultures: Relationships to Trust, Satisfaction, and E-Loyalty. *Journal of Management Information Systems*, 24(4), 47–72. <https://doi.org/10.2753/MIS0742-1222240402>
- Czepiel, J. A., & Rosenberg, L. J. (1977). Consumer satisfaction: Concept and measurement. *Journal of the Academy of Marketing Science*, 5(4), 403–411. <https://doi.org/10.1007/BF02722070>
- Dabholkar, P. A., Shepherd, C. D., & Thorpe, D. I. (2000). A comprehensive framework for service quality: An investigation of critical conceptual and measurement issues through a longitudinal study. *Journal of Retailing*, 76(2), 139–173.
- Dalati, S. (2018). Measurement and Measurement Scales. In J. Marx Gómez & S. Mouselli (Eds.), *Modernizing the Academic Teaching and Research Environment* (pp. 79–96). Springer International Publishing. https://doi.org/10.1007/978-3-319-74173-4_5
- Daowd, A., Hasan, R., Eldabi, T., Rafi-ul-Shan, P. M., Cao, D., & Kasemsarn, N. (2021). Factors affecting eWOM credibility, information adoption and

- purchase intention on Generation Y: A case from Thailand. *Journal of Enterprise Information Management*, 34(3), 838–859.
- Das, K., & Ara, A. (2015). Growth of e-commerce in India. *Growth*, 2(4), 25–33.
- Dasgupta, S., & Kothari, R. (2018). The impact of digital word-of-mouth communication on consumer decision-making processes: With special reference to fashion apparel industry. In *Holistic Approaches to Brand Culture and Communication Across Industries* (pp. 176–198). IGI Global.
- Daugherty, T., & Hoffman, E. (2017). Neuromarketing: Understanding the Application of Neuroscientific Methods Within Marketing Research. In A. R. Thomas, N. A. Pop, A. M. Iorga, & C. Ducu (Eds.), *Ethics and Neuromarketing* (pp. 5–30). Springer International Publishing. https://doi.org/10.1007/978-3-319-45609-6_2
- Davis, D. L., Guiltinan, J. P., & Jones, W. H. (1979). Service characteristics, consumer search, and the classification of retail services. *Journal of Retailing*, 55(3), 3.
- Dawson, J. F. (2014). Moderation in management research: What, why, when, and how. *Journal of Business and Psychology*, 29(1), 1–19.
- De Oliveira Lima, L. A., da Silva, J. M. S., de Oliveira Santos, A., Marques, F. R. V., da Silva Leao, A. P., Carvalho, M. da C. L., Estevam, S. M., & Ferreira, A. B. S. (2024). The Influence of Green Marketing on Consumer Purchase Intention: A Systematic Review. *Revista de Gestao Social e Ambiental*, 18(3), e05249–e05249.
- Dellarocas, C. (2003). The Digitization of Word of Mouth: Promise and Challenges of Online Feedback Mechanisms. *Management Science*, 49(10), 1407–1424. <https://doi.org/10.1287/mnsc.49.10.1407.17308>
- Devderea, C., & Toader, F. (2018). Consumer behavior towards apparel e-commerce in Romania. *Management Dynamics in the Knowledge Economy*, 6(3/21), 471–487.
- Dholakia, U. M., Bagozzi, R. P., & Pearo, L. K. (2004). A social influence model of consumer participation in network-and small-group-based virtual communities. *International Journal of Research in Marketing*, 21(3), 241–263.
- Dickson, P. R., & Sawyer, A. G. (1990). The Price Knowledge and Search of Supermarket Shoppers. *Journal of Marketing*, 54(3), 42–53. <https://doi.org/10.1177/002224299005400304>

- Dilalla, L. F. (2000). 15 - Structural equation modeling: Uses and issues. In H. E. A. Tinsley & S. D. Brown (Eds.), *Handbook of Applied Multivariate Statistics and Mathematical Modeling* (pp. 439–464). Academic Press.
<https://doi.org/10.1016/B978-012691360-6/50016-1>
- Ding, Z. (2016). *The present and future of C2B e-commerce in China: Case Kadang*.
- Djafarova, E., & Bowes, T. (2021). ‘Instagram made Me buy it’: Generation Z impulse purchases in fashion industry. *Journal of Retailing and Consumer Services*, 59, 102345.
- Djafarova, E., & Foots, S. (2022). Exploring ethical consumption of generation Z: Theory of planned behaviour. *Young Consumers*, 23(3), 413–431.
- Dodds, W. B., Monroe, K. B., & Grewal, D. (1991). Effects of Price, Brand, and Store Information on Buyers’ Product Evaluations. *Journal of Marketing Research*, 28(3), 307–319. <https://doi.org/10.1177/002224379102800305>
- Donthu, N., Kumar, S., Pandey, N., Pandey, N., & Mishra, A. (2021). Mapping the electronic word-of-mouth (eWOM) research: A systematic review and bibliometric analysis. *Journal of Business Research*, 135, 758–773.
- Doong, H.-S., & Lai, H. (n.d.). *Exploring usage continuance of e-negotiation systems: Expectation and disconfirmation approach*.
- Dorie, A., & Loranger, D. (2024). Word on the street: Apparel-related critical incidents leading to eWOM and channel behaviour among millennial and Gen Z consumers. *Journal of Consumer Marketing*, 41(2), 148–161.
- Dos Santos Capelo, I. R. (2014). *Millennials Brand Awareness* [Master’s Thesis, Universidade Catolica Portuguesa (Portugal)].
- Duchscher, J. E. B., & Cowin, L. (2004). Multigenerational nurses in the workplace. *JONA: The Journal of Nursing Administration*, 34(11), 493–501.
- Duffett, R. G. (2017). Influence of social media marketing communications on young consumers’ attitudes. *Young Consumers*, 18(1), 19–39.
- Eagly, A. H., Karau, S. J., & Makhijani, M. G. (1995). Gender and the effectiveness of leaders: A meta-analysis. *Psychological Bulletin*, 117(1), 125.
- Egerova, D., Komárková, L., & Kutlák, J. (2021). *Generation Y and generation Z employment expectations: A generational cohort comparative study from two countries*.
- Eichhorn, B. R. (2014). *Common Method Variance Techniques*.

- Elkhani, N., & Bakri, A. B. (n.d.). *REVIEW ON “EXPECTANCY DISCONFIRMATION THEORY” (EDT) MODEL IN B2C E-COMMERCE*.
- Elwalda, A., & Lu, K. (2016). The impact of online customer reviews (OCRs) on customers’ purchase decisions: An exploration of the main dimensions of OCrs. *Journal of Customer Behaviour*, 15(2), 123–152.
- Engelbertink, A., & Van Hullebusch, S. (2013). The effects of education and income on consumers’ motivation to read online hotel reviews. *Research in Hospitality Management*, 2(1–2), 57–61. <https://doi.org/10.1080/22243534.2013.11828292>
- Erkan, I., & Evans, C. (2016). The influence of eWOM in social media on consumers’ purchase intentions: An extended approach to information adoption. *Computers in Human Behavior*, 61, 47–55.
- Euajarusphan, A. (2021). Online social media usage behavior, attitude, satisfaction, and online social media literacy of Generation X, Generation Y, and Generation Z. *PSAKU International Journal of Interdisciplinary Research*, 10(2).
- Fan, A., Shin, H. W., Shi, J. (Jade), & Wu, L. (2023). Young People Share, But Do So Differently: An Empirical Comparison of Peer-to-Peer Accommodation Consumption Between Millennials and Generation Z. *Cornell Hospitality Quarterly*, 64(3), 322–337. <https://doi.org/10.1177/19389655221119463>
- Fan, L., & Suh, Y.-H. (2014). Why do users switch to a disruptive technology? An empirical study based on expectation-disconfirmation theory. *Information & Management*, 51(2), 240–248.
- Farris, C., Treat, T. A., Viken, R. J., & McFall, R. M. (2008). Sexual coercion and the misperception of sexual intent. *Clinical Psychology Review*, 28(1), 48–66.
- Filieri, R., Raguseo, E., & Vitari, C. (2021). Extremely Negative Ratings and Online Consumer Review Helpfulness: The Moderating Role of Product Quality Signals. *Journal of Travel Research*, 60(4), 699–717. <https://doi.org/10.1177/0047287520916785>
- Fischer, E., & Reuber, A. R. (2011). Social interaction via new social media:(How) can interactions on Twitter affect effectual thinking and behavior? *Journal of Business Venturing*, 26(1), 1–18.

- Flavian, C., Guinalíu, M., & Gurrea, R. (2006). The role played by perceived usability, satisfaction and consumer trust on website loyalty. *Information & Management*, 43(1), 1–14.
- Fogg, B. J., & Tseng, H. (1999). The elements of computer credibility. *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems the CHI Is the Limit - CHI '99*, 80–87. <https://doi.org/10.1145/302979.303001>
- Foris, T., & Foris, D. (2018). Adjusting the touristic educational system to the exchange of generation. *J. Tour. Hosp. Manag*, 6(10.17265), 2328–2169.
- Forman, C., Ghose, A., & Wiesenfeld, B. (2008). Examining the Relationship Between Reviews and Sales: The Role of Reviewer Identity Disclosure in Electronic Markets. *Information Systems Research*, 19(3), 291–313. <https://doi.org/10.1287/isre.1080.0193>
- Fornell, C., & Larcker, D. F. (1981). Evaluating Structural Equation Models with Unobservable Variables and Measurement Error. *Journal of Marketing Research*, 18(1), 39. <https://doi.org/10.2307/3151312>
- Francis, T., & Hoefel, F. (2018). True Gen’: Generation Z and its implications for companies. *McKinsey & Company*, 12(2).
- Franklin, K. K., & Shemwell, D. W. (1995). *Disconfirmation Theory: An Approach to Student Satisfaction Assessment in Higher Education*.
- Frazier, P. A., Tix, A. P., & Barron, K. E. (2004). “ Testing moderator and mediator effects in counseling psychology research”: Correction to Frazier et al.(2004).
- Fusilier, M., & Durlabhji, S. (2005). An exploration of student internet use in India: The technology acceptance model and the theory of planned behaviour. *Campus-Wide Information Systems*, 22(4), 233–246.
- Gao, B., Hu, N., & Bose, I. (2017). Follow the herd or be myself? An analysis of consistency in behavior of reviewers and helpfulness of their reviews. *Decision Support Systems*, 95, 1–11.
- Garbarino, E., & Johnson, M. S. (1999). The Different Roles of Satisfaction, Trust, and Commitment in Customer Relationships. *Journal of Marketing*, 63(2), 70–87. <https://doi.org/10.1177/002224299906300205>
- Gardial, S. F., Clemons, D. S., Woodruff, R. B., Schumann, D. W., & Burns, M. J. (1994). Comparing consumers’ recall of prepurchase and postpurchase product evaluation experiences. *Journal of Consumer Research*, 20(4), 548–560.

- Geisser, S. (1974). *A predictive approach to the random effect model. Biometrik. 61* (1), 101–107.
- Ghazali, E. M., Mutum, D. S., Pua, M. H.-J., & Ramayah, T. (2020). Status-quo satisfaction and smartwatch adoption: A multi-group analysis. *Industrial Management & Data Systems, 120*(12), 2319–2347.
- Giancola, F. (2006). The generation gap: More myth than reality. *Human Resource Planning, 29*(4).
- Giri, C., Jain, S., Zeng, X., & Bruniaux, P. (2019). A detailed review of artificial intelligence applied in the fashion and apparel industry. *IEEE Access, 7*, 95376–95396.
- Giuffrida, M., Mangiaracina, R., Perego, A., & Tumino, A. (2017). Cross-border B2C e-commerce to Greater China and the role of logistics: A literature review. *International Journal of Physical Distribution & Logistics Management, 47*(9), 772–795.
- Gold, A. H., Malhotra, A., & Segars, A. H. (2001). Knowledge Management: An Organizational Capabilities Perspective. *Journal of Management Information Systems, 18*(1), 185–214. <https://doi.org/10.1080/07421222.2001.11045669>
- Goldsmith, R. E., & Horowitz, D. (2006). Measuring Motivations for Online Opinion Seeking. *Journal of Interactive Advertising, 6*(2), 2–14. <https://doi.org/10.1080/15252019.2006.10722114>
- Gonzalez-Rodríguez, M. R., Diaz-Fernandez, M. C., Bilgihan, A., Okumus, F., & Shi, F. (2022). The impact of eWOM source credibility on destination visit intention and online involvement: A case of Chinese tourists. *Journal of Hospitality and Tourism Technology, 13*(5), 855–874.
- Gonzalez-Rodríguez, M. R., Martínez-Torres, R., & Toral, S. (2016). Post-visit and pre-visit tourist destination image through eWOM sentiment analysis and perceived helpfulness. *International Journal of Contemporary Hospitality Management, 28*(11), 2609–2627.
- Gremler, D. D., Gwinner, K. P., & Brown, S. W. (2001). Generating positive word-of-mouth communication through customer-employee relationships. *International Journal of Service Industry Management, 12*(1), 44–59.
- Grover, S., Chakraborty, K., & Basu, D. (2010). Pattern of Internet use among professionals in India: Critical look at a surprising survey result. *Industrial Psychiatry Journal, 19*(2), 94–100.

- Guo, W., & Luo, Q. (2023). Investigating the impact of intelligent personal assistants on the purchase intentions of Generation Z consumers: The moderating role of brand credibility. *Journal of Retailing and Consumer Services*, 73, 103353.
- Gupta, P., & Harris, J. (2010). How e-WOM recommendations influence product consideration and quality of choice: A motivation to process information perspective. *Journal of Business Research*, 63(9–10), 1041–1049.
- Ha, Q.-A., Chen, J. V., & Nguyen, T. H. T. (2021). Continuance use of enterprise social network sites as knowledge sharing platform: Perspectives of tasks-technology fit and expectation disconfirmation theory. *International Journal of Knowledge Management Studies*, 12(4), 429–451.
- Ha, S., & Stoel, L. (2012). Online apparel retailing: Roles of e-shopping quality and experiential e-shopping motives. *Journal of Service Management*, 23(2), 197–215.
- Hai Ming, L., Gang, L., Hua, H., & Waqas, M. (2022). Modeling the influencing factors of electronic word-of-mouth about CSR on social networking sites. *Environmental Science & Pollution Research*, 29(44).
- Hair, J. F., Ringle, C. M., Gudergan, S. P., Fischer, A., Nitzl, C., & Menictas, C. (2019). Partial least squares structural equation modeling-based discrete choice modeling: An illustration in modeling retailer choice. *Business Research*, 12(1), 115–142. <https://doi.org/10.1007/s40685-018-0072-4>
- Hair, J. F., Risher, J. J., Sarstedt, M., & Ringle, C. M. (2019). When to use and how to report the results of PLS-SEM. *European Business Review*, 31(1), 2–24. <https://doi.org/10.1108/EBR-11-2018-0203>
- Hajli, N. (2015). Social commerce constructs and consumer's intention to buy. *International Journal of Information Management*, 35(2), 183–191.
- Hajli, N., & Lin, X. (2015). Consumer Adoption of Social Commerce. In F. Fui-Hoon Nah & C.-H. Tan (Eds.), *HCI in Business* (Vol. 9191, pp. 279–287). Springer International Publishing. https://doi.org/10.1007/978-3-319-20895-4_26
- Hajli, N., Sims, J., Zadeh, A. H., & Richard, M.-O. (2017). A social commerce investigation of the role of trust in a social networking site on purchase intentions. *Journal of Business Research*, 71, 133–141.
- Hall, A., Towers, N., & Shaw, D. R. (2017). Understanding how millennial shoppers decide what to buy: Digitally connected unseen journeys. *International Journal of Retail & Distribution Management*, 45(5), 498–517.

- Hamad, H., Elbeltagi, I., Jones, P., & El-Gohary, H. (2015). Antecedents of B2B e-commerce adoption and its effect on competitive advantage in manufacturing SMEs. *Strategic Change*, 24(5), 405–428.
- Handayani, R., Sofiandi, M., Putra, D. A. D., Valiant, R., Fauzan, R., & Hidayat, Y. F. (2021). The effect of hedonic shopping motivation on impulse purchase of fashion products in pandemic times (Case study on generation Z consumers of several e-commerce in Bandung). *Rigeo*, 11(3).
- Harari, T. T., Sela, Y., & Bareket-Bojmel, L. (2023). Gen Z during the COVID-19 crisis: A comparative analysis of the differences between Gen Z and Gen X in resilience, values and attitudes. *Current Psychology*, 42(28), 24223–24232. <https://doi.org/10.1007/s12144-022-03501-4>
- Harman, H. H. (1976). *Modern factor analysis*. University of Chicago press.
- Harrison-Walker, L. J. (2001). The Measurement of Word-of-Mouth Communication and an Investigation of Service Quality and Customer Commitment As Potential Antecedents. *Journal of Service Research*, 4(1), 60–75. <https://doi.org/10.1177/109467050141006>
- Hasan, M. R. (2019). Continuity of Using Social Networking Sites and the Expectation Disconfirmation Theory. *Journal of Business*, 40(3).
- Hayes, A. F. (2018). Partial, conditional, and moderated moderated mediation: Quantification, inference, and interpretation. *Communication Monographs*, 85(1), 4–40. <https://doi.org/10.1080/03637751.2017.1352100>
- Heaney, J.-G. (2007). Generations X and Y's internet banking usage in Australia. *Journal of Financial Services Marketing*, 11(3), 196–210. <https://doi.org/10.1057/palgrave.fsm.4760052>
- Hennig-Thurau, T. (2004). Customer orientation of service employees: Its impact on customer satisfaction, commitment, and retention. *International Journal of Service Industry Management*, 15(5), 460–478.
- Hennig-Thurau, T., Gwinner, K. P., Walsh, G., & Gremler, D. D. (2004). Electronic word-of-mouth via consumer-opinion platforms: What motivates consumers to articulate themselves on the internet? *Journal of Interactive Marketing*, 18(1), 38–52.
- Hennig-Thurau, T., Houston, M. B., & Walsh, G. (2007). Determinants of motion picture box office and profitability: An interrelationship approach. *Review of Managerial Science*, 1(1), 65–92. <https://doi.org/10.1007/s11846-007-0003-9>

- Hennig-Thurau, T., Walsh, G., & Walsh, G. (2003). Electronic Word-of-Mouth: Motives for and Consequences of Reading Customer Articulations on the Internet. *International Journal of Electronic Commerce*, 8(2), 51–74. <https://doi.org/10.1080/10864415.2003.11044293>
- Henseler, J., Ringle, C. M., & Sarstedt, M. (2015). A new criterion for assessing discriminant validity in variance-based structural equation modeling. *Journal of the Academy of Marketing Science*, 43(1), 115–135. <https://doi.org/10.1007/s11747-014-0403-8>
- Henseler, J., Ringle, C. M., & Sarstedt, M. (2016). Testing measurement invariance of composites using partial least squares. *International Marketing Review*, 33(3), 405–431. <https://doi.org/10.1108/IMR-09-2014-0304>
- Hien, N. N., Long, N. T., Liem, V. T., & Luu, D. X. (2024). Customer Responses to Airline Service Failure: Perspectives from Expectation Disconfirmation Theory. *SAGE Open*, 14(2), 21582440241248334.
- Hirst, A., & Omar, O. (2007). *Assessing Women's Apparel Shopping Behaviour on the Internet*.
- Hooda, S., & Singh, N. (2018). Online apparel shopping. *Man-Made Textiles in India*, 46(3).
- Hossain, M. A., & Quaddus, M. (2012). Expectation–confirmation theory in information system research: A review and analysis. *Information Systems Theory: Explaining and Predicting Our Digital Society, Vol. 1*, 441–469.
- Hossain, M. J. (2019). Redefining expectancy disconfirmation theory using LIS SERVQUAL+: An integrated framework for evaluating library service quality and user satisfaction. *International Information & Library Review*, 51(3), 203–216.
- Hsieh, C.-C. (2010). Assessing blog-user satisfaction using the expectation and disconfirmation approach. *Computers in Human Behavior*.
- Hsieh, J.-K., & Li, Y.-J. (2020). Will You Ever Trust the Review Website Again? The Importance of Source Credibility. *International Journal of Electronic Commerce*, 24(2), 255–275. <https://doi.org/10.1080/10864415.2020.1715528>
- Hsieh—2010—Assessing blog-user satisfaction using the expecta.pdf. (n.d.).
- Hu, L.-T., & Bentler, P. M. (1995). *Evaluating model fit*. <https://psycnet.apa.org/record/1995-97753-005>

- Hu, N., Koh, N. S., & Reddy, S. K. (2014). Ratings lead you to the product, reviews help you clinch it? The mediating role of online review sentiments on product sales. *Decision Support Systems*, 57, 42–53.
- Hu, X. (Simon), & Yang, Y. (2021). What makes online reviews helpful in tourism and hospitality? A bare-bones meta-analysis. *Journal of Hospitality Marketing & Management*, 30(2), 139–158. <https://doi.org/10.1080/19368623.2020.1780178>
- Hult, G. T. M., Hair, J. F., Proksch, D., Sarstedt, M., Pinkwart, A., & Ringle, C. M. (2018). Addressing Endogeneity in International Marketing Applications of Partial Least Squares Structural Equation Modeling. *Journal of International Marketing*, 26(3), 1–21. <https://doi.org/10.1509/jim.17.0151>
- Hung, S.-W., Chang, C.-W., & Chen, S.-Y. (2023). Beyond a bunch of reviews: The quality and quantity of electronic word-of-mouth. *Information & Management*, 60(3), 103777.
- Hussain, S., Song, X., & Niu, B. (2020). Consumers' motivational involvement in eWOM for information adoption: The mediating role of organizational motives. *Frontiers in Psychology*, 10, 3055.
- Vijay, T. S., Prashar, S., Gupta, S., & Indian Institute of Management Raipur. (2018). Intention to Provide Online Reviews: An Expectation Confirmation Model with Review Involvement. *Pacific Asia Journal of the Association for Information Systems*, 25–54. <https://doi.org/10.17705/1pais.10202>
- Ismagilova, E., Slade, E. L., Rana, N. P., & Dwivedi, Y. K. (2020). The Effect of Electronic Word of Mouth Communications on Intention to Buy: A Meta-Analysis. *Information Systems Frontiers*, 22(5), 1203–1226. <https://doi.org/10.1007/s10796-019-09924-y>
- Jabar, A. A., & Ogunsola, A. (2022). Analytical Review Of E-Commerce Business Models. *African Journal Of Accounting And Financial Research*, 5(2), 48–60.
- Jain, S. (2020). Assessing the moderating effect of subjective norm on luxury purchase intention: A study of Gen Y consumers in India. *International Journal of Retail & Distribution Management*, 48(5), 517–536.
- Jaiswal, R., Khan, M. I. A., & Kumar, M. (2024). Charting the course: Exploring the changing terrain of online shopping and future directions for research. *International Journal of Electronic Business*, 19(1), 56–79. <https://doi.org/10.1504/IJEB.2024.135653>

- James, O. (2009). Evaluating the Expectations Disconfirmation and Expectations Anchoring Approaches to Citizen Satisfaction with Local Public Services. *Journal of Public Administration Research and Theory*.
- Jedrzejczak-Gas, J., Barska, A., & Sinicakova, M. (2019). Level of development of e-commerce in EU countries. *Management*, 23(1), 209–224. <https://doi.org/10.2478/manment-2019-0012>
- Jiang, L., Jun, M., & Yang, Z. (2016). Customer-perceived value and loyalty: How do key service quality dimensions matter in the context of B2C e-commerce? *Service Business*, 10, 301–317.
- Johnson, M. D., Nader, G., & Fornell, C. (1996). Expectations, perceived performance, and customer satisfaction for a complex service: The case of bank loans. *Journal of Economic Psychology*, 17(2), 163–182.
- Joshi, J. M., & Dumbre, G. M. (2017). Basic concept of e-commerce. *International Research Journal of Multidisciplinary Studies*, 3(3), 1–5.
- Joshi, M., & Singh, V. K. (2017). Electronic word of mouth and influence on consumer purchase intention. *Dynamics of Public Administration*, 34(2), 149–159.
- Jr, J. F. H. (2017). *PLS-SEM or CB-SEM: updated guidelines on which method to use*.
- Jr., J. F. H., Matthews, L. M., Matthews, R. L., & Sarstedt, M. (2017). PLS-SEM or CB-SEM: Updated guidelines on which method to use. *International Journal of Multivariate Data Analysis*, 1(2), 107. <https://doi.org/10.1504/IJMDA.2017.087624>
- Kalia, P., Kaur, N., & Singh, T. (2018). E-Commerce in India: Evolution and revolution of online retail. In *Mobile commerce: Concepts, methodologies, tools, and applications* (pp. 736–758). IGI Global.
- Kandampully, J., & Suhartanto, D. (2000). Customer loyalty in the hotel industry: The role of customer satisfaction and image. *International Journal of Contemporary Hospitality Management*, 12(6), 346–351.
- Karavidas, M., Lim, N. K., & Katsikas, S. L. (2005). The effects of computers on older adult users. *Computers in Human Behavior*, 21(5), 697–711.
- Katz, E., Lazarsfeld, P. F., & Roper, E. (2017). *Personal influence: The part played by people in the flow of mass communications*. Routledge.
- Katz, R., Ogilvie, S., Shaw, J., & Woodhead, L. (2022). *Gen Z, explained: The art of living in a digital age*. University of Chicago Press.

- Kaur, D., & Kaur, R. (2022). Elucidating the role of gender differences via TAM in e-recruitment adoption in India: A multi-group analysis using MICOM. *The Bottom Line*, 35(2/3), 115–136. <https://doi.org/10.1108/BL-11-2021-0104>
- Kaur, D., & Kaur, R. (2023). Does electronic word-of-mouth influence e-recruitment adoption? A mediation analysis using the PLS-SEM approach. *Management Research Review*, 46(2), 223–244.
- Kaur, K., & Singh, T. (2020). Visual information impacting electronic word of mouth adoption: Mediating role of perceived eWOM review credibility. *International Journal of Indian Culture and Business Management*, 21(1), 78. <https://doi.org/10.1504/IJICBM.2020.109351>
- Kautish, P., & Rai, S. K. (2019). Fashion portals and Indian consumers: An exploratory study on online apparel retail marketing. *International Journal of Electronic Marketing and Retailing*, 10(3), 309-331.
- Khammash, D. M. (2008). *ELECTRONIC WORD-OF-MOUTH: ANTECEDENTS OF READING CUSTOMER REVIEWS IN ON-LINE OPINION PLATFORMS: A QUANTITATIVE STUDY FROM THE UK MARKET*.
- Khammash, M. (2005). *ELECTRONIC WORD-OF-MOUTH: MOTIVES FOR READING CUSTOMER OPINIONS ONLINE: RESEARCH PLAN FOR THE UK MARKET*.
- Khan, N., Sarwar, A., & Tan, B. C. (2021). Determinants of purchase intention of halal cosmetic products among Generation Y consumers. *Journal of Islamic Marketing*, 12(8), 1461–1476.
- Khan, S., Rashid, A., Rasheed, R., & Amirah, N. A. (2023). Designing a knowledge-based system (KBS) to study consumer purchase intention: The impact of digital influencers in Pakistan. *Kybernetes*, 52(5), 1720–1744.
- Khandelwal, H. (2024). Evolution of E-Commerce in India. *Available at SSRN 4768013*.
- Khosla, M., & Kumar, H. (2017). Growth of e-commerce in India: An analytical review of literature. *IOSR Journal of Business and Management (IOSR-JBM)*, 19(6), 91–95.
- Kietzmann, J., & Canhoto, A. (2013). Bittersweet! Understanding and Managing Electronic Word of Mouth. *Journal of Public Affairs*, 13(2), 146–159. <https://doi.org/10.1002/pa.1470>

- Kim, E. E. K., Mattila, A. S., & Baloglu, S. (2011). Effects of Gender and Expertise on Consumers' Motivation to Read Online Hotel Reviews. *Cornell Hospitality Quarterly*, 52(4), 399–406. <https://doi.org/10.1177/1938965510394357>
- Kim, E., & Johnson, K. K. (2004). The US Apparel Industry. *Clothing & Textiles Research Journal*.
- Kim, E., & Johnson, K. K. P. (2007). The U.S. Apparel Industry: Futuring With Undergraduate Students in Apparel Majors. *Clothing and Textiles Research Journal*, 25(4), 283–306. <https://doi.org/10.1177/0887302X07306909>
- Kim, J., & Gupta, P. (2012). Emotional expressions in online user reviews: How they influence consumers' product evaluations. *Journal of Business Research*, 65(7), 985–992.
- Kim, J., Jin, B., & Swinney, J. L. (2009). The role of etail quality, e-satisfaction and e-trust in online loyalty development process. *Journal of Retailing and Consumer Services*, 16(4), 239–247.
- Kim, J.-U., Shim, S.-K., & Kim, B.-G. (2004). An empirical study of the influence of expectation, perceived performance, and disconfirmation on information systems user satisfaction. *Asia Pacific Journal of Information Systems*, 14(1), 101–123.
- Kim, T. T., Kim, W. G., & Kim, H.-B. (2009). The effects of perceived justice on recovery satisfaction, trust, word-of-mouth, and revisit intention in upscale hotels. *Tourism Management*, 30(1), 51–62.
- Kim, W. G., Ng, C. Y. N., & Kim, Y. (2009). Influence of institutional DINESERV on customer satisfaction, return intention, and word-of-mouth. *International Journal of Hospitality Management*, 28(1), 10–17.
- Kokthi, E., & Kruja, D. (2017). Consumer expectations for geographical origin: Eliciting willingness to pay (WTP) using the Disconfirmation of Expectation Theory (EDT). *Journal of Food Products Marketing*, 23(8), 873–889.
- Koleva, V. (2023). E-recruitment and generation Z job-seekers. *HR and Technologies*, 1, 25–36.
- Kraus, M. (2017). Comparing Generation X and Generation Y on their preferred emotional leadership style. *Journal of Applied Leadership and Management*, 5, 62–75.

- Kristensen, K., Martensen, A., & Gronholdt, L. (1999). Measuring the impact of buying behaviour on customer satisfaction. *Total Quality Management*, 10(4–5), 602–614. <https://doi.org/10.1080/0954412997587>
- Kumar, N., Anusara, J., Hossin, M. A., Sarkar, M. K., Chanthamith, B., Shah, S., & Russel, M. I. H. (2018). Challenges and opportunities of e-commerce in India: Pathway for sustainable e-commerce. *Int. J. Eng. Bus. Manag*, 2, 13–21.
- Kumar, S., & Sadarangani, P. (2021). An Empirical Study on Shopping Motivation among Generation Y Indian. *Global Business Review*, 22(2), 500–516. <https://doi.org/10.1177/0972150918807085>
- Kumar, S., & Sadarangani, P. H. (2018). Study of shopping motivation and buying behaviour among generation Y in India. *ISSN No. 2362, 7832*, 341.
- Kumari, S. (2016). Future Prospects of E-Commerce in India. *International Journal in Management & Social Science*, 4(6), 237–247.
- Kuo, H.-C., & Nakhata, C. (2019). The Impact of Electronic Word-of-Mouth on Customer Satisfaction. *Journal of Marketing Theory and Practice*, 27(3), 331–348. <https://doi.org/10.1080/10696679.2019.1615840>
- Kupperschmidt, B. R. (2000). Multigeneration employees: Strategies for effective management. *The Health Care Manager*, 19(1), 65–76.
- Kwak, S. Y., Shin, M., Lee, M., & Back, K.-J. (2023). Integrating the reviewers' and readers' perceptions of negative online reviews for customer decision-making: A mixed-method approach. *International Journal of Contemporary Hospitality Management*, 35(12), 4191–4216.
- Lahkani, M. J., Wang, S., Urbański, M., & Egorova, M. (2020). Sustainable B2B E-commerce and blockchain-based supply chain finance. *Sustainability*, 12(10), 3968.
- Lankton, N. K., & McKnight, H. D. (2012). Examining two expectation disconfirmation theory models: Assimilation and asymmetry effects. *Journal of the Association for Information Systems*, 13(2), 1.
- Lankton, N., & McKnight, D. H. (2006). Using expectation disconfirmation theory to predict technology trust and usage continuance intentions. *Eli Broad College of Business, Minnesota*.
- Lankton, N., McKnight, D. H., & Thatcher, J. B. (2014). Incorporating trust-in-technology into expectation disconfirmation theory. *The Journal of Strategic Information Systems*, 23(2), 128–145.

- LaTour, S. A., & Peat, N. C. (1979). Conceptual and Methodological Issues in Consumer Satisfaction Research. *Advances in Consumer Research*, 6(1).
- Lau, G. T., & Ng, S. (2001). Individual and Situational Factors Influencing Negative Word-of-Mouth Behaviour. *Canadian Journal of Administrative Sciences / Revue Canadienne Des Sciences de l'Administration*, 18(3), 163–178. <https://doi.org/10.1111/j.1936-4490.2001.tb00253.x>
- Lee, C.-P., Hung, M.-J., & Chen, D.-Y. (2022). Factors affecting citizen satisfaction: Examining from the perspective of the expectancy disconfirmation theory and individual differences. *Asian Journal of Political Science*, 30(1), 35–60.
- Lee, D., Moon, J., Kim, Y. J., & Mun, Y. Y. (2015). Antecedents and consequences of mobile phone usability: Linking simplicity and interactivity to satisfaction, trust, and brand loyalty. *Information & Management*, 52(3), 295–304.
- Lee, E.-J., & Overby, J. W. (2004). Creating value for online shoppers: Implications for satisfaction and loyalty. *Journal of Consumer Satisfaction, Dissatisfaction and Complaining Behavior*, 17, 54–67.
- Lee, E.-J., & Shin, S. Y. (2014). When do consumers buy online product reviews? Effects of review quality, product type, and reviewer's photo. *Computers in Human Behavior*, 31, 356–366.
- Lee, J., & Kim, Y.-K. (2020). Online Reviews of Restaurants: Expectation-Confirmation Theory. *Journal of Quality Assurance in Hospitality & Tourism*, 21(5), 582–599. <https://doi.org/10.1080/1528008X.2020.1712308>
- Lee, J., Park, D.-H., & Han, I. (2008). The effect of negative online consumer reviews on product attitude: An information processing view. *Electronic Commerce Research and Applications*, 7(3), 341–352.
- Lee, M., & Youn, S. (2009). Electronic word of mouth (eWOM): How eWOM platforms influence consumer product judgement. *International Journal of Advertising*, 28(3), 473–499. <https://doi.org/10.2501/S0265048709200709>
- Lee, S., & Choeh, J. Y. (2017). Exploring the determinants of and predicting the helpfulness of online user reviews using decision trees. *Management Decision*, 55(4), 681–700.
- Leung, D. (2021). Unraveling the interplay of review depth, review breadth, and review language style on review usefulness and review adoption. *International Journal of Hospitality Management*, 97, 102989.

- Leung, K. H., Choy, K. L., Siu, P. K., Ho, G. T., Lam, H. Y., & Lee, C. K. (2018). A B2C e-commerce intelligent system for re-engineering the e-order fulfilment process. *Expert Systems with Applications*, 91, 386–401.
- Levesque, T., & McDougall, G. H. G. (1996). *Determinants of customer satisfaction in retail banking*.
- Levy, S., & Gvili, Y. (2015). How credible is e-word of mouth across digital-marketing channels?: The roles of social capital, information richness, and interactivity. *Journal of Advertising Research*, 55(1), 95–109.
- Li, C., Chen, J. E., Peng, S., Huang, J., & Sha, X. (2024). Examining the effects of weather on online shopping cart abandonment: Evidence from an online retailing platform. *Journal of Retailing and Consumer Services*, 78, 103738.
- Li, F., Frederick, S., & Gereffi, G. (2019). E-Commerce and Industrial Upgrading in the Chinese Apparel Value Chain. *Journal of Contemporary Asia*, 49(1), 24–53. <https://doi.org/10.1080/00472336.2018.1481220>
- Li, H., Ye, Q., & Law, R. (2013). *Determinants of Customer Satisfaction in the Hotel Industry: An Application of Online Review Analysis*.
- Li, H., Zhang, Z., Meng, F., & Zhang, Z. (2019). “When you write review” matters: The interactive effect of prior online reviews and review temporal distance on consumers’ restaurant evaluation. *International Journal of Contemporary Hospitality Management*, 31(3), 1273–1291.
- Li, J., & Zhan, L. (2011). Online persuasion: How the written word drives WOM: Evidence from consumer-generated product reviews. *Journal of Advertising Research*, 51(1), 239–257.
- Li, K., Chen, Y., & Zhang, L. (2020). Exploring the influence of online reviews and motivating factors on sales: A meta-analytic study and the moderating role of product category. *Journal of Retailing and Consumer Services*, 55, 102107.
- Li, S. S., & Karahanna, E. (2015). Online recommendation systems in a B2C E-commerce context: A review and future directions. *Journal of the Association for Information Systems*, 16(2), 2.
- Liang, Y., & Liu, C. (2019). Comparison of consumers’ acceptance of online apparel mass customization across web and mobile channels. *Journal of Global Fashion Marketing*, 10(3), 228–245. <https://doi.org/10.1080/20932685.2019.1619469>

- Lim, Y. S., Heng, P. C., Ng, T. H., & Cheah, C. S. (2016). Customers' online website satisfaction in online apparel purchase: A study of Generation Y in Malaysia. *Asia Pacific Management Review*, 21(2), 74–78. <https://doi.org/10.1016/j.apmr.2015.10.002>
- Limbu, Y. B., & Huhmann, B. A. (2024). What influences consumers' online medication purchase intentions and behavior? A scoping review. *Frontiers in Pharmacology*, 15, 1356059.
- Lin, C. A., & Xu, X. (2017). Effectiveness of online consumer reviews: The influence of valence, reviewer ethnicity, social distance and source trustworthiness. *Internet Research*, 27(2), 362–380.
- Lin, Y., Hong, Y. A., Henson, B. S., Stevenson, R. D., Hong, S., Lyu, T., & Liang, C. (2020). Assessing patient experience and healthcare quality of dental care using patient online reviews in the United States: Mixed methods study. *Journal of Medical Internet Research*, 22(7), e18652.
- Lina, Y., Hou, D., & Ali, S. (2022). Impact of online convenience on generation Z online impulsive buying behavior: The moderating role of social media celebrity. *Frontiers in Psychology*, 13, 951249.
- Litvin, S. W., Goldsmith, R. E., & Pan, B. (2008). Electronic word-of-mouth in hospitality and tourism management. *Tourism Management*, 29(3), 458–468.
- Liu, S.-Y., & Yuan, G.-X. (2022). The virtual fashion in the global apparel industry in the post-epidemic era. *Journal of Fiber Bioengineering and Informatics*, 15(2), 117–130.
- Liu, Z., & Park, S. (2015). What makes a useful online review? Implication for travel product websites. *Tourism Management*, 47, 140–151.
- Lockie, M., Waiguny, M. K. J., & Grabner-Kräuter, S. (2015). How Style, Information Depth and Textual Characteristics Influence the Usefulness of General Practitioners' Reviews. *Australasian Marketing Journal*, 23(3), 168–178. <https://doi.org/10.1016/j.ausmj.2015.01.005>
- Lu, L., Li, G. Y., Swindlehurst, A. L., Ashikhmin, A., & Zhang, R. (2014). An overview of massive MIMO: Benefits and challenges. *IEEE Journal of Selected Topics in Signal Processing*, 8(5), 742–758.
- Lu, X., Li, Y., Zhang, Z., & Rai, B. (2014). Consumer learning embedded in electronic word of mouth. *Journal of Electronic Commerce Research*, 15(4), 300.

- Ludwig, S., De Ruyter, K., Friedman, M., Brüggem, E. C., Wetzels, M., & Pfann, G. (2013). More than Words: The Influence of Affective Content and Linguistic Style Matches in Online Reviews on Conversion Rates. *Journal of Marketing*, 77(1), 87–103. <https://doi.org/10.1509/jm.11.0560>
- MacKinnon, D. P. (2011). Integrating Mediators and Moderators in Research Design. *Research on Social Work Practice*, 21(6), 675–681. <https://doi.org/10.1177/1049731511414148>
- Maes, J., Leroy, H., & Sels, L. (2014). Gender differences in entrepreneurial intentions: A TPB multi-group analysis at factor and indicator level. *European Management Journal*, 32(5), 784–794.
- Mahajan, P., & Agarwal, M. (2015). Exploring the Potential of E-Commerce in the Digital Age: Challenges and Opportunities for Commerce Education. *IUP Journal of Information Technology*, 11(4).
- Mahmud, Md. S., Islam, Md. N., Ali, Md. R., & Mehjabin, N. (2024). Impact of Electronic Word of Mouth on Customers' Buying Intention Considering Trust as a Mediator: A SEM Approach. *Global Business Review*, 25(2_suppl), S184–S198. <https://doi.org/10.1177/0972150920976345>
- Malhotra, N., & Dash, S. (2013). Future of research in marketing in emerging economies. *Marketing Intelligence & Planning*, 31(2).
- Mangiaracina, R., Marchet, G., Perotti, S., & Tumino, A. (2015). A review of the environmental implications of B2C e-commerce: A logistics perspective. *International Journal of Physical Distribution & Logistics Management*, 45(6), 565–591.
- Mangiaracina, R., Perego, A., Seghezzi, A., & Tumino, A. (2019). Innovative solutions to increase last-mile delivery efficiency in B2C e-commerce: A literature review. *International Journal of Physical Distribution & Logistics Management*, 49(9), 901–920.
- Martensen, A., Gronholdt, L., & Kristensen, K. (2000). The drivers of customer satisfaction and loyalty: Cross-industry findings from Denmark. *Total Quality Management*, 11(4–6), 544–553. <https://doi.org/10.1080/09544120050007878>
- Masuda, H., Han, S. H., & Lee, J. (2022). Impacts of influencer attributes on purchase intentions in social media influencer marketing: Mediating roles of characterizations. *Technological Forecasting and Social Change*, 174, 121246.

- Mathew, B. (2015). A study on changing trends in online shopping of Indian consumers in apparel segment. *Int. J. of Appl. Res*, 1(9), 207–214.
- Matthews, L., Hair, J. O. E., & Matthews, R. (2018). PLS-SEM: The holy grail for advanced analysis. *Marketing Management Journal*, 28(1).
- Mazanec, J., & Harantová, V. (2024). Gen z and their sustainable shopping behavior in the second-hand clothing segment: Case study of the Slovak Republic. *Sustainability*, 16(8), 3129.
- McCoy, L., Wang, Y.-T., & Chi, T. (2021). Why is collaborative apparel consumption gaining popularity? An empirical study of US gen Z consumers. *Sustainability*, 13(15), 8360.
- McKinney, V., & Yoon, K. (2002). The Measurement of Web-Customer Satisfaction: An Expectation and Disconfirmation Approach. *INFORMATION SYSTEMS RESEARCH*, 13(3).
- Mehyar, H., Saeed, M., Baroom, H., Al-JaaAfreh, A., & Al-Adaileh, R. (2005). THE IMPACT OF ELECTRONIC WORD OF MOUTH ON CONSUMERS PURCHASING INTENTION *Vol.*, 02.
- Melian-Gonzalez, S., Bulchand-Gidumal, J., & González López-Valcárcel, B. (2013). Online Customer Reviews of Hotels: As Participation Increases, Better Evaluation Is Obtained. *Cornell Hospitality Quarterly*, 54(3), 274–283. <https://doi.org/10.1177/1938965513481498>
- Memon, M. A., Cheah, J.-H., Ramayah, T., Ting, H., Chuah, F., & Cham, T. H. (2019). Moderation analysis: Issues and guidelines. *Journal of Applied Structural Equation Modeling*, 3(1), 1–11.
- Menaka, B., & Seethal, K. (2018). Recent trends in e-commerce. *Shanlax International Journal of Commerce*, 6(S1), 40–44.
- Meng, Y., Yang, N., Qian, Z., & Zhang, G. (2020). What makes an online review more helpful: An interpretation framework using XGBoost and SHAP values. *Journal of Theoretical and Applied Electronic Commerce Research*, 16(3), 466–490.
- Meuter, M. L., McCabe, D. B., & Curran, J. M. (2013). Electronic Word-of-Mouth Versus Interpersonal Word-of-Mouth: Are All Forms of Word-of-Mouth Equally Influential? *Services Marketing Quarterly*, 34(3), 240–256. <https://doi.org/10.1080/15332969.2013.798201>

- Miller, T. I., & Miller, M. A. (1991). Standards of excellence: US residents' evaluations of local government services. *Public Administration Review*, 503–514.
- Millsap, R. E., & Yun-Tein, J. (2004). Assessing Factorial Invariance in Ordered-Categorical Measures. *Multivariate Behavioral Research*, 39(3), 479–515. https://doi.org/10.1207/S15327906MBR3903_4
- . Mishra, A., Dash, S., Malhotra, N., & Cyr, D. (2015). Measuring consumer design perceptions for digital devices: A multi-dimensional scale. *Journal of Brand Management*, 22(7), 603–630. <https://doi.org/10.1057/bm.2015.30>
- Mishra, A., & Satish, S. M. (2016). eWOM: Extant Research Review and Future Research Avenues. *Vikalpa: The Journal for Decision Makers*, 41(3), 222–233. <https://doi.org/10.1177/0256090916650952>
335. Mittal, V., Kumar, P., & Tsiros, M. (1999). Attribute-Level Performance, Satisfaction, and Behavioral Intentions over Time: A Consumption-System Approach. *Journal of Marketing*, 63(2), 88–101. <https://doi.org/10.1177/002224299906300206>
- Mohd Sam, M. F., & Tahir, M. N. H. (2009). Website quality and consumer online purchase intention of air ticket. *International Journal of Basic & Applied Sciences*, 9(10).
- Mohtaramzadeh, M., Ramayah, T., & Jun-Hwa, C. (2018). B2B E-Commerce Adoption in Iranian Manufacturing Companies: Analyzing the Moderating Role of Organizational Culture. *International Journal of Human-Computer Interaction*, 34(7), 621–639. <https://doi.org/10.1080/10447318.2017.1385212>
- Monaco, S. (2018). Tourism and the new generations: Emerging trends and social implications in Italy. *Journal of Tourism Futures*, 4(1), 7–15.
- Montano, D. E., & Kasprzyk, D. (2015). Theory of reasoned action, theory of planned behavior, and the integrated behavioral model. *Health Behavior: Theory, Research and Practice*, 70(4), 231.
- Moorman, R. H., Niehoff, B. P., & Organ, D. W. (1993). Treating employees fairly and organizational citizenship behavior: Sorting the effects of job satisfaction, organizational commitment, and procedural justice. *Employee Responsibilities and Rights Journal*, 6(3), 209–225. <https://doi.org/10.1007/BF01419445>

- Morgan, R. M., & Hunt, S. D. (1994). The Commitment-Trust Theory of Relationship Marketing. *Journal of Marketing*, 58(3), 20–38.
<https://doi.org/10.1177/002224299405800302>
- Moslehpour, M., Chaipayruk, P., Faez, S., & Wong, W.-K. (2021). Generation Y's sustainable purchasing intention of green personal care products. *Sustainability*, 13(23), 13385.
- Mudambi, S. M., & Schuff, D. (2010). Research note: What makes a helpful online review? A study of customer reviews on Amazon. com. *MIS Quarterly*, 185–200.
- Mude, G., & Undale, S. (2023). Social media usage: A comparison between Generation Y and Generation Z in India. *International Journal of E-Business Research (IJEER)*, 19(1), 1–20.
- Mukhopadhyay, S., Pandey, R., & Rishi, B. (2023). Electronic word of mouth (eWOM) research—a comparative bibliometric analysis and future research insight. *Journal of Hospitality and Tourism Insights*, 6(2), 404–424.
- Mulyani, V. G., Najib, M. F., & Guteres, A. D. (2021). The Effect of Perceived Usefulness, Trust and Visual Information on Attitude and Purchase Intention of Instagram Food Blogger. *Journal of Marketing Innovation*, 1(1), 78–93.
- Muralidhar, A., & Raja, A. S. (2019). Understanding the purchase intention characteristics of Gen Y and Gen Z and introspecting the modern demand variables in fashion industry. *International Journal of Scientific and Engineering Research*, 10(12), 144–170.
- Murray, K. B. (1991). A Test of Services Marketing Theory: Consumer Information Acquisition Activities. *Journal of Marketing*, 55(1), 10–25.
<https://doi.org/10.1177/002224299105500102>
- Mutz, D. C., & Reeves, B. (2005). The new videomalaise: Effects of televised incivility on political trust. *American Political Science Review*, 99(1), 1–15.
- Nam, K., Baker, J., Ahmad, N., & Goo, J. (2020). *Determinants of Writing Positive and Negative Electronic Word-of-Mouth: Empirical Evidence for Two Types of Expectation Confirmation*.
- Nam, K., Baker, J., Ahmad, N., & Goo, J. (2020). Determinants of writing positive and negative electronic word-of-mouth: Empirical evidence for two types of expectation confirmation. *Decision Support Systems*, 129, 113168.
<https://doi.org/10.1016/j.dss.2019.113168>

- Nanda, M. C. (2020). Gen-Z shopping: Separating myth from reality. *Business of Fashion*.
- Nandankar, S., & Sachan, A. (2023). Government-to-Business (G2B) E-Marketplace Adoption for E-Procurement: Indian Public Sector Perspective. *SCMS Journal of Indian Management*, 20(3).
- Nayak, R., Padhye, R., Wang, L., Chatterjee, K., & Gupta, S. (2015). The role of mass customisation in the apparel industry. *International Journal of Fashion Design, Technology and Education*, 8(2), 162–172. <https://doi.org/10.1080/17543266.2015.1045041>
- Nevo, D., & Chan, Y. E. (2007). A Delphi study of knowledge management systems: Scope and requirements. *Information & Management*, 44(6), 583–597.
- Ngah, R., Azizan, N. A., Kadir, M., Thuraishamy, R., Mohamad, Z., & Danila, N. (2021). Exploring antecedents of online purchasing behavioral intention of generation z: An integrated model of four theories. *Malaysian Journal of Consumer and Family Economics*, 27(1), 1–24.
- NGO, T. T. A., LE, T. M. T., NGUYEN, T. H., LE, T. G., NGO, G. T., & NGUYEN, T. D. (2022). The impact of sns advertisements on online purchase intention of generation z: An empirical study of tiktok in vietnam. *The Journal of Asian Finance, Economics and Business*, 9(5), 497–506.
- Ngo, T. T. A., Vuong, B. L., Le, M. D., Nguyen, T. T., Tran, M. M., & Nguyen, Q. K. (2024). The impact of eWOM information in social media on the online purchase intention of Generation Z. *Cogent Business & Management*, 11(1), 2316933. <https://doi.org/10.1080/23311975.2024.2316933>
- Nilashi, M., Abumalloh, R. A., Alghamdi, A., Minaei-Bidgoli, B., Alsulami, A. A., Thanoon, M., Asadi, S., & Samad, S. (2021). What is the impact of service quality on customers' satisfaction during COVID-19 outbreak? New findings from online reviews analysis. *Telematics and Informatics*, 64, 101693.
- OCass, A., & Choy, E. (2008). Studying Chinese generation Y consumers' involvement in fashion clothing and perceived brand status. *Journal of Product & Brand Management*, 17(5), 341–352.
- Ocloo, C. E., Xuhua, H., Akaba, S., Shi, J., & Worwui-Brown, D. K. (2020). The Determinant Factors of Business to Business (B2B) E-Commerce Adoption in Small- and Medium-Sized Manufacturing Enterprises. *Journal of Global*

- Information Technology Management*, 23(3), 191–216.
<https://doi.org/10.1080/1097198X.2020.1792229>
- Oguta, H., & Cezara, A. (2012). The factors affecting writing reviews in hotel websites. *Procedia-Social and Behavioral Sciences*, 58, 980–986.
- Oliver, C. (1997). Sustainable competitive advantage: Combining institutional and resource-based views. *Strategic Management Journal*, 18(9), 697–713.
- Oliver, R. L. (1980). A Cognitive Model of the Antecedents and Consequences of Satisfaction Decisions. *Journal of Marketing Research*, 17(4), 460–469.
<https://doi.org/10.1177/002224378001700405>
- Oliver, R. L. (1993). Cognitive, affective, and attribute bases of the satisfaction response. *Journal of Consumer Research*, 20(3), 418–430.
- Olshavsky, R. W. (1979). Task complexity and contingent processing in decision making: A replication and extension. *Organizational Behavior and Human Performance*, 24(3), 300–316.
- Ordun, G. (2015). Millennial (Gen Y) consumer behavior their shopping preferences and perceptual maps associated with brand loyalty. *Canadian Social Science*, 11(4), 40–55.
- Osborne, J. W., & Banjanovic, E. S. (2016). *Exploratory factor analysis with SAS*. Sas Institute.
- Owusu-Bempah, E., Opoku, D., & Sam-Mensah, R. (2022). Gender Differences in E-Learning Success in a Developing Country Context: A Multi-Group Analysis. *European Journal of Education and Pedagogy*, 3(4), 61–69.
<https://doi.org/10.24018/ejedu.2022.3.4.410>
- Ozbuluk, T., & Akdogan, K. (2022). The role of online source credibility and influencer identification on consumers' purchase decisions. *International Journal of Internet Marketing and Advertising*, 16(1/2), 165.
<https://doi.org/10.1504/IJIMA.2022.120974>
- Pan, Y., & Zhang, J. Q. (2011). Born unequal: A study of the helpfulness of user-generated product reviews. *Journal of Retailing*, 87(4), 598–612.
- Panigrahi, C. M. A., Upadhyaya, R., & Raichurkar, P. P. (2016). E-commerce services in India: Prospects and problems. *International Journal on Textile Engineering and Processes*, 2(1).
- Parasuraman, A., Zeithaml, V. A., & Berry, L. L. (1988). Servqual: A multiple-item scale for measuring consumer perc. *Journal of Retailing*, 64(1), 12.

- Parikh, A. A., Behnke, C., Nelson, D., Vorvoreanu, M., & Almanza, B. (2015). A Qualitative Assessment of Yelp.Com Users' Motivations to Submit and Read Restaurant Reviews. *Journal of Culinary Science & Technology*, 13(1), 1–18. <https://doi.org/10.1080/15428052.2014.952474>
- Park, C., & Lee, T. M. (2009). Antecedents of Online Reviews' Usage and Purchase Influence: An Empirical Comparison of U.S. and Korean Consumers. *Journal of Interactive Marketing*, 23(4), 332–340. <https://doi.org/10.1016/j.intmar.2009.07.001>
- Park, C. W., Sutherland, I., & Lee, S. K. (2021). Effects of online reviews, trust, and picture-superiority on intention to purchase restaurant services. *Journal of Hospitality and Tourism Management*, 47, 228–236.
- Park, D.-H., & Kim, S. (2008). The effects of consumer knowledge on message processing of electronic word-of-mouth via online consumer reviews. *Electronic Commerce Research and Applications*, 7(4), 399–410.
- Park, D.-H., Lee, J., & Han, I. (2006). *Information overload and its consequences in the context of online consumer reviews*.
- Park, D.-H., Lee, J., & Han, I. (2007). The Effect of On-Line Consumer Reviews on Consumer Purchasing Intention: The Moderating Role of Involvement. *International Journal of Electronic Commerce*, 11(4), 125–148. <https://doi.org/10.2753/JEC1086-4415110405>
- Park, J., Hyun, H., & Thavisay, T. (2021). A study of antecedents and outcomes of social media WOM towards luxury brand purchase intention. *Journal of Retailing and Consumer Services*, 58, 102272.
- Park, S., & Nicolau, J. L. (2015). Asymmetric effects of online consumer reviews. *Annals of Tourism Research*, 50, 67–83.
- Patalano, C. (2008). *A study of the relationship between generational group identification and organizational commitment: Generation X vs. Generation Y*. Nova Southeastern University.
- Patterson, M. G., West, M. A., Lawthom, R., & Nickell, S. (1997). *Impact of people management practices on business performance* (Vol. 22). Citeseer.
- Patterson, P. G., Johnson, L. W., & Spreng, R. A. (1997). Modeling the determinants of customer satisfaction for business-to-business professional services. *Journal of the Academy of Marketing Science*, 25, 4–17.

- Pelzang, R., & Hutchinson, A. M. (2018). Patient safety issues and concerns in Bhutan's healthcare system: A qualitative exploratory descriptive study. *BMJ Open*, 8(7), e022788.
- Peng, C.-H., Yin, D., Wei, C.-P., & Zhang, H. (2014). *How and when review length and emotional intensity influence review helpfulness: Empirical evidence from Epinions. com.*
- Peng, M. Y. P., Liang, Z., Fatima, I., Wang, Q., & Rasheed, M. I. (2023). The nexus between empowering leadership, job engagement and employee creativity: Role of creative self-efficacy in the hospitality industry. *Kybernetes*.
- Picazo-Vela, S. (2009). *The Effect of Online Reviews on Customer Satisfaction: An Expectation Disconfirmation Approach.*
- Pico-Saltos, R., Sabando-Vera, D., Yonfa-Medrandá, M., Garzías, J., & Redchuk, A. (2022). Hierarchical Component Model (HCM) of Career Success and the Moderating Effect of Gender, from the Perspective of University Alumni: Multigroup Analysis and Empirical Evidence from Quevedo, Ecuador. *Sustainability*, 15(1), 540.
- Polit, D. F., & Beck, C. T. (2008). *Nursing research: Generating and assessing evidence for nursing practice.* Lippincott Williams & Wilkins.
- Pooja, K., & Upadhyaya, P. (2024). What makes an online review credible? A systematic review of the literature and future research directions. *Management Review Quarterly*, 74(2), 627–659. <https://doi.org/10.1007/s11301-022-00312-6>
- Popa, A., Barbu, C. A., & Ionaşcu, A. E. (2023). The New Paradigm of Online Marketing: A Study of Generation Z Consumers' Behaviour and Their Attitude Towards Brands. *New Trends in Sustainable Business and Consumption*, 359–368.
- Pradana, M. (2015). Klasifikasi jenis-jenis bisnis e-commerce di Indonesia. *Neo-Bis*, 9(2), 32–40.
- Prajapati, D., Chan, F. T., Chelladurai, H., Lakshay, L., & Pratap, S. (2022). An internet of things embedded sustainable supply chain management of B2B E-commerce. *Sustainability*, 14(9), 5066.
- Prakash, N., Alagarsamy, S., & Hawaldar, A. (2022). Demographic characteristics influencing financial wellbeing: A multigroup analysis. *Managerial Finance*, 48(9/10), 1334–1351.

- Prasanth, V. S., & Jyothsna, M. (2018). E-commerce Business Models. *International Journal of Business, Management and Allied Sciences*, 11–15.
- Priporas, C.-V., Stylos, N., & Fotiadis, A. K. (2017). Generation Z consumers' expectations of interactions in smart retailing: A future agenda. *Computers in Human Behavior*, 77, 374–381.
- Priporas, C.-V., Stylos, N., Rahimi, R., & Vedanthachari, L. N. (2017). Unraveling the diverse nature of service quality in a sharing economy: A social exchange theory perspective of Airbnb accommodation. *International Journal of Contemporary Hospitality Management*, 29(9), 2279–2301.
- Puiu, S., Demyen, S., Tanase, A.-C., Varzaru, A. A., & Bocean, C. G. (2022). Assessing the adoption of mobile technology for commerce by generation Z. *Electronics*, 11(6), 866.
- Purwianti, L., & Niawati, N. (2022). Analysis of e-WOM, Brand Attitude, Brand Image on Purchase Intention. *SEIKO: Journal of Management & Business*, 5(1), 356–366.
- Qader, I. K. A., & Omar, A. B. (2013). The evolution of experiential marketing: Effects of brand experience among the millennial generation. *International Journal of Academic Research in Business and Social Sciences*, 3(7), 331.
- Qazi, A., Tamjidyamcholo, A., Raj, R. G., Hardaker, G., & Standing, C. (2017a). Assessing consumers' satisfaction and expectations through online opinions: Expectation and disconfirmation approach. *Computers in Human Behavior*, 75, 450–460.
- Qazi, A., Tamjidyamcholo, A., Raj, R. G., Hardaker, G., & Standing, C. (2017b). Assessing consumers' satisfaction and expectations through online opinions: Expectation and disconfirmation approach. *Computers in Human Behavior*, 75, 450–460. <https://doi.org/10.1016/j.chb.2017.05.025>
- Qin, C., Zeng, X., Liang, S., & Zhang, K. (2023). Do Live Streaming and Online Consumer Reviews Jointly Affect Purchase Intention? *Sustainability*, 15(8), 6992. <https://doi.org/10.3390/su15086992>
- Qiu, H., Wang, X., Wu, M.-Y., Wei, W., Morrison, A. M., & Kelly, C. (2023). The effect of destination source credibility on tourist environmentally responsible behavior: An application of stimulus-organism-response theory. *Journal of Sustainable Tourism*, 31(8), 1797–1817. <https://doi.org/10.1080/09669582.2022.2067167>

- Qu, W. G., Pinsonneault, A., Tomiuk, D., Wang, S., & Liu, Y. (2015). The impacts of social trust on open and closed B2B e-commerce: A Europe-based study. *Information & Management*, 52(2), 151–159.
- Quaschnig, S., Pandelaere, M., & Vermeir, I. (2015). When consistency matters: The effect of valence consistency on review helpfulness. *Journal of Computer-Mediated Communication*, 20(2), 136–152.
- Rachbini, W., Anggraeni, D., & Wulanjani, H. (2021). The influence of electronic service quality and electronic word of mouth (eWOM) toward repurchase intention (study on e-commerce in Indonesia). *Jurnal Komunikasi: Malaysian Journal of Communication*, 37(1), 42–58.
- Rachmiani, R., Oktadinna, N. K., & Fauzan, T. R. (2024). The Impact of Online Reviews and Ratings on Consumer Purchasing Decisions on E-commerce Platforms. *International Journal of Management Science and Information Technology*, 4(2), 504-515.
- Rajasa, E. Z., Manap, A., Ardana, P. D. H., Yusuf, M., & Harizahayu, H. (2023). Literature Review: Analysis Of Factors Influencing Purchasing Decisions, Product Quality And Competitive Pricing. *Jurnal Ekonomi*, 12(01), 451–455.
- Raport, J. F., & Jaworski, B. J. (2001). E-Commerce. *Wydawnictwa Internet Standard (2009–2013)*.
- Rausch, T. M., & Kopplin, C. S. (2021). Bridge the gap: Consumers' purchase intention and behavior regarding sustainable clothing. *Journal of Cleaner Production*, 278, 123882.
- Raziei, S. (2020). Evaluation of the implementation of C2B, B2C, B2B, A2C and A2B models of e-commerce in excellence education system of academic institutions using AHP and fuzzy AHP. *International Journal of E-Education, e-Business, e-Management and e-Learning*, 10(1), 13–24.
- Reisenwitz, T. H., & Iyer, R. (2009). Differences in generation X and generation Y: Implications for the organization and marketers. *Marketing Management Journal*, 19(2).
- Rekha, R. S., Islam, M. A., & Hossain, M. I. (2016). MEASURING CUSTOMER SATISFACTION USING ATM CARD IN BANGLADESH: AN APPLICATION OF EXPECTANCY-DISCONFIRMATION THEORY.

CLEAR International Journal of Research in Commerce & Management, 7(10).

- Roldan Bravo, M. I., Llorens Montes, F. J., & Ruiz Moreno, A. (2017). Open innovation in supply networks: An expectation disconfirmation theory perspective. *Journal of Business & Industrial Marketing*, 32(3), 432–444.
- Ruiz-Mafe, C., Bigné-Alcañiz, E., & Currás-Pérez, R. (2020). The effect of emotions, eWOM quality and online review sequence on consumer intention to follow advice obtained from digital services. *Journal of Service Management*, 31(3), 465–487.
- Ruiz-Mafe, C., & Veloutsou, C. (2017). Information flow and WOM in social media and online communities. *Online Information Review*, 41(7), 902–904.
- Saag, M. S., Benson, C. A., Gandhi, R. T., Hoy, J. F., Landovitz, R. J., Mugavero, M. J., Sax, P. E., Smith, D. M., Thompson, M. A., & Buchbinder, S. P. (2018). Antiretroviral drugs for treatment and prevention of HIV infection in adults: 2018 recommendations of the International Antiviral Society–USA Panel. *Jama*, 320(4), 379–396.
- Safitriani, A., & Auliya, Z. F. (2023). THE EFFECT OF CREDIBILITY, QUALITY, AND QUANTITY OF EWOM ON PURCHASE INTENTION. *Efektif: Jurnal Bisnis Dan Ekonomi*, 14(1 Juni), 40–57.
- Sakshi, S., Gao, Y., Rana, S., Ravichandran, S. S., Kharub, M., & Jasim, K. M. (2024). Decoding Gen Y Online Shopping Patterns: A Model-based Study. *Vision: The Journal of Business Perspective*, 09722629231216822. <https://doi.org/10.1177/09722629231216822>
- Santos, J. (2003). E-service quality: A model of virtual service quality dimensions. *Managing Service Quality: An International Journal*, 13(3), 233–246.
- Santos, V., Augusto, T., Vieira, J., Bacalhau, L., Sousa, B. M., & Pontes, D. (2023). E-commerce: Issues, opportunities, challenges, and trends. *Promoting Organizational Performance through 5G and Agile Marketing*, 224–244.
- Sarstedt, M., Hair, J. F., Cheah, J.-H., Becker, J.-M., & Ringle, C. M. (2019). How to Specify, Estimate, and Validate Higher-Order Constructs in PLS-SEM. *Australasian Marketing Journal*, 27(3), 197–211. <https://doi.org/10.1016/j.ausmj.2019.05.003>
- Satheeshkumar, D. R., Thiagarajan, V., Krishnan, D. S. G., & Rawath, S. S. (2022). A Study on Customers Perspective on Opportunities and Challenges of E-

- Commerce in India. *A Study on Customers Perspective on Opportunities and Challenges of E-Commerce in India. International Journal of Economics, Finance and Management Sciences*, 10(4), 229–23.
- Satinover Nichols, B., & Wehr Holt, J. (2023). A comparison of sustainability attitudes and intentions
- Schiffman, L. G. (1972). Perceived Risk in New Product Trial by Elderly Consumers. *Journal of Marketing Research*, 9(1), 106–108.
<https://doi.org/10.1177/002224377200900125>
- Schiffman, L. G., Kanuk, L. L., & Kumar, S. R. (1951). Consumer. *Marketing*.
- Cheah, J.-H., Thurasamy, R., Memon, M. A., NUST Business School, Chuah, F., Ting, H; (2020). Multigroup Analysis using SmartPLS: Step-by-Step Guidelines for Business Research. *Asian Journal of Business Research*, 10(3).
<https://doi.org/10.14707/ajbr.200087>
- Schroer, J. E. (2011). *The Psychosocial Effects of the French Republican Model of Education*. University of Cincinnati.
- Schuckert, M., Liu, X., & Law, R. (2015). Hospitality and Tourism Online Reviews: Recent Trends and Future Directions. *Journal of Travel & Tourism Marketing*, 32(5), 608–621. <https://doi.org/10.1080/10548408.2014.933154>
- Schwarz, C., & Zhu, Z. (2015). The impact of student expectations in using instructional tools on student engagement: A look through the expectation disconfirmation theory lens. *Journal of Information Systems Education*, 26(1), 47.
- Selnes, F. (1998). Antecedents and consequences of trust and satisfaction in buyer-seller relationships. *European Journal of Marketing*, 32(3/4), 305–322.
- Serenko, A., & Stach, A. (2009). The impact of expectation disconfirmation on customer loyalty and recommendation behavior: Investigating online travel and tourism services. *Journal of Information Technology Management*, 20(3), 26–41.
- Serrano, C. I., Shah, V., & Abramoff, M. D. (2018). Use of expectation disconfirmation theory to test patient satisfaction with asynchronous telemedicine for diabetic retinopathy detection. *International Journal of Telemedicine and Applications*, 2018(1), 7015272.

- Sethna, B. N., Hazari, S., & Bergiel, B. (2017). *Influence of user generated content in online shopping: Impact of gender on purchase behaviour, trust, and intention to purchase.*
- Setyarini, T., Wanto, A. H., & Sentanu, I. G. E. P. S. (2024). Moderating Gender in Work From Home Policy Implementation on State Civil Apparatus Performance using Multigroup Analysis. *Jurnal Borneo Administrator*, 20(1), 71–84.
- Shadrach, F. D., Santhosh, M., Vignesh, S., Sneha, S., & Sivakumar, T. (2022). Smart virtual trial room for apparel industry. *2022 IEEE International Conference on Distributed Computing and Electrical Circuits and Electronics (ICDCECE)*, 1–5.
- Shah, C. S., & Unnithan, A. B. (2020). *Why People Read Online Reviews: Scale Development to Measure Motivations.*
- Shah, H., Carrel, A. L., & Le, H. T. K. (2024). Impacts of teleworking and online shopping on travel: A tour-based analysis. *Transportation*, 51(1), 99–127. <https://doi.org/10.1007/s11116-022-10321-9>
- Sharma, P. N., Liengard, B. D., Hair, J. F., Sarstedt, M., & Ringle, C. M. (2023). Predictive model assessment and selection in composite-based modeling using PLS-SEM: Extensions and guidelines for using CVPAT. *European Journal of Marketing*, 57(6), 1662–1677. <https://doi.org/10.1108/EJM-08-2020-0636>
- Shaw, N., Eschenbrenner, B., & Baier, D. (2022). Online shopping continuance after COVID-19: A comparison of Canada, Germany and the United States. *Journal of Retailing and Consumer Services*, 69, 103100.
- Shek, D. T. L., & Yu, L. (2014). Confirmatory factor analysis using AMOS: A demonstration. *International Journal on Disability and Human Development*, 13(2). <https://doi.org/10.1515/ijdhhd-2014-0305>
- Sheth, J. N. (1971). Word-of-Mouth in low risk innovations. *Journal of Advertising*, 11(3), 15–18.
- Shin, E., Kincade, D. H., & Han, J. (2022). Exploring Online Consumer Reviews Regarding Customized Apparel Products Through the Eyes of Expectation-Confirmation Theory. *International Textile and Apparel Association Annual Conference Proceedings*, 79(1).
- Shin, H.-R., & Choi, J.-G. (2021). The Moderating Effect of ‘Generation’ on the Relations between Source Credibility of Social Media Contents, Hotel Brand

- Image, and Purchase Intention. *Sustainability*, 13(16), 9471.
<https://doi.org/10.3390/su13169471>
- Shmueli, G., Sarstedt, M., Hair, J. F., Cheah, J.-H., Ting, H., Vaithilingam, S., & Ringle, C. M. (2019). Predictive model assessment in PLS-SEM: Guidelines for using PLSpredict. *European Journal of Marketing*, 53(11), 2322–2347.
<https://doi.org/10.1108/EJM-02-2019-0189>
- Shrestha, N. (2021). Factor Analysis as a Tool for Survey Analysis. *American Journal of Applied Mathematics and Statistics*, 9(1), 4–11.
<https://doi.org/10.12691/ajams-9-1-2>
- Siering, M., Muntermann, J., & Rajagopalan, B. (2018). Explaining and predicting online review helpfulness: The role of content and reviewer-related signals. *Decision Support Systems*, 108, 1–12.
- Singh, A. P., & Dangmei, J. (2016). Understanding the generation Z: The future workforce. *South-Asian Journal of Multidisciplinary Studies*, 3(3), 1–5.
- Singh, M., Kulshrestha, S., Goel, M. R., Kumar, N., & Kumar, M. R. (2024). THE EFFECT OF AI ON INDIAN E-COMMERCE MARKET. *Journal of Digital Economy*, 3(2), 392–401.
- Singh, R. K. (2019a). E-commerce in India: Opportunities and challenges. *Proceedings of 10th International Conference on Digital Strategies for Organizational Success*.
- Sinha, S., Jawahar, I. M., Ghosh, P., & Mishra, A. (2020). Assessing employers' satisfaction with Indian engineering graduates using expectancy-disconfirmation theory. *International Journal of Manpower*, 41(4), 473–489.
- SivaKumar, A., & Gunasekaran, A. (2017). An empirical study on the factors affecting online shopping behavior of millennial consumers. *Journal of Internet Commerce*, 16(3), 219–230.
- Skare, M., Gavurova, B., & Rigelsky, M. (2023). Innovation activity and the outcomes of B2C, B2B, and B2G E-Commerce in EU countries. *Journal of Business Research*, 163, 113874.
- Slootweg, E., & Rowson, B. (2018). My generation: A review of marketing strategies on different age groups. *Research in Hospitality Management*, 8(2), 85–92.
- Soewandi, M. (2015). The impact of social media communication forms on brand equity dimensions and consumer purchase intention. *iBuss Management*, 3(2).

- Sohrabi, B., & Khanlari, A. (2015). G2C Marketing: Dimensions and Functions of ZRM. In *Marketing and Consumer Behavior: Concepts, Methodologies, Tools, and Applications* (pp. 2183–2199). IGI Global.
- Song, S. W., & Shin, M. (2024). Uncanny Valley Effects on Chatbot Trust, Purchase Intention, and Adoption Intention in the Context of E-Commerce: The Moderating Role of Avatar Familiarity. *International Journal of Human-Computer Interaction*, 40(2), 441–456. <https://doi.org/10.1080/10447318.2022.2121038>
- Sotiriadis, M. D., & Van Zyl, C. (2013). Electronic word-of-mouth and online reviews in tourism services: The use of twitter by tourists. *Electronic Commerce Research*, 13, 103–124.
- Sparks, B. A., & Browning, V. (2010). Complaining in Cyberspace: The Motives and Forms of Hotel Guests' Complaints Online. *Journal of Hospitality Marketing & Management*, 19(7), 797–818. <https://doi.org/10.1080/19368623.2010.508010>
- Spears, N., & Singh, S. N. (2004). Measuring Attitude toward the Brand and Purchase Intentions. *Journal of Current Issues & Research in Advertising*, 26(2), 53–66. <https://doi.org/10.1080/10641734.2004.10505164>
- Spreng, R. A., MacKenzie, S. B., & Olshavsky, R. W. (1996). A reexamination of the determinants of consumer satisfaction. *Journal of Marketing*, 60(3), 15–32.
- Spurling, G. K., Mansfield, P. R., Montgomery, B. D., Lexchin, J., Doust, J., Othman, N., & Vitry, A. I. (2010). Information from pharmaceutical companies and the quality, quantity, and cost of physicians' prescribing: A systematic review. *PLoS Medicine*, 7(10), e1000352.
- Srisathan, W. A., Wongsachia, S., Gebombut, N., Naruetharadhol, P., & Ketkaew, C. (2023). The green-awakening customer attitudes towards buying green products on an online platform in Thailand: The multigroup moderation effects of age, gender, and income. *Sustainability*, 15(3), 2497.
- Steffes, E. M., & Burgee, L. E. (2009). Social ties and online word of mouth. *Internet Research*, 19(1), 42–59.
- Su, B.-C., Wu, L.-W., Lin, H., & Lin, C.-A. (2023). The mediating effect of herd behavior and brand attitude towards the impact of spokesman credibility, source fit, and online word-of-mouth on purchase intention. *Sustainability*, 15(1), 888.

- Sudirjo, F., Lotte, L. N. A., Sutaguna, I. N. T., Risdwiyanto, A., & Yusuf, M. (2023). The Influence of Generation Z Consumer Behavior on Purchase Motivation in E-Commerce Shoppe. *Profit: Jurnal Manajemen, Bisnis Dan Akuntansi*, 2(2), 110–126.
- Sun, Y., & Xing, J. (2022). The impact of social media information sharing on the green purchase intention among generation Z. *Sustainability*, 14(11), 6879.
- Sundaram, D. S., Mitra, K., & Webster, C. (1998). Word-of-mouth communications: A motivational analysis. *Advances in Consumer Research*, 25(1).
- Surucu, L., & Maslakci, A. (2020). Validity and reliability in quantitative research. *Business & Management Studies: An International Journal*, 8(3), 2694–2726.
- Sussman, S. W., & Siegal, W. S. (2003). Informational Influence in Organizations: An Integrated Approach to Knowledge Adoption. *Information Systems Research*, 14(1), 47–65. <https://doi.org/10.1287/isre.14.1.47.14767>
- Swan, J. E., & Trawick, I. F. (1981). Disconfirmation of expectations and satisfaction with a retail service. *Journal of Retailing*.
- Swarbrooke, J., & Horner, S. (2007). *Consumer behaviour in tourism*. Routledge.
- Swarnakar, P., Kumar, A., & Kumar, S. (2016). Why generation Y prefers online shopping: A study of young customers of India. *International Journal of Business Forecasting and Marketing Intelligence*, 2(3), 215. <https://doi.org/10.1504/IJBFMI.2016.078604>
- Sweeney, J. C., Soutar, G. N., & Mazzarol, T. (2008). Factors influencing word of mouth effectiveness: Receiver perspectives. *European Journal of Marketing*, 42(3/4), 344–364.
- Szymkowiak, A., Melovic, B., Dabić, M., Jeganathan, K., & Kundi, G. S. (2021). Information technology and Gen Z: The role of teachers, the internet, and technology in the education of young people. *Technology in Society*, 65, 101565.
- Tabassum, S., Khwaja, M. G., & Zaman, U. (2020). Can Narrative Advertisement and eWOM Influence Generation Z Purchase Intentions? *Information*, 11(12), 545. <https://doi.org/10.3390/info11120545>
- Taherdoost, H. (2023). E-Business Models and Strategies. In H. Taherdoost, *E-Business Essentials* (pp. 25–50). Springer Nature Switzerland. https://doi.org/10.1007/978-3-031-39626-7_2

- Tan, K.-L., Sim, A. K., & Donohue, T. (2022). To predict and to explain: A multigroup analysis of gender on job and family satisfaction among hospitality employees. *Gender in Management: An International Journal*, 37(7), 891–911.
- Tehseen, S., Ramayah, T., & Sajilan, S. (2017). Testing and Controlling for Common Method Variance: A Review of Available Methods. *Journal of Management Sciences*, 4(2), 142–168. <https://doi.org/10.20547/jms.2014.1704202>
- Thakur, S., Kashyap, S. K., & Nim, D. (2020). E-Governance Dimensions and Performance Measures: Conceptual Framework with Reference to G2B Initiatives. *Information and Communications Technology (ICT)*, 29(03), 5442–5455.
- Thangavel, P., Pathak, P., & Chandra, B. (2022). Consumer Decision-making Style of Gen Z: A Generational Cohort Analysis. *Global Business Review*, 23(3), 710–728. <https://doi.org/10.1177/0972150919880128>
- Thompson, B. (2004). Exploratory and confirmatory factor analysis: Understanding concepts and applications. *Washington, DC*, 10694(000), 3.
- Tian, G., Lu, L., & McIntosh, C. (2021). What factors affect consumers' dining sentiments and their ratings: Evidence from restaurant online review data. *Food Quality and Preference*, 88, 104060.
- Tiwari, A., Kumar, A., Kant, R., & Jaiswal, D. (2024). Impact of fashion influencers on consumers' purchase intentions: Theory of planned behaviour and mediation of attitude. *Journal of Fashion Marketing and Management: An International Journal*, 28(2), 209–225.
- Tiwari, P., & Joshi, H. (2020). Factors influencing online purchase intention towards online shopping of Gen Z. *International Journal of Business Competition and Growth*, 7(2), 175. <https://doi.org/10.1504/IJBCG.2020.111944>
- Tran, M., Pham, T., Phan, T., Hoang, T., Do, D., & Dinh, T. (2019). Factors influencing independent audit fees: Multi-group analysis PLS-SEM and moderate model. *Management Science Letters*, 9(10), 1599–1608.
- Trenz, M., & Berger, B. (2013). *Analyzing online customer reviews-an interdisciplinary literature review and research agenda*.
- Tsai, C.-F., Chen, K., Hu, Y.-H., & Chen, W.-K. (2020). Improving text summarization of online hotel reviews with review helpfulness and sentiment. *Tourism Management*, 80, 104122.

- Tse, D. K., & Wilton, P. C. (1988). Models of consumer satisfaction formation: An extension. *Journal of Marketing Research*, 25(2), 204–212.
- Tseng, L. Y., Xu, H. N., Lian, Y. Y., & Xue, J. Y. (2022). The Influencing Mechanism of Perceived UGC Quality on Gen Z Consumers' Loyalty—An Empirical Analysis. *2022 3rd International Conference on E-Commerce and Internet Technology (ECIT 2022)*, 237–247.
494. Tseng, L.-Y., Chang, J.-H., & Zhu, Y. L. (2024). What drives the travel switching behavior of Chinese Generation Z consumers. *Journal of Tourism Futures*, 10(1), 131–146.
- Tsichla, E., Hatzithomas, L., & Boutsouki, C. (2016). Gender differences in the interpretation of web atmospherics: A selectivity hypothesis approach. *Journal of Marketing Communications*, 22(6), 563–586. <https://doi.org/10.1080/13527266.2014.903507>
- Utomo, S. B., Jamali, H., Arief, I., Saputra, M. N., & Priambodo, C. G. (2023). Analysis of The Influence of Hedonic Digital Lifestyle on Consumptive E-Shopping Behavior of Generation Z Through E-Commerce Applications. *Jurnal Sistim Informasi Dan Teknologi*, 85–91.
- Vafaei-Zadeh, A., Wong, T.-K., Hanifah, H., Teoh, A. P., & Nawaser, K. (2022). Modelling electric vehicle purchase intention among generation Y consumers in Malaysia. *Research in Transportation Business & Management*, 43, 100784.
- Valaei, N., & Nikhashemi, S. R. (2017). Generation Y consumers' buying behaviour in fashion apparel industry: A moderation analysis. *Journal of Fashion Marketing and Management: An International Journal*, 21(4), 523–543.
- Van Ryzin, G. G. (2006). Testing the expectancy disconfirmation model of citizen satisfaction with local government. *Journal of Public Administration Research and Theory*, 16(4), 599–611.
- Van Ryzin, G. G. (2013). An experimental test of the expectancy-disconfirmation theory of citizen satisfaction. *Journal of Policy Analysis and Management*, 32(3), 597–614.
- Vana, P., & Lambrecht, A. (2021). The Effect of Individual Online Reviews on Purchase Likelihood. *Marketing Science*, 40(4), 708–730. <https://doi.org/10.1287/mksc.2020.1278>

- Vasan, M. (2023). Impact of promotional marketing using Web 2.0 tools on purchase decision of Gen Z. *Materials Today: Proceedings*, 81, 273–276.
- Vazquez, E. E., Patel, C., Alvidrez, S., & Siliceo, L. (2023). Images, reviews, and purchase intention on social commerce: The role of mental imagery vividness, cognitive and affective social presence. *Journal of Retailing and Consumer Services*, 74, 103415.
- Vazquez-Casielles, R., Suárez-Álvarez, L., & del Río-Lanza, A.-B. (2013). The word of mouth dynamic: How positive (and negative) WOM drives purchase probability: An analysis of interpersonal and non-interpersonal factors. *Journal of Advertising Research*, 53(1), 43–60.
- Venkatesh, V., & Goyal, S. (2010). Expectation disconfirmation and technology adoption: Polynomial modeling and response surface analysis. *MIS Quarterly*, 281–303.
- Venkatesh, V., & Morris, M. G. (2000). Why don't men ever stop to ask for directions? Gender, social influence, and their role in technology acceptance and usage behavior. *MIS Quarterly*, 115–139.
- Verma, D., & Dewani, P. P. (2021). eWOM credibility: A comprehensive framework and literature review. *Online Information Review*, 45(3), 481–500.
- Verma, S., & Yadav, N. (2021). Past, Present, and Future of Electronic Word of Mouth (EWOM). *Journal of Interactive Marketing*, 53, 111–128. <https://doi.org/10.1016/j.intmar.2020.07.001>
- Vinerean, S., Opreana, A., Budac, C., & Mihaiu, D. M. (2025). Does Gender Matter for Electronic Word-of-Mouth Interactions in Social Media Marketing Strategies? An Empirical Multi-Sample Approach. *Journal of Theoretical and Applied Electronic Commerce Research*, 20(2), 79.
- Vizcaya-Moreno, M. F., & Pérez-Cañaveras, R. M. (2020). Social media used and teaching methods preferred by generation z students in the nursing clinical learning environment: A cross-sectional research study. *International Journal of Environmental Research and Public Health*, 17(21), 8267.
- Walsh, G., Hennig-Thurau, T., Sassenberg, K., & Bornemann, D. (2010). Does relationship quality matter in e-services? A comparison of online and offline retailing. *Journal of Retailing and Consumer Services*, 17(2), 130–142.

- Walsh, V. (2003). A theory of magnitude: Common cortical metrics of time, space and quantity. *Trends in Cognitive Sciences*, 7(11), 483–488.
- Wang, E. T. G., Yeh, H., & Jiang, J. J. (2006). The relative weights of Internet shopping fundamental objectives: Effect of lifestyle differences. *Psychology & Marketing*, 23(5), 353–367. <https://doi.org/10.1002/mar.20116>
- Wang, J. J., Zhang, S., & Zhang, J. J. (2019). Moderating Effects of Gender and Life Cycle in the Relationship between Desired Self-Image and Sport Participation Behavior: A Multi-Group Analysis. *Measurement in Physical Education and Exercise Science*, 23(4), 337–350. <https://doi.org/10.1080/1091367X.2018.1528977>
- Wang, R. (2015). Internet use and the building of social capital for development: A network perspective. *Information Technologies & International Development*, 11(2), pp-19.
- Wang, Y., & Kuchmaner, C. A. (2024). Revisiting online reviews: Signals of latent reviewer traits mediate the review length-helpfulness relationship. *Journal of Marketing Theory and Practice*, 32(3), 346–361. <https://doi.org/10.1080/10696679.2023.2196636>
- Wathen, C. N., & Burkell, J. (2002). Believe it or not: Factors influencing credibility on the Web. *Journal of the American Society for Information Science and Technology*, 53(2), 134–144. <https://doi.org/10.1002/asi.10016>
- Wei, Z., Tang, Q., & Zhen, F. (2024). Spatial and social heterogeneities of residents' online shopping behaviors within a large Chinese city: The case of Weifang. *Applied Geography*, 167, 103289.
- Westbrook, R. A., & Reilly, M. D. (1983). Value-percept disparity: An alternative to the disconfirmation of expectations theory of consumer satisfaction. *Advances in Consumer Research*, 10(1).
- Westerman, J. W., & Yamamura, J. H. (2007). Generational preferences for work environment fit: Effects on employee outcomes. *Career Development International*, 12(2), 150–161.
- Weston, J. F. (2015). *The greatest generation II: A narrative study of post-9/11 veterans in higher education*
- Wey Smola, K., & Sutton, C. D. (2002). Generational differences: Revisiting generational work values for the new millennium. *Journal of Organizational Behavior*, 23(4), 363–382. <https://doi.org/10.1002/job.147>

- White, M. M. (2019). Gearing up for Gen Z: An analysis of employers' recruitment marketing targeting the new, Generation Z, workforce.
- Wiedmann, K.-P., Walsh, G., & Mitchell, V.-W. (2001). The Mannmaven: An agent for diffusing market information. *Journal of Marketing Communications*, 7(4), 195–212. <https://doi.org/10.1080/13527260127413>
- Willemsen, L. M., Neijens, P. C., Bronner, F., & De Ridder, J. A. (2011). "Highly recommended!" The content characteristics and perceived usefulness of online consumer reviews. *Journal of Computer-Mediated Communication*, 17(1), 19–38.
- Williams, B., Onsman, A., & Brown, T. (2010). Exploratory Factor Analysis: A Five-Step Guide for Novices. *Australasian Journal of Paramedicine*, 8, 1–13. <https://doi.org/10.33151/ajp.8.3.93>
- Williams, K. C., Page, R. A., Petrosky, A. R., & Hernandez, E. H. (2010). Multi-generational marketing: Descriptions, characteristics, lifestyles, and attitudes. *The Journal of Applied Business and Economics*, 11(2), 21.
- Wolf, M. M., Wolf, M., & Lecat, B. (2022). Wine market segmentation by age generations in the Western US: Expectations after the COVID-19 pandemic. *International Journal of Wine Business Research*, 34(3), 373–391.
- Wong, K. K.-K. (2013). *Partial Least Squares Structural Equation Modeling (PLS-SEM) Techniques Using SmartPLS*.
- Wong, K. K.-K. (2016). Mediation analysis, categorical moderation analysis, and higher-order constructs modeling in Partial Least Squares Structural Equation Modeling (PLS-SEM): A B2B Example using SmartPLS. *Marketing Bulletin*, 26(1), 1–22.
- Workman, J. E., & Lee, S.-H. (2017). A Critical Appraisal of 25 Years of Research Related to Fashion Adoption Groups: Part 2. Analysis of Variables, Research Propositions, and Research Trends. *Clothing and Textiles Research Journal*, 35(4), 272–289. <https://doi.org/10.1177/0887302X17721367>
- Wu, P. C. S., Yeh, G. Y.-Y., & Hsiao, C.-R. (2011). The Effect of Store Image and Service Quality on Brand Image and Purchase Intention for Private Label Brands. *Australasian Marketing Journal*, 19(1), 30–39. <https://doi.org/10.1016/j.ausmj.2010.11.001>

- Wu, Y., Ngai, E. W., Wu, P., & Wu, C. (2020). Fake online reviews: Literature review, synthesis, and directions for future research. *Decision Support Systems*, 132, 113280.
- Xiang, L., Zheng, X., Zhang, K. Z., & Lee, M. K. (2018). Understanding consumers' continuance intention to contribute online reviews. *Industrial Management & Data Systems*, 118(1), 22–40.
- Xiao, A., Yang, S., & Iqbal, Q. (2018). Factors affecting purchase intentions in generation Y: An empirical evidence from fast food industry in Malaysia. *Administrative Sciences*, 9(1), 4.
- Xu, Y., Armony, M., & Ghose, A. (2021). The Interplay Between Online Reviews and Physician Demand: An Empirical Investigation. *Management Science*, 67(12), 7344–7361. <https://doi.org/10.1287/mnsc.2020.3879>
- Yadav, M., & Singh, P. (2020). Challenges and Opportunities of E-Commerce in India: Future Perspective. *E-Business: Issues and Challenges of 21st Century*, 76.
- Yang, S., Hu, M. (Mandy), Winer, R. S., Assael, H., & Chen, X. (2012). An Empirical Study of Word-of-Mouth Generation and Consumption. *Marketing Science*, 31(6), 952–963. <https://doi.org/10.1287/mksc.1120.0738>
- Ye, Q., Law, R., & Gu, B. (2009). The impact of online user reviews on hotel room sales. *International Journal of Hospitality Management*, 28(1), 180–182.
- Yeh, Y.-H., & Choi, S. M. (2011). MINI-lovers, maxi-mouths: An investigation of antecedents to eWOM intention among brand community members. *Journal of Marketing Communications*, 17(3), 145–162. <https://doi.org/10.1080/13527260903351119>
- Yi, Y. (1990). A critical review of consumer satisfaction. *Review of Marketing*, 4(1), 68–123.
- Yu, L.-H., & Wang, W.-T. (2017). *Examination of green IT adoption in organizations: Based on the expectation disconfirmation theory*.
- Zablocki, A., Makri, K., & Houston, M. J. (2019). Emotions within Online Reviews and their Influence on Product Attitudes in Austria, USA and Thailand. *Journal of Interactive Marketing*, 46(1), 20–39. <https://doi.org/10.1016/j.intmar.2019.01.001>
- Zablocki, A., Schlegelmilch, B., & Houston, M. J. (2019). How valence, volume and variance of online reviews influence brand attitudes. *Ams Review*, 9, 61–77.

- Zhang, K. Z., Cheung, C. M., & Lee, M. K. (2014). Examining the moderating effect of inconsistent reviews and its gender differences on consumers' online shopping decision. *International Journal of Information Management*, 34(2), 89–98.
- Zhang, L., Anjum, M. A., & Wang, Y. (2024). The Impact of Trust-Building Mechanisms on Purchase Intention towards Metaverse Shopping: The Moderating Role of Age. *International Journal of Human-Computer Interaction*, 40(12), 3185–3203. <https://doi.org/10.1080/10447318.2023.2184594>
- Zhang, M., & Luo, L. (2023). Can Consumer-Posted Photos Serve as a Leading Indicator of Restaurant Survival? Evidence from Yelp. *Management Science*, 69(1), 25–50. <https://doi.org/10.1287/mnsc.2022.4359>
- Zhang, N. (2006). Gender role egalitarian attitudes among Chinese college students. *Sex Roles*, 55, 545–553.
- Zhang, N., Yu, P., Li, Y., & Gao, W. (2022). Research on the Evolution of Consumers' Purchase Intention Based on Online Reviews and Opinion Dynamics. *Sustainability*, 14(24), 16510. <https://doi.org/10.3390/su142416510>
- Zhang, X., & Kim, H.-S. (2021). Customer Experience and Satisfaction of Disneyland Hotel through Big Data Analysis of Online Customer Reviews. *Sustainability*, 13(22), 12699. <https://doi.org/10.3390/su132212699>
- Zheng, R., Li, Z., & Na, S. (2022). How customer engagement in the live-streaming affects purchase intention and customer acquisition, E-tailer's perspective. *Journal of Retailing and Consumer Services*, 68, 103015.
- Zhenxiang, W., & Lijie, Z. (2011). Case study of online retailing fast fashion industry. *International Journal of E-Education, e-Business, e-Management and e-Learning*, 1(3), 195.
- Zhou, M. (2014). Gender difference in web search perceptions and behavior: Does it vary by task performance? *Computers & Education*, 78, 174–184.
- Zhou, Y., & Yang, S. (2019). Roles of review numerical and textual characteristics on review helpfulness across three different types of reviews. *IEEE Access*, 7, 27769–27780.
- Zhu, L., Li, H., Wang, F.-K., He, W., & Tian, Z. (2020). How online reviews affect purchase intention: A new model based on the stimulus-organism-response (S

- O - R) framework. *Aslib Journal of Information Management*, 72(4), 463–488. <https://doi.org/10.1108/AJIM-11-2019-0308>
- Zhu, L., Yin, G., & He, W. (2014). Is this opinion leader's review useful? Peripheral cues for online review helpfulness. *Journal of Electronic Commerce Research*, 15(4), 267.
- Ziegele, M., & Weber, M. (2015). Example, please! Comparing the effects of single customer reviews and aggregate review scores on online shoppers' product evaluations. *Journal of Consumer Behaviour*, 14(2), 103–114. <https://doi.org/10.1002/cb.1503>
- Zigmond, W. G., Babin, B. J., Carr, J. C., & Griffin, M. (2012). *Business Research Methods (Intl Ed) Andover: Cengage Learning*.
- Zinko, R., Stolk, P., Furner, Z., & Almond, B. (2020). A picture is worth a thousand words: How images influence information quality and information load in online reviews. *Electronic Markets*, 30, 775–789.

ANNEXURE 1

Research Questionnaire

Dear Sir/Madam,

I am Yashu, a research scholar at Mittal School of Business, Lovely Professional University. I am carrying out research on the topic 'Influence of online reviews on Gen Z consumers with reference to apparels.' The aim of this research is to understand how online reviews influence the Gen Z consumers while they purchase online apparels. I request you to kindly spare your valuable time to complete this questionnaire. I assure you your responses will be kept confidential and the data will be utilized only for academic research purpose.

Yashu

Research Scholar

Lovely Professional University, Punjab

Section A

Demographic Profile of Gen Z consumers

Name.....

Age.....

Q1. Gender

Male ☐

Female ☐

Q2. Educational Qualification

Below Matriculation/10th ☐

10th/Matriculation ☐

10+2 ☐

Under Graduate ☐

Post Graduate ☐

Any Other.....

Q3. Occupation

Student ☐

Private Employee ☐

Government Employee ☐

Business / Self Employed ☐

Unemployed ☐

Q4. District and Tehsils you belongs to:-

Districts

Tehsils

☐ Amritsar	Amritsar 2 ☐	Ajnala	Amritsar1 ☐
☐ Jalandhar	Jalandhar 1 ☐	☐ Jalandhar 2	Phillaur ☐
☐ Ludhiana	Ludhiana (East) ☐	Ludhiana (West) ☐	Jagraon ☐
☐ Ferozepur	Ferozepur ☐	Zira ☐	Guru Har Sahai ☐
☐ Gurdaspur	Gurdaspur ☐	Batala ☐	Dera Baba Nanak ☐
☐ Hoshiarpur	Hoshiarpur ☐	Dasuya ☐	Mukeria ☐

Q5. Monthly Income (in Rs.)

Less than 10000 ☐	10001- 20000 ☐
20001- 40000 ☐	40001- 60000 ☐
Above 60001 ☐	

Section B

Online Buying Pattern of Gen Z Consumers

Q6. Do you shop online? If yes, kindly proceed further

Yes ☐ No ☐

Q7. Which device do you mostly use for online shopping? (Tick only one option)

Desktop ☐	Laptop ☐	Smartphone ☐
Tablet ☐		

Q8. How often you purchase apparels online?

Less than once a month ☐	Once in a month ☐
Two times a month ☐	Three times a month ☐
More than three times a month ☐	

Q9. How much you spend in a month on apparels while online shopping?

Less than 2000 ☐

2001 to 4000 ☐

4001 to 6000 ☐

More than 6001 ☐

Q10. Select your favourite online shopping website from you purchase apparel (Tick only one option which mostly preferred)

Meesho ☐

Myntra ☐

Amazon ☐

Ajio ☐

Flipkart ☐

Q11. Select the category of apparel that you prefer to purchase online (Tick only one option)

Western Wear ☐

Woolen Clothes ☐

Ethnic Wear ☐

Sports Wear ☐

Formal Wear ☐

Section- C

Q12. Please indicate your degree of agreement or disagreement with the following statements are related with motives to read online reviews while online shopping.

1 = Strongly Disagree, 2 = Disagree, 3 = Neutral, 4 = Agree, 5 = Strongly Agree.

Statements	SD	D	N	A	SA
I read online reviews to avoid mistakes while choosing a product					
I read online reviews to evaluate the quality of product					
I read online reviews to know about the experiences of other consumers.					
I read online reviews to know about durability of the product					
I read online reviews to reduce the time taken while					

choosing the product.					
I read online reviews to get information about the product					
I read online reviews to make my purchases confidently					
I read online reviews to evaluate the overall satisfaction of consumers					
I read online reviews in order to avoid wrong choice of product with bad performance.					
I read online reviews to reduce anxiety caused by not-seeing or touching product.					
I read online reviews to avoid financial loss caused by wrong decision.					
I read online reviews to learn how a product is to be consumed					
I read online reviews to get information about the new products					
I read online reviews to compare the products and services					
I read online reviews to ensure that product meets with my specific requirements					
I read online reviews to protect myself from fraudulent schemes					

Section-D

Q13. Please indicate your degree of agreement or disagreement with the following dimensions of online reviews that influence your purchase intention.

1 = Strongly Disagree, 2 = Disagree, 3 = Neutral, 4 = Agree, 5 = Strongly Agree.

Construct	Statements	SD	D	N	A	SA
Review Quantity	Number of online reviews available about a product is important to me					
	More Number of online reviews about a product gets my attention					
	Number of online reviews are helpful in decision making					
	Number of online reviews provide more information about product if they are more in number					
	Number of online reviews denotes the popularity of the product/brand					
Review Quality	Online reviews are useful in my purchasing decision if content of the reviews is understandable					
	Online reviews are useful in my information need if content of the online reviews is relevant					
	Online reviews are more useful in my purchasing decision if they are factual and elaborate					
	Online Reviews are useful if they present both the pros and cons of a product/brand rather than one sided review.					
	Online reviews with visual presentation of product help in my online purchase decision.					

	Online reviews are useful if they are current					
Source Credibility	I feel that if the reviewer's identity is disclosed reviews are more credible.					
	I feel that reviewer who post online reviews are trustworthy.					
	I feel that reviewer who post online reviews are reliable.					
	I feel that reviewer should be experienced about the product being reviewed.					
	I feel that reviewer should be an expert in evaluating the product being reviewed.					
	I feel that knowledge level of usage of the product by reviewer is important to me.					
	I feel that person who posted the online reviews should be verified users					
Usefulness of online reviews	Online reviews improve the quality of my online shopping.					
	Online reviews make it easier for me to shop online					
	Online reviews are quite helpful in my online purchase decision making process.					
	Online reviews helps me to accomplish my purchasing task more quickly.					
Review Credibility	Online reviews are accurate					
	Online reviews are credible if it is unbiased					
	Online reviews are credible if it is authentic					

	Online reviews are credible if it is believable					
	The online reviews are trustworthy					
Purchase Intention	I am quite likely to buy the product that is recommended by the reviewer.					
	Based on online reviews I intend to purchase the product online.					
	I would make a special effort to buy the product/ brand recommended by the reviewers					
	I would like to recommend the product to my friends based on online reviews.					

Section-E

Q14. Please indicate your degree of agreement or disagreement with the following dimensions that effects your satisfaction

1 = Strongly Disagree, 2 = Disagree, 3 = Neutral, 4 = Agree, 5 = Strongly Agree.

Construct	Statement	SD	D	N	A	SA
Expectation	I expected the accuracy of information by reading online reviews					
	I expected that online reviews have ability to meet my personal needs					
	I expected the quality of product by reading online reviews					
	I expected reviewers provide the detailed information about product					
Perceived	Online reviews improve my learning					

performance	Online reviews improve my skill of decision making					
	Online reviews enable me to access a lot of useful information					
	Online reviews are worth using as it easily accessible					
Disconfirmation	My experience to use the product was better than what I had expected					
	The information provided by online reviews was better than what I had expected.					
	Overall, most of my expectations from the online reviews were matched					
	Expectations based on online reviews were met after using it					
	The extent of help provided by online reviews was better than expected					
Satisfaction	The information provided by reviewers makes me feel satisfied					
	Using the online reviews makes me feel very connected with others					
	Using the online reviews makes me feel very pleased					
	I feel contented by using online reviews					

Thank you

Warm Regards

Yashu (Research Scholar)

Email- yashu97406@gmail.com

Under the guidance of-

Dr. Krishan Gopal (Supervisor)

Associate Professor (HOD-Marketing)

Lovely Professional University

ANNEXURE 2

LIST OF PUBLICATIONS

Sr. No.	Article Type	Article Title	Authors	Status	Indexation	Name of the Journals	Scimago Rank
1.	Research Paper	Threads of insight: Exploring the narrative of online reviews (2002-2022) in the apparel industry through bibliometrics	Yashu Garg, Krishan Gopal, Ajay Chandel	Published	Scopus	Fashion, Style & Popular Culture	Q2
2.	Research Paper	Online reviews and Gen Z consumers' satisfaction in the apparel industry: An expectation disconfirmation theory	Yashu Garg, Krishan Gopal	Published	Scopus	Fashion, Style & Popular Culture	Q2

YASHU GARG

Lovely Professional University

KRISHAN GOPAL

Lovely Professional University

AJAY CHANDEL

Lovely Professional University

Threads of insight: Exploring the narrative of online reviews (2002–22) in the apparel industry through bibliometrics

ABSTRACT

Online reviews have become crucial in research and consumer decision-making, providing insights into customer perspectives on products and services. In today's digital age, they are an essential tool for retailers to engage with their customers. This is particularly true in the apparel industry, where understanding consumer satisfaction and preferences is key to crafting effective marketing strategies. Despite the abundance of literature on the impact of online reviews on consumer evaluations of ready-made garments, there has been limited scientific analysis of this extensive body of work. This bibliometric study utilizes performance analysis and science mapping to rigorously examine the body of literature on online

KEYWORDS

apparel industry
bibliometric analysis
online retailers
decision making
user-generated content
performance analysis
science mapping

YASHU GARG

Lovely Professional University

KRISHAN GOPAL

Lovely Professional University

Online reviews and Gen Z consumers' satisfaction in the apparel industry: An expectation disconfirmation theory

ABSTRACT

This research article aims to analyse how online reviews influence the satisfaction level of Generation Z (Gen Z) consumers within the apparel industry by using the expectation disconfirmation theory as the analytical framework. Five hypotheses have been developed regarding the relationships between online reviews and satisfaction through literature review and were examined using partial least squares structural equation modelling (PLS-SEM). In the research article, data were gathered from 350 Gen Z consumers engaged in online shopping across three districts of Punjab. Questionnaires were distributed to the respondents in hard copy and Google Forms. The findings from this research article suggest a positive correlation between online reviews and the satisfaction level of Gen Z consumers in the apparel industry. The analysis reveals that online reviews play a significant role in influencing the online shopping of apparel.

KEYWORDS

digital marketing
digital natives
purchase intention
information credibility
usefulness of reviews
PLS-SEM

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ANNEXURE 3

LIST OF CONFERENCES

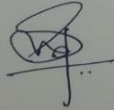


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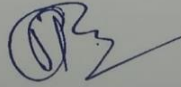
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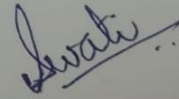
Prof./Dr./Mr./Mrs./Ms. YASHU GARG
of LOVELY PROFESSIONAL UNIVERSITY
has presented the research paper titled ONLINE REVIEWS & GENZ
CONSUMER SATISFACTION IN APPAREL INDUSTRY: AN
EXPECTATION DISCONFIRMATION THEORY in
Two Days International Research Conference on "Viksit Bharat @2047:
Voice of Youth" on April 5th and 6th, 2024 Organised by MET Institute of
Management in collaboration with Department of Commerce, University
Mumbai and Atlantis University, USA.



Prof. (Dr.) Sangeeta N Pawar
Professor & Head of Commerce Department
University of Mumbai



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Certificate of Presentation		
This is to certify that Dr./Mr./Ms. Yashu Garg of Lovely Professional University has participated and presented a paper title "Online reviews and Gen Z consumer's purchase intention in Apparel Industry: A Multigroup Analysis" in the International Conference on "Sustainable Future: Technology, Business Transformation & Circular Economy" held from 3rd May 2024 to 4th May 2024 , organized by Mittal School of Business, Lovely Professional University, Punjab.		
Date of Issue : 21-05-2024 Place : Phagwara (Punjab), India	Prepared by (Administrative Officer-Records)	Joint Organizing Secretary Dr. Pawan Kumar
		Head of School Dr. Rajesh Verma