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ISTANBUL AYDIN UNIVERSITY
INSTITUTE OF GRADUATE STUDIES

CONSUMER BEHAVIOUR TOWARDS ONLINE BUSINESS AND THE ROLE OF SOCIAL MEDIA ENGAGEMENT IN ADOPTING ONLINE SHOPPING: AN EXPLORATORY STUDY OF YEMENI MARKET

DOCTORATE'S THESIS

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Department of Business
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THESIS EXAM REPORT

DECLARATION

I hereby declare with the respect that the study “consumer behavior towards online business and the role of social media engagement in adopting online shopping: an exploratory study of Yemeni market”, which I submitted as a Doctorate thesis, is written without any assistance in violation of scientific ethics and traditions in all the processes from the project phase to the conclusion of the thesis and that the works I have benefited are from those shown in the References. (13 /03 /2024)

Nasr Abdulaziz Ghaleb MURSHED

FOREWORD

I write this foreword to my PhD thesis with a heart full of gratitude. This journey has tested my resilience and determination but also filled me with a sense of accomplishment. I have learned so much about myself, about my field of study, and about the world around me. When I started my Ph.D. program, I was so excited then quickly felt like I was drowning. There have been many times when I wanted to give up. But every time, I found the strength to keep going.

Through it all, I had the unwavering support from my wife. she believed in me even when I didn't believe in myself. she cheered me on when I was feeling down and celebrated every small success along the way. I am eternally grateful for her unconditional love and support. To my mom, dad and brothers, your love and solid belief in my potential have been my constant source of strength. Your sacrifices and the endless encouragement I have received from you have lightened my path.

My supervisor Prof. Dr. Erginbay UĞURLU, your guidance has been instrumental in shaping not just this thesis, but my entire academic career. Your humility, prompt responsiveness to numerous concerns, and support have been nothing short of exceptional.

I dedicate this thesis to all those who have been a part of my life's narrative, both seen and unseen, for it is with your collective influence that I have grown and thrived.
I am grateful for the opportunity to have conducted this research and I hope that my research has a good impact on my society and opens new economic opportunities.

As I pen down this foreword, I am not just concluding an academic chapter, but I am also embarking on a new beginning with a heart full of gratitude and a spirit ignited by the possibilities of the future.

March, 2024 Nasr Abdulaziz Ghaleb MURSHED

CONSUMER BEHAVIOR TOWARDS ONLINE BUSINESS AND THE ROLE OF SOCIAL MEDIA ENGAGEMENT IN ADOPTING ONLINE SHOPPING: AN EXPLORATORY STUDY OF YEMENI MARKET

ABSTRACT

This study explores the impact of social media engagement on online consumer behavior as well as the factors influencing online shopping adoption among Yemeni consumers. The research includes two main studies: an exploratory phase for scale development and a quantitative analysis phase. The study employs robust statistical techniques, including EFA, CFA, and SEM to validate measurement scales and analyze relationships.

The study, conducted with a sample size of 395 social media users in Yemen during May- October 2022, adopted three different scales for the Arabic language and the results showed that the social media engagement scale is a unidimensional concept, while the online consumer behavior scale is a multidimensional concept, consisting of three distinct factors: awareness, social cognition, and online business perception. The extended unified theory of acceptance and use of technology scale was found to be a valid measure of the three key factors that predict adoption: price value, usability, and adoption intention.

Key findings include demographic variables like gender, age, and education have limited impact on online shopping behavior. Social media engagement sets the foundation by influencing social cognition, which, in turn, enhances awareness of online shopping. This awareness then affects online business perception and perceived usability, leading to an impact on the perceived price value of online shopping. Finally, the perceived price value plays a crucial role in shaping the intention to adopt online shopping.

The study highlights the trail of online shopping as a moderating factor as it weakens the direct impact of social media engagement, social cognition, awareness, and usability while strengthening the influence of online business perception. The findings underscore the importance of considering indirect effects and mediating pathways in understanding the relationships among variables in the model.

This holistic perspective is essential for a comprehensive understanding of the dynamics and interplay within the model, providing valuable insights for researchers and practitioners in the context of online shopping behavior.

Keywords: Online shopping adoption, Online consumer behavior, social media engagement, Yemeni consumers, Scale development, Awareness, Social cognition, Online business perception, price value, Usability, Adoption intention.

ÇEVRİMİÇİ TİCARETE YÖNELİK TÜKETİCİ DAVRANIŞI VE ÇEVRİMİÇİ ALIŞVERİŞİ BENİMSEMEDE SOSYAL MEDYA KATILIMININ ROLÜ: YEMEN PAZARINA İLİŞKİN BİR KEŞİF ÇALIŞMASI

ÖZET

Bu araştırma, Yemenli tüketiciler arasında çevrimiçi alışveriş benimsemesini etkileyen faktörler ve sosyal medya etkileşiminin çevrimiçi tüketici davranışı üzerindeki etkisini araştırmaktadır. Araştırma iki ana çalışmadan oluşmaktadır: ölçek geliştirme için keşifse bir aşama ve nicel analiz aşaması. Çalışma, ölçme araçlarını doğrulamak ve ilişkileri analiz etmek için EFA, CFA ve SEM gibi sağlam istatistiksel teknikler kullanmaktadır.

Çalışma, Mayıs-Ekim 2022'de Yemen'deki 395 sosyal medya kullanıcısının örneklem büyüklüğü ile yürütüldü ve Arapça dilinde üç farklı ölçeği benimsedi ve bu ölçekleri doğrulamıştır. Ana bulgular arasında sosyal medya etkileşim ölçeğinin tek boyutlu bir yapı olduğu, çevrimiçi tüketici davranışı ölçeğinin ise üç farklı faktörden oluşan çok boyutlu bir yapı olduğu yer almaktadır: farkındalık, sosyal biliş ve çevrimiçi işletme algısı. Benimsenmeyi tahmin eden üç ana faktörü ölçmek için genişletilmiş Birleşik Teknoloji Kabul ve Kullanım Teorisi (UTAUT) ölçeğinin geçerli bir ölçme aracı olduğu bulunmuştur.

Cinsiyet, yaş ve eğitim gibi demografik değişkenlerin çevrimiçi alışveriş davranışı üzerinde sınırlı bir etkisi vardır. Sosyal medya etkileşimi, sosyal bilişi etkileyerek çevrimiçi alışveriş farkındalığını artırarak temel oluşturmaktadır. Bu farkındalık daha sonra çevrimiçi iş algısını ve algılanan kullanılabilirliği etkileyerek çevrimiçi alışverişin algılanan fiyat değerine etki eder.

Son olarak, algılanan fiyat değeri, çevrimiçi alışveriş benimseme niyetini şekillendirmede önemli bir rol oynamaktadır. Çalışma, çevrimiçi alışveriş deneyimi izini, sosyal medya etkileşimi, sosyal biliş, farkındalık ve kullanılabilirliğin doğrudan

etkisini zayıflatırken çevrimiçi iş algısının etkisini güçlendiren bir moderatör faktör olarak vurgulamaktadır. Bulgular, modeldeki değişkenler arasındaki ilişkileri anlamak için dolaylı etkileri ve aracılık yollarını dikkate almanın önemini vurgulamaktadır.

Bu bütünsel bakış açısı, model içindeki dinamikleri ve etkileşimleri kapsamlı bir şekilde anlamak için gereklidir ve araştırmacılara ve uygulayıcılara çevrimiçi alışveriş davranışları bağlamında değerli bilgiler sağlamaktadır.

Anahtar Kelimeler: Çevrimiçi alışveriş benimsemesi, Çevrimiçi tüketici davranışı, Sosyal medya etkileşimi, Yemenli tüketiciler, Ölçek geliştirme, Farkındalık, Sosyal biliş, Çevrimiçi işletme algısı, Fiyat değeri, Kullanılabilirlik, Benimseme niyeti.

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LIST OF ABBREVIATIONS

SME	: Social Media Engagement
OCB	: Online Consumer Behavior
UTAUT	: Unified Theory of Acceptance and Use of Technology
UAT	: Use and Acceptance of Technology.
AW	: Awareness
OBP	: Online Business Perception
US	: Usability
PV	: Price Value
SC	: Social Cognition
AI	: Adoption Intention
SEM	: Structural Equation Modeling
CFI	: Comparative Fit Index
TLI	: Tucker-Lewis Index
NNFI	: Non-Normed Fit Index
NFI	: Non-Normed Fit Index
GFI	: Goodness-of-Fit Index
RMSEA	: Root Mean Square Error of Approximation
SRMR	: Standardized Root Mean Square Residual
CR	: Composite Reliability
SPSS	: Statistical Package for Social Sciences
EFA	: Exploratory Factor Analysis
CFA	: Confirmatory Factor Analysis

I. INTRODUCTION

The Internet and digital technology have transformed the environment for business leading to the emergence of online business and e-commerce platforms. Online shopping has witnessed remarkable growth and has become increasingly popular worldwide, allowing customers to buy products and services from the comfort of their own homes. In the context of Yemen, a developing country, online business is gradually gaining traction, presenting new opportunities and challenges for businesses operating in the region.

The rapid advancement of technology and the widespread use of the internet have transformed the way businesses operate, particularly in the realm of online business. Online shopping has gained significant popularity globally, offering accessibility, availability, and a wide range of products and services to consumers. Yemen, as a developing country, is also experiencing a growing interest in online business and e-commerce platforms. However, there is a shortage of comprehensive studies focusing on consumer behavior towards online business and the specific factors that influence the adoption of online shopping in the Yemeni market.

This research emphases on understanding consumer behavior towards online business in Yemen and aims to explore the role of social media engagement in the adoption of online shopping. The Yemeni market represents a unique and understudied context, characterized by specific cultural, economic, and technological factors that influence consumer decision-making and online shopping practices. By conducting an in-depth exploration of consumer behavior and the factors that influence the adoption of online shopping, this research seeks to provide valuable insights for businesses, marketers, and policymakers operating in Yemen.

The rationale behind this research is to address the gap in understanding consumer behavior towards online business in Yemen and to explore the role of social media engagement in the adoption of online shopping. By conducting an in-depth exploration of consumer behavior, attitudes, motivations, and barriers related to online shopping in Yemen, this study aims to provide valuable insights for businesses, marketers, and policymakers in leveraging the potential of online business and optimizing their marketing strategies.

Understanding the factors that influence consumer behavior towards online business is crucial for businesses seeking to establish a strong online presence and effectively target the Yemeni market. By investigating consumer attitudes, preferences, trust, perceived benefits, and perceived risks associated with online shopping, this research will contribute to the existing body of knowledge on consumer behavior in the context of online business, with a specific focus on the Yemeni market.

Moreover, this study recognizes the growing significance of social media platforms as communication and marketing channels. Social media engagement has the potential to play an important role in shaping consumer behavior and influencing their adoption of online shopping. Hence, exploring the relationship between social media engagement and consumer behavior in the Yemeni context will provide insights into the effectiveness of social media as a tool for promoting online business and enhancing consumer engagement.

By conducting an exploratory study, this research aims to generate comprehensive and context-specific insights into consumer behavior towards online business in Yemen. The findings will contribute to theory development in the field of consumer behavior and provide practical implications for businesses and policymakers to effectively engage with Yemeni consumers, drive online shopping adoption, and promote sustainable growth of the online business sector in Yemen.

The objectives of this research on consumer behavior towards online business and the role of social media engagement in adopting online shopping in the Yemeni market are as follows:

Firstly, to examine the current state of online shopping adoption among Yemeni consumers: This objective aims to assess the extent to which Yemeni consumers have embraced online shopping as a viable alternative to traditional brick-and-mortar retail. It involves investigating the prevalence of online shopping, the frequency and types of products/services purchased online, and the factors influencing consumer adoption of online shopping in Yemen.

The secondary goal is to investigate how engagement on social media shapes consumer behavior regarding online shopping. This objective aims to comprehend the effects of platforms like Facebook, Instagram, and Twitter on consumer attitudes, perceptions, and actions concerning online shopping. It involves analyzing the correlation between social media interaction and intentions to shop online within the framework of Yemen's context.

The third objective is to pinpoint the determinants impacting consumer behavior in online shopping within Yemen. This aim involves identifying and examining the pivotal factors that drive the decision-making process among Yemeni consumers when they participate in online shopping. Additionally, it aims to scrutinize demographic variables that could potentially influence consumer behavior regarding online shopping.

Finally, the aim is to deliver actionable recommendations to businesses and policymakers, drawing from the study's findings. These recommendations intend to guide strategies that can boost the adoption of online shopping and maximize the effective utilization of social media engagement within Yemen's context.

It involves providing insights into effective marketing strategies, customer engagement techniques, policy interventions, and infrastructure development initiatives that can support the growth of the online business sector and improve consumer experiences.

By achieving these objectives, the study holds immense value in contributing to academic knowledge, providing valuable insights for businesses to formulate effective strategies, and guiding policymakers in the development of policies pertaining to online shopping and social media marketing in Yemen.

The significance of this research extends to various stakeholders, including businesses seeking to enhance their online presence, marketers aiming to optimize their social media engagement, policymakers aiming to foster e-commerce growth, and researchers investigating consumer trends in the Yemeni market as follows:

Firstly, this study will contribute to the existing body of academic knowledge on consumer behavior and online business practices, particularly within the context of Yemen. As Yemen represents a unique and understudied market, this research will fill the research gap by providing insights specific to the Yemeni consumer behavior landscape. The findings will expand theoretical frameworks and understanding related to online shopping adoption, social media engagement, and factors influencing consumer behavior in a developing country setting.

The study's findings will offer practical insights for businesses operating in Yemen or those planning to enter the Yemeni market. Understanding consumer preferences associated with online shopping will enable businesses to develop targeted marketing strategies and enhance their online presence. Businesses can optimize their product offerings, improve customer engagement, and design effective promotional campaigns based on the identified factors influencing consumer behavior.

Furthermore, by uncovering the role of social media engagement in adopting online shopping, this research will help businesses leverage social media platforms effectively to engage with Yemeni consumers. Social media has become a powerful tool for communication and marketing, and understanding how social media influences consumer behavior will enable businesses to enhance customer engagement, build trust, and foster loyalty. The study will provide insights into the types of social media content and engagement strategies that resonate with Yemeni consumers.

In addition to business implications, the findings hold significance for policymakers in Yemen. The findings of this study can inform policymakers in Yemen about the opportunities and challenges associated with online business. Policymakers can use these insights to develop policies and regulations that promote the growth of the online business sector, ensuring a favorable environment for businesses and consumers. Effective policies can encourage innovation, support e-commerce infrastructure development, and protect consumer rights, ultimately fostering economic growth and job creation in the digital economy.

As for strategic decision-making, the study's outcomes will assist businesses and marketers in making informed strategic decisions regarding their online business initiatives. The insights gained from this research can guide investment decisions, resource allocation, and marketing budget optimization. By understanding consumer behavior and preferences, businesses can align their online business strategies with the needs and expectations of Yemeni consumers, ultimately leading to improved customer satisfaction and business performance.

Lastly, as an exploratory study, this research will lay the groundwork for future investigations in consumer behavior, online business practices, and social media engagement within the Yemeni context. The findings and methodologies employed in this study can serve as a foundation for subsequent research, enabling scholars to delve deeper into specific aspects or conduct comparative studies across different countries or regions.

The study seeks to contribute valuable insights for businesses, inform effective marketing strategies, and guide policymakers in shaping the e-commerce landscape in Yemen. Despite the comprehensive approach, this research may have certain limitations that could affect the generalizability of the findings.

Higher education leadership is essential to the success of students in promoting the growth of skills such as the ability to engage in interpersonal relationships, the fulfillment of major and career goals, and the promotion of student self-exploration (NACADA, 2006). Academic leaders are a catalyst for improving the student learning climate, as they help students manage their personal growth and provide a link to the resources of the faculty, education, and campus, as well as resources beyond the university community (Spratley, 2020). In addition to academic counselors, educators, and prospective employers, they all play a related role in recognizing student growth through leadership education. It is necessary to better understand the role of academic counselors in helping students build leadership skills if they are to become educated, active members of society.

The pedagogical method of promoting the learning of leadership in an attempt to develop human potential guided by the theory of leadership and science. It respects and requires instruction as well as co-curricular educational contexts (Andenoro, et al., 2013). Holistic approach in higher education leadership seeks to empower students to improve their self-efficacy as leaders and to understand how they can make a difference, by understanding one 's self-better and working with others, students can become informed and productive members of society.

Over the second half-century, the conventional aim and community role of HE have been challenged by new pressures (The National Task Force, 2012). One might claim that the aim of HE appears to be to obtain new understanding and to prepare one for the labor force. On the other hand, one would also suggest that HE institutions would strive for more suitable impacts on the culture of the nation. That challenge has created continual problems about the public role and purpose of HE in the 21st century (Abowitz, 2008; Brighouse & Mcpherson, 2015; Dungy, 2012; Levine, 2014; Shapiro, 2005).

Universities are in a market shift where they must continuously demonstrate their importance and interest in modern civilization (Bok, 2003; Suspitsyna, 2012). Historically, HE institutions operate to educate students on public service life, advance knowledge through research, and build leaders for various public service areas (ACE, 1949). In rapidly changing environments, today's labor market needs highly skilled workers at all levels to cope with rapid industrialization (Ramley, 2014b). HE institutions need to redefine and redesign college curricula, pedagogy, to meet current societal needs. And appraisal policies to ensure that all graduates have the requisite skills and competences to add to the global economy and to engage in democracy effectively (Fein, 2014; Kirst & Stevens, 2015).

II. THEORETICAL BACKGROUND

In Yemen, a nation grappling with economic and political challenges, the emergence of e-commerce and the utilization of social media platforms for online shopping have presented a unique landscape. Understanding consumer behavior in this context is crucial for both academic research and business development. This section aims to provide a comprehensive understanding of the factors influencing consumer behavior in the Yemeni market concerning online shopping and the role played by social media engagement.

A. Consumer Behavior in Online Business

1. Conceptualization and Theories of Consumer Behavior

Consumer behavior is a multidimensional field of study within marketing and behavioral sciences that aims to understand and analyze the actions, decisions, and cognitive processes individuals, groups, or organizations undertake when acquiring, using, and disposing of products, services, experiences, or ideas to meet their needs and desires (Schiffman & Kanuk, 2010; Solomon, 2019; Kotler et al., 2019).

This area of research delves into the complexities of consumer decision-making, exploring the interplay of internal and external factors that shape consumer preferences and behavior.

The conceptualization of consumer behavior revolves around a central understanding of the underlying motivations and influences that drive consumer actions. Internally, consumers' psychological factors, such as perceptions, attitudes, beliefs, personality traits, and individual preferences, contribute to their choices. Externally, social, cultural, economic, and situational factors come into play, including societal norms, cultural values, family influences, reference groups, marketing communications, pricing strategies, and the overall market environment (Engel et al., 2014).

The process of consumer decision-making typically follows a series of stages. It starts with problem identification, in which consumers recognize a need or desire for a specific product or service. Consumers then conduct an information search to obtain relevant data and evaluate potential options. This leads to the consideration of various options, culminating in the final purchase decision. After the purchase, consumers may experience post-purchase evaluation, which can influence their future behavior, such as repeat purchases or brand loyalty (Blackwell et al., 2006; Belch & Belch, 2018).

Consumer behavior is a dynamic field that continually evolves with societal changes, technological advancements, and shifts in consumer preferences and expectations (Hawkins et al., 2021). The digital revolution has significantly impacted consumer behavior, with the proliferation of online shopping, social media engagement, and the generation of vast consumer data for analysis.

Customer behavior researchers and marketers use a variety of theories and models to investigate the complexity of customer decision-making. Maslow's Hierarchy is one such foundational concept, which proposes that people have a hierarchical arrangement of wants, ranging from basic physiological to higher-level needs like belongingness and self-actualization. As consumers fulfill lower-level needs, they are motivated to address higher-level needs, thereby influencing their purchasing behavior and choices (Maslow, 1943).

The Theory of Reasoned Action (TRA) is another important theory that proposes that a person's desire to engage in a given conduct is impacted by their attitudes and subjective norms. Subjective norms reflect perceived social pressures or expectations surrounding the action, whereas attitudes contain the individual's ideas and opinions about the behavior (Fishbein & Ajzen, 1975). Marketers can use consumer attitudes and social influences to anticipate their intentions and subsequent behavior toward a product or service in this environment.

Moreover, the Theory of Planned Behavior (TPB) extends the Theory of Reasoned Action (TRA) by introducing the concept of perceived behavioral control, which considers an individual's perception of their capability to perform a certain behavior. Within TPB, the inclination to partake in a behavior is shaped not only by attitudes and subjective norms but also by the perceived level of control over the particular activity. By incorporating this supplementary dimension, as suggested by Ajzen (1991), researchers and marketers gain a more comprehensive understanding of the factors that impact customers' decision-making processes.

Additionally, Behavioral Economics plays a significant role in understanding consumer behavior by merging principles from psychology and economics. It recognizes that consumers may not always act rationally and can be influenced by cognitive biases and heuristics. These biases and mental shortcuts impact decision-making, such as the way choices are framed or the reliance on mental rules of thumb when making decisions (Thaler & Sunstein, 2008). By understanding these behavioral patterns, marketers can craft more effective marketing strategies that resonate with consumers' inherent tendencies.

These theories offer valuable frameworks for comprehending consumer motivations and the intricacies of decision-making processes. Armed with these insights, researchers and marketers can better navigate the consumer landscape, optimize marketing strategies, and ultimately improve consumer satisfaction and brand loyalty.

2. Factors Influencing Consumer Behavior in Online Business

Consumer behavior influences in online business can be classified into several important dimensions. These factors are critical in affecting consumers' views, intentions, and behaviors when shopping online. The following are some of the key factors identified in prior research:

Firstly, trust and perceived credibility which stand as foundational pillars. To participate in online transactions, consumers must have complete trust in the confidentiality of their personal information as well as the reliability of online vendors (Flavián, Guinalíu, & Gurrea, 2006). Trust is an important factor in online business because consumers must have confidence in the confidentiality of their personal information and in the reliability of online sellers .

As for Perceived credibility, including the reputation and trustworthiness of the website and online sellers, encourages consumers to participate in online transactions (Liébana-Cabanillas, Sánchez-Fernández, & Muñoz-Leiva, 2014).

Moreover, the perceived usefulness and ease of use of online platforms and shopping websites play an important role in the adoption of online shopping. Consumers' perception of the usefulness and ease of use of online platforms and shopping websites significantly influences their adoption of online shopping (Liao & Cheung, 2001). When consumers perceive online shopping as a convenient and efficient means to fulfill their needs, they are more motivated to engage in online transactions (Liébana-Cabanillas et al., 2014).

Another key dimension is the perception of risk correlated with online shopping. This includes concerns regarding product quality, security, privacy, and the reliability of online sellers. Consumers' perception of these risks can significantly impact their willingness to make online purchases (Doolin, Dillon, & Thompson, 2005). Online shopping involves certain risks, for example concerns about product quality, security, privacy, and the reliability of online sellers, Consumers' perception of these risks can affect their willingness to make online purchases (Lee & Turban, 2001).

Another compelling facet of online consumer behavior is social influence which plays an important role in shaping consumer attitudes and driving purchase decisions within the online business landscape. Recommendations stemming from trusted sources such as friends, family, and online communities, alongside the powerful testimonials and online reviews.

This influence is well-documented in the researches of online consumer behavior. Chen, Fay, and Wang (2011) have underscored the significant impact of family, friends, and online communities on consumers' decision-making processes within the digital marketplace.

Additionally, Yoo and Gretzel (2008) have emphasized how social recommendations, testimonials, and online reviews can exert a profound effect on consumers' attitudes and ultimately guide their purchase decisions. In an era where information flows freely and social networks are robust, the opinions and experiences shared by others hold remarkable influence in the online shopping journey.

Furthermore, the business landscape cannot be overstated. It serves as a cornerstone upon which consumer decisions are built. The quality and accessibility of this information, available on websites and through various online channels, form a important aspect of the online shopping experience.

Detailed and precise product descriptions provide consumers with a comprehensive understanding of the product's features, benefits, and specifications. When combined with high-quality images, these descriptions offer a visual representation that allows consumers to assess the product from various angles, virtually inspecting it before purchase. Such detailed and accurate information fosters a sense of transparency and trust, bolstering consumer confidence in making online purchases.

Equally influential are trustworthy customer reviews, as emphasized by Liébana-Cabanillas et al. (2014). These reviews provide real-life insights into the product's performance, quality, and overall satisfaction from other consumers who have made similar purchases. They offer a peer-to-peer perspective that is highly valuable to prospective buyers, aiding them in their decision-making process.

Additionally, consumers' perception of price fairness and the perceived value they derive from online transactions are important factors that deeply influence their decision-making processes within the online business landscape. These dimensions act as compasses, guiding consumers toward choices that align with their expectations and preferences. In the pursuit of a satisfactory online shopping experience, consumers frequently embark on a journey of price comparisons. They meticulously scrutinize the cost of products or services across various online sellers, seeking the best deals and competitive pricing.

This practice of price comparison is not merely about cost but also about discerning the perceived fairness of the prices offered. Assessing discounts and promotions is another integral facet of this process. Consumers evaluate the incentives presented by different online sellers, seeking to maximize their value for money. Whether it's special offers, seasonal discounts, or promotional bundles, these elements are carefully weighed in the pursuit of a favorable deal.

All these actions serve a singular purpose: to ascertain the perceived value they anticipate receiving from their online transactions. This value assessment extends beyond the simple cost-to-price ratio and delves into the holistic perception of what the online shopping experience offers in return for their investment (Alreck and Settle ,2004).

As highlighted by Alreck and Settle (2004), understanding the dynamics of consumers' price fairness perceptions and their appraisal of value is important for businesses operating in the online sphere. It informs pricing strategies, promotion planning, and customer engagement approaches, all with the ultimate goal of aligning offerings with consumer expectations and enhancing satisfaction.

These factors shed light on the complicated dynamics of consumer behavior in online shopping. To attract and retain online customers, firms must understand and manage these aspects successfully. Businesses can optimize their strategies and improve consumer engagement in the online marketplace by focusing on trust-building, improving usability, minimizing perceived risks, leveraging social influence, providing comprehensive product information, and offering competitive pricing and perceived value.

a. Awareness and Information Processing

In the context of online business, awareness and information processing are vital factors that influence consumer behavior. When buying online, consumers must be aware of the available products or services and process the required information in order to make informed purchasing decisions.

Awareness plays a crucial task in consumer behavior as it involves the consumer's information and recognition of the products or services offered in the online marketplace.

Li and Zhang (2002) found that online consumer reviews contribute to the formation of product-specific reputation, which influences consumer awareness and perception. Positive reviews and word-of-mouth recommendations can enhance consumer awareness and generate interest in specific products or services (Liu, 2006).

Information processing refers to the cognitive processes through which consumers acquire, interpret, and evaluate information to make decisions. In the online environment, consumers have access to a vast amount of information, and how they process that information influences their purchase decisions.

Korgaonkar and Wolin (1999) conducted a study on web usage and identified that consumers engage in information search and evaluation when making online purchase decisions. They found that the amount of time spent on websites and the number of pages visited contribute to the information processing process.

The acceptance and utilization of online platforms also impacts consumers' awareness and information processing. Hsu and Lin (2008) explored the acceptance of blog usage and highlighted the role of technology acceptance and social influence in information processing. They found that consumers' motivation to share knowledge and opinions on blogs positively influences information processing and awareness.

Moreover, the quality of the online platform and the satisfaction derived from the online experience significantly influence consumers' information processing and awareness.

Kim, Jin, and Swinney (2009) explored the development of online loyalty and identified that e-service quality, e-satisfaction, and e-trust positively influence consumers' awareness and information processing. Carlson and O'cass (2012) emphasized the importance of e-service quality in content-driven e-service websites, indicating that it positively affects consumers' information processing and awareness.

In summary, awareness and information processing are essential factors in consumer behavior in the online business context. Factors such as online reviews, word-of-mouth recommendations, information search and evaluation, acceptance of online platforms, and the quality of online experiences all contribute to consumers' awareness and information processing, shaping their purchase decisions.

b. Social Cognition and Culture Effect

Consumer behavior in online business is influenced not just by individual characteristics, but also by social cognition and cultural effects. Social cognition is the perception, processing, and interpretation of social information, whereas cultural influences are the effects of cultural norms, values, and beliefs on consumer behavior.

In the context of online business, social cognition has a substantial impact on consumer behavior. Wang and Sun (2010) investigated social influence in online purchasing and discovered that social elements such as social presence and social influence had a substantial impact on customers' attitudes and purchase intentions.

They came to the conclusion that consumers' impressions of other people's activities and opinions influence their own behavior when shopping online.

Additionally, the concept of social proof is closely tied to social cognition and has implications for consumer behavior. Social proof refers to individuals' tendency to rely on others' actions or opinions to guide their own behavior. Chatterjee and Brown (2005) explored the impact of social proof on online shopping decisions and discovered that consumers are more willing to make purchases when they believe others have had positive experiences with the product or service.

Cultural effects shape consumer behavior in online business. Cultural norms, values, and beliefs influence consumers' preferences, decision-making processes, and perceptions of online businesses. Hofstede's cultural dimensions theory (1980) is often used to analyze the impact of cultural differences on consumer behavior.

For instance, a study by Pham and Wu (2019) explored the influence of cultural dimensions on consumers' trust and purchase intention in e-commerce. They found that individualism, uncertainty avoidance, and long-term orientation significantly impact consumers' trust in online businesses and subsequent purchase intentions.

Moreover, cultural values can shape consumers' perceptions of online security and privacy. Krishnamurthy (2001) explored the impact of cultural elements in customers' views of online privacy and discovered that cultural values connected to individuality and collectivism influence consumers' privacy concerns and readiness to share personal information online.

c. Price Value and Perception of Online Products

In online business, the perception of price value is a critical aspect affecting consumer behavior. Consumers compare the price of online goods and services to the perceived value they expect to obtain. Price value perception is a consumer's appraisal of the benefits they will receive from a product or service in relation to its cost.

Consumers often seek value for money in their online purchases, aiming to maximize the benefits while minimizing the costs. Zeithaml (1988) proposed the concept of perceived value, which suggests that consumers' assessment of the overall worth of a product or service is based on their assessment of its perceived benefits relative to its price. Consumers are more likely to make online purchases when they believe the benefits outweigh the costs.

Furthermore, the perception of price value is a critical factor that deeply effects how consumers assess the value of products or services, especially in the context of online shopping.

Huang and Oppewal (2006) conducted a notable study that sheds light on this aspect of consumer behavior. Their research highlighted that consumers' perceptions of online pricing fairness have a direct and significant impact on their perceived value and subsequent purchase intentions. In other words, when consumers perceive the pricing of products or services as fair, they are more inclined to see higher value in those offerings.

This perception of fairness can be a important driver in their decision to make a purchase. The association between price fairness and perceived value is closely intertwined. When consumers believe that they are getting a fair deal for the price they pay, it enhances their perception of value. It's not just about the absolute cost; it's about the fairness of the exchange. This dynamic underscore the importance of transparent and equitable pricing strategies for online businesses.

In essence, Huang and Oppewal's research underscores that pricing isn't solely about setting the right cost; it's also about communicating that price fairly to consumers. Businesses that can effectively convey the fairness of their pricing are more likely to resonate with consumers, leading to higher perceived value and increased purchase intentions.

Moreover, the presentation of price information and the use of pricing strategies impact consumers' perception of price value. Chang, Chang, and Huang (2012) investigated the effects of pricing strategies on consumer purchase intentions in online business. They found that strategies such as price discounting and promotional pricing positively influence consumers' perception of price value, leading to higher purchase intentions.

Additionally, consumers' prior experiences and reference prices also affect their perception of price value. Han, Nunes, and Drèze (2010) conducted a study on the impact of reference prices on consumer judgments of price fairness and value. They found that consumers' reference prices, formed based on past experiences or external cues, significantly influence their perception of price value. Consumers compare the online product's price to their reference prices to determine its value.

d. Usability and User Experience in Online Shopping

The usability and user experience of an online shopping platform are pivotal determinants influencing consumer behavior. Factors such as ease of use, functionality, and the overall encounter with the platform play a substantial role in shaping consumers' satisfaction levels, engagement levels, and intentions to make purchases.

To begin with, the usability of an online shopping website or application is critical to attracting and maintaining customers. The ease with which users can browse, engage with, and complete tasks on a website or application is referred to as usability. Usability is defined by Nielsen (1993) as a mix of qualities such as learnability, efficiency, memorability, mistake prevention, and user satisfaction. Consumers are more likely to engage with an online platform that is simple, user-friendly, and efficient, and to explore items or services and make purchases.

Moreover, a positive user experience contributes to consumer behavior in online shopping. User experience encompasses the overall perception, emotions, and attitudes that users develop when interacting with a website or application. Hassenzahl (2006) defines user experience as a combination of pragmatic aspects (e.g., usability) and hedonic aspects (e.g., enjoyment, aesthetics).

When customers have a pleasant user experience, they are more likely to view the online shopping platform as trustworthy, enjoyable, and dependable, which leads to higher satisfaction and repeat purchases.

The design elements, layout, and visual appeal of an online platform also influence consumers' perception of usability and user experience. Lohse and Spiller (1998) investigated the effect of website design elements on customer trust and purchase intention. They discovered that a visually appealing and professional website design affects consumers' perceptions of usability, credibility, and overall satisfaction. Consumers are likely to engage with and trust an online platform that organizes and visually appeals to them.

Additionally, personalized and tailored experiences contribute to enhanced usability and user experience in online shopping. Personalization involves customizing content, recommendations, and promotions based on consumers' preferences, past behaviors, and demographic information.

A study by Li, Zhang, and Zhang (2014) examined the effects of personalized recommendations on consumers' satisfaction and purchase intentions in online retailing. They found that personalized recommendations positively impact consumers' perceived usefulness, satisfaction, and intention to purchase. When consumers receive personalized product suggestions or offers, they feel valued and engaged, leading to a more favorable user experience.

e. Adoption Intention and Decision-Making Process

The adoption intention and decision-making process are important aspects of consumer behavior in online business. Understanding how consumers form their intentions to adopt online shopping and the factors that influence their decision-making process is crucial for businesses to effectively target and engage potential customers.

Adoption intention refers to consumers' propensity or tendency to use online shopping as their preferred means of obtaining goods or services. It entails assessing perceived utility, simplicity of use, and other important aspects that influence consumers' intentions to engage in online shopping. Perceived usefulness and perceived ease of use are major drivers of individuals' intentions to adopt a new technology or system, according to the Technology Acceptance Model (Davis, 1989).

In the context of online shopping, consumers' perception of factors such as time savings, convenience, accessibility, and the availability of a wide range of products contribute to consumers' positive adoption intentions (Chen & Tan, 2004).

The decision-making process in online shopping involves several stages that consumers go through before making a purchase. This procedure involves problem identification, information search, alternative evaluation, purchase choice, and post-purchase evaluation. Consumers actively look for relevant product information, read reviews, compare prices, and evaluate various online shops. Personal preferences, product attributes, perceived dangers, trust in the online platform, and social influence all have an impact on the decision-making process.

One prominent theory that explains the decision-making process in online shopping is the Theory of Planned Behavior (Ajzen, 1991). According to this theory, individuals' behavioral intentions are influenced by their attitudes towards the behavior, subjective norms (perceived social pressure), and perceived behavioral control (perceived ease or difficulty of performing the behavior).

Consumer attitudes toward online buying, the influence of friends and family, and their perceived control over the online purchasing process all play a part in determining their decision-making process and subsequent adoption intentions in the context of online shopping.

Furthermore, consumer decision-making in online shopping is often influenced by factors such as trust, security, and perceived risks. Trust is a crucial element in building confidence and reducing perceived risks associated with online transactions (Jarvenpaa, Tractinsky, & Vitale, 2000). Consumers' trust in the online platform, including its security measures, privacy policies, and reliability, significantly affects their decision-making process and adoption intentions.

B. Social Media and Online Business

1. The Rise of Social Media Era

The modern era has undergone a profound transformation in communication, connection, and commerce, primarily driven by the emergence of social media platforms. The development and widespread adoption of these platforms have redefined the way we interact and conduct business, with far-reaching implications for society.

The journey of social media can be traced back to the early days of the internet, with the likes of SixDegrees and Friendster attempting to connect people in the late 1990s (Boyd & Ellison, 2007). However, it wasn't until the mid-2000s that we witnessed a significant shift in the social media landscape with platforms like Facebook, Twitter, and YouTube (Kaplan & Haenlein, 2010).

In the realm of social networking, there exists a rich broad platform such as blogs, forums, business networks, photo-sharing websites, social media platforms, microblogs, messaging apps, and even news networks. These channels have profound connections among people, reshaping the way we communicate and share our lives.

The reach of social networking is truly global. In 2020, the worldwide rate of social media penetration surged to 49%, with the highest penetration rates observed in East Asia and North America at 71% and 69%, respectively. Europe followed closely at 67%, with northern Europe at 67% (Jin, Muqaddam & Ryu, 2019). The influence of social networking is an ever-expanding force. According to Clement (2020), by 2023, it is projected that nearly one-third of the world's population, around 3.43 billion individuals, will actively engage with social media every month. China alone is set to contribute approximately 800 million users, while India will add nearly 450 million to this global count.

Leading social networks have attained monumental user bases and offer unique and compelling user experiences. For instance, Facebook stands as the pioneer, being the first social network to breach the threshold of 1 billion active monthly users. By the first quarter of 2020, it had a staggering 2.6 billion monthly active users across the globe, firmly establishing its place as one of the most popular social networks worldwide (Clement, 2020).

Instagram, the photo-sharing powerhouse, has also solidified its presence among the giants of social media. With over one billion monthly active users and a recent surge in daily usage, including its Stories feature, Instagram remains a pivotal platform for visual storytelling. Alongside Instagram, messaging apps such as Facebook Messenger, WeChat, and WhatsApp hold a firm grip on the social networking landscape, bridging communication and connectivity (Schouten, Janssen & Verspaget, 2019).

The appeal of social networking continues to be irresistible, with both the number of users and their engagement levels on the rise. On average, digital people now spend 144 minutes each day within these digital realms, underlining the profound impact of social networks on our daily lives (Kees & Andrews, 2019).

The impact of social media on communication and information dissemination has been nothing short of revolutionary. These platforms have empowered individuals to express themselves, forge connections, and drive social and political movements (Kaplan & Haenlein, 2010). From citizen journalism to influencer marketing and the rapid spread of news and trends, social media has reshaped how we interact with information and each other (Smith et al., 2012).

The business world has been irrevocably altered by the advent of the social media era. Companies quickly recognized the potential of these platforms for marketing, customer engagement, and e-commerce (Kaplan & Haenlein, 2010).

The ability to reach a global audience directly and instantaneously has given rise to an explosion in online businesses. With each passing year, the data underscores the undeniable influence that social media wields in driving online business growth and success.

2. Definition and Importance of Social Media Engagement

The level of interaction, participation, and connection between users and social media platforms is referred to as social media engagement. It includes activities like liking, sharing, commenting, and uploading material, as well as following and connecting with other people and brands. Social media engagement is important in online consumer behavior since it reveals how much people are actively involved with and influenced by social media platforms.

Engagement on social media platforms is crucial for businesses as it allows them to establish and maintain relationships with their target audience. According to Li and Bernoff (2011), social media engagement is essential for building brand awareness, fostering customer loyalty, and driving customer satisfaction. By actively engaging with consumers through social media, businesses can create a sense of community, facilitate dialogue, and develop a two-way communication channel with their audience.

Furthermore, social media engagement enables businesses to gather valuable insights and feedback from consumers. By monitoring user interactions, comments, and discussions on social media, companies can gain a better understanding of consumer preferences, needs, and behaviors. This information can be used to tailor marketing strategies, improve products or services, and make informed business decisions (Hanna, Rohm, & Crittenden, 2011).

The significance of social media engagement arises from its ability to influence consumer views and buying decisions. Consumers are more likely to trust and be affected by suggestions from their peers or social media influencers (Muntinga, Moorman, & Smit, 2011). Engaging with customers on social media enables businesses to capitalize on the power of word-of-mouth marketing and user-generated content, which may have a substantial impact on consumer attitudes, brand perception, and buying intentions.

Moreover, social media engagement contributes to the overall customer experience. By actively responding to customer inquiries, providing timely support, and delivering personalized content, businesses can enhance customer satisfaction and loyalty. According to a study by Verhoef et al. (2010), engaged customers are more likely to become brand advocates and recommend a brand or product to others. Therefore, fostering social media engagement can lead to positive customer advocacy and ultimately drive business growth.

3. Social Media Influence on Online Consumer Behavior

Social media platforms have had a tremendous impact on online consumer behavior. Because of the extensive use of social media, customers now have access to a variety of information, social interactions, and user-generated material that shape their attitudes, perceptions, and purchasing decisions.

The power of social influence and peer recommendations is one of the primary ways in which social media influences consumer behavior. Consumers are more likely to trust and be persuaded by recommendations from their peers or social media influencers than traditional forms of advertising, (Muntinga, Moorman, & Smit, 2011). Individuals can use social media channels to express their product and brand experiences, views, and recommendations. Consumers actively seek and rely on user-generated content to help them make purchasing decisions.

Social media also serves as a platform for social comparison and information-seeking behavior. Consumers often turn to social media platforms to gather information about products, read reviews, and compare prices and features before making a purchase (Hoffman & Fodor, 2010). The accessibility and convenience of social media platforms make them an ideal resource for consumers to gather real-time information and seek social validation.

Furthermore, social media has transformed the way consumers engage with brands and participate in the buying process. Consumers now have the ability to directly interact with brands through social media channels, providing feedback, asking questions, and seeking support (Hanna, Rohm, & Crittenden, 2011). This interactive nature of social media allows for a more personalized and engaging experience, fostering a sense of connection and loyalty between consumers and brands.

Moreover, the widespread adoption of social media has paved the way for influencer marketing, a strategy that involves brands partnering with social media influencers to promote their products or services. These influencers, who have cultivated trust and a sizeable following on social media platforms, can exert a considerable influence on consumer behavior through their product recommendations and endorsements (Muntinga, Moorman, & Smit, 2011). Consumers often perceive influencers as relatable and trustworthy, making their recommendations influential in shaping consumer attitudes and purchase decisions.

Overall, social media platforms have a profound influence on consumer behavior in the online environment. They provide consumers with access to user-generated content, peer recommendations, information-seeking opportunities, and interactive brand engagement. Understanding the impact of social media on consumer behavior is crucial for businesses to effectively leverage these platforms in their marketing strategies and adapt to the changing dynamics of online consumer behavior.

C. Online Shopping in The Yemeni Market

1. Current Landscape Of Online Shopping İn Yemen

The conflict and instability in Yemen have posed significant challenges to gathering comprehensive and up-to-date market data, making it difficult to obtain precise market share figures and growth rates for online businesses. However, amidst these challenges, niche opportunities may have emerged, particularly in sectors related to humanitarian aid, medical services, and basic necessities. E-commerce for essential goods could have shown potential for growth in this context.

One the other hand , despite low internet penetration, the prevalent use of mobile phones for communication and limited internet access may have created opportunities for mobile-based businesses, including mobile apps and mobile content delivery services.

The current landscape of online shopping in Yemen is characterized by a growing trend of digitalization and an increasing adoption of e-commerce platforms. Despite challenges related to infrastructure, logistics, and internet penetration, online shopping is gaining momentum in Yemen.

Several studies shed light on the current landscape of online shopping in Yemen, revealing a notable growth and evolving consumer behavior. Research conducted by Al-Haimi, Hammad, and Alqershi (2020) indicates a significant increase in the adoption of online shopping among Yemeni consumers. The study found that approximately 40% of Yemeni consumers have engaged in online shopping activities, showcasing a growing interest in e-commerce.

This trend is further supported by the increasing number of internet users in Yemen. According to a report by We Are Social and Hootsuite (2021), the country has witnessed a rise in internet penetration, with around 18 million individuals having access to the internet. Furthermore, the proliferation of mobile devices has played a important role in shaping online shopping habits in Yemen, with more than 70% of the population owning a mobile phone.

The growth of online shopping in Yemen is further evidenced by the expanding e-commerce platforms and marketplaces in the country. Several local and regional e-commerce platforms have emerged, providing Yemeni consumers with a diverse range of products and services. For instance, platforms like "Yemenstore" and "Yemen Souq" have gained popularity among consumers, offering a wide selection of goods ranging from electronics and clothing to household items (Al-Kalabani & Alharthi, 2017).

These platforms have contributed to the convenience and accessibility of online shopping, allowing consumers to browse and make purchases from the comfort of their homes. Additionally, international e-commerce giants like Amazon and AliExpress have also made their mark in Yemen, providing access to a broader range of products and attracting a significant number of consumers (Al-Subhi & Al-Jardani,2017).

Accoding to Al-Makrami, Al-Amri, and Alqahtani (2018) , consumer preferences and behaviors in online shopping have also been influenced by the availability of different payment methods. Cash on delivery (COD) remains the dominant payment method in Yemen, preferred by a large portion of consumers due to factors such as trust issues and limited access to electronic payment systems.

However, there has been a gradual shift towards electronic payment methods, with the introduction of mobile payment services like "M-Paisa" and the increasing acceptance of debit and credit card payments. This shift indicates a growing acceptance and trust in digital payment systems, which in turn contributes to the growth of online shopping in Yemen.

Furthermore, studies have highlighted the impact of social media on online shopping behavior in Yemen. Social media platforms, particularly Facebook and Instagram, have become popular channels for promoting products, engaging with consumers, and facilitating online transactions. The active presence of businesses and sellers on social media platforms has created a vibrant online marketplace, allowing consumers to discover new products, read reviews, and make purchase decisions (Amri & Siam ,2020).

The influence of social media extends beyond product discovery, as it also plays a role in building trust and credibility. Consumers often rely on recommendations and feedback from their social networks, including friends and influencers, to guide their online shopping decisions (Al-Meshal & Abdul Rahman ,2020).

2. Challenges and Barriers to Online Shopping Adoption in Yemen

The adoption of online shopping in Yemen faces several challenges and barriers that hinder its widespread acceptance and usage among consumers. These challenges arise from various factors and can be categorized into several key areas.

Access to reliable and high-speed internet connectivity is crucial for a seamless online shopping experience. However, Yemen faces challenges in terms of limited internet infrastructure and connectivity, particularly in remote areas. According to a study by Al-Subhi, Al-Jardani, and Al-Madani (2015), inadequate internet coverage and slow connection speeds were reported as significant barriers to online shopping adoption in Yemen. The study emphasized the need for improved internet infrastructure to enhance the accessibility of online shopping platforms for consumers across the country.

Trust is a critical factor influencing consumers' willingness to engage in online shopping. In Yemen, concerns regarding the security and privacy of personal information during online transactions have been identified as barriers to adoption. Al-Shareef, Aldweesh, and Al-Yahya (2018) found that trust in online sellers and concerns about the security of online payment systems were major factors influencing online purchase intention among Yemeni consumers. Building trust through secure online platforms, robust data protection measures, and transparent transaction processes can help alleviate these concerns.

Perceived risks associated with online shopping can act as barriers to adoption. Yemeni consumers may have concerns about the authenticity and quality of products, as well as the reliability of online sellers. Research by Al-Mahfadi and Al-Arashi (2016) highlighted perceived risks as a significant barrier to online shopping intention among Yemeni consumers. Ensuring product quality, providing reliable product information, and implementing effective return and refund policies are essential to mitigate these perceived risks and instill confidence in online shopping.

The availability and acceptance of online payment methods play a crucial role in online shopping adoption. In Yemen, limited options for online payment can hinder the growth of e-commerce. Al-Zaraee and Al-Qershi (2019) identified a lack of widely accepted and secure payment gateways as a barrier to enhancing consumers' online shopping experience in Yemen. Expanding the range of secure and convenient payment options, including mobile payment solutions and cash-on-delivery services, can help address this barrier and increase consumer trust in online transactions.

Yemen's unique geographic landscape and ongoing conflict pose logistical challenges for online shopping. Limited transportation infrastructure, customs procedures, and security concerns can result in delays and uncertainties in product delivery. Al-Haimi, Zain, Ramayah, and Noor (2020) emphasized the significance of logistics and delivery challenges as barriers to online shopping adoption in Yemen. Collaborative efforts between e-commerce platforms, logistics providers, and government agencies are required to improve the efficiency and reliability of product delivery, thereby enhancing the overall online shopping experience.

The development of a robust e-commerce infrastructure is vital for online shopping adoption. In Yemen, the e-commerce landscape is still evolving, with a relatively small number of online marketplaces and businesses. Al-Kalabani and Alharthi (2017) found that the limited availability of online platforms and the absence of specialized e-commerce services were barriers to online shopping behavior among Yemeni consumers. Enhancing the e-commerce ecosystem, fostering the growth of online marketplaces, and providing necessary support systems for online sellers can help overcome this barrier and expand consumer access to online shopping.

Limited digital literacy and awareness can hinder online shopping adoption, particularly among certain segments of the population. Yemeni consumers may lack the necessary skills and knowledge to navigate online platforms, compare prices, and make informed purchasing decisions. Al-Harbi and Mahmood (2020) highlighted the importance of digital literacy programs to enhance consumers' online shopping readiness in Yemen. Promoting digital literacy initiatives and providing accessible educational resources can empower consumers and bridge the digital divide, enabling wider participation in online shopping.

Cultural norms and social practices can also influence the adoption of online shopping in Yemen. Traditional shopping experiences, such as visiting physical stores and engaging in face-to-face interactions with sellers, hold cultural significance for many Yemeni consumers. Al-Boloshi and Mahmood (2019) emphasized the influence of cultural values and social norms on online shopping behavior in Yemen. Addressing cultural perceptions, fostering familiarity with online shopping, and emphasizing the convenience and benefits of digital commerce can help overcome these cultural barriers.

By understanding and addressing these challenges and barriers, stakeholders including the government, businesses, and service providers can work collaboratively to promote and facilitate the adoption of online shopping in Yemen.

III. LITERATURE REVIEW

Building upon the prior context provided regarding consumer behavior, social media impact, and online shopping examines the specific dynamics of Yemen's consumer landscape. By synthesizing and critically analyzing existing research studies conducted globally and within Yemen, this literature review aims to synthesize, analyze, and critically evaluate the body of knowledge and findings from previous studies. It intends to explore the multifaceted aspects of consumer behavior, emphasizing the impact of social media marketing strategies, determinants influencing online shopping behaviors, and consumer attitudes toward online shopping. By delving into these aspects, the literature review aims to identify gaps, inconsistencies, or emerging trends in existing research and contribute to a deeper understanding of the complexities shaping consumer behaviors.

A. Previous Studies

In recent years, consumer behavior in Yemen has been increasingly influenced by the rise of social media and the growing popularity of online shopping. Numerous research studies have been conducted to explore the impact of these trends on consumer buying behavior and attitudes in the Yemeni market. These studies shed light on the factors that influence consumers' intentions and decisions to shop online, as well as the role of social media in shaping their attitudes and behaviors.

A cluster of studies has been dedicated to investigating the relationship between social media marketing and consumer behavior in Yemen. Amri and Siam (2020) found that social media marketing has a positive influence on consumers' attitudes, purchase intention, and actual purchasing behavior. Similarly, Al-Meshal and Abdul Rahman (2020) discovered that social media significantly influences consumers' brand awareness, purchase decision, and post-purchase behavior. These findings highlight the significant impact of social media platforms on shaping consumer perceptions and choices in Yemen's dynamic marketplace.

Another line of research has focused on exploring the various factors that influence consumers' online shopping behavior in Yemen. Al-Haimi et al. (2020) revealed that trust, perceived benefits, and social influence are key determinants of consumers' intention to shop online. Al-Shareef, Aldweesh, and Al-Yahya (2018) found that social media usage positively influences consumers' intention to purchase online. Moreover, Al-Kalabani and Alharthi (2017) and Al-Subhi and Al-Jardani (2017) both identified trust, perceived benefits, website quality, and social influence as significant factors influencing consumers' online shopping behavior. These studies underscore the importance of building consumer trust and delivering perceived benefits to drive online purchasing decisions in Yemen.

Furthermore, Al-Makrami, Al-Amri, and Alqahtani (2018) found that consumers in Yemen hold positive attitudes towards online shopping, which are influenced by factors such as convenience, trust, and perceived risks. Al-Sharafi, Hassan, and Al-Kahtani (2015) investigated the effect of social media marketing activities on customer loyalty and found a positive influence on customer loyalty. These studies provide valuable insights into the preferences and behaviors of Yemeni consumers in the realm of e-commerce.

Studies by Al-Harbi and Alghazi (2019) delved into the influence of online reviews and testimonials on consumer decision-making in Yemen. Their findings revealed that positive online reviews significantly impact consumers' trust and purchase intentions, emphasizing the pivotal role of user-generated content in shaping purchasing behavior.

Moreover, Al-Mansoori and Al-Hadhrami (2021) investigated the impact of digital payment methods on consumers' propensity to shop online in Yemen. Their research elucidated that the availability and ease of secure digital payment options significantly influence consumers' willingness to engage in online transactions.

Additionally, Al-Bahadly and Al-Ezzi (2019) examined the effects of personalized marketing strategies on consumer engagement and loyalty in Yemen. Their study highlighted that personalized marketing approaches tailored to individual preferences positively impact consumer engagement and foster long-term loyalty among Yemeni consumers.

Furthermore, research conducted by Al-Dhubaibi and Al-Mamari (2018) focused on the role of mobile applications in enhancing the online shopping experience for consumers in Yemen. Their findings underscored the significance of user-friendly mobile interfaces and personalized app features in driving consumer satisfaction and repeat purchases.

These studies collectively contribute to a more comprehensive understanding of the intricate dynamics shaping consumer behavior and the e-commerce landscape in Yemen. However, while shedding light on various aspects, gaps in knowledge persist, urging further exploration, specifically in the Yemeni market exploring the specific dynamics, trends, and factors that influence consumer behavior towards online business and the role of social media engagement.

Beyond Yemen, research conducted globally has delved into consumer behavior, particularly in relation to the impact of social media and online shopping. In Southeast Asia, Tan, Lim, and Lee (2020) investigated the effectiveness of social media marketing on consumer purchasing behaviors, highlighting how cultural differences influence responses to marketing strategies. Similarly, Müller and Schmidt (2019) explored the European market, emphasizing the pivotal role of trust and convenience in influencing online shopping behaviors.

Across the United States, Johnson and Smith (2021) conducted studies that highlighted the diverse effects of different social media platforms on consumer attitudes and brand engagement. In East Asia, Wu, Chen, and Li (2018) provided insights into consumer preferences for mobile shopping applications, emphasizing the critical role of user interface design in driving consumer satisfaction and engagement.

In Africa, Abiodun and Mohammed (2017) investigated e-commerce adoption and consumer behaviors, considering factors such as infrastructure and cultural perceptions. Their findings shed light on the unique challenges and preferences shaping online shopping behaviors in African markets.

Moreover, in the Middle East, Khalid and Ahmed (2020) examined the impact of digital payment systems on e-commerce adoption. Their research highlighted the evolving consumer preferences for secure and convenient payment options in the region.

The collective findings from these diverse global studies contribute significantly to understanding the multifaceted nature of consumer behavior, online shopping trends, and the intricate influence of social media across different cultural, economic, and geographical contexts. These cross-regional studies not only offer insights into shared factors shaping consumer behaviors but also emphasize the nuanced variations and preferences specific to each region.

IV. EMPIRICAL APPLICATION

This research will be considered as one of the few first if not the first study to analyze online shopping environment in Yemen and give businesses insights into how the social media users behave towards online shopping. which will help online businesses understand the major factors which influence overall consumer behavior.

The outcome of this research will help businesses to build suitable strategies to target new consumers for their online business as well as maintain the current ones by understanding and improving on the most affected factors to create more positive behavior towards online shopping.

A. Research Design

This research comprises two distinct phases. The first phase is aimed to adopt multiple scales into Arabic and in the specific context of Yemen. In this initial phase, the goal is to construct a novel research tool that captures the online shopping behavior within the Yemeni environment.

Following the scales adaptation is construction of the model at the second phase of the research employs an analytical design in a quantitative research approach. This phase focuses on testing and discussing hypotheses derived from the newly developed model, providing empirical insights into online shopping behavior in Yemen. Exploratory research, which used in these study , is particularly valuable when dealing with novel, intricate phenomena or when exploring an unfamiliar environment, allowing for a deeper comprehension before proceeding to a more structured investigation.

B. Methodology

The research employed a comprehensive array of statistical techniques. Exploratory Factor Analysis (EFA) was utilized to reveal underlying data patterns and identify key dimensions, while Confirmatory Factor Analysis (CFA) validated these patterns, ensuring the measurement scales' validity. Various approaches were used to assess validity and reliability, including content, construct, and criterion methods, alongside Cronbach's alpha coefficient and item-total correlations.

For group comparisons with unequal variances, Welch's t-test was applied, determining the statistical significance of observed differences. Additionally, Analysis of Variance (ANOVA) evaluated means among multiple groups, and Games-Howell post-hoc analysis identified specific differences. Correlation analyses explored relationships between variables. Lastly, Structural Equation Modeling (SEM) unveiled complex interactions between latent constructs and observed variables, enhancing the research's depth and accuracy.

Each of these methods plays a distinct role in analyzing and interpreting the collected data, contributing to a comprehensive understanding of the research objectives.

1. Exploratory Factor Analysis

Exploratory factor analysis (EFA) is a statistical method used to identify patterns in a set of variables and to identify the underlying structure of a dataset. According to Cureton & D'Agostino (2017), EFA can be used to identify the underlying factors or dimensions that explain the relationships among the variables in the dataset.

EFA can be useful for researchers trying to understand a dataset's structure and the relationships among variables. It can help identify important patterns in the data and underlying factors that may not be immediately obvious from the raw data.

Communalities, typically calculated through factor loadings, represent the correlation coefficients between variables and these factors. High communalities suggest a strong relationship between a variable and the underlying constructs it represents, making it a robust indicator of the measured construct. Researchers often use a range of 0.25 to 0.4 as an acceptable cutoff for communalities, with values at or above 0.7 being highly preferable (Eaton, Frank, Johnson, & Willoughby, 2019).

Maximum Likelihood Factor Analysis (MLFA) estimates factor loadings and variances by maximizing the likelihood function, which quantifies the probability of observing the sample data given the factor structure (Finch, 2020). MLFA is favored for its efficiency and robustness, especially when compared to methods like Principal Component Analysis (PCA). It acknowledges variable interdependence and accounts for measurement errors, making it suitable for estimating the number of factors, factor structure, and factor scores that can predict variable scores (Finch, 2020).

To address the strong correlation between factors, the study employs Promax rotations and Kaiser normalization. Promax rotation enables the correlation of factors, enhancing the interpretability of the factor structure and maximizing the variance of squared loadings for each factor. Kaiser normalization scales factor loadings to a mean of 0 and a standard deviation of 1, contributing to improved factor analysis interpretability and stability (Hayton, Allen, & Scarpello, 2004).

In the field of exploratory factor analysis (EFA), the Kaiser-Meyer-Olkin (KMO) test and Bartlett's test are fundamental statistical tools used to assess the suitability of data for factor analysis. These tests play a crucial role in determining whether the dataset contains enough common variance and intercorrelation among variables to support the extraction of meaningful factors (Vogt & Johnson, 2016).

To evaluate sampling adequacy for factor analysis, two common statistical tests are used: the Kaiser-Meyer-Olkin (KMO) test and the Bartlett's test of sphericity.

The KMO test measures the proportion of variance in the variables that can be explained by underlying factors. Higher KMO values indicate better sampling adequacy. A KMO value of 0.8 or higher is considered excellent, while a value of 0.6 or higher is considered moderate. Values below 0.6 suggest poor sampling adequacy (Vogt & Johnson, 2016) . The Bartlett's test of sphericity assesses whether the observed correlations among variables in the dataset are significantly different from zero. A significant p-value from the Bartlett's test (usually less than 0.05) suggests that the observed correlations are significantly different from zero, providing evidence that the dataset is suitable for factor analysis (Vogt & Johnson, 2016).

Both help researchers evaluate the presence of common variance and significant correlations among variables, which are essential for extracting meaningful factors and uncovering the underlying structure of the data.

Additionally, total variance explained (TVE) in exploratory factor analysis (EFA) refers to the proportion of total variability in the data that is accounted for by the extracted factors. It provides a measure of the goodness of fit of the factor solution and gives indications of how well the factors represent the underlying structure of the data. In social research, the acceptable percentage of variance in factor analysis can vary depending on the specific research question and study design. However, generally, a minimum of 50% of the total variance in the data is considered a good starting point in social research (Pallant, 2016).

2. Confirmatory Factor Analysis

Confirmatory Factor Analysis (CFA) is used to test the measurement model of a construct. Specifically, it is used to assess whether a set of observed variables measures a specific underlying construct (also known as a latent variable). Confirmatory Factor Analysis (CFA) and Exploratory Factor Analysis (EFA) are two different types of factor analysis that are used to analyze the structure of a set of variables. While both methods produce a loadings matrix, the loadings matrix in CFA and EFA serve different purposes and are used for different types of analysis.

In CFA, the loadings matrix displays the factor loadings for each observed variable in the model. The factor loadings are estimated based on a priori hypotheses about the data's underlying structure, representing the correlations between the observed variables and the latent factors in the model. The loadings matrix in CFA is used to assess the model's fit and to interpret the analysis results (Hair, Black, Babin, & Anderson, 2010).

To evaluate the significance of the factor loadings in the CFA, z-value is used, as a high positive z-value indicates that the factor loading estimate is significantly different from zero and supports the presence of an association between the observed variable and the latent factor. In contrast, a high negative z-value indicates that the factor loading estimate is significantly different from zero but in the opposite direction. In general, a z-value is statistically significant if it is greater than 1.96 (Kline, 2016).

On the other hand, the covariance matrix displays the covariances between all pairs of observed variables in the data. The covariance matrix provides important information about the associations between the observed variables and can be used to assess the fit of the CFA model (Kline, 2016).

A good fit between the estimated covariances and the observed covariances indicates that the model is capturing the underlying structure of the data well, and the factor loadings are accurate representations of the associations between the observed variables and the latent factors.

While a poor fit between the estimated covariances and the observed covariances indicates that the model is not capturing the underlying structure of the data well, and the factor loadings may not be accurate representations of the associations between the observed variables and the latent factors (Cureton & D'Agostino, 2017).

Confirmatory Factor Analysis is used to test a model's goodness of fit and make comparisons between competing models. Additionally, it allows the estimation of factor loadings, which can be used to determine the relationship between an observed variable and the underlying construct it is measuring.

In Confirmatory Factor Analysis (CFA), fit indices are used to assess the goodness-of-fit of the model to the data. Hu and Bentler (1999) conducted a simulation study to investigate the rejection rates under correct models by using various cut-off values for many fit indices, such as:

Comparative Fit Index (CFI): A measure of how well the proposed model fits the data compared to a baseline or null model. A commonly used cut-off value is .90, meaning that the proposed model fits the data better than a baseline model by a margin of at least .90. Values above .95 are generally considered an excellent fit.

Tucker-Lewis Index (TLI): Similar to CFI, but also considers the parsimony of the model in addition to its fit to the data, a commonly used cut-off value is .90, with values above .95 indicating an excellent fit.

Bentler-Bonett Non-normed Fit Index (NNFI) and Bentler-Bonett Normed Fit Index (NFI): Measures of the goodness of fit of a model, with NNFI correcting for sample size and NFI normalized by a baseline model. A value of .95 or higher is generally considered a good fit.

The goodness of fit index (GFI): A measure of how well the proposed model fits the data, A value of .95 or higher is generally considered a good fit.

Root mean square error of approximation (RMSEA): A measure of the difference between the observed covariance matrix and the covariance matrix implied by the model, value of .08 or lower is generally considered a good fit, with values closer to 0 indicating a better fit.

Standardized root mean square residual (SRMR): A measure of the difference between the observed and predicted covariance matrices, a value of .08 or lower, is generally considered a good fit, with values closer to 0 indicating a better fit.

Hu and Bentler's study has gained significant traction, and many researchers now use their suggested cut-offs (West et al., 2012).

3. Validity and Reliability

Validity is a fundamental aspect of measurement, reflecting the extent to which a scale accurately assesses its intended construct. Reise, Widaman, and Pugh (1993) identify various types of validity, including content validity, which assesses the scale's comprehensive coverage of the construct, and criterion-related validity, which involves predictive validity (the scale's ability to forecast future performance) and concurrent validity (its correlation with concurrent measures of the construct). Additionally, construct validity examines the scale's alignment with other measures of the same construct not used concurrently. These validity types collectively ensure that a scale effectively measures what it is meant to gauge.

To establish the validity of a new scale, researchers typically conduct several types of validity analyses, such as Exploratory Factor Analysis (EFA) and Confirmatory Factor Analysis (CFA), which have already been done in previous steps. Hence the Convergent and discriminant validity analyses and reliability tests will be done in the following analysis.

Cronbach's alpha coefficient is a commonly used measure of internal consistency, which is a type of reliability that assesses the extent to which items on a test or scale are measuring the same construct. It is a measure of the average correlation between all possible combinations of items on a scale.

Item-total correlations method, which refers to the statistical relationship between individual items on a survey and the total score of the survey. These correlations are used to assess the internal consistency of the test or survey, so we can say that the purpose of calculating item-total correlation is to determine the extent to which individual items are contributing to the overall score and to identify items that may be problematic (e.g., too difficult, or too easy, ambiguous, poorly worded, etc.) (Groth-Marnat, 2003).

A high item-total correlation indicates that an item is strongly related to the overall score and is a good indicator of the measured construct. On the other hand, a low item-total correlation suggests that an item may not be a good indicator of the construct and may need to be revised or removed. One common measure of item-total correlation is Pearson's correlation coefficient, which ranges from -1 to 1. A value of .6 or higher is generally considered a strong correlation, a value between .3 and .5 is considered a moderate correlation, and a value below .3 is considered a weak correlation. (Hair, C., Babin, & Anderson, 2010).

4. ANOVA and Post hoc

Two common statistical tests used to analyze the effect of demographic variables on research outcomes are ANOVA (Analysis of Variance) and t-tests. ANOVA is used to compare the means of more than two groups and can determine whether there is a statistically significant difference between the means of the groups. If ANOVA indicates a significant difference between the groups, post-hoc tests are used to determine which groups are significantly different from each other. This can be useful when analyzing the impact of demographic variables on multiple groups, such as the impact of age on research outcomes for different age groups (Howell, 2012).

Post hoc tests are used to determine which specific groups in a significant ANOVA result are different from each other. This is necessary because an ANOVA only tells us that there is a significant difference between groups, but not which specific groups are different. Post hoc tests are typically used after an ANOVA has found a statistically significant result (Howell, 2012).

There are several post hoc tests that can be used, such as Tukey's Honestly Significant Difference (HSD) test, Bonferroni correction, and Scheffe's method.

Tukey's HSD test is a commonly used post hoc test that compares all possible pairs of means and identifies which pairs are significantly different from each other. This test is considered the most appropriate when the sample sizes are equal and the variances are homogenous (Howell, 2012).

In this research, Games-Howell post-hoc test has been used. The Games-Howell test is a non-parametric alternative to the Tukey test, which does not assume equal variances or sample sizes. It is a more conservative test than the Tukey test and is suitable for situations where the assumption of equal variances is violated. The Games-Howell test computes a unique confidence interval for each pairwise comparison, taking into account the unequal variances and sample sizes (Bakeman,2005) ,

5. Welch's t-test

t-test is used to compare the means of two groups and can determine whether there is a statistically significant difference between the means of the two groups. This can be useful when analyzing the impact of demographic variables on two specific groups, such as the impact of gender on research outcomes for male and female participants (Howell, 2012).

Both t-test and ANOVA test null hypothesis posits that there is no statistically significant difference between the means of the compared groups. Conversely, the alternative hypothesis suggests that a significant difference does indeed exist between these means. To determine the significance of this difference, test statistics are computed by dividing the disparity between the sample means by the standard error of that difference, as outlined by Howell (2012). This statistical approach helps assess whether the observed distinctions between group means are likely to be attributed to genuine differences.

In this research, the independent samples t-test has been used, however, to overcome its limits Welch's t-test was done which is a modification of the independent samples t-test that allows for unequal variances since the unequal variance assumption is often violated when the sample sizes of the two groups being compared are different or when the standard deviations of the two groups are different. This can occur, for example, when one group has a larger variance than the other or when the sample sizes are different between the two groups (Welch, 1947)

Welch's t-test adjusts the degrees of freedom used in the t-test to account for the unequal variances, which leads to more accurate results and more reliable conclusions (Welch, 1947). Moreover, Welch's t-test is more robust than the traditional t-test because it does not assume equal variances, making it suitable for a wider range of situations (Howell, 2012).

6. Structural Equation Modeling

Structural Equation Modeling (SEM) stands as a robust statistical approach employed to unravel intricate connections among variables (Hoyle & Panter, 1995). This sophisticated tool empowers researchers to scrutinize not only the direct but also the indirect relationships that exist among these variables (Byrne, 2016). SEM holds extensive prominence within the realms of the social and behavioral sciences, serving as a vital instrument for testing theoretical models and delving into the interplay between latent variables (Kline, 2016).

SEM involves the use of path analysis to estimate the relationships between observed variables and latent variables (Byrne, 2016). It allows for the inclusion of measurement error in the analysis and can be used to test the fit of the model to the data (Kline, 2016). SEM can also be used to test mediation and moderation effects, which are important in understanding the mechanisms through which variables influence each other (MacKinnon et al., 2007).

Overall, SEM is a valuable tool for researchers to examine complex relationships among variables and to test theoretical models. Its use has become increasingly widespread in social and behavioral sciences due to its ability to account for measurement errors and to test the fit of the model to the data (Kline, 2016).

According to Kline (2016), to build a model using SEM, we can follow these general steps:

1. Develop a conceptual model: This involves identifying the variables of interest, their relationships, and how they fit into the broader theoretical framework. This step requires a thorough review of existing literature and theories.

2. Select a software program: SEM requires specialized software to analyze the data and estimate the model parameters. Popular software programs for SEM include Amos, Mplus, and lavaan.
3. Collect data: SEM requires a sample of data that reflects the population of interest. The sample size should be sufficient to achieve adequate statistical power for the model estimation.
4. Measure the variables: SEM requires valid and reliable measures of the variables of interest. This may involve developing new measures or using established ones from previous studies.
5. Specify the model: This involves specifying the relationships among the variables using mathematical equations that reflect the hypothesized causal pathways. The model should be grounded in theory and supported by existing research.
6. Estimate the model: This involves using the software to estimate the model parameters, including the strength and direction of the relationships among the variables.
7. Evaluate the model fit: This involves evaluating how well the model fits the data. This can be done by examining goodness-of-fit indices, such as the chi-square test, CFI, and RMSEA.
8. Interpret the results: This involves interpreting the estimates of the model parameters and assessing their statistical significance. This step requires a careful consideration of the theoretical and practical implications of the results.
9. Revise the model: If the model fit is poor or the results are not consistent with the theoretical framework, the model may need to be revised. This may involve adding or removing variables, specifying alternative relationships, or using different measures.
10. Present the results: The results should be presented in a clear and concise manner, using tables, graphs, and narrative descriptions as appropriate.

The results of the analysis allowed for the "direction" (positive or negative) of the relationship as well as the strength of the association between adoption intentions for online shopping and other variables. A significance level was set at $p \leq 0.05$ for both analyses as well as those that came after (Kline, 2016).

The model offered standardized regression coefficients (β) that demonstrated the degree of the connected variables' associations. The product of the regression coefficients discovered along the predictor's path was used to calculate the predictor's direct and indirect effects on adoption intentions for online shopping (Kline, 2016).

The error term (also known as a disturbance term) represents the part of the variance of a latent or observed variable that is not explained by the model's predictors. It is an unobserved variable that captures the effects of all other variables that are not included in the model or that are too complex to be explicitly modeled. The error term is included in the structural equation model to account for the fact that the observed variables are not perfectly predicted by the model's predictors. The error term is typically assumed to be normally distributed with a mean of zero and a constant variance (Kline, 2016).

Arrows indicate the direction of the relationship between variables, and the path coefficient represents the strength of the relationship. Error terms represent the residual variance in the manifest variables and are represented as small circles attached to the rectangles in the path diagram (Kline, 2016).

Moreover, covariance represents the relationship between two latent variables and is represented as a double-headed arrow between the two circles representing the latent variables. Unidirectional arrows indicate the direction of causality between the variables in the model, with causal relationships usually depicted as unidirectional arrows (Kline, 2016).

The statistical significance of the coefficients can be assessed using p-values. A p-value less than 0.05 is typically considered statistically significant, indicating that the relationship between the variables is unlikely to have occurred by chance. Overall, interpreting SEM results involves a combination of examining the path coefficients, standard errors, and statistical significance, as well as considering the theoretical implications of the relationships between the variables in the proposed model

(Kline,2016).

In practice, statistical power and anticipated effect size are important considerations when determining the appropriate sample size for a study. By specifying a desired level of statistical power and an anticipated effect size, researchers can estimate the minimum sample size required to achieve sufficient statistical power and detect the effect of interest (Jackson, Gillaspy & Purc-Stephenson, 2009).

One the other hand, SEM fit analysis is a statistical technique used to evaluate the fit of a structural equation model to the observed data. It involves assessing the degree of discrepancy between the theoretical model and the observed data. A well-fitting model has a small discrepancy between the observed data and the theoretical model, indicating that the model accurately explains the relationships between the variables in the data.

In order to conduct SEM fit analysis, several fit indices can be used; according to Smith (2020), Kline (2016), and Hu and Bentler (1999); including chi-square test, comparative fit index (CFI), Tucker-Lewis index (TLI), root mean square error of approximation (RMSEA), and standardized root mean square residual (SRMR). A well-fitting model typically has a significant chi-square test, CFI and TLI values above 0.9, RMSEA values below 0.08, and SRMR values below 0.05.

Understanding SEM results involves analyzing the estimated coefficients, standard errors, and statistical significance of the relationships between the variables in the proposed model. These results can provide valuable insights into the strength and direction of the relationships between the variables, as well as their significance in predicting the outcome variable (Byrne, 2016). Schreiber et al. (2006) provided a comprehensive review of best practices for reporting structural equation modeling and confirmatory factor analysis results in academic research.

Interpreting structural equation modeling (SEM) results involves a sequential analysis of key elements. Firstly, it's important to examine the path coefficients, which reveal both the strength and direction of relationships between variables. Next in line are the standard errors associated with these coefficients. These standard errors quantify the level of uncertainty in the estimated coefficients. Smaller standard errors suggest more precise estimates, which enhances the reliability of the results.

Furthermore, in line with Blalock's insights (1986), SEM is often utilized to explore both direct and indirect effects of one variable on another. The total effect of one variable on another combines both direct and indirect effects. Direct effects illustrate the influence of one variable on another without the mediation of any additional variables in the model. In contrast, indirect effects represent the influence of one variable on another through the mediation of one or more intervening variables in the model. This comprehensive analysis of SEM results enables a deeper understanding of the complex relationships within a model.

C. Adopting the Research Scale

1. Introduction

Over the last decade, there has been a major increase in the literature on online consumer behavior (Darley, Blankson, & Luethge, 2010), and as a result, it has become an emergent subject of research. Hence after examination of previous research reveals that researchers drew hypotheses from traditional consumer behavior research such as attitude models (Fishbein, 1975), information processing (Bettman,1979), personality research (Folkes, 1988), and behavioral learning (Skinner, 1990). However, we acknowledge that the application is not as simple as merely copying theories because there are substantial distinctions between customers' online and offline behavior.

With the growing popularity of online shopping in Yemen, the advancement of technology, and increased access to the Internet, online shopping has become increasingly popular in Yemen. Despite being in the middle of a civil war, the country is experiencing a growing trend in online shopping and e-commerce, which is why it has become important to understand the behavior of online consumers in the country.

Understanding social media engagement is important when examining online consumer behavior in Yemen because it can influence purchasing decisions and provide valuable insights into consumer behavior, such as their preferences, attitudes, and opinions, helping businesses to understand their target market better and tailor their marketing strategies accordingly.

It can also facilitate communication between businesses and consumers, allowing for direct feedback and engagement, which can improve customer relationships and loyalty. Overall, understanding social media engagement is crucial in the digital age as it can greatly impact online consumer behavior in Yemen.

Researchers mostly use Online Consumer Behavior scales (OCBS) to understand consumer behavior in the online environment. However, most OCBS were developed in English and may not be suitable for the Yemeni environment. This study aims to minimize the gap between the availability of valid research scales in Arabic compared to English and build a valid scale to understand and examine the behavior of online consumers in Yemen and identify key trends and challenges in the e-commerce market.

To do that, the research adopted three different scales from English into Arabic and made the needed editions to make it most suitable for the Yemeni environment; the original scales are:

First: The online consumer behavior scale developed by Ansari (2019) contains 35 items defined into seven variables: Attitude, Trust, Cultural factors, Social factors, Situational factors, Web atmosphere, and E-Retailors image.

Second: Social Media Engagement scale developed by Ni et al. (2020) contains 11 items defined into three variables which are: Behavioral Engagement, Cognitive Engagement, and Affective Engagement

Third: Extended scale from the unified theory of acceptance and use of tech developed by Venkatesh, Thong, & Xu (2012), which contains 17 items defined into five variables: Performance expectancy, Effort expectancy, Facilitating condition, Price value, and Behavioral intentions.

In Venkatesh et al. (2012), there are more dimensions of the "unified theory of acceptance and use of tech" (UTAUT2). As Hedonic motivation, habit, and social influence; however, we did not include them to this research due to the following reasons:

Firstly, research focus: The scope and focus of this research have differed from the specific research objectives and context of the original UTAUT2 study. As a result, we have chosen to prioritize certain dimensions that were more relevant to my research question or hypothesis. As this research focuses on the adoption of online shopping in a Yemeni market which is still very new to this kind of shopping and people are not used to it while the UTAUT2 was mainly about keep using the technology which the consumers who may be familiar with it.

Secondly, Available resources: The inclusion of additional dimensions and items from UTAUT2 would require substantial data collection and analysis, especially in the structural equation model. Given the constraints of time, resources, and the specific objectives of my thesis, we have made choices to streamline the research process while still maintaining the integrity of the study.

Thirdly, Conceptual framework: The conceptual framework was developed for this research included an online consumer behavior scale that contains Attitude, Social Factors, and Situational Factors, those variables are close to Social Influence, Hedonic Motivation, and Habit from UTAUT2, of course not the same but may have some similarity, although in online consumer behavior scale the variables was closer to the research goals so we chose them instead.

The newly adopted scales have been properly validated and have demonstrated adequate reliability and validity. This includes evaluating the scale's internal consistency, its content, criterion-related, and construct validity, the scale's applicability to the population and research context, and its feasibility for administration and data analysis.

This research will be considered one of the few first, if not the first, studies to analyze the online shopping environment in Yemen and give businesses insights into how social media users behave towards online shopping, which will help online businesses to understand the major factors influencing overall consumer behavior. The outcome of this research will help businesses build suitable strategies to target new consumers for their online business and maintain the current ones by understanding and improving on the most affected factors to create more positive behavior towards online shopping.

2. Adoption Procedures

a. Translation Procedures

Before any process, the three scale developers were contacted through e-mail to request permission to adapt the original scale to the Arabic language, and the necessary permissions were received. After getting permission from the scale's developers and since the original scales are in English, further processes were needed to translate it into Arabic and make it suitable for the Yemeni environment.

The translation process from English into Arabic was a complex and delicate task, as it was important to maintain the meaning and intent of the original scale while also ensuring it was appropriate for the Yemeni context.

The back-translation procedure ensured a translated text's accuracy and cultural appropriateness. The back-translation procedure is crucial in ensuring the validity and reliability of translated research instruments and is widely used in cross-cultural research to overcome language and cultural barriers (Twinn,1997). The process involves translating the translated text back into the original language and comparing it with the original text to identify any differences or errors (Beins, 2013).

The back-translation process is commonly used in the translation of questionnaires, surveys, and other research instruments to ensure that the meaning and intent of the original text are preserved in the translated version. This is particularly important in cross-cultural research, where language and cultural context differences can result in misunderstandings or misinterpretations of the original text (Brislin, 1970).

According to Chapman & Carter (1979), The back-translation procedure involves the following steps:

1. Translation of the original text: A professional translator translates the original text into the target language.
2. Back-translation of the translated text: A second translator, who is unfamiliar with the original text, back-translates the translated text into the original language.
3. Comparison of the original text and back-translation: The original text

and back-translation are compared to identify any discrepancies or differences in meaning.

4. Revision and correction: If any discrepancies or differences are identified, the original translation is revised and corrected as necessary.
5. Final review: The final review is conducted by a team of experts to ensure the accuracy and cultural appropriateness of the translated text.

The first language experts who followed the required Arabic translation process was Ahmed Fuad Musawa, PhD, Osmania University, India, and the second expert was Mohammed Al-Ariqy, PhD, University of Utah, USA.

To verify the suitability of the scale items for the Yemeni environment (Face validity), two scholars reviewed and approved the Arabic version; the first approval was from Ahmed G. A. Gawas, PhD, Ankara Yildirim Beyazit University, Turkey, and the second one is Hosam Alsaeedi, PhD, from Sanaa University, Yemen.

The back translation processes were done to ensure that the Arabic versions of the scales are in good shape compared to the original English versions and are a good fit for the Yemeni context.

b. Ethics Approval

This study was conceded in accordance with the Istanbul Aydin University Institute of Graduate Studies Ethics Committee approval numbered 2022/13, and dated 04.08.2022.

3. Pilot study

The pilot study was conducted to ascertain the instrument's reliability after receiving favorable feedback on the face validity of the instrument from relevant experts. A link was prepared using google forms to reach a random sample of social media users in Yemen, and 100 responses were collected for the Pilot study analysis.

Respondents are also asked to provide any pertinent comments and feedback, including noting spelling mistakes, grammatical confusion, or ambiguous sentences, as well as any suggestions for enhancing an instrument's quality. The data from each completed questionnaire was then entered into the SPSS software version 28 for reliability analysis.

The degree of reliability and internal consistency of an instrument is highly dependent on the reliability of the instrument. According to Pallant (2016), Cronbach's alpha value of 0.6 or higher is regarded as reliable and in a respectable index range. The results of the pilot study indicate that the measurement scales used are highly reliable in assessing the intended constructs. The Social Media Engagement Scale, Online Consumer Behavior Scale, and Extended Scale from the Unified Theory of Acceptance and Use of Technology all exhibit strong internal consistency, as reflected by their respective high Cronbach's alpha values (0.855, 0.941, and 0.926).

These findings suggest that the scales provide consistent and stable measurements, enhancing the trustworthiness of the data collected in the study. Table 1 below shows the results:

Table 1 Reliability Statistics for The Pilot Study

Scale	Cronbach's alpha	N of items
Social Media Engagement scale	.855	11
Online consumer behavior scale	.941	34
Extended scale from the unified theory of acceptance and use of tech.	.926	17

4. Sample and Data Collection

The research population is social media network users in Yemen; according to Napoleoncat (2022), the population is 3.5 million, using the unlimited population formula and assuming a population proportion of 0.5 within 5% confidence intervals, a Confidence Level is 95% and that z score for a 95% confidence level is 1.96; the sample size is 385 respondents.

$$n = \frac{z^2 \times \hat{p}(1-\hat{p})}{\varepsilon^2} = \frac{1.96^2 \times 0.5(1-0.5)}{0.05^2} = 384.16$$

where

z is the z score

ε is the margin of error

N is the population size

$\hat{p}$ is the population proportion

The researcher prepared a link using google forms to gather the full data sample by online questionnaire in Yemen from May to October 2022, and 395 responses were collected. The questionnaire contains a total of 73 questions which are 11 demographical questions and 62 items in Likert 5-point style

The results showed that the scale means is 215.87, and variance is 1577.512 with a standard deviation of 39.718 and the inter-item covariances is 0.393, and the inter-item correlation is 0.274.

5. Testing Normality

In order to estimate the likelihood that a random variable underlying the data set is normally distributed, normality tests are used. Since the data size is above 300, the best way to check normality is by skewness, and kurtosis tests, as Hair et al. (2010) argued that data is considered normally distributed if skewness and kurtosis absolute value is between -2.58 and +2.58 at .01 significance level and the absolute value is between -1.96 and +1.96 at .05 significance level.

Table 2 and Table 3 below are the results of the analysis done by JASP 0.17.2 for all the survey questions except the demographic variables (Q1-Q11). The results showed that all items are normally distributed as the results support accepting the null hypothesis, which states that data are taken from a normally distributed population.

Table 2 Normality Test 1

	Skewness	Skewness S.E.	Kurtosis	Kurtosis S.E	Shapiro-Wilk	P-value
Q12	-1.001	0.123	-0.002	0.245	0.789	< .001
Q13	-0.908	0.123	0.290	0.245	0.824	< .001
Q14	-0.509	0.123	-0.981	0.245	0.859	< .001
Q15	-0.428	0.123	-0.643	0.245	0.891	< .001
Q16	-0.156	0.123	-0.844	0.245	0.912	< .001
Q17	-0.382	0.123	-0.864	0.245	0.887	< .001
Q18	-0.374	0.123	-0.741	0.245	0.891	< .001
Q19	0.147	0.123	-1.130	0.245	0.894	< .001
Q20	-0.406	0.123	-1.039	0.245	0.875	< .001
Q21	0.113	0.123	-1.109	0.245	0.901	< .001
Q22	0.097	0.123	-1.205	0.245	0.890	< .001
Q23	-0.324	0.123	-1.045	0.245	0.888	< .001
Q24	-0.916	0.123	-0.231	0.245	0.815	< .001
Q25	-1.131	0.123	0.500	0.245	0.787	< .001
Q26	-0.263	0.123	-1.019	0.245	0.895	< .001
Q27	-0.091	0.123	-1.061	0.245	0.905	< .001
Q28	-0.717	0.123	-0.174	0.245	0.862	< .001
Q29	-0.242	0.123	-0.912	0.245	0.899	< .001
Q30	-0.665	0.123	-0.368	0.245	0.866	< .001
Q31	-0.378	0.123	-0.762	0.245	0.896	< .001
Q32	-0.640	0.123	-0.429	0.245	0.870	< .001
Q33	-0.767	0.123	-0.269	0.245	0.853	< .001
Q34	0.005	0.123	-0.659	0.245	0.906	< .001
Q35	-0.276	0.123	-0.478	0.245	0.907	< .001
Q36	-0.612	0.123	-0.515	0.245	0.873	< .001
Q37	-0.016	0.123	-1.096	0.245	0.902	< .001
Q38	-0.152	0.123	-0.960	0.245	0.906	< .001
Q39	-0.247	0.123	-1.046	0.245	0.896	< .001
Q40	0.141	0.123	-1.141	0.245	0.891	< .001
Q41	-0.009	0.123	-0.932	0.245	0.906	< .001
Q42	-0.253	0.123	-0.808	0.245	0.905	< .001
Q43	-0.191	0.123	-0.861	0.245	0.906	< .001

Table 3 Normality Test 2

	Skewness	Skewness S.E.	Kurtosis	Kurtosis S.E.	Shapiro-Wilk	P-value
Q44	-0.103	0.123	-0.837	0.245	0.910	< .001
Q45	-0.199	0.123	-0.649	0.245	0.913	< .001
Q46	-0.247	0.123	-0.651	0.245	0.909	< .001
Q47	-0.849	0.123	-0.082	0.245	0.832	< .001
Q48	-0.266	0.123	-0.953	0.245	0.892	< .001
Q49	-1.107	0.123	0.311	0.245	0.785	< .001
Q50	-0.052	0.123	-0.984	0.245	0.908	< .001
Q51	-0.134	0.123	-1.075	0.245	0.899	< .001
Q52	-0.374	0.123	-0.763	0.245	0.889	< .001
Q53	-1.256	0.123	0.964	0.245	0.766	< .001
Q54	-0.607	0.123	-0.356	0.245	0.879	< .001
Q55	-0.249	0.123	-0.408	0.245	0.902	< .001
Q56	-0.473	0.123	-0.233	0.245	0.888	< .001
Q57	-0.381	0.123	-0.496	0.245	0.900	< .001
Q58	-0.835	0.123	0.029	0.245	0.839	< .001
Q59	-0.311	0.123	-0.674	0.245	0.888	< .001
Q60	-0.590	0.123	-0.500	0.245	0.865	< .001
Q61	-0.550	0.123	-0.647	0.245	0.869	< .001
Q62	-0.773	0.123	-0.397	0.245	0.834	< .001
Q63	-0.737	0.123	-0.092	0.245	0.851	< .001
Q64	-0.800	0.123	-0.125	0.245	0.839	< .001
Q65	-0.056	0.123	-0.523	0.245	0.913	< .001
Q66	-0.455	0.123	-0.569	0.245	0.886	< .001
Q67	-0.240	0.123	-0.573	0.245	0.893	< .001
Q68	-0.614	0.123	-0.460	0.245	0.859	< .001
Q69	-0.732	0.123	-0.274	0.245	0.853	< .001
Q70	-1.030	0.123	0.061	0.245	0.786	< .001
Q71	-0.749	0.123	-0.500	0.245	0.843	< .001
Q72	-0.317	0.123	-0.880	0.245	0.898	< .001
Q73	-0.510	0.123	-0.759	0.245	0.874	< .001

6. Analysis of The Adopted Scales

a. The need for new structure for the adopted scales

When adopting scales for measurement in research or practical applications, it is crucial to ensure that the chosen scales possess sound psychometric properties and accurately capture the constructs of interest.

Confirmatory Factor Analysis (CFA) is a statistical technique commonly employed to assess the fit between the observed data and a hypothesized factor structure. However, in cases where the fit indices indicate a poor fit, it becomes necessary to consider the need for a new factor structure for the adopted scales (Kline, 2016).

This need may arise due to discrepancies between the observed data and the hypothesized structure, limitations in the existing factor structure, or inadequacies in capturing the underlying constructs. Addressing this need involves exploring alternative factor structures through techniques like Exploratory Factor Analysis (EFA), revising or adapting existing scales, and refining the measurement model (Cureton & D'Agostino,2017).

By undertaking these steps, researchers can enhance the psychometric properties and validity of the scales, ensuring more accurate measurement and interpretation of the constructs under investigation (Loehlin ,2003),

According to Loehlin (2003), it is generally recommended to conduct CFA before EFA in scale development and validation due to those reasons:

Theory-driven approach: CFA assumes a specific factor structure based on theory or prior research. By conducting CFA first, you can evaluate whether the observed data supports the hypothesized factor structure. If the CFA results confirm the expected factor structure, it provides support for the underlying theory and justifies the use of the scale in subsequent analyses.

Reduction of Type I errors: If EFA is conducted before CFA, there is a higher risk of false-positive findings. EFA is exploratory in nature and may identify different factor structures based on the characteristics of the sample or chance. Without a pre-specified hypothesis tested by CFA, researchers may be tempted to interpret these exploratory findings as meaningful and definitive, leading to overinterpretation and potential false conclusions.

Data overfitting: When EFA is conducted first, researchers might tailor the factor structure based on the observed data, leading to potential overfitting. Overfitting occurs when the model fits the current data well but fails to generalize to new samples or contexts. By conducting CFA first, researchers can avoid this issue by specifying the factor structure before exploring the data.

A good fit is indicated by CFI and TLI values above 0.90 or 0.95, with higher values indicating better fit. For RMSEA, values below 0.06 or 0.08 indicate a good fit, with lower values indicating better fit. Similarly, SRMR values below 0.08 are considered indicative of a good fit, with lower values indicating better fit (Hu & Bentler,1999).

Table 4 Confirmatory Factor Analysis Fit Indices with Original Scales Structures

Value	cut-off values	SME	OCB	UAT
CFI	0.90	0.836	0.875	0.844
TLI	090	0.815	0.849	0.830
NNFI	0.90	0.815	0.849	0.830
NFI	090	0.808	0.831	0.816
GFI	0.90	0.890	0.868	0.878
RMSEA	0.08	0.091	0.096	0.087
SRMR	0.08	0.061	0.076	0.060

Based on the fit indices results in the Table 4 above for the scales (SME, OCB, UAT), we can interpret the results as follows:

Comparative Fit Index (CFI): The CFI values for all variables (SME: 0.836, OCB: 0.875, UAT: 0.844) are below the commonly suggested cutoff of 0.90. The Tucker-Lewis Index (TLI) and Bentler-Bonett Non-normed Fit Index (NNFI) values for all scales (SME: 0.815, OCB: 0.849, UAT: 0.830) are also below the cutoff of 0.90. Similarly to CFI, they indicate a relatively good fit, although not meeting the commonly suggested threshold.

The Bentler-Bonett Normed Fit Index (NFI) and Goodness of Fit Index (GFI) values for all scales (SME: 0.808, OCB: 0.831, UAT: 0.816, GFI: 0.890, OCB: 0.868, UAT: 0.878) are below the cutoff of 0.90 as well.

The Root Mean Square Error of Approximation (RMSEA) values for all variables (SME: 0.091, OCB: 0.096, UAT: 0.087) exceed the suggested cutoff of 0.08. These values indicate that the hypothesized factor structure may not fit the observed data well, suggesting some room for improvement.

Although The standardized Root Mean Square Residual (SRMR) values for all variables (SME: 0.061, OCB: 0.076, UAT: 0.060) are below the cutoff of 0.08, indicating a good fit between the hypothesized factor structure and the observed data.

Overall, the results suggest that the hypothesized factor structure shows a not very good fit to the observed data indicate room for improvement. As fit indices for the adopted scales in Confirmatory Factor Analysis (CFA) indicate a poor fit to the observed data, it suggests that the current factor structure may not adequately capture the underlying constructs. In such cases, there is a need for a new factor structure for the adopted scales.

To address this issue, exploring alternative factor structures through further analysis, such as conducting Exploratory Factor Analysis (EFA) will be done to identify the underlying factor structure in an exploratory manner. EFA allows for the data to drive the identification of factors rather than relying on a pre-defined structure. It can help in discovering new patterns, grouping of items, or potential revisions to the scale.

b. Exploratory factor analysis

To examine the adopted scales, an exploratory factor analysis for each scale was conducted using SPSS 28 software.

In factor analysis, the goal is to identify patterns of co-variation among a set of variables, and the communalities are used to measure the degree to which each variable is associated with the underlying factors. The communalities are usually represented as a proportion or percentage, with a value between 0 and 1. A value of 1 indicates that all the variance in the variable is explained by the factors, while a value of 0 indicates that the variable is unrelated to the factors. It has been suggested that communalities between 0.25 and 0.4 are acceptable cut-off values, with communalities of 0.7 or higher being preferable. (Eaton, Frank, Johnson, & Willoughby, 2019)

Table 5, Table 6, and Table 7 below show the communalities results for the factor analysis's three scales. However, before deleting any items with low communality, the item loading must be checked; the results are reported in the following tables.

Table 5 Communalities - Social Media Engagement Scale

	Initial	Extraction
Item1	.359	.369
Item2	.200	.212
Item3	.340	.355
Item4	.261	.272
Item5	.365	.341
Item6	.284	.218
Item7	.297	.296
Item8	.405	.394
Item9	.516	.537
Item10	.427	.399
Item11	.474	.494

Communalities results for Social Media Engagement scale showed that most of the communalities appear to be in the range of 0.2 to 0.5, with some items having communalities above 0.4 (e.g., Item9 and Item11). This suggests that the extracted factors explain a moderate to a substantial portion of the variance in these items, indicating that they are reasonably well-represented by the factors derived from the factor analysis.

Table 6 Communalities - Online Consumer Behavior Scale

	Initial	Extraction
Item1	.512	.492
Item2	.419	.393
Item3	.398	.359
Item4	.508	.588
Item5	.471	.505
Item6	.508	.525
Item7	.465	.498
Item8	.401	.301
Item9	.519	.472
Item10	.418	.350
Item11	.370	.339
Item12	.534	.610
Item13	.530	.589
Item14	.585	.697
Item15	.697	.726
Item16	.671	.731
Item17	.728	.809

As for extended scale from the unified theory of acceptance and use of tech most of the communalities have increased compared to their initial values. This suggests that the extracted factors explain a significant portion of the variance in these items, and they are well-represented by the factors derived from the factor analysis. Items 14, 15, 16, and 17, in particular, have very high communalities after extraction, indicating that the extracted factors explain a large portion of the variance in these items.

Finally, Communalities for online consumer behaviour scale showed some of the communalities have decreased compared to their initial values, which suggests that not all items are well-represented by the extracted factors. However, items with higher communalities after extraction still retain a substantial portion of their variance in the factor structure.

Table 7 Communalities - Extended Scale From The Unified Theory Of Acceptance And Use Of Tech.

	Initial	Extraction		Initial	Extraction
Item1	.566	.419	Item18	.510	.407
Item2	.454	.431	Item19	.550	.369
Item3	.458	.438	Item20	.487	.408
Item4	.462	.333	Item21	.253	.124
Item5	.421	.343	Item22	.539	.512
Item6	.476	.393	Item23	.422	.323
Item7	.559	.418	Item24	.502	.430
Item8	.403	.282	Item25	.498	.416
Item9	.463	.439	Item26	.541	.558
Item10	.308	.205	Item27	.615	.620
Item11	.216	.054	Item28	.634	.621
Item12	.502	.481	Item29	.393	.261
Item13	.605	.611	Item30	.488	.432
Item14	.589	.657	Item31	.405	.364
Item15	.553	.538	Item32	.553	.520
Item16	.511	.494	Item33	.506	.439
Item17	.604	.580	Item34	.557	.576

KMO test and Bartlett's test serve as initial steps in EFA to determine the adequacy of data for factor analysis. The KMO measure for the Social Media Engagement scale as seen in Table 8 below is 0.880, indicating excellent sampling adequacy. This suggests that the dataset is highly suitable for factor analysis.

Additionally, the Bartlett's test of sphericity yielded an approximate chi-square value of 1101.018 with 36 degrees of freedom, and a significance level of less than 0.001. The small p-value (<0.001) suggests that the observed correlations among variables in the dataset are significantly different from zero, providing further evidence supporting the suitability of the data for factor analysis.

Table 8 KMO And Bartlett's Test - Social Media Engagement Scale.

KMO and Bartlett's Test		Statices
Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.880
Bartlett's Test of Sphericity	Approx. Chi-Square	1101.018
	df	36
	Sig.	<.001

Online Consumer Behavior scale results in Table 9 below showed KMO values as 0.927, indicating excellent sampling adequacy. This suggests that the dataset is highly suitable for factor analysis.

Additionally, Bartlett’s test of sphericity yielded an approximate chi-square value of 3811.629 with 190 degrees of freedom, and a significance level of 0.000. The small p-value (0.000) suggests that the observed correlations among variables in the dataset are significantly different from zero, further supporting the suitability of the data for factor analysis.

Table 9 KMO And Bartlett's Test - Online Consumer Behavior Scale.

KMO and Bartlett's Test		Statices
Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.927
Bartlett's Test of Sphericity	Approx. Chi-Square	3811.629
	df	190
	Sig.	.000

Lastly, as seen in Table 10, KMO measure for the Extended Scale from the Unified Theory of Acceptance and Use of Technology is 0.915, indicating excellent sampling adequacy. This suggests that the dataset is highly suitable for factor analysis. Additionally, the Bartlett's test of sphericity yielded an approximate chi-square value of 2518.165 with 66 degrees of freedom, and a significance level of 0.000.

The small p-value (0.000) indicates that the observed correlations among variables in the dataset are significantly different from zero, providing further support for the suitability of the data for factor analysis.

Table 10 KMO And Bartlett's Test - Extended Scale from The Unified Theory of Acceptance and Use of Tech.

KMO and Bartlett's Test		Statices
Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.915
Bartlett's Test of Sphericity	Approx. Chi-Square	2518.165
	df	66
	Sig.	.000

Based on KMO and Bartlett's results, the data appears to be well-suited for conducting factor analysis. This indicates that meaningful factors can be extracted to understand the underlying structure, providing valuable insights into the factors influencing consumer’s' behavior and adoption of online shopping.

To extract the underlying structure in a set of variables Maximum Likelihood Factor Analysis (MLFA) method has been used in the Exploratory Factor Analysis (EFA).

It is also important to keep in mind that the goal of factor analysis in social research is not just to achieve a high percentage of explained variance but also to extract factors that are meaningful, interpretable, and have theoretical relevance to the research question. Ultimately, the decision about the acceptable percentage of variance will depend on the specific goals and context of the study. (Timmerman & Lorenzo-Seva, 2011).

As seen in Table 11, Table 12, and Table 13, the social media engagement scale has one factor with Eigenvalues above 1, which explains 41% of the underlying structure of the data. The online consumer behavior scale has three factors with eigenvalues above 1, which explain 47% of the underlying structure of the data. Finally, the extended scale from the unified theory of acceptance and use of tech has three factors with eigenvalues above 1, which explain 60% of the underlying structure of the data.

Table 11 Total Variance Explained - Social Media Engagement Scale.

Factor	Initial Eigenvalues		
	Total	% of variance	Cumulative %
1	4.516	41.055	41.055

Table 12 Total Variance Explained - Online Consumer Behavior Scale.

Factor	Initial Eigenvalues		
	Total	% of variance	Cumulative %
1	12.195	35.866	35.866
2	2.288	6.729	42.595
3	1.651	4.857	47.452

Table 13 Total Variance Explained - Extended Scale from The Unified Theory of Acceptance and Use of Tech.

Factor	Initial Eigenvalues		
	Total	% of variance	Cumulative %
1	7.819	45.996	45.996
2	1.284	7.553	53.549
3	1.143	6.721	60.270

The factor analysis results are reported in the Factor matrix, a table containing the factor loadings, which are the correlation coefficients between the variables and the factors. The factor loadings represent the degree to which each variable is associated with each factor. The factor matrix is used to obtain the patterns of covariances among the variables and identify the variables that are highly associated with a given factor.

It is an important tool for obtaining the factor loadings, which are the coefficients that indicate the degree of association between each variable and each factor. The factor loadings are used to determine which variables are most strongly associated with each factor and, therefore, the variables most indicative of the underlying construct being measured.

The factor loading for each newly developed item should be greater than 0.5. and for an already proven scale, every item should be 0.6 or higher (Awang, 2014); after choosing only the items with loadings equal to or above 0.5, the results will be as follows.

The social media engagement scale was measured and characterized by the ABC theory, introduced by Myers (1993), which stated that the structure of human attitude was made up of attachment, conduct, and cognition. However, in the Arabic-adopted scale, only one factor has been extracted from the data as well as dropping two items from the original scale as those items do not have the minimum required loadings.

As seen in Table 14 below, only nine items have loadings above 0.5 into one factor, which represents the whole social media engagement scale. Hollebeek (2011) stated that engagement is multi-dimensional, including behavior, cognition, and affection, consistent with past research and theory.

Table 14 Factor Loadings - Social Media Engagement Scale

	SME
Item1	.607
Item3	.596
Item4	.522
Item5	.584
Item7	.544
Item8	.628
Item9	.733
Item10	.631
Item11	.703

As for the online consumer behavior scale, the original English version has 35 items defined into seven factors; however, in the Arabic-adopted version, only three factors have been extracted, totaling 20 items.

Based on the results of the factor analysis shown in Table 15, the three extracted factors which include items that have loadings above 0.5 are online business perception (9 items), awareness (6 items), and social cognition (5 items).

Table 15 Factor Loadings - Online Consumer Behavior Scale

	Online, Business perception	Awareness	Social cognition
Item1		.689	
Item2		.616	
Item3		.565	
Item8		.539	
Item9		.743	
Item12			.510
Item13			.740
Item14			.853
Item15			.668
Item17			.529
Item19		.505	
Item22	.726		
Item24	.633		
Item25	.600		
Item26	.846		
Item27	.841		
Item28	.715		
Item32	.655		
Item33	.577		
Item34	.857		

Online business perception is one of the most discussed components in the literature, and it includes several web-specific aspects such as navigation; screen clarity, content relevance, link relevance; website characteristics, retailer image and reputation, and retailer reputation (Park, Han & Kaid, 2012). A retailer's image and reputation can help alleviate client anxiety by minimizing transaction risks and improving virtual interactions. In this regard, Kim & Lennon (2008) suggested that an online store's user interface be developed in such a way that it attracts and keeps cross-cultural customers.

Social cognition is the next component that has been addressed in consumer behavior literature (Adnan, 2014). Regarding social considerations, the theory of reasoned action (TRA) contends that even our best friends' wishes regarding purchasing specific products impact our purpose. Similarly, many researchers discovered that e-consumers' social impact is a powerful motivation for online purchases. Researchers also argued that social considerations, such as outside experiences, communication with people who share similar interests, peer group participation, and social standing, substantially influences online interferences and e-consumers, highlighting its importance in online consumer behavior. (Dubrovski, 2001).

Awareness refers to the consumer's understanding and recognition of the availability and convenience of purchasing products and services through the Internet. This can encompass an awareness of various e-commerce platforms, online payment methods, shipping options, and other key aspects of the online shopping experience. A consumer with a high level of awareness of online shopping is more likely to take advantage of these opportunities and make purchases through the Internet, whereas a consumer with low awareness may be less likely to engage in this type of shopping behavior (Kotler & Keller, 2016).

The last factor analysis was done on the adopted version of the extended scale from the unified theory of acceptance and use of tech, which in the original English version has 17 items defined into five factors. However, in the Arabic-adopted version, only three factors could be extracted, including 12 items. Based on the results of the factor analysis shown in Table 16, the three extracted factors, which include items that have loadings above 0.5, are price value (3 items), usability (6 items), and adoption intention (3 items).

Table 16 Factor Loadings - Extended Scale from The Unified Theory of Acceptance and Use of Tech.

	Usability	Adoption intention	Value
Item2	.521		
Item4	.842		
Item5	.676		
Item6	.733		
Item7	.657		
Item9	.605		
Item12			.783
Item13			.731
Item14			.853
Item15		.823	
Item16		.852	
Item17		.890	

Price value, the same factor in the original English scale, refers to the relationship between the price of a product or service and the perceived value or benefit that a consumer receives from purchasing it. In online shopping, consumers have access to a wide range of products and prices and are able to compare prices and values from different sellers and websites (Venkatesh & Davis, 2000).

Usability refers to perceived ease of use and perceived usefulness, which in the context of online shopping refer to consumers' attitudes and beliefs about the ease of use and the usefulness of e-commerce websites for purchasing products and services. Perceived ease of use refers to the degree to which an individual finds the online shopping process to be user-friendly and easy to navigate, including factors such as website design, functionality, and accessibility. Perceived usefulness refers to the degree to which an individual perceives online shopping as beneficial, including convenience, speed, product selection, and cost savings (Davis,1989).

Adoption intention, which is also the same factor in the original English scale, refers to a consumer's likelihood or desire to start using or continue using e-commerce websites to purchase products and services (Venkatesh & Davis, 2000).

Worth mentioning that the original scale the term behavioral intention was used instead of "Adaptation intention"; although in this research we will use Adoption intention as it may be a suitable term to convey the idea of consumers' willingness or intention to adapt or incorporate new technology into their lives. This terminology aligns well with the concept of technology acceptance and the process of individuals adapting to and adopting new technologies such as online shopping.

c. Confirmatory factor analysis

Based on the Loehlin (2003) loadings interpretation, we can say that the CFA loadings matrix in Table 17 for Social Media Engagement scale showed that the nine items in the factor have loadings range from 0.562 to 0.795, indicating moderate to strong associations between the variables and the factors.

Table 17 CFA Loadings Matrix - Social Media Engagement Scale

Factor	Indicator	Estimate	Std. Error	z-value	p
SME	SME1	0.683	0.023	29.459	< .001
	SME2	0.649	0.022	29.059	< .001
	SME3	0.562	0.022	25.019	< .001
	SME4	0.592	0.022	26.356	< .001
	SME5	0.587	0.023	25.922	< .001
	SME6	0.697	0.022	31.593	< .001
	SME7	0.795	0.021	37.242	< .001
	SME8	0.700	0.022	31.989	< .001
	SME9	0.758	0.022	35.165	< .001

Table 18 CFA Loadings Matrix - Online Consumer Behavior Scale

Factor	Indicator	Estimate	Std. Error	z-value	p
AW	AW1	0.739	0.017	44.025	< .001
	AW2	0.764	0.018	43.176	< .001
	AW3	0.771	0.018	42.917	< .001
	AW4	0.475	0.018	25.748	< .001
	AW5	0.626	0.018	34.667	< .001
	AW6	0.761	0.017	44.992	< .001
SC	SC1	0.813	0.015	52.896	< .001
	SC2	0.838	0.014	58.228	< .001
	SC3	0.785	0.014	54.668	< .001
	SC4	0.774	0.015	52.331	< .001
	SC5	0.754	0.016	48.166	< .001
OBP	OBP1	0.773	0.014	57.162	< .001
	OBP2	0.709	0.014	49.646	< .001
	OBP3	0.698	0.014	48.937	< .001
	OBP4	0.749	0.014	53.838	< .001
	OBP5	0.802	0.013	59.559	< .001
	OBP6	0.834	0.013	62.751	< .001
	OBP7	0.794	0.014	58.250	< .001
	OBP8	0.729	0.014	51.779	< .001
	OBP9	0.790	0.014	57.193	< .001

CFA loadings matrix for the online consumer behavior scale in Table 18 above showed that 20 items in the three factors had factor loadings ranging from 0.626 to 0.838, indicating moderate to strong associations between the variables and the factors.

A loading of 0.838 is a strong positive association, while a loading of 0.626 is a moderate positive association. Only one item (AW4) had a lower loading of 0.475 which may indicate a less moderated association than the other items although since it is still a significant association, there is no need to delete it.

Furthermore, CFA loadings matrix for extended scale from the unified theory of acceptance and use of tech in Table 19 showed that 12 items in the three factors had factor loadings ranging from 0.686 to 0.925, indicating moderate to strong associations between the variables and the factors. A loading of 0.925 is a strong positive association, while a loading of 0.686 is a moderate positive association.

Table 19 CFA Loadings Matrix - Extends Scale from The Unified Theory of Acceptance and Use of Tech.

Factor	Indicator	Estimate	Std. Error	z-value	p
PV	PV1	0.822	0.017	48.777	< .001
	PV2	0.817	0.017	47.615	< .001
	PV3	0.865	0.017	51.326	< .001
US	US1	0.686	0.018	38.657	< .001
	US2	0.760	0.017	45.328	< .001
	US3	0.759	0.017	45.486	< .001
	US4	0.773	0.017	46.165	< .001
	US5	0.750	0.017	43.441	< .001
	US6	0.730	0.017	42.897	< .001
AI	AI1	0.906	0.013	68.326	< .001
	AI2	0.886	0.013	67.924	< .001
	AI3	0.925	0.013	70.257	< .001

CFA covariance matrixes in Table 20 for the online consumer behavior scale indicate that there are moderate positive relationships between awareness (AW) and social cognition (SC) with a covariance of 0.666, awareness (AW) and online business perception (OBP) with a covariance of 0.681, and finally social cognition (SC) and business perception (OBP) with a covariance of 0.669.

Table 20 CFA Covariance Matrix - Extends Scale from The Unified Theory of Acceptance and Use of Tech.

			Estimate	Std. Error	z-value	p
PV	↔	US	0.698	0.018	39.393	< .001
PV	↔	AI	0.715	0.018	39.604	< .001
US	↔	AI	0.714	0.016	45.514	< .001

CFA covariance matrixes in Table 21 for extended scale from the unified theory of acceptance and use of tech indicate that there are moderate to strong positive relationships between Price value (PV) and Usability (US) with a covariance of 0.698, Price value (PV) and Adoption intentions (AI) with a covariance of 0.715, and finally Usability (US) and Adoption intentions (AI) with a covariance of 0.714.

Table 21 CFA Covariance Matrix - Online Consumer Behavior Scale

			Estimate	Std. Error	z-value	p
AW	↔	SC	0.666	0.017	40.307	< .001
AW	↔	OBP	0.681	0.014	49.921	< .001
SC	↔	OBP	0.669	0.012	55.318	< .001

Finally, all the relationships among variables in a Confirmatory Factor Analysis showed as a graphical representation called a path diagram which displays the factors (also referred to as latent variables or underlying constructs) and the observed variables in the model, and it represents the relationships among these variables in a graphical format as seen in Figure 1, Figure 2, and Figure 3 below.

The path diagram can be used to visually represent the structure of the CFA model, including the number of factors, the relationships among the variables, and the strength of the connections between the variables. Based on the CFA results, we can confirm that all the items have significant loadings into factors that have been extracted before during the EFA (Loehlin, 2003).

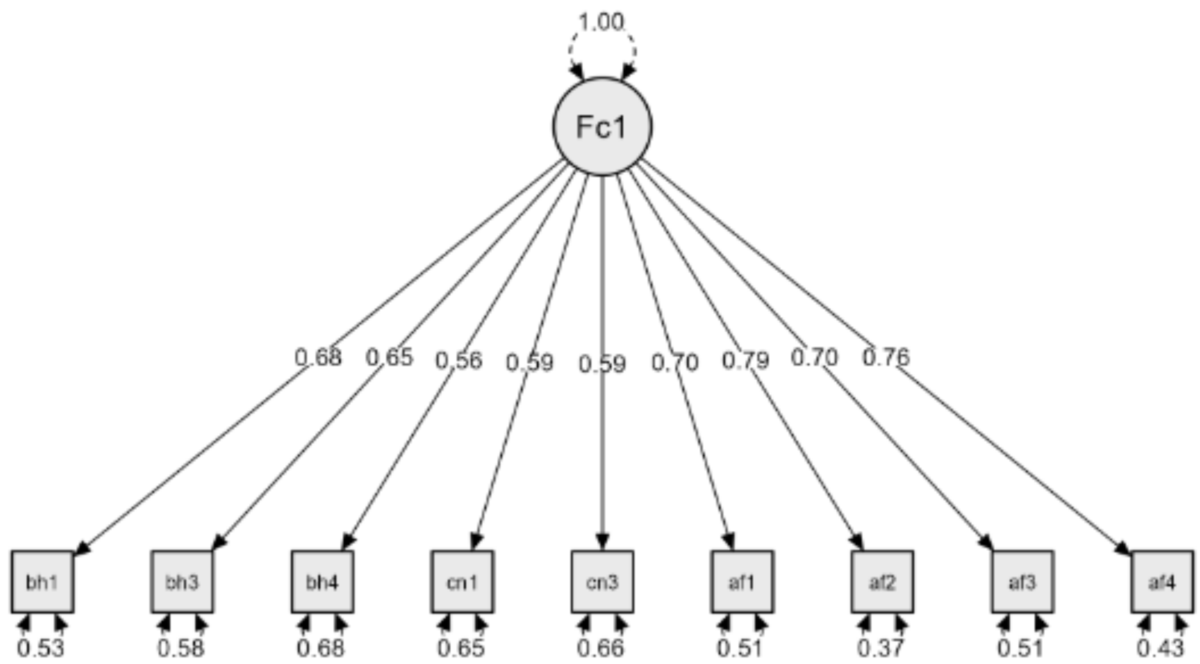

Figure 1 CFA Path Diagram - Social Media Engagement Scale

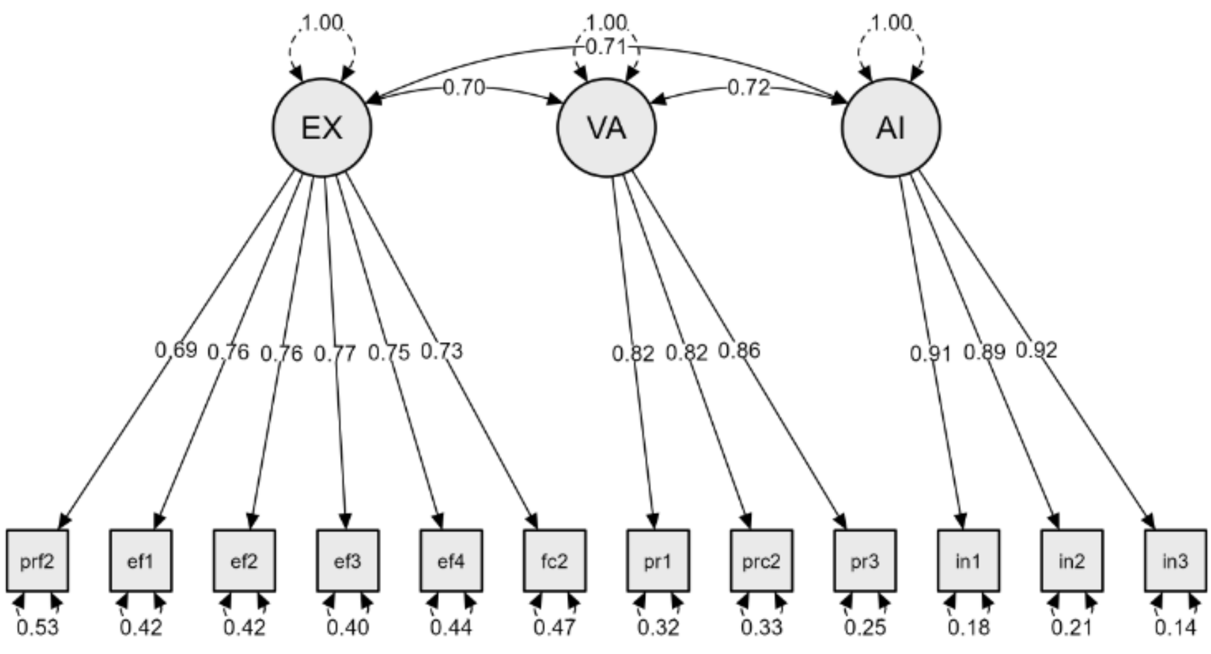

Figure 2 CFA Path Diagram - Extend Scale from The Unified Theory of Acceptance and Use of Tech.

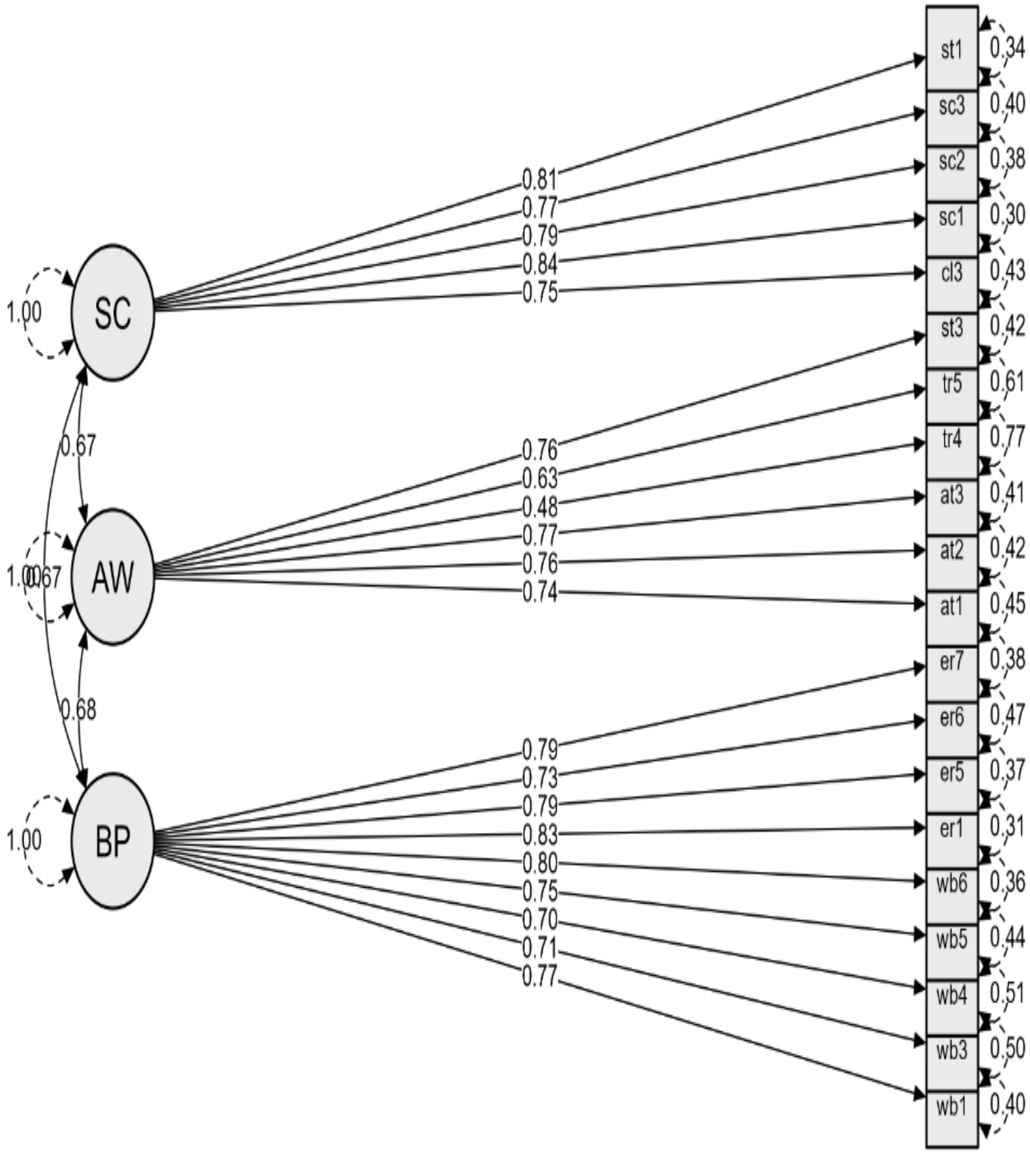

Figure 3 CFA Path Diagram - Online Consumer Behavior Scale

To examine the observed gap between theory and observation, a confirmatory factor analysis was conducted using JASP 0.16.4 software, and based on Hu and Bentler (1999) cut-offs, the results were as follows:

Table 22 Fit indices.

Value	cut-off values	SME	OCB	UAT
CFI	0.90	0.985	0.990	0.999
TLI	090	0.979	0.989	0.999
NNFI	0.90	0.979	0.989	0.999
NFI	090	0.979	0.984	0.997
GFI	0.90	0.988	0.988	0.997
RMSEA	0.08	0.080	0.066	0.027
SRMR	0.08	0.057	0.060	0.035

As seen in Table 22, the social media engagement scale (SME) had CFI=0.985, TLI=0.979, NNFI=0979, NFI=0.979, GFI=0.988, RMSEA= 0.08, and SRMR = 0.057. Online consumer behavior scale (OCB) had CFI=0.99, TLI=0.989, NNFI=0989, NFI=0.984, GFI=0.988, RMSEA= 0.066, and SRMR = 0.06. The extended scale from the unified theory of acceptance and use of tech (UAT) had CFI=0.999, TLI=0.999, NNFI=0999, NFI=0.997, GFI=0.997, RMSEA= 0.027, and SRMR = 0.035, which all in the accepted range of cut-offs values (Hu & Bentler,1999).

The results of the Confirmatory Factor Analysis indicate that the factors in the adopted scales are a good representation of the underlying structure of the data concluding that the CFA results support the validity of the adopted scales.

d. Validity and reliability of the adopted scales

Cronbach's alpha is often used to evaluate the internal consistency of a scale. The value of Cronbach's alpha is usually considered acceptable if it is greater than 0.7, and as seen in Table 23 below, all the factors have high Cronbach's alpha, which means they are reliable (Pallant, 2001).

Table 23 Reliability Analysis

scale	Variable	Cronbach's Alpha	N of Items
Social Media Engagement scale	scale	.847	9
Online consumer behavior scale	Awareness	.780	6
	Social cognition	.863	5
	Online Business perception	.901	9
	Full scale	.920	20
Extended scale from the unified theory of acceptance and use of tech.	Price Value	.873	3
	Usability	.848	6
	Adoption intention	.902	3
	Full scale	.909	12

The Social Media Engagement scale demonstrated good internal consistency, as indicated by a Cronbach's Alpha value of 0.847. This suggests that the items within the scale reliably measure social media engagement.

The Online Consumer Behavior scale encompassed multiple variables, including Awareness, Social Cognition, and Online Business Perception. The Awareness variable exhibited acceptable internal consistency, with a Cronbach's Alpha of 0.780, indicating reliable measurement of awareness. The Social Cognition variable demonstrated good internal consistency, with a Cronbach's Alpha of 0.863, suggesting that the items reliably measure social cognition. Similarly, the Online Business Perception variable displayed a Cronbach's Alpha of 0.901, indicating good internal consistency in measuring online business perception.

The overall Full Scale of the Online Consumer Behavior scale had a high level of internal consistency, with a Cronbach's Alpha of 0.920, suggesting reliable measurement of online consumer behavior as a whole.

The Extended Scale from the Unified Theory of Acceptance and Use of Technology consisted of variables such as Price Value, Usability, and Adoption

Intention. The Price Value variable exhibited good internal consistency, with a Cronbach's Alpha of 0.873, suggesting reliable measurement of price value. The Usability variable also demonstrated good internal consistency, with a Cronbach's Alpha of 0.848, indicating reliable measurement of usability.

Similarly, the Adoption Intention variable displayed good internal consistency, with a Cronbach's Alpha of 0.902, suggesting reliable measurement of adoption intention. The overall Full Scale of the Extended Scale had a Cronbach's Alpha of 0.909, indicating good internal consistency in measuring acceptance and use of technology.

Overall, Cronbach's Alpha values provided insights into the internal consistency of the scales used in the study. These values suggest that the items within each scale reliably measure the intended constructs, thereby increasing the confidence in the validity of the study's findings related to social media engagement, online consumer behavior, and acceptance and use of technology.

Following the reliability analysis, our next step is to assess convergent and discriminant validity through the item-total correlation method. This analysis allows us to examine how well the individual items within each scale are related to the overall score of their respective constructs.

First, let's consider the Social Media Engagement Scale. We observe that the corrected item-total correlation values as reported in Table 24 range from .480 to .664. These values indicate how strongly each individual item in the scale is correlated with the overall score for social media engagement. The results showed that all items within this scale are reasonably highly correlated with the overall construct of social media engagement.

Table 24 Item-Total Statistics - Social Media Engagement Scale

	Corrected Item-Total Correlation	Squared Multiple Correlation	Cronbach's Alpha if Item Deleted
SME1	.550	.351	.832
SME2	.540	.330	.833
SME3	.480	.240	.839
SME4	.518	.296	.835
SME5	.497	.279	.837
SME6	.583	.402	.829
SME7	.664	.514	.819
SME8	.585	.420	.828
SME9	.638	.471	.822

Table 25 Item-Total Statistics - Extended scale from the unified theory of acceptance and use of tech.

	Corrected Item-Total Correlation	Squared Multiple Correlation	Cronbach's Alpha if Item Deleted
PV1	.614	.521	.903
PV2	.622	.507	.903
PV3	.651	.560	.901
US1	.566	.388	.905
US2	.627	.483	.902
US3	.631	.458	.902
US4	.635	.482	.902
US5	.623	.452	.902
US6	.597	.441	.904
AI1	.701	.670	.899
AI2	.695	.647	.899
AI3	.727	.707	.897

The Extended Scale from the unified theory of acceptance and use of technology has been examined as well . The corrected item-total correlation values for this scale, reported in Table 25, range from .566 to .727. These values demonstrate a consistent and strong correlation between the individual items and the overall score for this construct. The range of .566 to .727 reflects a high degree of alignment among the items, indicating that they are effectively capturing the intended concept within this scale and contributing to its overall reliability.

Moving on to the Online Consumer Behavior Scale, we found that the corrected item-total correlation values reported in Table 26 span from .346 to .691. This range again indicates that the individual items in this scale exhibit a notable degree of correlation with the overall score for online consumer behavior.

Table 26 Item-Total Statistics - Online consumer behavior scale

	Corrected Item-Total Correlation	**Squared Multiple Correlation**	**Cronbach's Alpha if Item Deleted**
AW1	.537	.538	.917
AW2	.549	.410	.916
AW3	.551	.412	.916
AW4	.346	.301	.921
AW5	.482	.398	.918
AW6	.560	.529	.916
SC1	.650	.533	.914
SC2	.628	.584	.915
SC3	.570	.558	.916
SC4	.594	.510	.915
SC5	.591	.475	.915
OBP1	.629	.514	.915
OBP2	.578	.466	.916
OBP3	.582	.450	.916
OBP4	.592	.520	.915
OBP5	.647	.574	.914
OBP6	.691	.584	.914
OBP7	.663	.524	.914
OBP8	.599	.468	.915
OBP9	.610	.546	.915

While there is some variability in the strength of these correlations, the fact that they generally fall within this range suggests that the items within this scale are collectively measuring the same underlying construct, reinforcing the scale's reliability. As all items have high to middle item-total correlation, which indicatesthat the items on the scales item are highly correlated with the overall score, which indicates that they are measuring the same construct and are reliable.

7. Findings

This study highlights the significance of understanding consumer behavior towards online shopping in Arabic-speaking countries, especially Yemen, and the importance of having a valid research tool to examine that behavior.

The study, through many processes, adopted three different scales for the Arabic language, which suffered from the lack of quality scales in many fields and validated those scales using a sample of 395 random respondents from Yemeni social media users. The scales were the social media engagement scale developed by Ni et al. (2020), the online consumer behavior scale developed by Ansar (2019), and the extended scale from the unified theory of acceptance and use of tech developed by Venkatesh, Thong, & Xu (2012), as seen in Table 27 which shows the summary of scales before and after adoption.

The results of the exploratory factor analysis (EFA) showed that the social media engagement scale is a unidimensional concept, meaning that it can be measured with a single factor. The online consumer behavior scale, on the other hand, is a multidimensional concept, consisting of three distinct factors: awareness, social cognition, and online business perception. The extended Unified Theory of Acceptance and Use of Technology (UTAUT) scale was found to be a valid measure of the three key factors that predict adoption: price value, usability, and adoption intention.

The results of the confirmatory factor analysis also indicated that the factors in the adopted scales are a good representation of the underlying structure of the data as the values of all indicators such as CFI, TLI, NNFI, NFI, GFI, RMSEA, and SRMR represents excellent fit concluding that the results support the validity of the adopted scales.

Those adopted scales can help to build a new model for online consumer behavior to understand better the factors that may have the biggest effect in driving the adoption intention in the Arabic region so the businesses can adjust their targeting accordingly. The findings, which will come from the newly adopted scale, have practical implications for businesses looking to enter the online shopping market in Yemen and other Arabic-speaking countries.

By being aware of consumer behavior in these regions, businesses can better tailor their strategies to meet the needs and expectations of their customers. This can help them increase their chances of success in the online shopping market. Ultimately, this study underscores the importance of further research in the area of consumer behavior toward online shopping in Arabic-speaking countries.

Table 27 Summary of scales before and after adoption.

		SME	OCB	UAT
Before adopting	Number of items	11 items	35 items	17 items
	Variables	Behavioral Engagement, Cognitive Engagement, Affective Engagement	Attitude, Trust, Cultural Factors, Social Factors, Situational Factors, Web Atmosphere, E-Retailors Image	Performance expectancy, effort expectancy, facilitating condition, price value, Behavioral intentions.
	Fit indicates	CFI = 0.836, TLI = 0.815, NNFI = 0.815, NFI = 0.808, GFI = 0.890, RMSEA= 0.091, SRMR = 0.061.	CFI = 0.875, TLI = 0.849, NNFI = 0.849, NFI = 0.831, GFI = 0.868, RMSEA=0.096, SRMR = 0.076.	CFI = 0.844, TLI = 0.830, NNFI = 0.830, NFI = 0.816, GFI = 0.878, RMSEA = 0.087, SRMR = 0.060
After adopting	Number of items	9 items	20 items	12 items
	Variables	Social media engagement	Awareness, Social cognition, Online Business perception	Price Value, Usability, Adoption intention
	Fit indicates	CFI=0.985, TLI=0.979, NNFI=0979, NFI=0.979, GFI=0.988, RMSEA=0.08, SRMR = 0.057	CFI=0.99, TLI=0.989, NNFI=0989, NFI=0.984, GFI=0.988, RMSEA=0.066, SRMR = 0.06	CFI=0.999, TLI=0.999, NNFI=0999, NFI=0.997, GFI=0.997, RMSEA=0.027, SRMR = 0.035

D. Application and Findings

Building upon the development and validation of the research tool in pervious section, this section aimed to apply the research tool to investigate social media engagement, online consumer behavior, and technology acceptance in the Yemeni context. The study aimed to explore the prevalence of social media engagement and its impact on online consumer behavior, as well as the factors that contribute to online shopping adoption. By utilizing the validated research tool, the study aimed to provide valuable insights into the behavior of Yemeni online consumers and the factors that drive their online shopping behavior.

To achieve the study's objectives, a quantitative research design was used. The study utilized an online survey questionnaire that contained 41 Likert-scale items and 11 demographic questions. The questionnaire was designed to measure the constructs of interest, including awareness, social cognition, online business perception, price value, usability, and adoption intention, as well as the demographic variables of gender, age, education, current work status, occupation, income, city of residence, type of internet, main internet exploring device, previous travel abroad, and previous online shopping. The questionnaire was pilot tested to ensure its validity and reliability, and the final version was distributed to the participants via social media platforms.

The same data collected in study one was used which consist of a sample of a total of 395 Yemeni social media users using the previously developed questionnaire. The data were analyzed using structural equation modeling (SEM) to investigate the relationships between social media engagement, and online consumer behavior factors such as Awareness, Social cognition, Online Business perception, Price Value and Usability, on online shopping adoption intention.

As well as investigate the relationship between demographic variables and various factors related to online shopping behavior. Specifically, the study examined how gender, age, education, income, and trial affect awareness, social cognition, online business perception, price value, usability, and adoption intention of online shopping among consumers.

The study's results can inform marketing strategies aimed at targeting Yemeni online consumers and can contribute to the development of e-commerce platforms that cater to the unique needs and preferences of Yemeni consumers.

1. Research Problem and Hypothesizes

The research problem at hand revolves around understanding the key factors that influence consumers' behavior towards adopting online shopping. With the ever-increasing usage of social media platforms, it is also crucial to explore the role of social media engagement in shaping consumers' attitudes and behavior toward online shopping. This research aims to fill the gap in the literature by investigating the relationship between social media engagement and online shopping behavior while taking into consideration various demographic variables that may affect consumers' attitudes and intentions toward online shopping.

The research problem of this study is that social media engagement plays a significant role in shaping consumers' behavior towards online shopping and that there are several key factors that impact online shopping adoption. Specifically, it is hypothesized that factors such as awareness, social cognition, online business perception, price value, usability, and adoption intention all play a significant role in shaping consumers' attitudes toward online shopping. Moreover, it is expected that demographic variables such as gender, age, education, income, and type of internet access may have an impact on these factors and therefore, affect consumers' adoption of online shopping.

Through this research, we hope to gain valuable insights into the factors that impact online shopping behavior in the Yemeni context and to develop a better understanding of the role of social media engagement in shaping these behaviors. The findings of this research can inform marketing strategies aimed at targeting Yemeni online consumers and can contribute to the development of e-commerce platforms that cater to the unique needs and preferences of Yemeni consumers. We can conclude that the research questions are:

1. How do demographic variables impact online shopping behavior factors?

This research question aims to investigate the impact of demographic variables, such as age, gender, education, income, and occupation, on different factors that influence online shopping behavior, including social cognition, awareness, online business perception, usability, price value, and adoption intention. Previous studies have shown that demographic factors can have a significant effect on consumers' online shopping behavior. For example, younger consumers tend to be more comfortable with online shopping, while older consumers may have concerns about security and privacy. Additionally, consumers with higher education and income levels may be more likely to engage in online shopping due to convenience and accessibility.

2. How effective is social media engagement on consumers' online shopping behavior?

This research question explores the relationship between social media engagement and consumers' online shopping behavior. Social media platforms have become an important channel for businesses to interact with customers and promote their products and services. Previous research has shown that social media engagement can influence consumers' decision-making process and increase their intention to make a purchase. However, the effectiveness of social media engagement may depend on various factors, such as the type of product or service, the target audience, and the social media platform used.

3. What is the relationship between online shopping behavior factors and how do they affect each other?

This research question aims to investigate the complex relationships between different factors that influence online shopping behavior, such as social cognition, awareness, online business perception, usability, price value, and adoption intention. Previous studies have shown that these factors are interrelated and can have a significant impact on each other. For example, consumers' perception of online business may affect their usability experience, which in turn can influence their adoption intention. Understanding these relationships can provide valuable insights for businesses to improve their online shopping platforms and strategies.

4. What is the effect of the previous trial on online shopping behavior factors?

This research question explores the effect of previous online shopping experiences on consumers' behavior and attitudes toward online shopping. Previous studies have shown that consumers' previous experiences can influence their perceptions and decision-making processes, particularly in the context of online shopping. For example, a negative experience may lead to distrust and reluctance to engage in online shopping, while a positive experience may increase trust and confidence. Understanding the effect of previous trials can help businesses improve their online shopping platforms and provide better customer experiences.

5. What are the main factors that could create more adoption of online shopping?

This research question aims to identify the key factors that can influence consumers' adoption of online shopping. Previous studies have identified various factors that can affect consumers' adoption intention, including perceived usefulness, perceived ease of use, perceived risk, social influence, and trust. However, the relative importance of these factors may vary depending on the context and the target audience. Understanding the main factors that could create more adoption of online shopping can help businesses develop effective strategies to attract and retain customers.

Based on the previous discussion, we can build this research hypothesizes as followed:

H1: Social media engagement significantly influences social cognition.

Social cognition refers to the mental processes that people use to understand and interpret social information, such as the thoughts, emotions, and behaviors of others. Social media engagement involves the active participation of individuals in social media platforms, such as commenting, liking, and sharing posts (Sassenberg & Matthes, 2013).

The hypothesis suggests that the more individuals engage with social media, the more they are likely to develop their social cognition skills. This is because social media provides a platform for individuals to observe and interpret the thoughts, emotions, and behaviors of others, which in turn can enhance their social cognitive abilities. The proposed hypothesis implies that social media can have a positive impact on individuals' social cognition, which can potentially lead to better social interactions and relationships.

Previous research has shown that social media engagement can have a significant impact on social cognition. For example, studies have found that individuals who engage more frequently in social media activities have better social skills and are more capable of accurately interpreting social cues and emotions (Verduyn et al., 2015; Hampton et al., 2016). Moreover, research has suggested that social media use can increase empathy and emotional intelligence, which are key components of social cognition (Grieve et al., 2013; Liu et al., 2018).

Furthermore, research has indicated that social media provides individuals with the opportunity to observe and learn from the behaviors and attitudes of others, which can enhance their social cognitive abilities (Utz et al., 2011; Toma &Hancock, 2013). For instance, individuals can observe how others communicate, express emotions, and interact with each other on social media, which can facilitate the development of their social cognition skills.

Based on this previous research, it is reasonable to propose that social media engagement has a positive and direct effect on social cognition. The proposed hypothesis suggests that social media can play an important role in shaping individuals' social cognition abilities and improving their social interactions and relationships.

H2: Social cognition significantly increases awareness of online shopping.

Previous research has suggested that social cognition can impact individuals' awareness of new products and services (Liao & Cheng, 2017). Social cognition enables individuals to process and interpret social information, including information about new products and services, and make sense of it. As such, individuals with higher social cognition abilities are more likely to be aware of new products and services in their environment.

In the context of online shopping, individuals with higher social cognition may be better able to process and interpret the online information about products and services, leading to a greater awareness of online shopping options.

For instance, research has shown that individuals with higher social cognitive abilities are more likely to engage in online impulse buying, which requires a higher level of awareness of online shopping options (Liao & Cheng, 2017).

Based on these findings, it is hypothesized that social cognition has a positive and direct effect on awareness of online shopping. The proposed hypothesis suggests that individuals with higher social cognition may be more likely to become aware of online shopping options, potentially leading to greater adoption of online shopping behaviors.

H3: Awareness of online shopping has significant impact on online business perception.

Awareness of online shopping refers to individuals' knowledge and recognition of the availability and benefits of online shopping. Previous research has suggested that awareness of online shopping can impact individuals' perceptions of online businesses (Chen, Fay, & Wang, 2011).

Individuals who are aware of online shopping options may perceive online businesses more favorably than those who are not aware. This is because online shopping awareness may lead individuals to perceive online businesses as more modern, convenient, and accessible than traditional brick-and-mortar businesses. In addition, previous research has found that individuals who are more aware of online shopping options are more likely to engage in online shopping behaviors (Chen, Fay, & Wang, 2011).

Based on these findings, it is hypothesized that awareness of online shopping has a positive and direct effect on online business perception. The proposed hypothesis suggests that individuals who are more aware of online shopping options may perceive online businesses more favorably, potentially leading to greater adoption of online shopping behaviors.

H4: Awareness of online shopping significantly affect perceived usability of online shopping.

Perceived usability refers to the subjective assessment of how easy and efficient it is for individuals to use online shopping platforms. The proposed hypothesis suggests that individuals who are more aware of online shopping options may perceive online shopping platforms as more user-friendly and easier to use, potentially leading to greater adoption of online shopping behaviors. This is because awareness of online shopping may lead individuals to seek out and use online shopping platforms more frequently, becoming more familiar and comfortable with their use.

As a result, it is expected that individuals who are more aware of online shopping options will perceive online shopping platforms as more usable than those who are less aware.

Previous research has suggested that awareness of online shopping can impact individuals' perceptions of the usability of online shopping platforms. For instance, a study by Chiang and Dholakia (2003) found that individuals who were more aware of the benefits of online shopping were more likely to perceive online shopping platforms as easy to use and efficient. Similarly, a study by Wu and Chen (2017) found that individuals who were more aware of the availability and benefits of online shopping were more likely to perceive online shopping platforms as user-friendly and convenient.

These findings support the proposed hypothesis that awareness of online shopping has a positive and direct effect on the perceived usability of online shopping. Individuals who are more aware of online shopping options may have more positive perceptions of the usability of online shopping platforms, which may encourage greater adoption of online shopping behaviors.

H5: Perceived usability of online shopping significantly influences perceived price value of online shopping.

Perceived price value refers to the subjective assessment of the benefits and costs of online shopping in relation to its price. The proposed hypothesis suggests that individuals who perceive online shopping platforms as more usable may also perceive online shopping as providing greater value for its price.

This is because individuals who perceive online shopping platforms as easy to use and efficient may feel that they are getting more benefits for the same price compared to traditional shopping methods. As a result, it is expected that individuals who perceive online shopping platforms as more usable will also perceive online shopping as providing greater price value than those who perceive them as less usable.

Previous research has found evidence supporting the proposed hypothesis that perceived usability of online shopping is related to perceived price value. For instance, a study by Lee and Jun (2018) found that perceived usability of online shopping platforms positively influenced consumers' perceived value of online shopping. Similarly, a study by Chen and Barnes (2007) found that perceived ease of use of online shopping platforms positively influenced consumers' perceptions of price fairness.

These findings suggest that the more users perceive online shopping platforms as easy to use and efficient, the more they are likely to perceive online shopping as providing greater value for its price. Therefore, it is expected that the proposed hypothesis, which suggests a positive and direct effect of perceived usability of online shopping on perceived price value, will also be supported by empirical evidence.

H6: Online business perception significantly impacts perceived price value of online shopping.

Online business perception refers to the overall perception that individuals have about the trustworthiness, reliability, and credibility of online shopping platforms. The proposed hypothesis suggests that individuals who perceive online shopping platforms as more trustworthy and reliable may also perceive online shopping as providing greater value for its price. This is because individuals who have positive perceptions of online shopping platforms may feel more confident in their ability to find high-quality products at fair prices. As a result, it is expected that individuals who have more positive perceptions of online shopping platforms will also perceive online shopping as providing greater price value than those who have less positive perceptions.

Previous research has identified several web-specific aspects of online business perception, including navigation, screen clarity, content relevance, link relevance, website characteristics, and retailer image and reputation (Park, Han & Kaid, 2012). Kim and Lennon (2008) found that a retailer's image and reputation can help alleviate client anxiety by minimizing transaction risks and improving virtual interactions, which can lead to more positive perceptions of online shopping platforms and ultimately, higher perceived price value.

H7: Perceived price value of online shopping significantly influences online shopping adoption intention.

The hypothesis proposes that consumers' adoption intention towards online shopping is positively influenced by their perceived price value of online shopping. This is based on previous studies that have found a significant relationship between perceived price value and consumers' intention to adopt online shopping.

Previous research has established that perceived value is a significant predictor of purchase intention and has a strong impact on consumer behavior (Zeithaml, 1988; Sweeney & Soutar, 2001). Moreover, studies have highlighted the importance of perceived value as a key determinant of online shopping behavior (Lee & Lin, 2005; Liang & Huang, 2008). Specifically, Lee and Lin (2005) found a positive relationship between perceived value, online shopping satisfaction, and loyalty, while Liang and Huang (2008) identified perceived value as a significant predictor of online shopping behavior.

In the context of online shopping adoption, the perceived price value of online shopping has been found to be a crucial factor influencing consumers' intention to adopt online shopping (Degeratu, Rangaswamy, & Wu, 2000; Liu & Arnett, 2000). Degeratu et al. (2000) reported that consumers' perceived price value of online shopping was a significant predictor of their intention to adopt online shopping, while Liu and Arnett (2000) found that perceived price value was a key factor influencing consumers' intention to adopt online shopping. Overall, these studies suggest that the perceived value of online shopping, including its perceived price value, plays a crucial role in shaping consumers' adoption intention of online shopping.

These findings suggest that consumers' perception of the value they receive from online shopping in relation to the price they pay plays a crucial role in their decision to adopt online shopping. Therefore, it is hypothesized that consumers' perceived price value of online shopping has a positive and direct effect on their online shopping adoption intention.

Based on the hypotheses presented, the proposed model suggests that social media engagement can have an indirect positive effect on online shopping adoption intention through the mediating factors of social cognition, awareness of online shopping, online business perception, and perceived price value of online shopping. Furthermore, demographic variables such as age, gender, income, and education may also have an impact on the relationships among the variables in the model.

To test the proposed model, a statistical analysis such as structural equation modeling (SEM) can be employed to investigate the direct and indirect effects among the variables. The analysis can also examine the potential moderating effects of demographic variables on the relationships in the model. Moreover, non-direct effects among the variables can be explored, such as the possible indirect effects of social media engagement on online shopping adoption intention through other mediating variables beyond the ones proposed in the model.

Overall, the hypotheses presented in this section provide a framework, as seem in Figure 4, for exploring the complex relationships among social media engagement, social cognition, awareness of online shopping, online business perception, perceived price value of online shopping, and online shopping adoption intention. The proposed model can help researchers and practitioners understand the factors that influence consumers' online shopping behavior and develop strategies to enhance online shopping adoption.

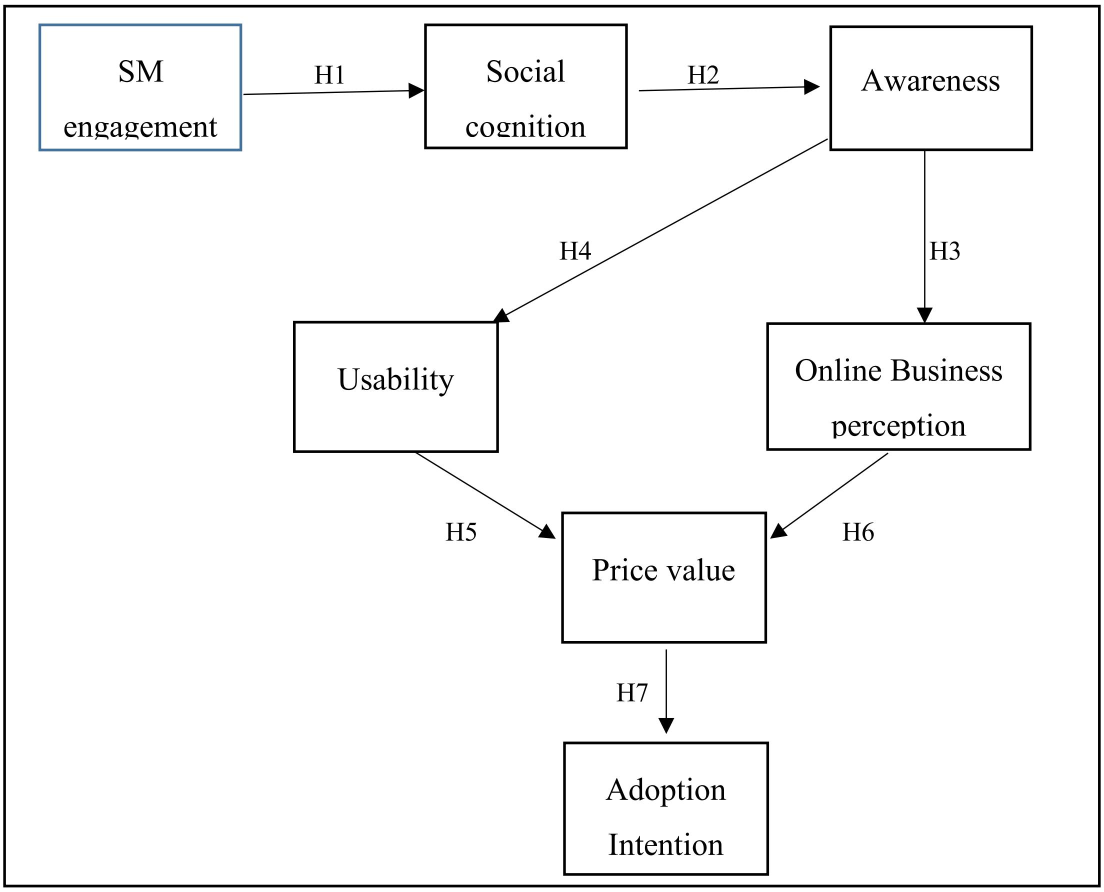

Figure 4 Conceptual Framework

2. Analysis of the Demographic Variables

Research studies are conducted to investigate various phenomena and explore the underlying factors that affect them. However, the effectiveness and accuracy of research findings can be influenced by various demographic variables, these variables can affect research participation, sample composition, outcomes, bias, and interpretation. Therefore, it is essential to consider demographic variables when conducting research studies to ensure that the results are generalizable and applicable to a wider population.

This research examined 11 demographic variables which are Gender, Age, Education, Current work status, Occupation, Income, City of residence, Type of Internet, Main Internet exploring device, Previous travel abroad, and Previous online shopping.

The effects of demographic variables on research factors which are social media engagement, Awareness, Social cognition, Online Business perception, Price Value, Usability, and Adoption intention were examined as well as explored their significance and provided examples of their impact on the research model. By doing so, we hope to increase awareness of the importance of demographic variables in research and emphasize the need to consider these variables when designing and conducting research studies.

a. Frequency analysis

According to Napoleoncat (2022) statics, in September 2022, there were 3,648,400 Facebook users in Yemen; the share of Facebook users is 11.4% of the country's total population, and 84.5% of them are men. The majority of users (36.4%) were between the ages of 18 and 24, and (35.7%) are between 25 and 34.

Table 28 Frequency Analysis

Demographic characteristics	Group	Frequency	Percentage %
Gender	Female	78	19.7%
	Male	317	80.3%
Age	Below 18	5	1.3%
	18 - 25	96	24.3%
	26 - 33	166	42.0%
	34 - 41	77	19.5%
	42 - 59	51	12.7%
	Above 59	1	0.3%
Education	Below High School	3	0.8%
	High School	44	11.1%
	Associate degree	26	6.6%
	Bachelor's degree	259	65.6%
	Master's degree and above	52	13.2%
Current work status	No	164	41.5%
	Yes	231	58.5%
Occupation	Student	79	20.0%
	Government employee	41	10.4%
	Private sector employee	140	35.4%
	Trader or investor	14	3.5%
	Freelancer or Self-employment	80	20.3%
	Unemployed	29	7.3%
	Others	12	3.0%
Income	below 200$	129	32.7%
	200 - 300$	90	22.8%
	301- 400 $	31	7.8%
	401 - 500$	29	7.3%
	501 - 600$	33	8.4%
	Above 600$	83	21.0%
City of residence	Sanaa	115	29.1%
	Aden	19	4.8%
	Taiz	147	37.2%
	Hadhramaut	6	1.5%
	Al Hudaydah	8	2.0%
	Ibb	23	5.8%
	Marib	7	1.8%
	Other	70	17.7%
Type of Internet	Home ADSL	158	40.0%
	3G,4G	149	37.7%
	Internet cafes	2	0.5%
	Internet Networks	67	17.0%
	Work Internet	19	4.8%
Main Internet exploring	Mobile	370	93.7%
	Tablet	2	0.5%
	Laptop	17	4.3%
	Desktop	6	1.5%
Previous travel abroad	No	184	46.6%
	Yes	211	53.4%
Previous online shopping	No	154	39.0%
	Yes	241	61.0%

Table 28 above shows the frequency analysis results for this study sample, which has been done using SPSS 28 software; the sample consists of 395 respondents and can be categorized firstly based on gender. As seen in Figure 5, the proportion of males is 80.3%, and the proportion of females is 19.7%.

On the other hand, when we analyzed the sample age in Figure 6, we can see that respondents who are 18 to 24 years old were the largest group (42%) due to the structure of social media networks in Yemen generally and Facebook specifically, as stated before.

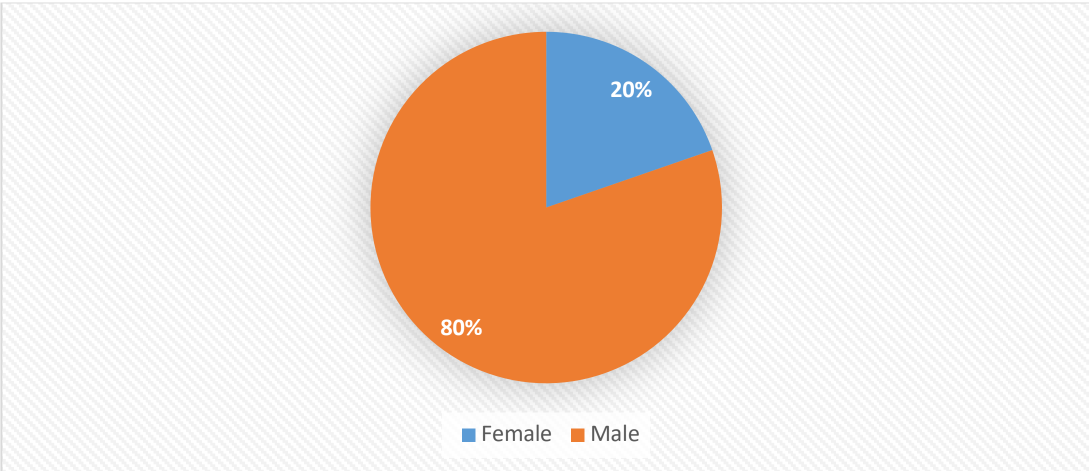

Figure 5 Gender Frequency Disruption.

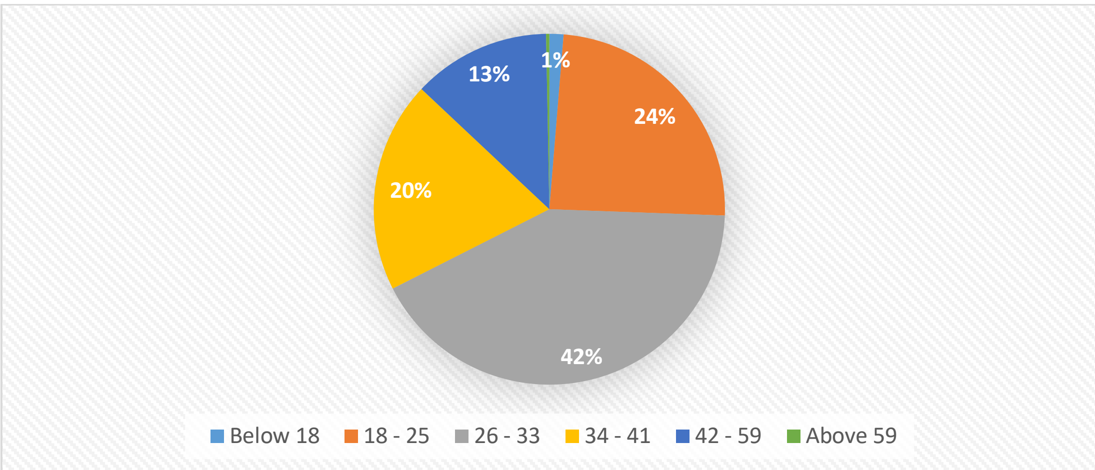

Figure 6 Age Frequency Disruption

As for education in Figure 7, most of the respondents are bachelor's degree holders with 65.6% and master's degree holders with 13.2%, and 11.1% are high school graduates, which is explained why social media networks are still considered to be famous among the higher level educated population and the majority of the population do not engage much with them.

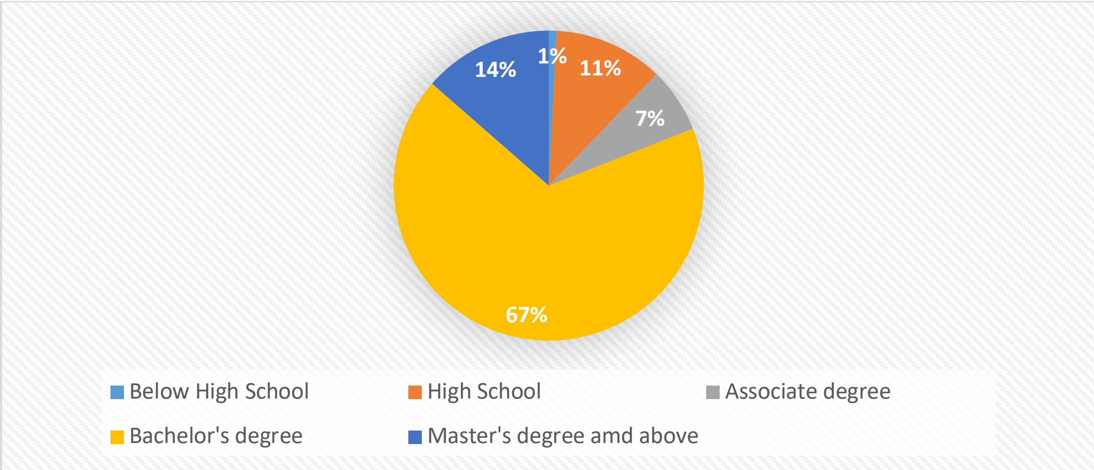

Figure 7 Education Frequency Disruption

Work situation in Figure 8, on the other hand, while 41.5% said they do not work at the moment, only 7.3% marked themselves as unemployed when they ask to choose from different occupations, most respondents (35.4%) are private sector employees, 20.3% are freelancers, and 20% are a student. In comparison, only 10.4% are government employees, which is understandable given the situation of Yemen nowadays and the low confidence in the government since most of the government workers do not get paid regularly.

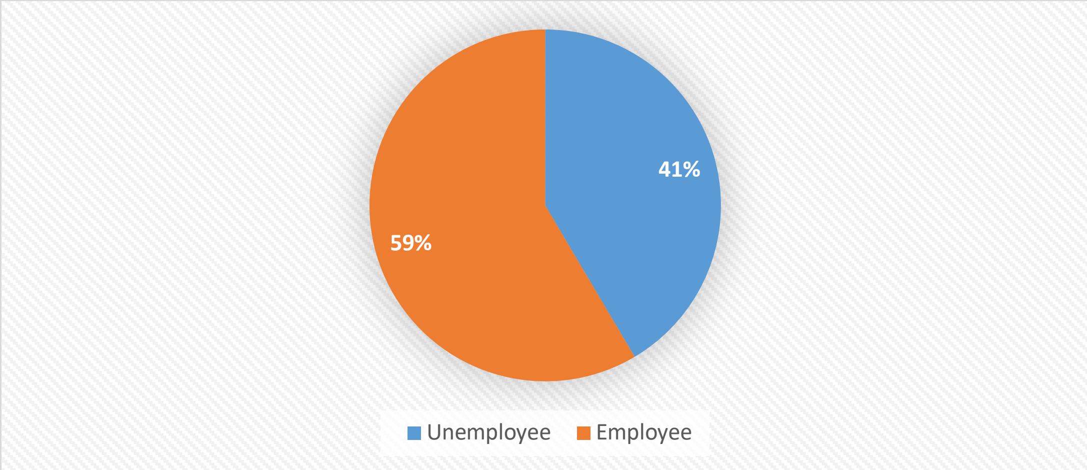

Figure 8 Work Situation Frequency Disruption.

When analyzing income in Figure 9; we can see a sample of social stratification in Yemen. 32.7% of the respondents have a below 200$ monthly income, 22.8% have a 200-300$ monthly income, and 21% have a monthly income above 600$, with only a small percentage in the middle categories.

According to the heritage foundation (2022), Yemen's average annual per capita income is 2213$, which is significantly less than that of other low-income nations. Yemen, one of the most impoverished Arab nations, depends heavily on the rapidly declining income from its comparatively modest oil and gas reserves.

Since 2014, a long-drawn civil war has exacerbated economic issues, unemployment, and shortages of food, water, and medical supplies, leading to a humanitarian crisis.

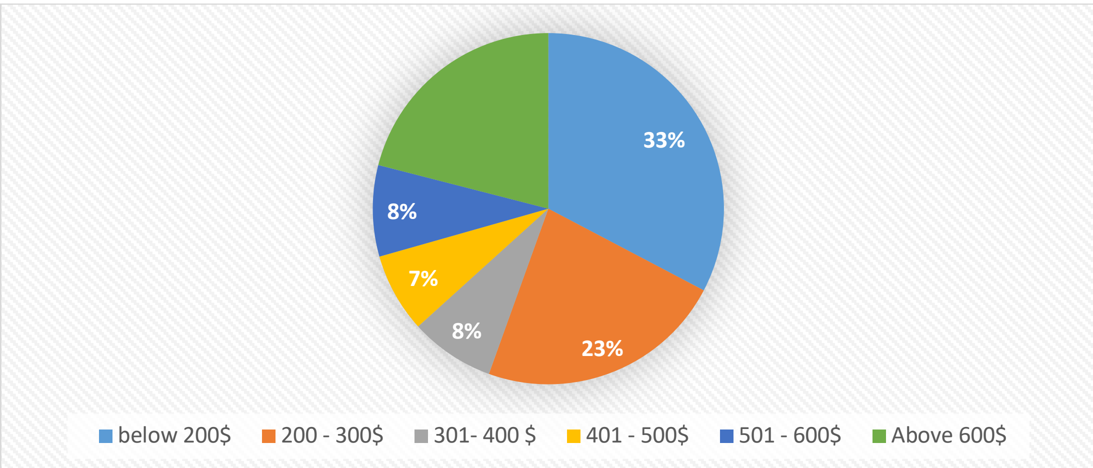

Figure 9 Income Frequency Disruption

Hence, the city of residence analysis in Figure 10 shows that 37.2% of the respondents are living in Taiz, which ranks first in terms of population in Yemen, as it has 12.2% of the population of the whole country, the second is the capital Sanaa with 29.1% of the respondents, and the rest respondents are in the other sites.

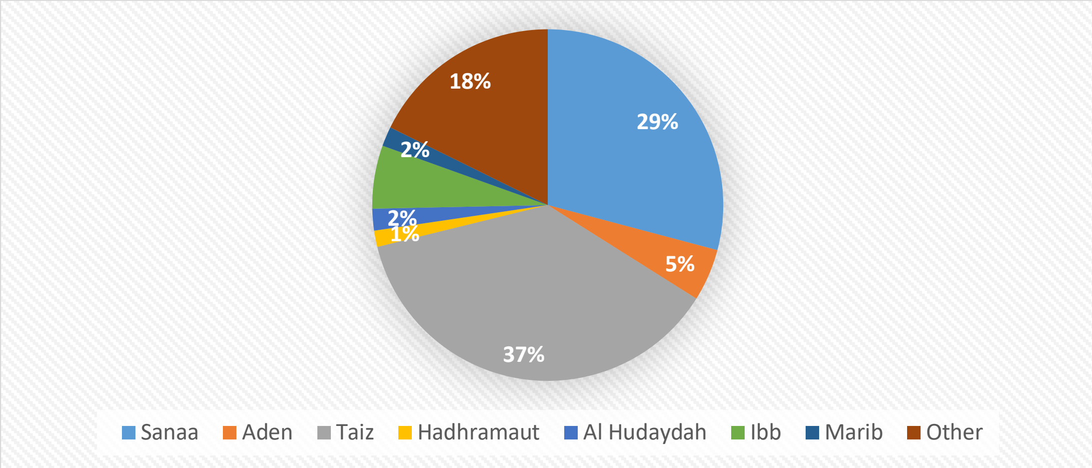

Figure 10 City Of Residence Frequency Disruption

Since the device which consumers use and the internet speed are playing a very big role in their online behavior, we can categorize the sample as 40% are using home ADSL, 37.7% are using a mobile network connection, and 93.7% are using mobile devices. Internet access is available to 27% of Yemenis, while only 2% of people have fixed broadband access, and only about half of the population is connected to mobile networks as seen in Figure 11. Mobile devices cannot access most internet services because their coverage is patchy and primarily restricted to 2G and 3G technology (Gebeily, 2022).

According to the web analysis service speed test (2022), Yemen has one of the slowest internet speeds in the world, with a median download speed of 9 Mbps for mobile while the global median is 33.17 Mbps, even the fixed broadband still considered very slow as the broadband median speed in Yemen is 3.23 Mbps while the global median is 71.39 Mbps. The rates of internet adoption are also low compared to a middle eastern average of three quarters as barely a quarter of Yemenis have access to the Internet.

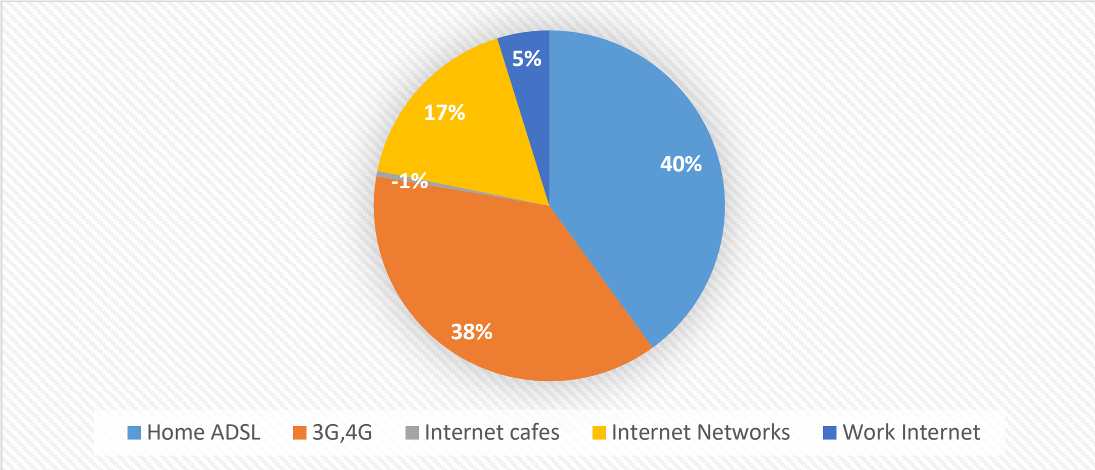

Figure 11 Internet Type Frequency Disruption

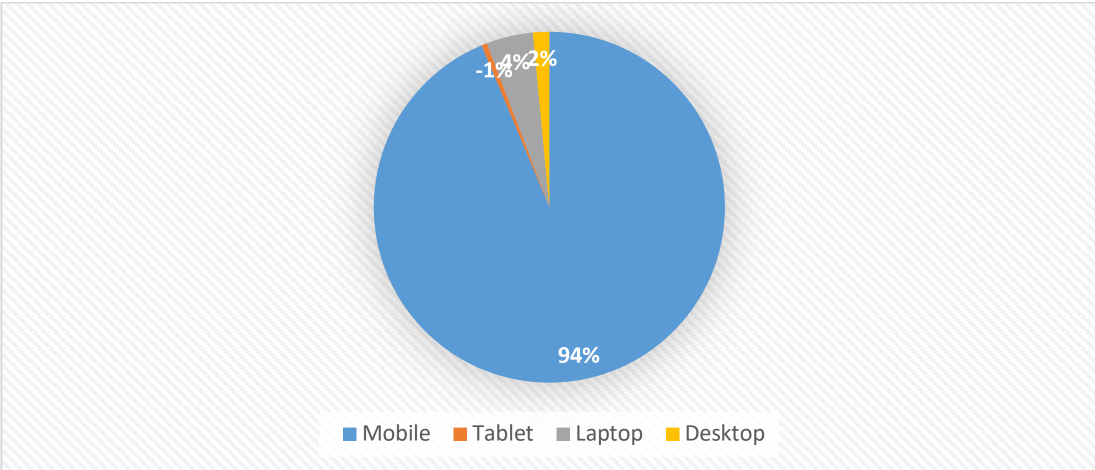

Figure 12 Main Device Frequency Disruption

Lastly, we examine two aspects that may influence this research model: previous travel abroad in Figure 13 , with 53.4% already traveled outside Yemen, and the previous trial for online shopping in Figure 14 , with 61% already tried online shopping at least one time before.

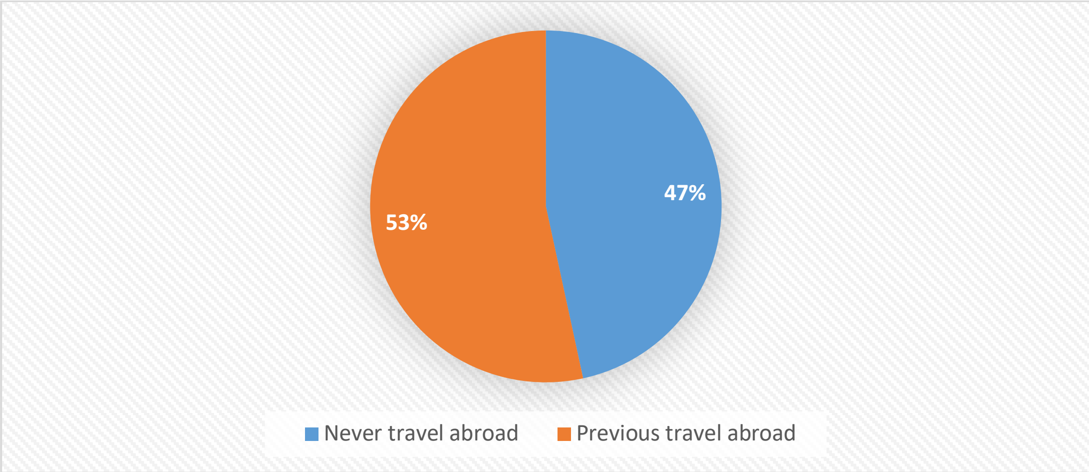

Figure 13 Travel Abroad Frequency Disruption

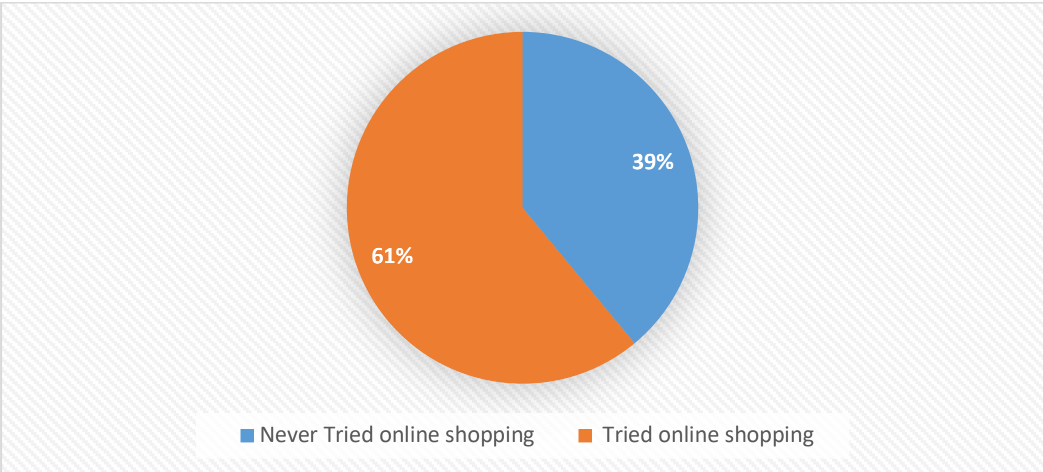

Figure 14 Trial Frequency Disruption

b. Demographic variables effects on research factors

Analyzing the effect of demographic variables on research factors is important for several reasons: First, to understand the impact of different demographic variables on research factors as demographic variables can have an impact on how people perceive and respond to different stimuli. By analyzing the effect of these variables on research factors, researchers can gain a better understanding of how different groups may respond to various stimuli.

Second, to tailor research approaches to specific demographic groups: By understanding the impact of demographic variables on research outcomes, researchers can tailor their research approaches to specific demographic groups in future studies. For example, if certain demographic groups respond better to important stimuli, researchers can use more cues in their research materials for that group.

Overall, analyzing the effect of demographic variables on research outcomes is important for understanding the nuances of human behavior and for tailoring research approaches to specific demographic groups.

In the case of this research, it has 11 demographic variables; eight demographical variables have more than two groups which are age, education, current work status, occupation, income, city of residence, type of internet, and main internet exploring device. For those variables, ANOVA has been used. On the other hand, four of them have two groups which are gender, current work status, previous travel abroad, and previous online shopping. For those variables, Welch's t-test has been used to examine their effects by testing the significant difference between their groups.

ANOVA was done by SPSS 28 software while Welch's t-test and Games-Howell post-hoc test were done using JASP 0.16.4 software to examine the effects of the demographic variables on research factors which are: Social media engagement, Awareness, Social cognition, Online Business perception, Price Value, Usability, and Adoption intention.

i. Gender

Gender can play a role in an individual's willingness to adopt new technologies or products. Several studies have found that men and women have different preferences when it comes to technology adoption. Women are often more interested in technologies that offer convenience, ease of use, and social connection, while men are often more interested in technologies that offer advanced features, performance, and power (Gefen & Straub, 1997).

However, it's important to note that these differences are not always consistent across all individuals as gender stereotypes and societal expectations can also impact an individual's willingness to try new technologies or products. For example, women may be discouraged from adopting certain technologies because of gender biases and stereotypes, while men may feel pressured to adopt certain technologies because of societal expectations of masculinity (Wang & Wang, 2008).

To test the Gender effect on our research variables, we used Welch's t-test with a two-tailed hypothesis test and the significance level (α) was set at 0.05 as seen in Table 29 below.

Table 29 Welch's t-test of Gender and Research Variables

	t	df	p
SME	1.100	126.003	0.273
OBP	-0.913	112.275	0.363
AW	-0.925	111.154	0.357
SC	0.169	109.977	0.866
US	-0.912	110.939	0.364
PV	-1.131	106.862	0.260
AI	-1.754	108.476	0.082

The results of the Welch's t-tests showed that there was no statistically significant difference between the means of the two groups (Male and Female) in terms of their social media engagement (p-value = 0.273), online business perception (p-value = 0.363), awareness (p-value = 0.357), social cognition (p-value = 0.866), usability (p-value = 0.364), perception of price value (p-value = 0.260) or adoption intention (p-value = 0.082) as all p-values are greater than the standard alpha level of 0.05.

This means that we can fail to reject the null hypothesis and conclude that there is not enough evidence to support the claim that there is a significant difference between the means of the two groups in terms of any of these variables.

Although, the p-value for adoption intention is 0.082, which is close to the significance level, so it is possible that there is a real difference between the two groups, but it is not strong enough to be statistically significant. If the study was repeated with a larger sample size, it might be possible to detect a statistically significant difference.

ii. Employment status

In general, being unemployed may have a negative effect on many personal aspects including this research variables. For example, unemployed individuals may have less disposable income, which could affect their perception of price value and adoption intention for certain products or services.

They may also have more free time, which could increase their social media engagement, awareness, and social cognition, but this may also depend on their motivation and interest in using social media platforms. Additionally, being unemployed may affect an individual's self-esteem and confidence, which could affect their perception of online business and usability (Smith& Johnson, 2019).

Therefore, Welch's t-test with a two-tailed hypothesis test was conducted to compare two groups (employee and unemployed), and based on the results in Table 30 below, we can interpret the results as follows.

Table 30 Welch’s t-test of Employment Status and Research Variables

	t	df	p
SME	1.088	360.642	0.277
OBP	-1.655	340.219	0.099
AW	-2.785	351.896	0.006*
SC	-1.017	340.055	0.310
US	-2.479	351.223	0.014*
AI	-2.257	353.748	0.025*

* p < .05

The results of the study showed that there was no significant difference between the means of the employee and unemployed groups in terms of their social media engagement (SME) (p-value = 0.277) and online business perception (OBP) (p-value = 0.099). This means that there is not enough evidence to conclude that there is a significant difference between the means of the two groups in terms of these variables.

However, there was a significant difference between the means of the two groups in terms of their awareness (AW) (p-value = 0.006), usability (US) (p-value = 0.014), perception of price value (PV) (p-value = 0.048), and adoption intention (AI) (p-value = 0.025). This means that we can reject the null hypothesis and conclude that there is a significant difference between the means of the two groups in terms of these variables.

These findings suggest that employment status may be a factor that influences user adoption of online shopping. Employees may be more aware of online shopping options, have a better understanding of how to use them, and be more likely to see the value in adopting them than unemployed people. This is likely due to a number of factors, such as the fact that employees have more disposable income, are more likely to be exposed to online shopping through their work and may have more opportunities to learn about and use online shopping platforms.

To look for evidence to support the idea that being unemployed has a negative effect on AW, US, PV, and AI, another Welch's t-test has been done but with a one-tail hypothesis to test whether the mean scores for the unemployed group are significantly lower than those in the employed group and the results are shown in Table 31 below.

Table 31 One-tail Welch’s t-test of Eemployment Status and Research Variables

	t	**df**	**p**
AW	-2.785	351.896	0.003*
US	-2.479	351.223	0.007*
PV	-1.981	339.582	0.024*
AI	-2.257	353.748	0.012*

* p < .05

The p-value for Awareness (AW) is 0.003 as for Usability (US), Price Value (PV), and Adoption Intention (AI), where the p-values are 0.007, 0.024, and 0.012, respectively, which is less than the typical threshold of 0.05 for statistical significance. The results of the study showed strong evidence to reject the null hypothesis and conclude that unemployed individuals have statistically significant lower levels of awareness, usability, price value perception, and adoption intention for online shopping than employed individuals.

This finding is consistent with the idea that employment status can have a significant impact on an individual's access to resources, such as disposable income, time, and information. These resources can all play a role in shaping an individual's awareness of online shopping options, their ability to use them effectively, and their willingness to adopt them.

For example, unemployed individuals may have less disposable income to spend on online shopping, which could limit their awareness of and access to online shopping options. They may also have less time to devote to online shopping, which could make it more difficult for them to learn how to use online shopping platforms effectively. Additionally, unemployed individuals may be less likely to see the value in online shopping, as they may not have the same financial security as employed individuals.

The findings of this study have implications for the design and marketing of online shopping platforms. Developers and marketers should take into account the different needs and preferences of employed and unemployed individuals when designing and marketing online shopping platforms. For example, they may need to make it easier for unemployed individuals to find and use online shopping platforms, and they may need to emphasize the value of online shopping for unemployed individuals.

iii. Travel abroad

Traveling abroad can have various effects on personal aspects such as social media engagement, awareness, social cognition, online business perception, price value, usability, and adoption intention. For instance, traveling abroad may expose individuals to new cultures, lifestyles, and experiences, which could increase their interest and motivation to engage with social media platforms and improve their social cognition and awareness (Nesi& Pratesi, 2018).

Moreover, exposure to new products, services, and marketing strategies in different countries may affect individuals' perception of online businesses, price value, usability, and adoption intention. Traveling abroad may also increase individuals' level of openness and curiosity, which could influence their perception and behavior towards the variables (Wu, Liang& Chen, 2016). However, the extent and direction of these effects may vary depending on several factors such as the individual's cultural background, personality traits, travel destination, and travel purpose.

In the context of Yemen, traveling abroad can have similar effects on the variables. Yemeni travelers may be exposed to new cultures, products, and marketing strategies that could affect their perception of online businesses, price value, and adoption intention. However, the impact of these effects may be limited by several factors, such as the Yemeni society's conservative values and limited access to the internet and social media platforms. Additionally, traveling abroad may not be accessible to all Yemenis due to economic, political, and security challenges.

Welch's t-test with a two-tailed hypothesis test was conducted, the null hypothesis is that there is no difference between the means of the two groups (who travel abroad before and who never did), and the results reported in Table 32 below.

Table 32 Welch’s t-test of Travel Abroad and Research Variables

	t	df	p
SME	1.684	381.179	0.093
OBP	-2.607	352.479	0.010*
AW	-3.855	347.293	< .001*
SC	-1.351	361.578	0.178
US	-3.171	366.030	0.002*
PV	-1.970	369.345	0.050*
AI	-3.232	368.350	0.001*

* $p < .05$

The p-values for the variables of social media engagement (SME; $p = 0.093$), online business perception (OBP; $p = 0.010$), awareness (AW; $p < 0.001$), usability (US; $p < 0.002$), perception of price value (PV; $p = 0.050$), and adoption intention (AI; $p < 0.001$) are all less than 0.05, which is the standard threshold for statistical significance.

This means that, with the exception of social cognition (SC; $p= 0.178$), there is strong evidence to reject the null hypothesis and conclude that there is a statistically significant difference between the means of the two groups in terms of these variables.

This finding is consistent with the idea that travel experience can help individuals to develop a broader perspective and to become more familiar with different cultures and ways of doing things. This can lead to a more positive attitude towards online shopping, as individuals who have traveled abroad may be more likely to see the convenience and value of shopping online.

For example, they may need to make it easier for travelers to find and use online shopping platforms, and they may need to emphasize the benefits of online shopping for travelers.

For further evidence to support the idea that traveling abroad has a positive effect on OBP, AW, US, PV, and AI, another Welch's t-test has been done but with a one-tail hypothesis to test whether the mean scores for the never traveled abroad before group is significantly lower than those in the traveled before the group and the results reported in Table 33 below.

Table 33 One-tail Welch’s t-test of Travel Abroad and Research Variables

	t	df	p
OBP	-2.607	352.479	0.005*
AW	-3.855	347.293	< .001*
US	-3.171	366.030	< .001*
PV	-1.970	369.345	0.025*
AI	-3.232	368.350	< .001*

* p < .05

The results showed that individuals who have traveled abroad before have a significantly higher awareness ($p < 0.001$), usability ($p < 0.001$), perception of price value ($p = 0.025$), online business perception ($p = 0.005$), and adoption intention ($p < 0.001$) for online shopping than those who have never traveled abroad.

Overall, the results suggest that traveling abroad has a positive impact on individuals' perception of online business prescription, awareness, price value, usability, and adoption intention. As individuals who have traveled abroad before may be more likely to see the benefits of online shopping and to be comfortable using online shopping platforms.

It is important to note that the extent of the effects of travel experience on online shopping adoption may vary depending on several factors, such as the destination and purpose of travel, as well as individual differences in personality and cultural background.

For example, individuals who travel to countries with a strong online shopping culture may be more likely to adopt online shopping than those who travel to countries with a weaker online shopping culture. Additionally, individuals who travel for business purposes may be more likely to adopt online shopping than those who travel for leisure purposes.

iv. Trail

Many researchers suggest that individuals who have tried online shopping may have higher levels of social media engagement, awareness, and social cognition compared to those who have never tried it. This could be due to the fact that online shopping requires the use of various social media platforms and online resources to research and purchase products.

Furthermore, individuals who have tried online shopping had a more positive perception of online businesses in terms of usability and adoption intention. They also placed a higher value on the price of products compared to those who have never tried online shopping (Bigne-Alcaniz, Ruiz-Mafe & Sanz-Blas, 2009).

On the other hand, individuals who have never tried online shopping before may have a lower level of social media engagement, awareness, and social cognition. This could be because they are less exposed to online resources and may rely more on traditional means of communication and information gathering. Additionally, they had a less positive perception of online businesses in terms of usability and adoption intention. This could be due to a lack of experience with online shopping and a lack of familiarity with the online shopping process.

Finally, they were less likely to place a high value on the price of products compared to those who have tried online shopping before (Liu, Li & Hu, 2014). To examine those theories in the context of this research variables, Welch's t-test has been conducted in two-tail hypothesis and the results reported in Table 34 below.

Table 34 Welch’s t-test of Trial and Research Variables

	t	df	p
SME	1.271	307.146	0.205
OBP	-4.311	250.474	< .001*
AW	-5.043	285.286	< .001*
SC	-2.838	279.841	0.005*
US	-5.365	280.063	< .001*
PV	-4.972	284.804	< .001*
AI	-4.685	263.134	< .001*

* p < .05

The results showed that there is no significant difference between the two groups those who have tried online shopping before and those who have never tried it) in terms of their social media engagement (SME), as the p-value associated with SME is 0.205, which is greater than the significance level of 0.05.

However, there is a significant difference between the two groups those who have tried online shopping before and those who have never tried it) in terms of their online business perception (OBP), awareness (AW), social cognition (SC), usability (US), perception of price value (PV), and adoption intentions (AI), as the p-values associated with these variables are < .001 , < .001 , 0.005 , < .001, < .001 , and < .001 respectively, which all less than the significance level of 0.05:

For farther understanding of the Trail effect, another Welch's t-test has been conducted with one-tail hypothesis with the alternative hypothesis specifies that group mean for those who have never tried online shopping before is less than group mean for those who have tried it before, and the results showed in the Table 35 below.

Table 35 One-tail Welch's t-test of Trial and Research Variables

	t	df	p
OBP	-4.311	250.474	< .001*
AW	-5.043	285.286	< .001*
SC	-2.838	279.841	0.002*
US	-5.365	280.063	< .001*
PV	-4.972	284.804	< .001*
AI	-4.685	263.134	< .001*

* p < .05

The results showed that people who have never tried online shopping have a significantly lower online business perception ($p < 0.001$), awareness ($p < 0.001$), social cognition ($p = 0.002$), usability ($p < 0.001$), perception of price value ($p < 0.001$), and adoption intentions ($p < 0.001$) than those who have tried it before.

The findings of this study suggest that people who have never tried online shopping have a more negative perception of online shopping than those who have tried it before. This is likely due to their lack of experience with online shopping. Developers and marketers of online shopping platforms should take these findings into account when designing and marketing their platforms.

For example, they may need to make it easier for first-time users to understand and use online shopping platforms, and they may need to emphasize the benefits of online shopping to those who have never tried it.

v. Age

Age can have various effects on online shopping behavior. Younger adults tend to be more engaged with social media compared to older adults, which may be due to differences in technology experience and preferences, as well as social and cultural factors (Hsiao& Chen, 2016).

Similarly, previous research has suggested that older adults may have different perceptions of online business compared to younger adults due to differences in experience and technology preferences according to Yi, Jackson, Park, and Probst (2006). Furthermore, previous research has suggested that younger adults may have higher levels of awareness of online shopping compared to older adults (Park & Lee, 2009).

On the other hand, older adults may have more developed social cognition skills compared to younger adults which can also influence online shopping behavior. In terms of usability, younger adults may be more comfortable with using technology and may find online shopping easier compared to older adults who may face more challenges with the user interface and navigation, although this may also depend on factors such as education level and exposure to technology (Park & Lee, 2009).

Finally, younger adults may be more price-sensitive compared to older adults who may prioritize other factors such as quality and convenience , as well as be more likely to adopt online shopping compared to older adults who may have more reservations and concerns about the process, but this may also depend on the design and functionality of the online shopping platform, as well as the level of support and guidance provided to users (Yi, Jackson, Park & Probst, 2006).

To examine the effect of Age on these research variables and compare it to previous suggestions, an ANOVA test has been conducted and the results are reported in Table 36 below.

Table 36 ANOVA Test of Age and Research Variables

		Sum of Squares	df	Mean Square	F	Sig.
SME	Between Groups	2.559	5	.512	.588	.709
	Within Groups	338.507	389	.870		
	Total	341.067	394			
OBP	Between Groups	8.107	5	1.621	1.759	.120
	Within Groups	358.624	389	.922		
	Total	366.731	394			
AW	Between Groups	4.841	5	.968	1.092	.364
	Within Groups	345.043	389	.887		
	Total	349.884	394			
SC	Between Groups	5.468	5	1.094	1.237	.291
	Within Groups	343.790	389	.884		
	Total	349.257	394			
US	Between Groups	4.276	5	.855	.966	.438
	Within Groups	344.424	389	.885		
	Total	348.700	394			
PV	Between Groups	3.978	5	.796	.867	.504
	Within Groups	357.121	389	.918		
	Total	361.099	394			
AI	Between Groups	6.326	5	1.265	1.453	.204
	Within Groups	338.754	389	.871		
	Total	345.080	394			

The ANOVA results show that there is no significant difference between the age groups in terms of their social media engagement ($p = 0.709$), online business perception ($p = 0.120$), awareness of online shopping ($p = 0.364$), social cognition ($p = 0.291$), usability ($p = 0.438$), perception of price value ($p = 0.504$), and adoption intentions ($p = 0.204$). This means that individuals in different age groups have similar levels in terms of these variables.

The lack of significant age difference in the current study may be due to the fact that the sample included a wide range of ages. This may have minimized the impact of age as a factor influencing online shopping behavior.

Additionally, other factors such as income, education, and cultural background may have a stronger influence on online shopping behavior than age alone. Future research could further explore the complex relationship between age and online shopping behavior, considering additional factors such as income, education, and cultural background.

vi. Education

Education level can play a significant role in influencing online shopping behavior. Studies have shown that individuals with higher levels of education tend to be more engaged with social media compared to those with lower levels of education. This may be due to differences in technology experience and preferences, as well as the use of social media for educational purposes (Chen & Barnes, 2007).

Higher levels of education may also lead to a more positive perception of online businesses. Individuals with higher levels of education may have more exposure to technology and may be more comfortable with using online platforms for various purposes, including shopping. They may also be more likely to trust online retailers and have higher expectations for the quality of products and services (Shih,2004).

Awareness of online shopping may also vary based on education level. Individuals with higher levels of education may have greater exposure to information about online shopping through various channels, such as online resources, social media, and educational programs. As a result, they may have higher levels of awareness and be more likely to engage in online shopping (Chen & Barnes, 2007).

Social cognition skills may also be influenced by education level. Individuals with higher levels of education may have more developed critical thinking skills and be better able to evaluate the credibility of online retailers and products. They may also have greater awareness of social norms and be better able to interpret social cues related to online shopping, such as reviews and ratings (Chen & Barnes, 2007).

Usability of online shopping may also be influenced by education level. Individuals with higher levels of education may be more comfortable with using technology and may find online shopping easier compared to those with lower levels of education who may face more challenges with the user interface and navigation. However, this may also depend on the design and functionality of the online shopping platform (Limayem, Khalifa & Frini, 2000).

Price value may also vary based on education level. Individuals with higher levels of education may have greater financial resources and be more willing to pay higher prices for quality products and services. They may also be more likely to consider factors such as ethical and environmental concerns when making purchasing decisions (Park, Lee & Han, 2007).

Finally, adoption intentions of online shopping may vary based on education level. Individuals with higher levels of education may be more likely to adopt online shopping compared to those with lower levels of education, due to greater exposure to technology and awareness of the benefits of online shopping. However, this may also depend on factors such as perceived risk, trust, and familiarity with technology (Shih,2004).

To investigate the influence of education on various research variables, an ANOVA test was performed, and the results are reported in Table 37 below.

The results showed that social media engagement (SME) p-value is .493, online business perception (OBP) p-value is .077, awareness of online shopping (AW) p-value is .693, social cognition (SC) p-value is .188, usability of online shopping (US) p-value is .340, price value (PV) p-value is .298, and adoption intentions of online shopping (AI) p-value is .462.

Table 37 ANOVA Test of Education and Research Variables

		Sum of Squares	df	Mean Square	F	Sig.
SME	Between Groups	3.825	5	.765	.882	.493
	Within Groups	337.242	389	.867		
	Total	341.067	394			
OBP	Between Groups	9.227	5	1.845	2.008	.077
	Within Groups	357.504	389	.919		
	Total	366.731	394			
AW	Between Groups	2.715	5	.543	.609	.693
	Within Groups	347.169	389	.892		
	Total	349.884	394			
SC	Between Groups	6.618	5	1.324	1.503	.188
	Within Groups	342.639	389	.881		
	Total	349.257	394			
US	Between Groups	5.023	5	1.005	1.137	.340
	Within Groups	343.677	389	.883		
	Total	348.700	394			
PV	Between Groups	5.585	5	1.117	1.222	.298
	Within Groups	355.514	389	.914		
	Total	361.099	394			
AI	Between Groups	4.073	5	.815	.929	.462
	Within Groups	341.007	389	.877		
	Total	345.080	394			

The p-values are all greater than 0.05, which is the conventional statistical significance level. As a result, the null hypothesis that there is no statistically significant difference in the means of the different education level groups for any of the variables cannot be rejected. It is worth noting, however, that the p-values for online business perception (OBP) are fairly close to 0.05.

This suggests that there is a little possibility that the null hypothesis is correct and that there is a genuine difference between the means of the various education level groups for these variables.

It is possible that the distribution of educational levels in the sample may not have been wide enough to detect significant differences. For instance, if the majority of participants in the sample have a high level of education, it may be difficult to detect differences between this group and those with lower levels of education. Cultural factors may also play a role in shaping attitudes toward online shopping and social media engagement, and these factors may vary between countries.

For example, in some cultures, social media may be more widely used for business purposes, while in others it may be more commonly used for personal communication.

Economic factors may also play a role in shaping attitudes toward online shopping and perceptions of price value. In countries where there are greater economic constraints, consumers may place greater emphasis on price value and be less willing to pay higher prices for quality products and services.

These are just a few possibilities, and further research would be needed to determine the specific factors contributing to the lack of significant effects of education on the research variables in the sample from Yemen.

vii. Occupation

Occupation can have a significant effect on online shopping behavior and related variables. For example, individuals with professional or managerial occupations may have more disposable income and be more willing to spend money online, while those in blue-collar or lower-paying jobs may be more price-sensitive and prefer traditional shopping methods (Kim, Fiore & Lee, 2007).

Additionally, occupation can influence social media engagement, as certain industries or job roles may require more use of social media for networking or marketing purposes (Cheung& Lee, 2010).

Researchers have also suggested that occupation can affect perceptions of online shopping, with those in technology-related fields tending to have more positive perceptions of online shopping and its benefits.

Similarly, occupation can impact awareness of online shopping, with those in technology-related fields or those who work from home being more likely to be aware of and utilize online shopping platforms (Papasolomou & Melanthiou, 2012).

In terms of social cognition, occupation can influence the level of trust and confidence that individuals have in online shopping and its associated platforms

(Grewal, Monroe& Krishnan, 1998). For example, those with occupations that require high levels of trust or financial responsibility may be more cautious and hesitant to engage in online shopping activities (Kim, Fiore & Lee, 2007).

To explore the effect of occupation on this research variables, an ANOVA test was conducted, and the resulting p-values are reported in Table 38 below as follows: social media engagement (SME) with a p-value of .255, online business perception (OBP) with a p-value of .358, awareness of online shopping (AW) with a p-value of .462, social cognition (SC) with a p-value of .618, usability of online shopping (US) with a p-value of .075, usability of online shopping (US) which showed a p-value of .075, price value (PV) with a p-value of .120, and adoption intentions of online shopping (AI) with a p-value of .316.

Table 38 ANOVA Test of Occupation and Research Variables

		Sum of Squares	df	Mean Square	F	Sig.
SME	Between Groups	6.732	6	1.122	1.302	.255
	Within Groups	334.335	388	.862		
	Total	341.067	394			
OBP	Between Groups	6.169	6	1.028	1.106	.358
	Within Groups	360.562	388	.929		
	Total	366.731	394			
AW	Between Groups	5.045	6	.841	.946	.462
	Within Groups	344.840	388	.889		
	Total	349.884	394			
SC	Between Groups	3.948	6	.658	.739	.618
	Within Groups	345.310	388	.890		
	Total	349.257	394			
US	Between Groups	10.099	6	1.683	1.929	.075
	Within Groups	338.601	388	.873		
	Total	348.700	394			
PV	Between Groups	9.238	6	1.540	1.698	.120
	Within Groups	351.861	388	.907		
	Total	361.099	394			
AI	Between Groups	6.184	6	1.031	1.180	.316
	Within Groups	338.896	388	.873		
	Total	345.080	394			

Those results showed no statistically significant difference in social media engagement, online business perception, awareness of online shopping, social cognition, usability, price value, or adoption intentions of online shopping between the different occupation groups. However, it is important to note that these results are specific to the sample in question and may not necessarily apply to other populations or contexts.

The results implied that individuals from different professional backgrounds tend to exhibit similar behaviors and perceptions in the context of online shopping, with the possible exception of usability, which may warrant further investigation. The lack of significant impact of occupation on the research variables in the sample from Yemen may be due to several reasons.

Firstly, the occupational distribution in the sample may not have been wide enough to detect significant differences. If the majority of participants in the sample were from a specific occupational group, it may have been difficult to detect differences between this group and other occupational groups. Cultural factors may also have played a role in shaping attitudes towards online shopping and social media engagement in Yemen, and these factors may vary between countries.

Additionally, economic factors could have influenced the extent to which individuals in Yemen engage with online shopping and social media. Consumers in Yemen may place greater emphasis on price value due to the economic challenges in the country, which could impact their willingness to pay higher prices for quality products and services.

Furthermore, the technological infrastructure in Yemen may be less developed than in other countries, which could also influence online shopping behavior and social media engagement.

It is important to note that these are just some possible explanations, and further research would be required to explore these factors and their impact on online shopping behavior and social media engagement in Yemen.

viii. Income

The effect of income on online shopping behavior and social media engagement can be complex and multifaceted. Firstly, income may affect social media engagement, as those with higher incomes may have more disposable income and leisure time to spend on social media. They may also be more likely to have access to newer technology and devices that facilitate social media engagement.

Additionally, those with higher incomes may use social media for networking and business purposes more than those with lower incomes (Al-Ghaith, Sanzogni & Sandhu, 2015).

Concerning online shopping behavior, income may influence the perception of value and the willingness to pay for products and services. Those with higher incomes may have higher expectations for the quality of products and services they purchase and may be more willing to pay a premium for these quality products. However, they may also be more discerning in their purchasing decisions, conducting more research before making a purchase and seeking out more exclusive or luxury brands (Chen & Barnes, 2007).

Furthermore, awareness of online shopping and the usability of online shopping platforms may also be affected by income levels. Those with lower incomes may have less exposure to online shopping platforms or may find the technology and user interfaces of these platforms to be intimidating or confusing. On the other hand, those with higher incomes may have more familiarity and experience with online shopping and may be more likely to use it as a regular shopping channel (Chiu, Wang, Fang & Huang, 2014).

In terms of adoption intentions of online shopping, income may play a significant role, as those with higher incomes may be more likely to have access to the necessary technology and internet connectivity required for online shopping. They may also have greater trust in the security and safety of online shopping platforms, which could positively influence their adoption intentions (Dwivedi, Rana & Williams, 2019).

Finally, it is important to note that cultural and economic factors may also interact with income levels to influence online shopping behavior and social media engagement. For instance, in countries with lower average incomes, the impact of income on these variables may be less pronounced, and other factors such as access to technology and cultural attitudes towards social media and online shopping may have a more significant impact (Yang & Peterson,2004).

To investigate the impact of income on the research variables, ANOVA test has been conducted and the results were reported in Table 39 below.

Table 39 ANOVA Test of Income and Research Variables

		Sum of Squares	df	Mean Square	F	Sig.
SME	Between Groups	9.626	5	1.925	2.260	.048
	Within Groups	331.441	389	.852		
	Total	341.067	394			
OBP	Between Groups	16.105	5	3.221	3.574	.004*
	Within Groups	350.626	389	.901		
	Total	366.731	394			
AW	Between Groups	14.570	5	2.914	3.380	.005*
	Within Groups	335.315	389	.862		
	Total	349.884	394			
SC	Between Groups	4.026	5	.805	.907	.476
	Within Groups	345.231	389	.887		
	Total	349.257	394			
US	Between Groups	23.067	5	4.613	5.511	<.001*
	Within Groups	325.633	389	.837		
	Total	348.700	394			
PV	Between Groups	10.851	5	2.170	2.410	.036
	Within Groups	350.248	389	.900		
	Total	361.099	394			
AI	Between Groups	17.387	5	3.477	4.128	.001*
	Within Groups	327.693	389	.842		
	Total	345.080	394			

* p < .05

The results showed that there is a significant difference in social media engagement (p-value = 0.048), online business perception (p-value = 0.004), awareness of online shopping (p-value = 0.005), usability of online shopping (p-value < 0.001), price value (p-value = 0.036), and adoption intentions of online shopping (p-value = 0.001) among different income groups. However, there is no significant difference in social cognition (p-value = 0.476) among different income groups.

These findings are consistent with previous research that suggests that income can play a significant role in shaping attitudes and behaviors related to online shopping (e.g., Choi & Kim, 2016; Gao & Bai, 2014). On the other hand, the lack of significant differences in income groups on social cognition suggests that other factors, such as age or cultural background, may play a stronger role in shaping these attitudes and behaviors (e.g., Alalwan et al., 2017; Lin & Lu, 2011).

For a further understanding of the different impacts of income groups on research variables, Games-Howell post hoc test was made to compare the mean scores of all pairs of income groups on the variables. The first comparison is between the income group and social media engagement and as the results in Table 40 below showed; the only statistically significant difference in the mean scores between the income group "below 100$" and the income group "301-400$" on the SME variable with a p-value of 0.028.

This means that individuals in the "301-400$" income group are more likely to engage with social media than individuals in the "below 100$" income group. However, there is no statistically significant differences observed between the other income groups on the SME variable. These findings suggest that income may have a limited effect on social media engagement, with only certain income groups showing significant differences.

Table 40 Post Hoc Comparisons of Income and Social Media Engagement

Comparison	Mean Difference	95% CI for Mean Difference Lower	Upper	SE	t	df	p_{tukey}	
below 100$ - 200 - 300$	0.048	-0.305	0.402	0.123	0.394	204.488	0.999	
below 100$ - 301- 400 $	0.576	0.041	1.110	0.180	3.198	48.234	0.028	*
below 100$ - 401 - 500$	0.093	-0.453	0.640	0.184	0.509	44.193	0.996	
below 100$ - 501 - 600$	0.280	-0.212	0.772	0.167	1.678	55.988	0.551	
below 100$ - Above 600$	0.135	-0.265	0.536	0.139	0.975	168.399	0.925	
200 - 300$ - 301- 400 $	0.527	-0.014	1.068	0.183	2.886	50.364	0.060	
200 - 300$ - 401 - 500$	0.045	-0.508	0.598	0.186	0.242	46.150	1.000	
200 - 300$ - 501 - 600$	0.231	-0.268	0.731	0.170	1.364	58.510	0.748	
200 - 300$ - Above 600$	0.087	-0.324	0.497	0.142	0.611	161.172	0.990	
301- 400 $ - 401 - 500$	-0.482	-1.154	0.190	0.228	-2.116	57.796	0.294	
301- 400 $ - 501 - 600$	-0.296	-0.927	0.335	0.215	-1.379	60.927	0.739	
301- 400 $ - Above 600$	-0.440	-1.010	0.130	0.194	-2.273	60.732	0.221	
401 - 500$ - 501 - 600$	0.186	-0.455	0.827	0.218	0.856	57.867	0.955	
401 - 500$ - Above 600$	0.042	-0.540	0.623	0.197	0.212	55.585	1.000	
501 - 600$ - Above 600$	-0.144	-0.676	0.387	0.181	-0.796	71.202	0.967	

* $p < .05$

The second comparison is between the income group and online business perception (OBP). The results in Table 41 indicate that there are two statistically significant differences in the mean scores between income groups.

Table 41 Post Hoc Comparisons of Income and Online Business Perception

Comparison	Mean Difference	95% CI for Mean Difference Lower	95% CI for Mean Difference Upper	SE	t	df	ptukey	
below 100$ - 200 - 300$	0.003	-0.396	0.402	0.139	0.023	186.713	1.000	
below 100$ - 301- 400 $	-0.160	-0.679	0.359	0.175	-0.912	51.341	0.942	
below 100$ - 401 - 500$	0.205	-0.425	0.835	0.211	0.973	40.241	0.924	
below 100$ - 501 - 600$	-0.387	-0.818	0.044	0.147	-2.630	70.240	0.103	
below 100$ - Above 600$	-0.419	-0.797	-0.041	0.131	-3.189	186.504	0.020	*
200 - 300$ - 301- 400 $	-0.163	-0.712	0.386	0.187	-0.873	62.467	0.952	
200 - 300$ - 401 - 500$	0.202	-0.453	0.856	0.220	0.916	47.087	0.940	
200 - 300$ - 501 - 600$	-0.390	-0.859	0.078	0.161	-2.429	85.785	0.158	
200 - 300$ - Above 600$	-0.422	-0.844	-3.330×10^{-4}	0.146	-2.885	170.559	0.050	*
301- 400 $ - 401 - 500$	0.365	-0.359	1.089	0.245	1.489	54.286	0.673	
301- 400 $ - 501 - 600$	-0.227	-0.797	0.343	0.193	-1.175	57.604	0.847	
301- 400 $ - Above 600$	-0.259	-0.794	0.276	0.182	-1.427	56.746	0.710	
401 - 500$ - 501 - 600$	-0.592	-1.262	0.078	0.226	-2.622	47.465	0.112	
401 - 500$ - Above 600$	-0.624	-1.267	0.019	0.216	-2.891	43.687	0.062	
501 - 600$ - Above 600$	-0.032	-0.483	0.419	0.154	-0.207	77.011	1.000	

* p < .05

Note. Results based on uncorrected means.

The first significant difference is between the income group "below 100$" and the income group "above 600$" with a p-value of 0.020. This means that individuals in the "above 600$" income group are more likely to have a positive perception of online business than individuals in the "below 100$" income group.

The second significant difference is between the income group "200-300$" and the income group "above 600$" with a p-value of 0.050. This means that individuals in the "above 600$" income group are more likely to have a positive perception of online business than individuals in the "200-300$" income group.

The Games-Howell post hoc comparisons for income and the variable "awareness of online shopping" (AW) in Table 42 below showed significant differences between certain income groups.

Table 42 Post Hoc Comparisons of Income and Awareness

Comparison	Mean Difference	95% CI for Mean Difference Lower	Upper	SE	t	df	p_{tukey}	
below 100$ - 200 - 300$	-0.013	-0.410	0.383	0.138	-0.097	174.356	1.000	
below 100$ - 301- 400 $	-0.164	-0.672	0.345	0.171	-0.954	48.809	0.930	
below 100$ - 401 - 500$	-0.207	-0.831	0.417	0.208	-0.994	38.627	0.917	
below 100$ - 501 - 600$	-0.366	-0.837	0.104	0.160	-2.296	56.400	0.213	
below 100$ - Above 600$	-0.468	-0.819	-0.116	0.122	-3.832	187.507	0.002	**
200 - 300$ - 301- 400 $	-0.150	-0.701	0.401	0.188	-0.800	64.945	0.966	
200 - 300$ - 401 - 500$	-0.193	-0.851	0.464	0.222	-0.872	48.308	0.951	
200 - 300$ - 501 - 600$	-0.353	-0.870	0.164	0.177	-1.996	75.936	0.354	
200 - 300$ - Above 600$	-0.454	-0.869	-0.039	0.144	-3.157	167.029	0.023	*
301- 400 $ - 401 - 500$	-0.043	-0.764	0.678	0.244	-0.177	54.092	1.000	
301- 400 $ - 501 - 600$	-0.203	-0.804	0.398	0.204	-0.993	61.029	0.918	
301- 400 $ - Above 600$	-0.304	-0.826	0.217	0.176	-1.724	53.334	0.522	
401 - 500$ - 501 - 600$	-0.160	-0.857	0.538	0.236	-0.676	52.133	0.984	
401 - 500$ - Above 600$	-0.261	-0.895	0.373	0.212	-1.229	41.416	0.820	
501 - 600$ - Above 600$	-0.101	-0.587	0.384	0.165	-0.615	61.776	0.990	

* p < .05, ** p < .01

Note. Results based on uncorrected means.

The first comparison is between the "below 100$" income group and the "above 600$" income group, which resulted in a significant difference with a p-value of 0.002. This means that individuals in the "above 600$" income group have higher awareness of online shopping than individuals in the "below 100$" income group. The second comparison is between the "200-300$" income group and the "above 600$" income group, which resulted in a significant difference with a p-value of 0.023. This means that individuals in the "above 600$" income group have higher awareness of online shopping than indivduals in the "200-300$" income group.

Table 43 Post Hoc Comparisons of Income and Usability

Comparison	Mean Difference	95% CI for Mean Difference Lower	Upper	SE	t	df	p_{tukey}	
below 100$ - 200 - 300$	-0.072	-0.457	0.313	0.134	-0.538	178.303	0.995	
below 100$ - 301- 400 $	-0.232	-0.745	0.282	0.173	-1.341	47.884	0.761	
below 100$ - 401 - 500$	-0.270	-0.824	0.284	0.185	-1.456	41.919	0.693	
below 100$ - 501 - 600$	-0.546	-0.998	-0.094	0.153	-3.559	58.615	0.009	**
below 100$ - Above 600$	-0.589	-0.953	-0.224	0.127	-4.650	177.893	< .001	***
200 - 300$ - 301- 400 $	-0.160	-0.709	0.390	0.187	-0.856	61.390	0.955	
200 - 300$ - 401 - 500$	-0.198	-0.785	0.389	0.198	-0.999	52.795	0.916	
200 - 300$ - 501 - 600$	-0.474	-0.967	0.020	0.169	-2.807	76.759	0.067	
200 - 300$ - Above 600$	-0.517	-0.934	-0.099	0.145	-3.565	170.624	0.006	**
301- 400 $ - 401 - 500$	-0.038	-0.707	0.630	0.227	-0.168	57.159	1.000	
301- 400 $ - 501 - 600$	-0.314	-0.907	0.279	0.201	-1.559	59.839	0.628	
301- 400 $ - Above 600$	-0.357	-0.893	0.180	0.182	-1.962	56.052	0.377	
401 - 500$ - 501 - 600$	-0.276	-0.902	0.351	0.212	-1.300	54.785	0.784	
401 - 500$ - Above 600$	-0.318	-0.893	0.256	0.194	-1.644	48.536	0.574	
501 - 600$ - Above 600$	-0.043	-0.521	0.436	0.163	-0.261	69.421	1.000	

** p < .01, *** p < .001 *Note.* Results based on uncorrected means.

The Games-Howell post hoc tests for income and the variable "usability of online shopping" (US) in Table 43 above resulted in several statistically significant differences between income groups.

Firstly, individuals in the "below 100$" income group had significantly lower mean scores on US compared to those in the "501-600$" income group, with a p-value of 0.009. Additionally, individuals in the "below 100$" income group had significantly lower mean scores on US compared to those in the "above 600$" income group, with a p-value of 0.001. Furthermore, individuals in the "200-300$" income group had significantly lower mean scores on US compared to those in the "above 600$" income group, with a p-value of 0.006. These results suggest that individuals with higher income levels are more likely to find online shopping usable compared to those with lower income levels.

Based on the Games-Howell Post Hoc Comparisons for the variable "price value" (PV) and income groups in Table 44 below, the only statistically significant difference in mean scores was between the "below 100$" income group and the "above 600$" income group, with a p-value of 0.035.

This suggests that individuals in the "above 600$" income group are more willing to pay higher prices for products and services compared to those in the "below 100$" income group. No significant differences were found between any of the other income groups.

Table 44 Post Hoc Comparisons of Income and Price Value

Comparison	Mean Difference	95% CI for Mean Difference Lower	Upper	SE	t	df	p_{tukey}	
below 100$ - 200 - 300$	-0.107	-0.494	0.281	0.135	-0.793	195.413	0.968	
below 100$ - 301- 400 $	-0.072	-0.618	0.475	0.184	-0.389	49.245	0.999	
below 100$ - 401 - 500$	-0.060	-0.643	0.522	0.196	-0.309	43.360	1.000	
below 100$ - 501 - 600$	-0.418	-0.942	0.106	0.178	-2.354	54.688	0.191	
below 100$ - Above 600$	-0.395	-0.774	-0.016	0.132	-3.004	188.907	0.035	*
200 - 300$ - 301- 400 $	0.035	-0.530	0.600	0.191	0.183	55.509	1.000	
200 - 300$ - 401 - 500$	0.046	-0.554	0.646	0.202	0.229	48.544	1.000	
200 - 300$ - 501 - 600$	-0.311	-0.855	0.233	0.185	-1.684	61.790	0.548	
200 - 300$ - Above 600$	-0.288	-0.696	0.119	0.141	-2.041	171.000	0.324	
301- 400 $ - 401 - 500$	0.011	-0.691	0.714	0.238	0.047	57.313	1.000	
301- 400 $ - 501 - 600$	-0.346	-1.005	0.312	0.224	-1.548	61.594	0.635	
301- 400 $ - Above 600$	-0.323	-0.883	0.236	0.189	-1.709	53.274	0.532	
401 - 500$ - 501 - 600$	-0.358	-1.045	0.329	0.233	-1.535	57.899	0.644	
401 - 500$ - Above 600$	-0.335	-0.930	0.260	0.200	-1.672	46.755	0.557	
501 - 600$ - Above 600$	0.023	-0.515	0.561	0.183	0.126	59.174	1.000	

* p < .05

Note. Results based on uncorrected means.

Based on the Games-Howell Post Hoc Comparisons for income and adoption intentions of online shopping (AI) in Table 45 below, the results show that there is a statistically significant difference in the mean scores between the income group "below 100$" and the income group "501-600$" with a p-value of 0.025, as well as between the income group "below 100$" and the income group "above 600$" with a p-value of 0.002. This means that individuals in the "501-600$" income group and those in the "above 600$" income group are more likely to have higher adoption intentions of online shopping than individuals in the "below 100$" income group.

Table 45 Post Hoc Comparisons of Income and Adoption Intentions

Comparison	Mean Difference	95% CI for Mean Difference Lower	95% CI for Mean Difference Upper	SE	t	df	p_{tukey}	
below 100$ - 200 - 300$	-0.161	-0.548	0.227	0.135	-1.192	186.171	0.840	
below 100$ - 301- 400 $	-0.280	-0.728	0.168	0.152	-1.841	59.535	0.448	
below 100$ - 401 - 500$	0.026	-0.576	0.627	0.201	0.127	40.693	1.000	
below 100$ - 501 - 600$	-0.544	-1.041	-0.046	0.169	-3.224	55.177	0.025	*
below 100$ - Above 600$	-0.480	-0.839	-0.121	0.125	-3.852	190.705	0.002	**
200 - 300$ - 301- 400 $	-0.119	-0.601	0.362	0.165	-0.725	73.813	0.978	
200 - 300$ - 401 - 500$	0.186	-0.440	0.812	0.211	0.883	47.956	0.949	
200 - 300$ - 501 - 600$	-0.383	-0.911	0.145	0.180	-2.127	67.271	0.286	
200 - 300$ - Above 600$	-0.320	-0.723	0.083	0.140	-2.287	169.593	0.205	
301- 400 $ - 401 - 500$	0.306	-0.353	0.964	0.222	1.374	50.479	0.742	
301- 400 $ - 501 - 600$	-0.264	-0.833	0.305	0.193	-1.363	61.264	0.748	
301- 400 $ - Above 600$	-0.200	-0.661	0.260	0.157	-1.280	63.614	0.795	
401 - 500$ - 501 - 600$	-0.569	-1.260	0.122	0.234	-2.432	55.412	0.163	
401 - 500$ - Above 600$	-0.506	-1.116	0.104	0.205	-2.471	43.076	0.155	
501 - 600$ - Above 600$	0.063	-0.446	0.572	0.173	0.366	58.866	0.999	

* $p < .05$, ** $p < .01$

Note. Results based on uncorrected means.

In summary, post hoc comparisons revealed significant differences in online shopping-related variables between different income groups. Specifically, individuals in higher income groups (above 600 dollars) showed significantly higher levels of online business perception, awareness of online shopping, social cognition, usability of online shopping, price value, and adoption intentions of online shopping compared to those in lower income groups (below 100 dollars or 200-300 dollars).

ix. City of residence

There is limited research on the effect of city of residence on social media engagement, online business perception, awareness of online shopping, social cognition, usability of online shopping, price value, and adoption intentions of online shopping in Yemen.

However, a study by Al-Ghaili and Al-Sakkaf (2019) found that the level of social media usage and engagement varies across different cities in Yemen, with Sana'a having the highest usage followed by Aden and then Taiz.

Another study by Al-Timimi and Abdulla (2020) reported that the adoption of online shopping in Yemen is low, with customers from different cities having varying perceptions of online shopping.

Additionally, a study by Al-Qudaimi and Khamis (2017) found that customers' perceptions of the usability of online shopping vary across different cities in Saudi Arabia, which is a neighboring country to Yemen. Therefore, it is possible that the city of residence may also have an effect on the variables of interest in Yemen. However, further research is needed to determine the extent of this effect.

To determine the imact of the city of residence on social media engagement, online business perception, awareness of online shopping, social cognition, usability of online shopping, price value, and adoption intentions of online shopping, a statistical analysis ANOVA was conducted.

The results showed that there is no significant difference in social media engagement (SME) (p-value = 0.147), online business perception (OBP) (p-value = 0.540), awareness of online shopping (AW) (p-value = 0.090), social cognition (SC)) (p-value = 0.600), usability of online shopping (US) (p-value = 0.221), price value (PV) (p-value = 0.181), or adoption intentions of online shopping (AI) (p-value = 0.535) between different city of residence groups as none of the variables were statistically significant at the 0.05 level. Full results are reported in Table 46 below.

Table 46 ANOVA Test of City of Residence and Research Variables

		Sum of Squares	df	Mean Square	F	Sig.
SME	Between Groups	9.339	7	1.334	1.556	.147
	Within Groups	331.728	387	.857		
	Total	341.067	394			
OBP	Between Groups	5.605	7	.801	.858	.540
	Within Groups	361.126	387	.933		
	Total	366.731	394			
AW	Between Groups	10.920	7	1.560	1.781	.090
	Within Groups	338.964	387	.876		
	Total	349.884	394			
SC	Between Groups	4.893	7	.699	.786	.600
	Within Groups	344.364	387	.890		
	Total	349.257	394			
US	Between Groups	8.376	7	1.197	1.361	.221
	Within Groups	340.324	387	.879		
	Total	348.700	394			
PV	Between Groups	9.282	7	1.326	1.459	.181
	Within Groups	351.816	387	.909		
	Total	361.099	394			
AI	Between Groups	5.310	7	.759	.864	.535
	Within Groups	339.770	387	.878		
	Total	345.080	394			

It is important to note that the lack of statistical significance for the variables does not necessarily mean that there is no effect of the city of residence on these variables. It may be possible that a larger sample size or a different method of analysis could reveal significant differences.

Additionally, it is important to consider the practical significance of any observed differences, even if they do not reach statistical significance.

x. **Internet type**

The type of internet connection used by individuals may have an effect on various variables related to online behavior. In terms of social media engagement, a study by Beldad and Hegner (2017) found that individuals with faster internet connections are more likely to engage with social media compared to those with slower connections. Similarly, a study by Alam and Momen (2019) reported that internet speed is positively associated with online shopping behavior, including awareness and adoption intentions.

Regarding online business perception, a study by Kim and Stoel (2004) found that individuals with high-speed internet connections have more favorable perceptions of online shopping compared to those with slower connections. In terms of social cognition, a study by Liu et al. (2016) found that high-speed internet connections are associated with increased online information seeking and sharing behavior.

In terms of usability of online shopping, a study by Kurnia et al. (2015) reported that individuals with faster internet connections perceive online shopping websites to be more usable compared to those with slower connections. Additionally, a study by Wang and Lin (2016) found that faster internet speeds are associated with a higher perceived value of online shopping. Regarding adoption intentions of online shopping, a study by Liang and Huang (2017) reported that individuals with faster internet connections are more likely to adopt online shopping compared to those with slower connections.

Overall, it seems that the type of internet connection used by individuals can have an impact on various variables related to online behavior, including social media engagement, online business perception, awareness of online shopping, social cognition, usability of online shopping, price value, and adoption intentions of online shopping.

To examine this research sample in Yemen and compare it to previous studies, ANOVA test was conducted for each of the seven variables of interest (SME, OBP, AW, SC, US, PV, and AI) when comparing across different types of internet access and the results reported in Table 47 below.

Table 47 ANOVA Test of Internet Type and Research Variables

		Sum of Squares	df	Mean Square	F	Sig.
SME	Between Groups	4.411	4	1.103	1.278	.278
	Within Groups	336.655	390	.863		
	Total	341.067	394			
OBP	Between Groups	3.071	4	.768	.823	.511
	Within Groups	363.660	390	.932		
	Total	366.731	394			
AW	Between Groups	4.065	4	1.016	1.146	.334
	Within Groups	345.820	390	.887		
	Total	349.884	394			
SC	Between Groups	4.994	4	1.249	1.414	.228
	Within Groups	344.263	390	.883		
	Total	349.257	394			
US	Between Groups	6.402	4	1.600	1.823	.123
	Within Groups	342.298	390	.878		
	Total	348.700	394			
PV	Between Groups	8.663	4	2.166	2.397	.050
	Within Groups	352.435	390	.904		
	Total	361.099	394			
AI	Between Groups	7.035	4	1.759	2.029	.090
	Within Groups	338.045	390	.867		
	Total	345.080	394			

The results showed that there was no statistically significant difference in social media engagement (SME), online business perception (OBP), awareness of online shopping (AW), social cognition (SC), and usability of online shopping (US) between the different internet types (p-values = 0.278, 0.511, 0.334, 0.228, and 0.123, respectively).

However, there was a borderline significant difference in price value (PV) between the different internet types (p-value = 0.050). Finally, there was no statistically significant difference in adoption intentions of online shopping (AI) between the different internet types (p-value = 0.090).

There could be several factors that make the internet speed not as effective in Yemen. One major factor could be the overall infrastructure and investment in the telecommunications industry in Yemen. Yemen has been facing ongoing conflicts and instability for many years, which could have a negative impact on the development and maintenance of telecommunications infrastructure.

Additionally, factors such as the availability and quality of electricity, which is essential for powering the telecommunications infrastructure, could also affect internet speed.

Another factor could be the limited competition in the telecommunications industry in Yemen, which could result in limited innovation and investment in improving internet speed. Finally, there could be limitations in the technology and equipment used in the telecommunications infrastructure in Yemen, which could also have an impact on internet speed.

xi. Device type

The device type used by individuals can have an effect on various variables related to online behavior. In terms of social media engagement, a study by Xu and Tan (2016) found that individuals who use mobile devices are more likely to engage with social media compared to those who use desktop devices.

Additionally, a study by Riegelsberger et al. (2005) reported that the device type used for social media can affect the type of content that is shared, with mobile devices being more associated with personal and contextual information sharing.

Regarding online business perception, a study by Kim and Stoel (2004) found that individuals who use mobile devices have less favorable perceptions of online shopping compared to those who use desktop devices.

However, a more recent study by Alam and Momen (2019) reported that device type does not have a significant effect on online shopping behavior, including awareness and adoption intentions.

In terms of social cognition, a study by Liu et al. (2016) found that individuals who use mobile devices are more likely to use online information seeking and sharing behavior compared to those who use desktop devices.

Regarding usability of online shopping, a study by Lee and Park (2019) reported that individuals who use mobile devices perceive online shopping websites to be less usable compared to those who use desktop devices. The same study also found that individuals who use mobile devices perceive online shopping websites to have lower perceived value compared to those who use desktop devices. However, this may be due to the limitations of mobile devices rather than the device type itself.

To examine this research sample and compare it to previous studies; ANOVA test had been conducted ,the results showed that device type has no significant effect on all variables expect one as device type had no significant effect on online business perception (OBP), awareness of online shopping (AW), social cognition (SC), usability of online shopping (US), perceived value (PV), and adoption intentions of online shopping (AI), with p-values of .272, .218, .624, .126, .273, and .259, respectively.

However, device type did have a significant effect on social media engagement (SME), with a p-value of .012. Full results are reported in Table 48 below.

Table 48 ANOVA Test of Device Type and Research Variables

		Sum of Squares	df	Mean Square	F	Sig.
SME	Between Groups	9.409	3	3.136	3.697	.012
	Within Groups	331.658	391	.848		
	Total	341.067	394			
OBP	Between Groups	3.637	3	1.212	1.305	.272
	Within Groups	363.094	391	.929		
	Total	366.731	394			
AW	Between Groups	3.942	3	1.314	1.485	.218
	Within Groups	345.942	391	.885		
	Total	349.884	394			
SC	Between Groups	1.566	3	.522	.587	.624
	Within Groups	347.691	391	.889		
	Total	349.257	394			
US	Between Groups	5.059	3	1.686	1.919	.126
	Within Groups	343.641	391	.879		
	Total	348.700	394			
PV	Between Groups	3.578	3	1.193	1.304	.273
	Within Groups	357.521	391	.914		
	Total	361.099	394			
AI	Between Groups	3.530	3	1.177	1.347	.259
	Within Groups	341.550	391	.874		
	Total	345.080	394			

Post-hoc comparisons were performed to analyze the differences in social media engagement between the browsing device groups, and the results are shown in Table 49 below. In terms of social media engagement, the results demonstrated a statistically significant difference between mobile and laptop users ($p = 0.006$). Mobile users engaged in social media at a higher rate than laptop users.

Table 49 Post Hoc Comparisons of Device Type and Social Media Engagement

		Mean Difference	95% CI for Mean Difference Lower	95% CI for Mean Difference Upper	SE	t	p_{tukey}	
Mobile	Tablet	-0.007	-1.691	1.678	0.653	-0.010	1.000	
	Laptop	0.747	0.158	1.336	0.228	3.270	0.006	**
	Desktop	0.270	-0.707	1.248	0.379	0.714	0.892	
Tablet	Laptop	0.754	-1.023	2.530	0.688	1.095	0.693	
	Desktop	0.277	-1.663	2.217	0.752	0.368	0.983	
Laptop	Desktop	-0.477	-1.605	0.652	0.437	-1.090	0.696	

Note. P-value and confidence intervals adjusted for comparing a family of 4 estimates (confidence intervals corrected using the tukey method).
* p < .05, ** p < .01

3. Analysis of Research Variables Relationships

By analyzing the relationships between online shopping adoption intentions, social media engagement, online business perception, awareness, social cognition, usability, and price value, we gain invaluable insights tailored to our specific research objectives.

This analysis enables us to pinpoint key drivers of online shopping adoption, prioritize interventions, validate research hypotheses, and make data-driven recommendations. Furthermore, it aids in crafting customized strategies and targeting approaches, ultimately empowering us to optimize our research outcomes and decision-making processes.

Table 50 below shows the Pearson correlation coefficients between various pairs of variables. Each cell in the table shows the correlation coefficient and the associated p-value for a specific pair of variables.

Table 50 Correlations

		SME	OBP	AW	SC	US	PV	AI
SME	Pearson Correlation	1	.148**	.167**	.282**	.133**	.205**	.135**
	Sig. (2-tailed)		.003	<.001	<.001	.008	<.001	.007
OBP	Pearson Correlation	.148**	1	.736**	.622**	.759**	.669**	.807**
	Sig. (2-tailed)	.003		<.001	<.001	<.001	<.001	<.001
AW	Pearson Correlation	.167**	.736**	1	.711**	.860**	.692**	.756**
	Sig. (2-tailed)	<.001	<.001		<.001	<.001	<.001	<.001
SC	Pearson Correlation	.282**	.622**	.711**	1	.640**	.699**	.678**
	Sig. (2-tailed)	<.001	<.001	<.001		<.001	<.001	<.001
US	Pearson Correlation	.133**	.759**	.860**	.640**	1	.735**	.753**
	Sig. (2-tailed)	.008	<.001	<.001	<.001		<.001	<.001
PV	Pearson Correlation	.205**	.669**	.692**	.699**	.735**	1	.738**
	Sig. (2-tailed)	<.001	<.001	<.001	<.001	<.001		<.001
AI	Pearson Correlation	.135**	.807**	.756**	.678**	.753**	.738**	1
	Sig. (2-tailed)	.007	<.001	<.001	<.001	<.001	<.001	

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

The correlations between the variables and adoption intentions (AI) are all positive and significant at the 0.01 level (2-tailed), indicating that these variables are positively related to adoption intentions. Specifically, online business perception (OBP) has the strongest correlation with AI (r = .807), followed by awareness of online shopping (AW) (r = .756) and usability of online shopping (US) (r = .753), perceived price value (PV) (r = .738). while social media engagement (SME) has the lowest correlation with adoption intentions (AI) (r = .135).

The results suggest that online business perception (OBP) has the strongest relationship with adoption intentions (AI). This implies that consumers who have a more favorable perception of online businesses are more likely to have the intention to adopt online shopping.

This may be due to the fact that individuals who view online businesses positively may trust technology more, which in turn may increase their willingness to adopt new technologies like online shopping.

Similarly, the positive correlation between awareness of online shopping (AW), usability of online shopping (US), and perceived price value (PV) with adoption intentions (AI) suggests that consumers who are aware of online shopping options, find online shopping easy to use, and perceive online shopping to be of good value are more likely to adopt online shopping. This could be because these individuals may already have positive experiences with online shopping and are more likely to be receptive to the benefits that online shopping can offer.

On the other hand, the weaker positive correlation between social media engagement (SME) and adoption intentions (AI) suggests that while social media may be an important tool for marketers to promote the benefits of online shopping, it may not be as influential as other factors like online business perception, awareness of online shopping, usability of online shopping, and perceived price value.

The correlations between the other variables are also significant and provide insights into their relationships with each other. For example, awareness of online shopping (AW) has the highest correlation with usability of online shopping (US) ($r = .860$) This suggests that individuals who are more aware of online shopping tend to find it more usable.

Furthermore, there is a strong positive correlation between online business perception (OBP) and usability of online shopping (US) ($r = .759$, $p < .01$). This indicates that individuals who perceive online businesses more positively tend to find online shopping more usable.

There is also a strong positive correlation between social cognition (SC) and awareness of online shopping (AW) ($r = .711$, $p < .01$). This suggests that individuals who have higher levels of social cognition tend to be more aware of online shopping.

Lastly, there is a moderate positive correlation between social cognition (SC) and usability of online shopping (US) ($r = .640$, $p < .01$). This indicates that individuals who have higher levels of social cognition tend to find online shopping more usable.

On the other hand, there is a weak positive correlation between social media engagement (SME) and all the other variables except for online business perception (OBP), with the strongest correlation being with social cognition (SC) ($r = .282$, $p < .01$). This indicates that individuals who are more engaged with social media tend to have higher levels of social cognition and are more aware of and find online shopping more usable, but there is no significant relationship with online business perception.

Overall, these results suggest that factors such as awareness of online shopping, online business perception, and perceived price value may play important roles in shaping adoption intentions of online shopping, while social media engagement may have a more indirect effect through its association with other factors such as social cognition and usability.

4. Structural Equation Modeling

A structural equation model was created as a result using Amos 25. The model tested the hypothesized causal relationships between the adoption intentions for online shopping with social media engagement, online business perception, Awareness of online shopping, social cognition, usability of online shopping, and price value. whereas those variables were viewed as endogenous variables, and as a result, they had error components.

First, we used descriptive statistics to describe the proportions and means of the important variables and to characterize the study population. Prior to analysis, missing values, outliers, and normality were checked to ensure that statistical procedures and rules were being followed. With SPSS 28, descriptive analyses were carried out. We then developed the causal model to evaluate the pathways to adoption intentions for online shopping based on logical and prior analyses.

In determining the minimum sample size required for conducting a structural equation model (SEM), an online software (Soper, 2023) was employed. The calculation aimed to achieve a statistical power of 0.99, indicating a high probability of detecting a genuine effect if present (Westland, 2010).

The analysis utilized a p-value of 0.01 and anticipated an effect size of 0.3, considered moderate in most fields (Westland, 2010). The SEM consisted of 7 latent variables and 41 observed variables.

The computed minimum sample size for this model was approximately 381 participants. However, for the analysis, a dataset comprising 395 participants was collected and utilized.

The key components of a SEM path diagram include rectangles, circles, arrows, error terms, covariance, and unidirectional arrows. Rectangles represent the manifest variables in the model, which are the observed variables that are directly measured in the study. Circles represent the latent variables in the model, which are unobserved variables that are inferred from the manifest variables (Kline, 2016).

As seen in Figure 15 below, the path diagram contains a total of 96 variables in the SEM model, with 41 observed endogenous variables, 7 unobserved endogenous variables (latent variables), and 48 unobserved exogenous variables (error term).

The appropriate sample size for SEM analysis depends on various factors, including the complexity of the model, the number of variables, the distribution of the variables, and the level of measurement.

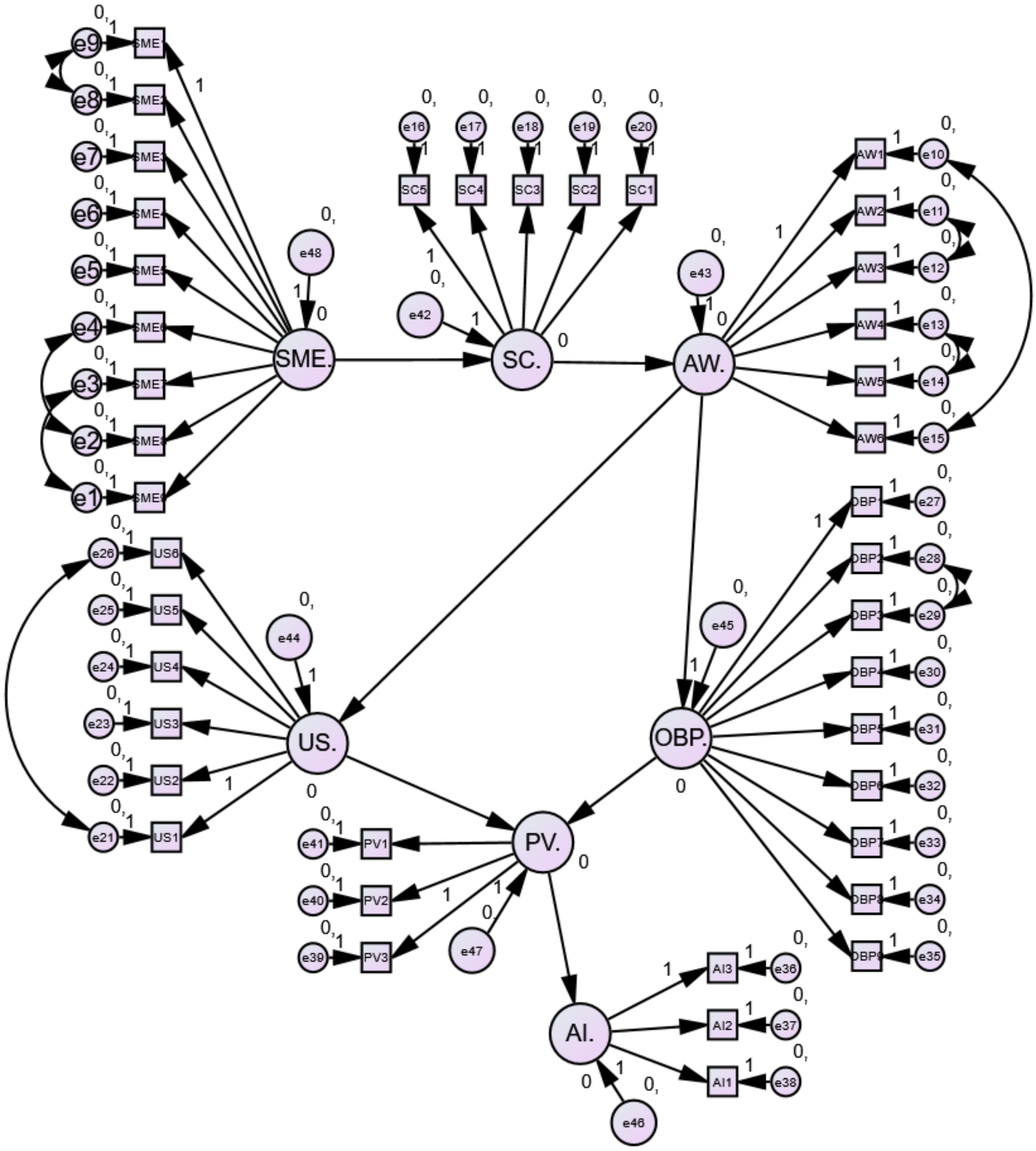

Figure 15 SEM Path Diagram

a. Structural equation modeling fit analysis

SEM fit analysis can be used to test the overall fit of the proposed model, which includes the direct effects of social media engagement on social cognition, awareness of online shopping, online business perception, and perceived price value of online shopping, as well as the direct effects of social cognition and awareness of online shopping on online business perception, and the direct effects of online business perception and perceived price value on online shopping adoption intention.

The model fit analysis produced the following results as seen in Table 51 below for the fit indices: chi-square statistics CMIN/DF = 1.963, CFI = 0.912, TLI = 0.906, IFI) = 0.913, and RMSEA = 0.049.

Table 51 Model Fit Indices

Index	Cut-off	Value
Chi-square statistics CMIN/DF	3	1.963
CFI	0.9	0.912
TLI	0.9	0.906
IFI	0.9	0.913
RMSEA	0.8	0.049

These results indicate that the proposed model has an acceptable fit to the data, as the CFI, TLI, and IFI values are above the recommended threshold of 0.9 and the RMSEA value is below the recommended threshold of 0.08. Chi-square value also is significant, which suggests that there is still some degree of discrepancy between the model and the observed data.

Overall, these findings provide support for the proposed model and suggest that it may be a useful framework for understanding online shopping behavior.

b. Model results

In recent years, SEM has become increasingly popular in the field of online shopping behavior research, where it is used to identify the factors that influence consumers' online shopping adoption intentions. By modeling the complex relationships between variables such as social media engagement, social cognition, online shopping awareness, online business perception, and perceived price value, SEM can provide valuable insights into the underlying factors that influence consumer decision-making in the online shopping context.

In this section, the results of a SEM analysis that was conducted to test the relationships between these variables and online shopping adoption intention will be presented and explained. The analysis will provide information on the strength and direction of the direct and indirect effects of each variable on online shopping adoption intention, as well as the overall fit of the proposed model. These results will help us to better understand the factors that influence online shopping behavior and inform the development of effective interventions aimed at increasing online shopping adoption.

Structural equation modeling (SEM) can be performed using either standardized or unstandardized data. Standardized SEM involves standardizing all variables to have a mean of 0 and a standard deviation of 1 before analyzing them, while unstandardized SEM uses the original, raw data without standardizing it (Kline, 2016).

Standardized SEM is often used when comparing models with different sets of variables, as it allows for easier comparisons between coefficients (Kline, 2016). On the other hand, unstandardized SEM is often used when the scale of measurement is meaningful for the research question or when comparing coefficients between models is not a priority (MacCallum, Browne, & Sugawara, 1996).

The choice of whether to report standardized or unstandardized SEM results depends on the research question and the purpose of the analysis. If the focus is on the strength and direction of relationships between variables and comparing the magnitudes of these relationships across different models or variables, reporting standardized SEM coefficients may be more appropriate as seen in Figure 16 (Kline, 2016).

Conversely, if the focus is on the practical significance of relationships between variables and interpreting coefficients in their original units of measurement, reporting unstandardized SEM coefficients may be more appropriate seen in Figure 16 (MacCallum, Browne, & Sugawara, 1996).

In some cases, both types of coefficients may be necessary to answer research questions that involve both examining the strength of relationships and their practical significance. Regardless of which type of SEM coefficients are reported, it's important to provide information on the fit of the overall model, the significance of individual coefficients, and any potential sources of bias or limitations of the analysis (Kline, 2016; MacCallum, Browne, & Sugawara,1996).

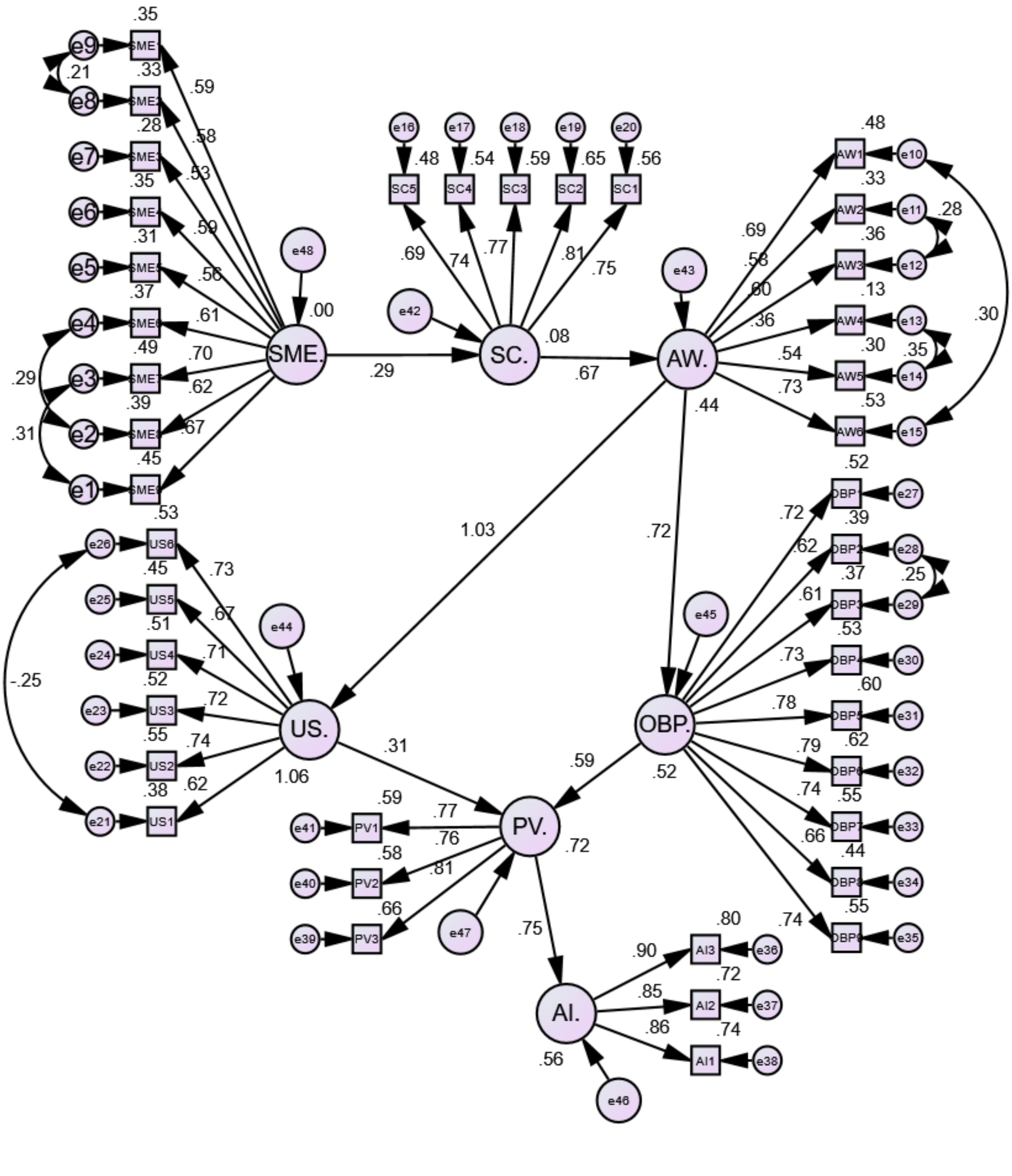

Figure 16 Standardized SEM Path Diagram

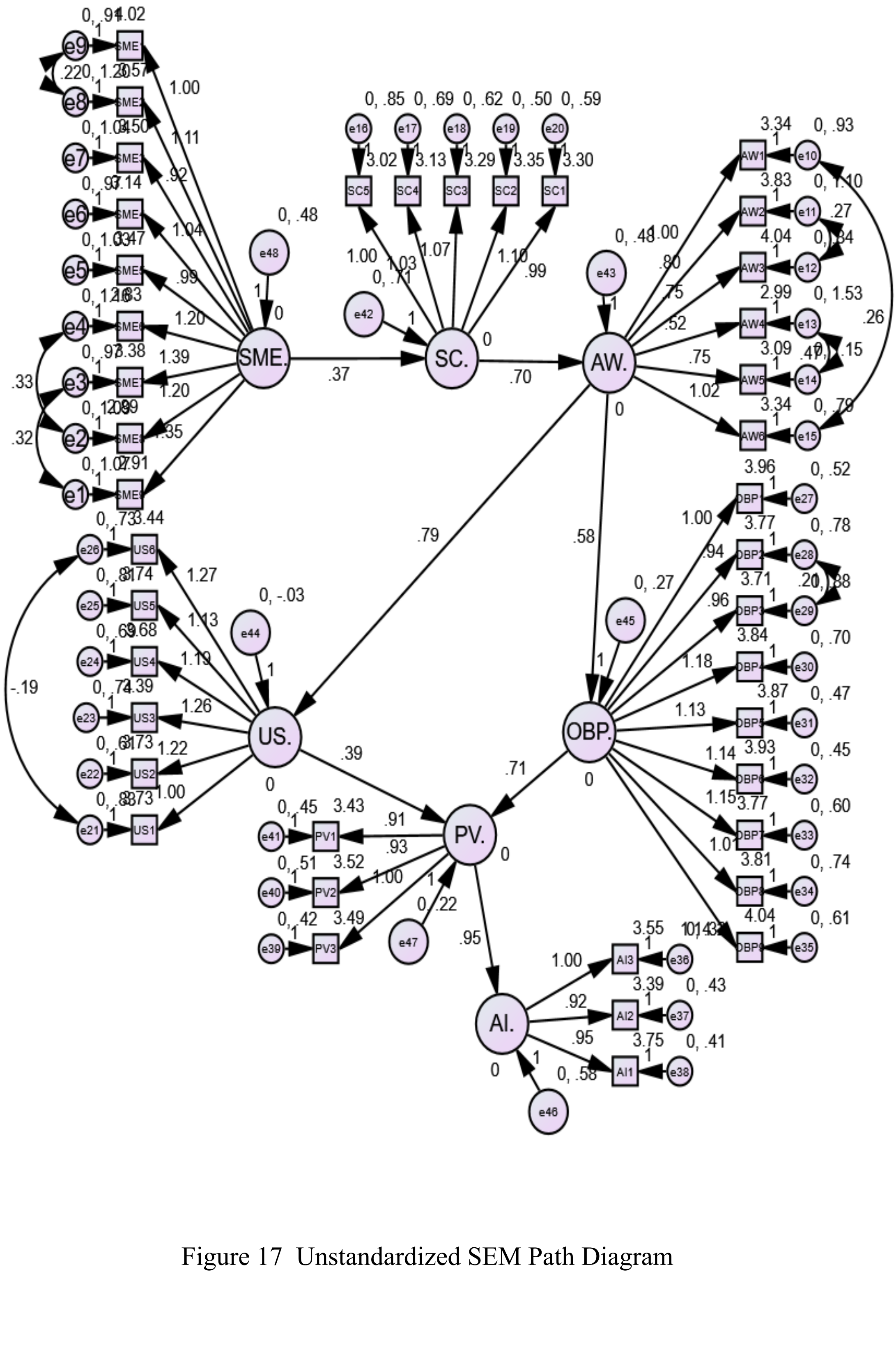

Figure 17 Unstandardized SEM Path Diagram

Table 53 and Table 54 below shows the Regression Weights of structural equation modeling (SEM) analysis. In an SEM, unobserved variables, also known as latent variables, are inferred based on the observed variables (i.e., items) that are regressed onto them.

Table 52 Observed Variables Regression to Latent Variables

			Estimate	S.E.	C.R.	P
SME9	<---	SME.	1.346	.140	9.627	***
SME8	<---	SME.	1.201	.130	9.261	***
SME7	<---	SME.	1.385	.140	9.908	***
SME6	<---	SME.	1.199	.131	9.135	***
SME5	<---	SME.	.986	.114	8.635	***
SME4	<---	SME.	1.036	.116	8.959	***
SME3	<---	SME.	.916	.111	8.290	***
SME2	<---	SME.	1.113	.111	10.021	***
SME1	<---	SME.	1.000			
AW1	<---	AW.	1.000			
AW2	<---	AW.	.797	.073	10.872	***
AW3	<---	AW.	.747	.066	11.379	***
AW4	<---	AW.	.524	.075	6.959	***
AW5	<---	AW.	.751	.073	10.297	***
AW6	<---	AW.	1.021	.063	16.311	***
SC5	<---	SC.	1.000			
SC4	<---	SC.	1.031	.079	13.091	***
SC3	<---	SC.	1.066	.079	13.523	***
SC2	<---	SC.	1.100	.078	14.113	***
SC1	<---	SC.	.987	.074	13.279	***
US1	<---	US.	1.000			
US2	<---	US.	1.219	.101	12.106	***
US3	<---	US.	1.256	.106	11.832	***
US4	<---	US.	1.193	.102	11.744	***
US5	<---	US.	1.134	.101	11.177	***
US6	<---	US.	1.274	.119	10.737	***

Table 53 Observed Variables Regression to Latent Variables 2

			Estimate	S.E.	C.R.	P
OBP1	<---	OBP.	1.000			
OBP2	<---	OBP.	.940	.078	11.980	***
OBP3	<---	OBP.	.956	.082	11.655	***
OBP4	<---	OBP.	1.178	.084	14.032	***
OBP5	<---	OBP.	1.126	.075	15.010	***
OBP6	<---	OBP.	1.137	.075	15.171	***
OBP7	<---	OBP.	1.147	.080	14.336	***
OBP8	<---	OBP.	1.014	.080	12.748	***
OBP9	<---	OBP.	1.141	.080	14.247	***
AI3	<---	AI.	1.000			
AI2	<---	AI.	.924	.042	22.251	***
AI1	<---	AI.	.947	.042	22.751	***
PV3	<---	PV.	1.000			
PV2	<---	PV.	.935	.058	16.159	***
PV1	<---	PV.	.906	.055	16.356	***

The results display the standardized regression weights of each item onto its corresponding latent variable, indicating the strength and direction of the relationship between the latent variables (SME, AW, SC, US, OBP, PV, and AI) and their respective observed variables (SME1-SME9, AW1-AW6, SC1-SC5, US1-US6, OBP1-OBP9, PV1-PV3, and AI1-AI3).

Therefore, this table provides valuable information about the relationships between the latent variables and the observed variables, informing our understanding of the underlying structure of the data.

The measured variables within the SME (SME1-SME9) construct exhibited regression weights spanning from 0.916 to 1.385, with SME9 demonstrating the highest weight of 1.346. In a similar vein, the observed variables comprising the AW (AW1-AW6) construct displayed regression weights ranging from 0.524 to 1.021, with AW6 showcasing the highest weight of 1.021.

The measured variables containing the SC (SC1-SC5) construct displayed regression weights that spanned from 0.987 to 1.100, with SC2 yielding the highest weight of 1.100. As for the US construct, the observed variables (US1-US6) exhibited regression weights ranging from 1.134 to 1.274, with US6 attaining the highest weight of 1.274.

Turning to the OBP construct, the observed variables (OBP1-OBP9) displayed regression weights ranging from 0.940 to 1.178, with OBP4 registering the highest weight of 1.178. Similarly, within the PV construct, the observed variables (PV1-PV3) displayed regression weights ranging from 0.906 to 0.935, with PV3 achieving the highest weight of 1.000.

Finally, the measured variables comprising the AI construct featured regression weights spanning from 0.924 to 1.000, with AI3 demonstrating the highest weight of 1.000.

These findings suggest that SME, AW, SC, US, OBP, PV, and AI can be effectively measured by their respective observed variables and can provide meaningful insights into understanding the underlying constructs of interest in the study. However, the strength of the relationships between the observed and latent variables varies across different latent variables and observed variables.

Table 54 below shows the unstandardized regression weights for the SEM model. The variables are represented by their abbreviations, and the arrows indicate the direction of the relationship. The estimate column shows the standardized regression weight for each path. The S.E. column shows the standard error of the estimate,

The C.R. or composite reliability values indicate the significance of the relationships between the variables. Values greater than 1.96 (at $p<0.05$) or 2.58 (at $p<0.01$) indicate statistical significance. Finally, the P column shows the p-value for each path (Kline, 2016).

Table 54 Unstandardized Regression Weights

			Estimate	S.E.	C.R.	P
SC.	<---	SME.	.369	.081	4.567	***
AW.	<---	SC.	.702	.072	9.792	***
US.	<---	AW.	.790	.069	11.377	***
OBP.	<---	AW.	.585	.053	10.962	***
PV.	<---	OBP.	.709	.084	8.452	***
PV.	<---	US.	.392	.082	4.805	***
AI.	<---	PV.	.952	.068	14.096	***

According to the results, social cognition (SC) is positively related to social media engagement (SME), with a regression weight of .369 (S.E. = .081, C.R. = 4.567, $p < .001$). Awareness (AW) is positively related to social cognition (SC), with a regression weight of .702 (S.E. = .072, C.R. = 9.792, $p < .001$). Usability (US) is positively related to awareness (AW), with a regression weight of .790 (S.E. = .069, C.R. = 11.377, $p < .001$). Online business perception (OBP) is positively related to awareness (AW), with a regression weight of .585 (S.E. = .053, C.R. = 10.962, $p < .001$). Price value (PV) is positively related to OBP, with a regression weight of .709 (S.E. = .084, C.R. = 8.452, $p < .001$), and to US, with a regression weight of .392 (S.E. = .082, C.R. = 4.805, $p < .001$). Finally, adoption intentions (AI) are positively related to PV, with a regression weight of .952 (S.E. = .068, C.R. = 14.096, $p < .001$).

Based on the critical ratio (C.R.) values presented in the table, all of the effects are considered statistically significant at a p-value of less than 0.001. The strength of the effects can be evaluated based on the magnitude of the regression weights. In this case, the highest regression weight is for AI <--- PV (0.952), which suggests a very strong relationship between these two variables. The other effects have regression weights ranging from 0.369 to 0.790, indicating moderate to strong relationships.

It is noteworthy that all the observed variables in the SEM analysis show significant regression with their corresponding latent variables, as indicated by p-values less than or equal to 0.05.

Nevertheless, it is important to consider that the measurement scales of the independent variables are different, which means that unstandardized regression coefficients might not be useful for direct comparison. This is because a larger unstandardized coefficient value may not necessarily indicate a larger effect size, especially when comparing coefficients of variables measured on different scales.

Therefore, to accurately determine the size of each variable's effect, it is essential to standardize the regression coefficients. Standardization of regression coefficients allows for the comparison of the effects of variables measured on different scales by converting them into a common metric, making them comparable in magnitude. (Levine, 2014).

Table 55 below shows standardized regression weights obtained from a structural equation model (SEM) analysis with seven latent variables (SME, AW, SC, US, OBP, PV, and AI) and their corresponding observed variables.

Table 55 Standardized Regression Weight

			Estimate
SC.	<---	SME.	.290
AW.	<---	SC.	.667
US.	<---	AW.	1.028
OBP.	<---	AW.	.721
PV.	<---	OBP.	.593
PV.	<---	US.	.311
AI.	<---	PV.	.746

In this case, we can see that SC has a standardized regression weight of .290 with SME, which means that SC has a moderate positive effect on SME. Similarly, AW has a larger standardized regression weight of .667 with SC, indicating a strong positive effect of SC on AW.

Furthermore, US has a higher standardized regression weight of 1.028 with AW, indicating a strong positive effect of AW on US. OBP has a slightly lower standardized regression weight of .721 with AW, indicating a moderate positive effect of AW on OBP.

Moreover, we can observe that PV has a moderate positive effect on OBP with a standardized regression weight of .593, and a smaller positive effect on US with a standardized regression weight of .311.

Finally, AI has the highest standardized regression weight of .746 with PV, indicating a strong positive effect of PV on AI.

Those results are supported by other research as a study by Yu and Lu (2019) found that SME has a positive impact on AI in the context of social commerce, which refers to online shopping via social media platforms. Similarly, Park et al. (2017) found that OBP has a positive impact on AI in the context of traditional online shopping.

In contrast, Hwang and Lee (2018) found that AW has a positive impact on AI in the context of mobile banking. Chen and Lin (2018) found that SC has a positive impact on AI in the context of online group buying. Lastly, a study by Lai and Chen (2011) found that US has a positive impact on AI in the context of mobile banking.

Furthermore, correlations between errors in SEM are known as covariances, and they represent the degree to which two or more observed variables share unique variance that is not explained by the latent variables in the model. These covariances can arise for a variety of reasons, such as measurement error, omitted variables, or unmodeled interactions between variables (Kline, 2016).

Including covariances between errors in an SEM model allows for a more accurate representation of the relationships between the observed variables and their corresponding latent variables. By modeling the covariances between errors, we are accounting for the shared variance between observed variables that cannot be explained by the latent variables in the model.

Additionally, modeling covariances between errors can help identify potential sources of measurement bias or confounding variables that may not have been accounted for in the model (Byrne, 2016). Furthermore, by including covariances between errors, we can improve the overall fit of the SEM model, as it allows for a more precise estimation of the relationships between the variables (Jaccard & Wan, 995).

As seen in Table 56 below, all the covariances have significant C.R. values greater than 1.96 or less than -1.96, indicating statistical significance at $p < .05$).

Table 56 Covariances

			Estimate	S.E.	C.R.	P	Label
e28	<-->	e29	.205	.046	4.448	***	par_36
e13	<-->	e14	.472	.073	6.485	***	par_37
e11	<-->	e12	.272	.053	5.148	***	par_38
e10	<-->	e15	.260	.051	5.091	***	par_39
e8	<-->	e9	.216	.063	3.448	***	par_40
e2	<-->	e4	.328	.072	4.583	***	par_41
e1	<-->	e3	.316	.073	4.358	***	par_42
e21	<-->	e26	-.192	.043	-4.431	***	par_49

The positive covariances (e28 <--> e29, e13 <--> e14, e11 <--> e12, e10 <--> e15, e2 <--> e4, and e1 <--> e3) suggest a positive relationship between the pairs of observed variables. The negative covariance (e21 <--> e26) suggests a negative relationship between the two observed variables.

Overall, the covariances provide insight into the relationships between the observed variables, which can help to inform the underlying latent variables and their relationships in the SEM analysis.

i. Mediation Analysis for Indirect Effects

In the SEM regression results, we saw the direct effects of each variable on the outcome variable (adoption intentions). A direct effect is the direct influence of one variable on another, without the mediating effect of other variables. However, we can also calculate the indirect effects of variables, which are the effects of one variable on another variable that are mediated through one or more intervening variables. Indirect effects can be calculated using a path analysis or mediation analysis.

In this case, we could calculate the indirect effects of variables such as social media engagement, awareness, social cognition, usability, and online business perception on adoption intentions, mediated through other variables in the model.

Table 57 below shows the Standardized Indirect Effects table displays the indirect effects of a predictor variable on other variables in the model through the mediating effects of other variables. The values in the cells are standardized coefficients, which represent the magnitude and direction of the effect.

Table 57 Standardized Indirect Effects

	SME.	SC.	AW.	OBP.	US.
SC.	.000	.000	.000	.000	.000
AW.	.194	.000	.000	.000	.000
OBP.	.140	.481	.000	.000	.000
US.	.199	.686	.000	.000	.000
PV.	.145	.499	.748	.000	.000
AI.	.108	.372	.558	.443	.232

The SEM analysis revealed a number of significant indirect effects of the latent variables in the model. These indirect effects reflect the influence of one variable on another variable, mediated by other variables in the model.

Firstly, the results indicate that social media engagement (SME) has a significant indirect effect on awareness (AW), online business perception (OBP), usability (US), price value (PV), and adoption intentions (AI) through the mediating effects of other variables in the model. Specifically, the indirect effects of SME on AW, OBP, US, PV, and AI are .194, .140, .199, .145, and .108, respectively. These results suggest that SME indirectly affects the other latent variables in the model by influencing other variables in the model, such as social cognition (SC).

In addition to the indirect effects of SME, the SEM analysis also revealed a number of indirect effects of other latent variables on the remaining variables in the model. For example, social cognition (SC) has a significant indirect effect on OBP, US, PV, and AI, through the mediating effects of other variables in the model. Specifically, the indirect effects of SC on OBP, US, PV, and AI are .481, .686, .499, and .372, respectively. These results suggest that social cognition indirectly affects these variables by influencing other variables in the model.

Similarly, awareness (AW) has a significant indirect effect on price value (PV) and adoption intentions (AI), through the mediating effects of other variables in the model. Specifically, the indirect effects of AW on PV and AI are .748 and .558, respectively. Online business perception (OBP) also has a significant indirect effect on adoption intentions (AI), with an indirect effect of .443. Lastly, usability (US) has a significant indirect effect on adoption intentions (AI), with an indirect effect of .232.

There have been several previous studies that support the results of this study regarding the indirect effects of social media engagement, social cognition, awareness, online business perception, usability, and price value on adoption intentions.

For example, a study by Lee, Kwon& Sung (2017) found that social media engagement positively affects consumers' awareness, which in turn positively affects their adoption intentions. Similarly, a study by Hsieh, Rai & Keil (2016) found that social media engagement positively affects consumers' perception of online business, which also positively affects their adoption intentions.

Regarding the indirect effects of social cognition on adoption intentions, a study by Ryu, Lee & Kim (2016) found that social cognition positively affects consumers' perception of online shopping convenience, which in turn positively affects their adoption intentions. Another study by Yu, Lu, & Wang. (2017) found that social cognition positively affects consumers' perception of the value of online shopping, which also positively affects their adoption intentions.

Moreover, a study by Park and Chen (2018) found that awareness positively affects consumers' perception of the value of online shopping, which in turn positively affects their adoption intentions. Another study by Park, Kim & Sung (2019) found that online business perception positively affects consumers' willingness to adopt new technologies.

Finally, a study by Liu, Li & Hu (2017) found that usability positively affects consumers' satisfaction with the online shopping experience, which in turn positively affects their adoption intentions. All of these previous studies provide additional support for the results of this study regarding the indirect effects of various factors on consumers' adoption intentions.

ii. Moderator Effects of Previous Online Shopping Trial

To analyze the moderator effect of the trial on the SEM, a comparison was conducted between two groups: one group of participants who reported having previous experience with online shopping and another group of participants who did not have such experience, and another comparison between participants who reported having previous experience of traveling abroad and another group of participants who did not have such experience.

There were 211 participants who reported having previously traveled abroad, while 184 participants reported no such experience. Additionally, 241 participants reported having engaged in online shopping before, while 154 participants had not.

Comparing the results of the standardized total effects for social media engagement between the two groups (not tried vs. yes tried), we can observe that the magnitudes of the effects are generally smaller for the group with a previous trail of online shopping. Specifically, the standardized total effects for SC, AW, OBP, US, PV, and AI are all smaller for the yes trailed group compared to the not trailed group in Table 58 and Table 59.

Table 58 Standardized Total Effects (Group number no - Default model)

	SME.	SC.	AW.	OBP.	US.	PV.	AI.
SC.	.337	.000	.000	.000	.000	.000	.000
AW.	.235	.697	.000	.000	.000	.000	.000
OBP.	.162	.479	.687	.000	.000	.000	.000
US.	.243	.721	1.035	.000	.000	.000	.000
PV.	.181	.537	.770	.571	.365	.000	.000
AI.	.136	.402	.578	.428	.274	.750	.000

Table 59 Standardized Total Effects (Group number yes - Default model)

	SME.	SC.	AW.	OBP.	US.	PV.	AI.
SC.	.288	.000	.000	.000	.000	.000	.000
AW.	.181	.626	.000	.000	.000	.000	.000
OBP.	.132	.459	.732	.000	.000	.000	.000
US.	.185	.642	1.025	.000	.000	.000	.000
PV.	.123	.427	.681	.625	.218	.000	.000
AI.	.087	.301	.480	.440	.153	.704	.000

The results showed that the previous trail of online shopping may have a moderating effect on the relationships between social media engagement and the dependent variables (SC, AW, OBP, US, PV, and AI). In other words, the impact of social media engagement on these variables may be weaker for individuals who have previously tried online shopping compared to those who have not.

It is possible that individuals who have tried online shopping before may already have preconceived notions or established preferences for certain brands or products, which could reduce the influence of social media engagement on their purchasing decisions.

Alternatively, it could be that those who have not tried online shopping may be more receptive to social media marketing and more likely to be influenced by it. Another possible explanation is that the trial of online shopping may have influenced participants' cognitive processes, leading to different patterns of processing social media information (Alosaimi, Alyahya & Altuwaijri, 2018).

For instance, participants who have tried online shopping may have developed a more critical approach towards evaluating online information, leading to a weaker relationship between social media engagement and social cognition as for the other factors (Appel, Crusius& Gerlach, 2016).

Based on the standardized total effects of social cognition, we can observe that the group with a trail of online shopping has slightly weaker effects for most predictors on US and AI compared to the group without a trail. Specifically, we can see that the standardized total effects on AW, OBP, US, PV, and AI are lower for the group with a trail of online shopping compared to the group without.

This suggests that the trail of online shopping may moderate the relationship between these factors and social cognition. However, it is important to note that the effects of the predictors are still relatively strong in both groups, indicating that the trial of online shopping may not have a significant impact on the overall relationship between the factors and social cognition although the overall effects of social cognition relatively strong in both groups.

Also, based on the standardized total effects of Awareness, it appears that the relationship between Awareness and the four predictors (OBP, US, PV, AI) is generally stronger for the group without a trail of online shopping compared to the group with a trail.

These results suggest that the trial of online shopping may moderate the relationship between Awareness and some predictors of online behavior, such as usability, price value, and adoption intention. One possible explanation is that participants who have previous experience with online shopping may have already formed certain perceptions and attitudes towards online businesses, which could influence the impact of Awareness on these predictors (Venkatesh, Morris, Davis& Davis, 2003).

We can also observe that for the group with a trail of online shopping, the effect of online business perception (OBP) on price value (PV) and adoption intention (AI) appears to be slightly stronger compared to the group without a trail. Specifically, the standardized total effect of OBP on PV and AI is higher for the group with a trail of online shopping (PV: 0.625, AI: 0.440) compared to the group without (PV: 0.571, AI: 0.428).

Similarly, for usability (US), the standardized total effect on PV and AI appears to be weaker for the group with a trail of online shopping compared to the group without. The standardized total effect of US on PV and AI is lower for the group with a trail of online shopping (PV: 0.218, AI: 0.153) compared to the group without (PV: 0.365, AI: 0.274).

Additionally, for price value (PV), the standardized total effect on adoption intention (AI) appears to be slightly weaker for the group with a trail of online shopping compared to the group without. The standardized total effect of PV on AI is lower for the group with a trail of online shopping (0.704) compared to the group without (0.750).

These results suggest that the trail of online shopping may have a moderating effect on the relationships between online business perception, usability, price value, and adoption intention. Specifically, the effect of online business perception on price value and adoption intention appears to be stronger for the group with a trail of online shopping, while the effect of usability on price value and adoption intention appears to be weaker.

Additionally, the effect of price value on adoption intention appears to be slightly weaker for the group with a trail of online shopping. However, more research is needed to confirm these findings and to understand the underlying reasons for these effects.

Previous research has shown the impact of experience on technology adoption. Studies have found that individuals who are more experienced with technology tend to have higher expectations for usability and are more critical of user interfaces that are difficult to use (Hsu & Lu, 2007).

In addition, research has also shown that social cognition plays an important role in technology adoption, as it shapes individuals' perceptions and attitudes towards technology. Specifically, individuals who have a better understanding of the social context and benefits of technology are more likely to adopt it (Liao & Chen, 2011).

Therefore, the weaker effects observed in the group with a trail of online shopping can be explained by the fact that they already have a higher level of trust and familiarity with technology, which reduces the impact of social cognition on adoption intention. Moreover, previous research has shown that people who are more experienced with technology tend to have higher expectations for usability and are more critical of user interfaces that are difficult to use (Mäntymäki, & Riemer, 2014).

Therefore, it is possible that participants with a pervious trail of online shopping were more demanding in terms of usability and less forgiving of poor design, leading to a weaker relationship between usability and price value and adoption intention (O'Brien & Toms, 2008).

5. Summary of Hypotheses results

This section provides a detailed report of the results obtained from the statistical tests carried out on the data, with the aim of verifying or rejecting the research hypotheses.

In this study, we aimed to investigate the relationships between social media engagement, social cognition, awareness of online shopping, online business perception, perceived usability of online shopping, perceived price value of online shopping, and online shopping adoption intention. Seven were proposed to test these relationships as followed and to test these hypotheses, data was collected from a sample of 395 social media users.

The data were analyzed using structural equation modeling (SEM) and the results based on Standardized Regression weight which reported in Table 54 and explained in the previous section, the results were as followed:

Ho1: Social media engagement does not significantly influence social cognition.

$\beta = 0.290$, $p < 0.05$. This result indicates a significant positive relationship between social media engagement and social cognition, providing evidence to reject the null hypothesis.

Ho2: Social cognition does not significantly increase awareness of online shopping.

$\beta = 0.667$, $p < 0.01$. This result indicates a strong positive relationship between social cognition and awareness, providing evidence to reject the null hypothesis.

Ho3: Awareness of online shopping has no significant impact on online business perception.

$\beta = 1.028$, $p < 0.01$. This result indicates a strong positive relationship between awareness and usability, providing evidence to reject the null hypothesis.

Ho4: Awareness of online shopping does not significantly affect perceived usability of online shopping.

$\beta = 0.721$, $p < 0.01$. This result indicates a strong positive relationship between awareness and online business perception, providing evidence to reject the null hypothesis.

Ho5: Perceived usability of online shopping does not significantly influence perceived price value of online shopping.

$\beta = 0.593$, $p < 0.01$. This result indicates a significant positive relationship between online business perception and perceived price value, providing evidence to reject the null hypothesis.

Ho6: Online business perception does not significantly impact perceived price value of online shopping.

$\beta = 0.311$, $p < 0.05$. This result indicates a significant positive relationship between usability and perceived price value, providing evidence to reject the null hypothesis.

Ho7: Perceived price value of online shopping does not significantly influence online shopping adoption intention.

$\beta = 0.746$, $p < 0.01$. This result indicates a strong positive relationship between perceived price value and adoption intention, providing evidence to reject the null hypothesis.

The results of our analysis revealed that the null hypothesis was rejected for all seven hypotheses, indicating that there were significant direct effects between the variables. The alternative hypothesis was accepted for all seven hypotheses, indicating that the variables had a significant direct effect on each other.

Table 60 Hypotheses Test Results Summary

Hypotheses	Results	Hypotheses	Explanation	Support from Past Research
H_{o1}: Social media engagement does not significantly influence social cognition.	$\beta = 0.290$, $p < 0.05$.	Reject the null hypothesis.	More exposure to social cues on social media improves understanding of others	Verduyn et al. (2015), Hampton et al. (2016), Grieve et al. (2013), Liu et al. (2018)
H_{o2}: Social cognition does not significantly increase awareness of online shopping.	$\beta = 0.667$, $p < 0.01$.	Reject the null hypothesis	Higher social skills make individuals better equipped to process online information	Liao & Cheng (2017)
H_{o3}: Awareness of online shopping has no significant impact on online business perception.	$\beta = 1.028$, $p < 0.01$.	Reject the null hypothesis	Knowledge of online shopping options leads to more positive views of online businesses	Chen, Fay, & Wang (2011)

Table 61 Hypotheses Test Results Summary 2

Hypotheses	Results	Hypotheses	Explanation	Support from Past Research
H_{o4}: Awareness of online shopping does not significantly affect perceived usability of online shopping.	$\beta = 0.721, p < 0.01$.	Reject the null hypothesis	Familiarity with online shopping options leads to perceiving platforms as easier to use	Chiang & Dholakia (2003), Wu & Chen (2017)
H_{o5}: Perceived usability of online shopping does not significantly influence perceived price value of online shopping.	$\beta = 0.593, p < 0.01$.	Reject the null hypothesis	Easier platforms create a perception of getting more for the price	Lee & Jun (2018), Chen & Barnes (2007)
H_{o6}: Online business perception does not significantly impact perceived price value of online shopping.	$\beta = 0.311, p < 0.05$	Reject the null hypothesis	Trustworthy platforms lead to feeling confident in finding good deals	Kim & Lennon (2008)
H_{o7}: Perceived price value of online shopping does not significantly influence online shopping adoption intention.	$\beta = 0.746, p < 0.01$.	Reject the null hypothesis	Feeling like you get a good deal encourages trying online shopping	Degeratu et al. (2000), Liu & Arnett (2000), Lee & Lin (2005), Liang & Huang (2008)

6. Findings Summary

The research aimed to investigate the factors influencing consumers' behavior towards online shopping, with a specific focus on the role of social media engagement and its impact on key variables such as awareness, social cognition, online business perception, price value, usability, and adoption intention. The study utilized an online survey questionnaire with Likert-scale items and demographic questions. To test the proposed hypotheses, data was collected from a sample of 395 social media users.

The data highlights some key trends in the sample population. Most respondents were young males aged 18 to 24, with bachelor's degrees and currently not employed. Income distribution was diverse, with one-third earning less than $200 monthly, and a quarter earning over $600. Notably, the majority used mobile devices for internet access. Additionally, a significant portion had prior online shopping experience, and about half had traveled outside Yemen.

The findings revealed important insights into the impact of various factors on consumers' behavior towards online shopping. The study utilized analytical design and a quantitative research style, employing t-test and ANOVA tests to analyze the data.

The results indicated that gender, age, education and occupation don’t play a significant role in awareness, usability, price value, social media engagement, online business perception, social cognition, and adoption intention regarding online shopping. Employment status on the other hand had an influence, as unemployed individuals exhibited lower scores in awareness, usability, price value, and adoption intention compared to employed individuals.

Furthermore, the study highlighted the positive effects of traveling abroad and previous online shopping experiences, with individuals who had traveled abroad or tried online shopping before showing higher scores in various variables, such as online business perception, awareness, social cognition, usability, price value, and adoption intention.

Income level demonstrated a significant impact, with higher-income groups displaying higher scores in most online shopping-related variables, specifically, individuals in higher income groups (above 600 dollars) showed significantly higher levels of online business perception, awareness of online shopping, social cognition, usability of online shopping, price value, and adoption intentions of online shopping compared to those in lower income groups (below 100 dollars or 200-300 dollars).

One the other hand, city of residence, type of internet, and main internet exploring device did not show significant effects, except for device type, which influenced social media engagement.

Moving to correlation analysis, the results showed that while OBP, awareness of online shopping (AW), social cognition (SC), and perceived price value (PV) exhibited statistically significant relationships with adoption intentions, social media engagement (SME) and usability of online shopping (US) did not show significant relationships. Although SME and US may still have some influence on adoption intentions, the strength and consistency of these relationships are not as pronounced as the other variables.

The collected data were analyzed using structural equation modeling (SEM) to determine the causal relationships among these variables. The results of the model fit analysis indicate that the proposed model fits the data reasonably well. The fit indices, such as CFI, TLI, IFI, and RMSEA, all meet the recommended thresholds, suggesting an acceptable fit.

The unstandardized regression weights for the SEM model provide valuable insights into the strength and direction of the relationships between the variables. The findings of the study reveal several significant relationships among the variables examined in the context of online shopping behavior.

Social cognition (SC) was found to have a positive effect on social media engagement (SME), indicating that individuals with higher social cognition tend to engage more with social media in relation to online shopping.

Furthermore, awareness (AW) was found to be positively related to social cognition (SC), suggesting that individuals with higher social cognition have greater awareness of online shopping. This awareness, in turn, has a positive influence on usability (US), indicating that individuals who are more aware of online shopping perceive it as more usable.

Online business perception (OBP) was found to be positively related to awareness (AW), suggesting that individuals with higher awareness of online shopping tend to have more positive perceptions of online businesses.

Moreover, perceived price value (PV) was found to have a positive effect on both online business perception (OBP) and usability (US), indicating that individuals who perceive online shopping as offering good value for the price are more likely to have positive perceptions of online businesses and find online shopping more usable.

Importantly, adoption intentions (AI) were found to be strongly influenced by perceived price value (PV), indicating that individuals who perceive online shopping as offering good value for the price are more likely to have the intention to adopt online shopping behaviors.

The analysis uncovers important indirect effects within the model. Social media engagement (SME) indirectly affects awareness (AW), online business perception (OBP), usability (US), price value (PV), and adoption intentions (AI) through various mediating variables, highlighting its influence on the overall model. Similarly, social cognition indirectly impacts OBP, US, PV, and AI through mediation. Moreover, awareness indirectly affects PV and AI, while OBP indirectly influences AI. US also indirectly impacts AI.

Moreover, the study also investigated the potential moderating effect of prior experience (trial) on the relationships within the SEM model. A comparison was conducted between two groups: one group with previous experience and another without such experience.

The study discerns a consistent pattern of moderation by previous trials in online shopping across various facets of online shopping behavior. The impact of social media engagement is notably weaker on Social Cognition (SC), Awareness (AW), Online Business Perception (OBP), Usability (US), Price Value (PV), and Adoption Intention (AI).

Similarly, social cognition exhibits weakened effects on Awareness (AW), Online Business Perception (OBP), Usability (US), Price Value (PV), and Adoption Intention (AI). Moreover, the influence of Awareness (AW) on predictors (OBP, US, PV, AI) and Usability on predictors (PV, AI) is consistently weaker. The relationship between Price Value (PV) and Adoption Intention (AI) is notably lower.

Interestingly, the effect of Online Business Perception (OBP) on Price Value (PV) and Adoption Intention (AI) appears slightly stronger. However, additional research is required to fully understand and validate these findings.

Overall, the study contributes to the understanding of the complex relationships among various factors influencing online shopping adoption intention. These findings suggest that factors such as social cognition, awareness, online business perception, perceived price value, and usability play crucial roles in shaping consumers' behavior and attitudes towards online shopping.

V. CONCLUSION AND RECOMMENDATIONS

A. Conclusion

The present study aimed to answer several research questions related to online shopping behavior and its influencing factors. The findings provide valuable insights into the impact of demographic variables, the effectiveness of social media engagement, the relationships between online shopping behavior factors, the effect of previous trial on behavior, and the main factors that drive adoption of online shopping.

Regarding the first research question on the impact of demographic variables, the study revealed important associations between demographic characteristics and online shopping behavior factors. By examining variables such as age, gender, income, and education, although individuals with greater disposable income and exposure to diverse cultures are more open to new experiences and technologies, such as online shopping, the findings suggest that Traditional demographic factors might no longer be the primary drivers of online shopping behavior. In today's rapidly evolving digital landscape, it is factors such as technological familiarity, personal preferences, and user experience may play more substantial roles.

The second research question focused on the effectiveness of social media engagement on consumers' online shopping behavior. The results demonstrated a significant positive relationship between social media engagement and various online shopping behavior factors.

The study found that higher levels of social media engagement were associated with increased awareness, improved social cognition, and greater usability, which in turn influenced consumers' perceptions of online business, price value, and ultimately their adoption intentions.

These findings highlight the importance of social media as a powerful tool for online businesses to engage with consumers, enhance their online shopping experience, and ultimately drive adoption.

The third research question aimed to explore the relationships between different online shopping behavior factors and how they affect each other. The structural equation model revealed significant and positive relationships between the latent variables, indicating a complex interplay among factors. For example, social cognition was found to have a positive effect on social media engagement, while awareness positively influenced both social cognition and usability. Additionally, online business perception had a positive relationship with awareness, and price value was associated with both online business perception and usability.

These findings emphasize the interconnected nature of online shopping behavior factors and suggest that businesses should adopt a holistic approach when designing their online platforms and strategies.

In response to the fourth research question regarding the effect of previous trials on online shopping behavior factors, the study reveals a consistent and discernible pattern of moderation. Individuals with prior online shopping experiences exhibit weakened relationships across several crucial facets of online shopping behavior, on the other hand, only the effect of Online Business Perception on Price Value (PV) and Adoption Intention appears to be slightly stronger.

These findings collectively underscore the impact of prior online shopping experiences in shaping the intricate dynamics of online shopping behavior and suggest that individuals with previous trials may possess preconceived notions or established preferences, influencing their responsiveness to key factors such as social media engagement, social cognition, awareness, usability, and price value.

Lastly, the study aimed to identify the main factors that could drive greater adoption of online shopping. The findings revealed several important factors that influence consumers' adoption intentions, including awareness, social cognition, usability, online business perception, and price value.

These factors collectively contribute to consumers' overall perception of the online shopping experience and their willingness to engage in online shopping. To encourage greater adoption, online businesses should focus on improving these factors by enhancing their visibility, providing user-friendly interfaces, delivering positive online business experiences, offering competitive prices, and communicating the value proposition effectively.

Overall, the study provides valuable insights into the complex interplay of factors that influence consumers' behavior towards online shopping. The findings underscore the importance of social media engagement, awareness, social cognition, online business perception, usability, and price value in shaping consumers' attitudes and intentions. These insights can be utilized by marketers and businesses to better understand their target audience and design effective strategies to promote online shopping adoption.

B. Limitations

While the study provides valuable insights, it is essential to acknowledge further limitations that affect the generalizability and applicability of the findings. The data collection for this study occurred during the period of August to October 2022, which may limit the study's relevance to contexts beyond that time frame, given the rapid evolution of online trends and consumer behavior.

Furthermore, the reliance on an online survey questionnaire introduced the potential for self-reporting biases. Respondents may have answered questions in a manner they believed was socially desirable or based on their perceptions at the time of the survey, potentially affecting the accuracy and generalizability of the results.

Moreover, the study primarily focused on a specific geographical location or region, which can restrict the extent to which the findings can be applied to more diverse or global populations. Different cultural, economic, and social factors can significantly impact consumer behavior, and these were not adequately explored in this study.

In addition, the research concentrated on a subset of variables relevant to online shopping behavior, which may not capture the full complexity of factors affecting consumer decisions in the digital marketplace. To enhance our understanding, future research should consider incorporating a broader array of variables and dimensions.

To strengthen the robustness of the proposed relationships and their general applicability, it is vital for researchers to replicate and validate the results across various samples and time periods. Diverse populations and changing contexts should be explored to ensure the results hold across different settings and over time.

In light of these additional limitations, researchers and practitioners should exercise caution when extrapolating the findings of this study to broader contexts and when making decisions based on its outcomes. Further investigations that address these limitations are essential for a more comprehensive understanding of consumer behavior in the dynamic landscape of online shopping.

C. Implications for Practice and Theory

The study's findings have major significance for both online shopping practitioners and consumer behavior researchers.

In terms of practical implications, practitioners should recognize the importance of social media engagement as a driver of consumers' attitudes and intentions towards online shopping. They can utilize social media platforms to actively engage with their target audience, provide valuable content, and foster positive interactions. By doing so, they can enhance consumers' social cognition, which in turn influences their adoption intentions. This highlights the need for businesses to invest in social media marketing strategies and leverage these platforms to create meaningful connections with their customers.

Another important implication is the significance of increasing consumers' awareness of online shopping. Businesses should focus on implementing targeted marketing campaigns and initiatives that aim to educate consumers about the benefits and convenience of online shopping. Leveraging social media platforms for information dissemination can be particularly effective in this regard. By enhancing awareness, businesses can improve consumers' overall perception of online shopping, leading to increased adoption intentions.

Additionally, the study underscores the importance of online business perception. Creating a positive perception of online business is crucial for attracting and retaining customers. Businesses should invest in building a trustworthy and reputable online presence, ensuring a seamless user experience, and addressing any concerns related to security and privacy. By doing so, they can positively influence consumers' perception of online businesses, ultimately leading to higher adoption intentions.

Usability and price value are two other critical factors identified in the study. Businesses should prioritize usability and strive to offer a user-friendly online shopping experience. This includes optimizing website design, navigation, and checkout processes. Moreover, businesses should focus on providing competitive pricing and demonstrating the value proposition of their products or services. By enhancing usability and price value, businesses can increase consumers' satisfaction, loyalty, and ultimately drive higher adoption intentions.

The study advances our theoretical understanding of the mediating impacts of variables such as social cognition, awareness, and online business perception. These findings highlight the significance of taking into account the underlying cognitive processes and intermediate variables that relate social media activity to online shopping adoption. Researchers might investigate these mediating mechanisms further in order to enhance theoretical models of consumer behavior in the setting of online shopping.

The study also highlights the need for investigating contextual factors that influence consumers' attitudes and intentions towards online shopping. Variables such as gender, age, education, and income can play a significant role in shaping consumer behavior. To create a more thorough understanding of online buying behavior, researchers should continue to investigate the impact of these contextual elements in various cultural and socioeconomic contexts.

Furthermore, future research could employ longitudinal designs to explore the dynamics of consumers' behavior towards online shopping over time. This would provide valuable insights into the temporal relationships between variables and capture the evolving nature of online shopping adoption.

In conclusion, the implications for practice suggest that businesses can leverage social media engagement, enhance awareness, improve online business perception, and focus on usability and price value to drive adoption intentions in online shopping. The theoretical implications emphasize the mediating role of variables and highlight the importance of contextual factors and longitudinal research. By considering these implications, practitioners can develop effective strategies, and researchers can advance theoretical frameworks in the field of consumer behavior and online shopping.

D. Recommendations for Online Businesses

Several recommendations for online businesses can be made based on the study's findings and implications.

Firstly, online businesses should prioritize social media engagement. It is important for businesses to actively engage with their target audience on social media platforms. This involves creating and sharing valuable content, responding to customer inquiries and feedback, and fostering meaningful interactions. By building a strong social media presence, businesses can enhance consumers' social cognition and positively influence their adoption intentions.

Secondly, businesses should focus on enhancing awareness among consumers. Implementing targeted marketing campaigns and initiatives can help increase consumers' awareness of the benefits and convenience of online shopping. Businesses can utilize social media platforms, online advertisements, and collaborations with influencers to effectively reach and educate their target audience about the value of their products or services.

Thirdly, online businesses should strive to improve usability. Ensuring that their websites or mobile applications are user-friendly and intuitive can significantly impact consumers' online shopping experiences. Simplifying the browsing and purchasing processes, providing clear product descriptions and images, and offering seamless payment options can enhance consumers' perceived usability. This, in turn, can positively influence their adoption intentions and increase the likelihood of repeat purchases.

Additionally, businesses should focus on cultivating a positive online business perception. This can be achieved by providing excellent customer service, maintaining high product quality standards, and actively seeking and responding to customer feedback. Businesses should also emphasize transparency, reliability, and security in their online transactions to build trust and credibility among consumers. Positive online business perception not only enhances consumers' adoption intentions but also encourages them to recommend the business to others, leading to increased customer acquisition and retention.

Furthermore, businesses should consider the importance of price value. While offering competitive prices is crucial, it is equally important to communicate the value proposition effectively. Highlighting the unique features, benefits, or additional services that differentiate the business from competitors can justify the price and enhance consumers' perception of value. Offering discounts, promotions, or loyalty programs can also incentivize consumers to choose the business over alternatives.

These recommendations emphasize the significance of social media engagement, awareness, usability, online business perception, and price value for online businesses. By implementing these strategies, businesses can enhance consumers' attitudes and behaviors towards online shopping, ultimately driving their adoption intentions and fostering long-term customer relationships.

E. Recommendations for Future Research

In light of this study's findings and limitations, numerous recommendations for future research can be made to improve our understanding of consumers' online shopping behavior.

Investigate the role of cultural factors: Future research could explore the influence of cultural factors on consumers' behavior towards online shopping. Examining how cultural values, norms, and beliefs impact consumers' attitudes, preferences, and adoption intentions can provide valuable insights for businesses operating in diverse cultural contexts.

Longitudinal studies: Conducting longitudinal studies can provide a deeper understanding of the dynamics and changes in consumers' behavior over time. Tracking individuals' online shopping behaviors, attitudes, and perceptions at multiple points in time can help identify patterns, trends, and factors that influence their adoption intentions.

Qualitative research methods: Incorporating qualitative research methods can offer a deeper understanding of consumers' experiences, motivations, and decision-making processes related to online shopping. Qualitative studies can uncover underlying reasons behind the observed relationships and provide valuable context for the quantitative findings.

Cross-cultural comparisons: Comparing online shopping behavior and perceptions across different cultural contexts can help identify similarities and differences in consumer preferences, attitudes, and adoption intentions. This can contribute to the development of global strategies for online businesses and inform targeted marketing approaches.

Examination of trust and security concerns: Trust and security are critical factors influencing consumers' willingness to engage in online shopping. Future research should delve deeper into understanding how trust is built, what factors contribute to consumers' perceived security, and how businesses can effectively address and mitigate trust and security concerns to increase adoption intentions.

Mobile shopping behavior: With the increasing use of mobile devices for online shopping, it is essential to investigate consumers' behavior and preferences specifically related to mobile shopping. Understanding the unique characteristics of mobile shopping experiences, including mobile interface design, convenience factors, and mobile payment options, can provide valuable insights for businesses in optimizing their mobile platforms.

Adoption of emerging technologies: As new technologies, such as virtual reality (VR) and augmented reality (AR), gain prominence in online shopping experiences, future research should explore consumers' perceptions and adoption intentions towards these technologies. Investigating the impact of VR and AR on online shopping behavior can inform businesses about the potential benefits and challenges associated with implementing these technologies.

The role of social influence: Examining the influence of social factors, such as social norms, peer recommendations, and social influence, on consumers' online shopping behavior can provide a comprehensive understanding of how social interactions shape adoption intentions. Exploring the impact of social media influencers, online reviews, and social comparison processes can offer valuable insights for businesses in leveraging social influence to drive online shopping engagement.

These recommendations for future research aim to expand our knowledge of consumers' behavior towards online shopping by considering cultural factors, employing longitudinal and qualitative research methods, conducting cross-cultural comparisons, examining trust and security concerns, investigating mobile shopping behavior, exploring emerging technologies, and studying the role of social influence.

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APPENDICES

Appendix 1: Final English scales

Table 62 Final Social Media Engagement Scale Variables and Items

Code	Items
SME1	Using social media is my daily habit.
SME2	Even if it's late, I'll take a look at social media before sleep.
SME3	I often use social media to relax in habit
SME4	I get fulfilled from the attention and comments of others on social media.
SME5	Using social media, I am satisfied with the relationship between myself and my friends.
SME6	Compared to the real world, social media makes me feel more comfortable.
SME7	I feel bored when I can't use social media.
SME8	Compared to the real world, I am happier when I socialize on social media.
SME9	I feel anxious when I can't use social media

Table 63 Final Extended Scale from The Unified Theory of Acceptance and Use of Tech Variables and Items

Variable	Code	Items
Price Value	PV1	Online shopping is reasonably priced.
	PV2	Online shopping is a good value for the money
	PV3	At the current price, online shopping provides a good value
Usability	US1	Using online shopping helps me accomplish things more quickly
	US2	Learning how to use online shopping is easy for me.
	US3	My interaction with online shopping is clear and understandable.
	US4	I find online shopping easy to use.
	US5	It is easy for me to become skillful at using online shopping.
	US6	I have the knowledge necessary to use online shopping

Adoption intention	AI1	I intend to continue using online shopping in the future.
	AI2	I will always try to use online shopping in my daily life
	AI3	I plan to continue to use online shopping frequently

Table 64 Final Online consumer behavior scale variables and items

Variable	Code	Items
Awareness	AW1	I am aware of online shopping
	AW2	I know that I can shop world class brands from home
	AW3	I know that I can shop from anywhere in the world from home
	AW4	I feel my personal information is kept confidential by online shopping sites.
	AW5	My financial information is safe and secure with online shopping sites.
	AW6	I have sufficient knowledge of using internet shopping.
Social cognition	SC1	I feel online shopping is more convenient.
	SC2	I get motivated when my reference group prefers online shopping.
	SC3	I get convinced when my friends do shopping from online sites.
	SC4	I feel encouraged when my family members shop from online sites.
	SC5	Online shopping suits my customs and traditions.
Online Business perception	OBP1	Easy navigation in online websites makes it more convenient to shop
	OBP2	I feel delighted with color combination (attractiveness) of the website.
	OBP3	Video and 3D displays encourages online shopping.
	OBP4	Clarity of the website influences my decision of purchase.
	OBP5	Speed of the shopping website improves my search among varied collection of products.
	OBP6	Online shopping provides a wide range of product selection.
	OBP7	Good customer support/service motivates me for online shopping.
	OBP8	Flexible payments systems attract me to shop online.
	OBP9	Shopping sites which preserve good return policy motivate me to shop online.

Appendix 2: Final Arabic scales

Table 65 Final Scales Variables and Items in Arabic

م	المتغير	الفقرات
المشاركة على وسائل التواصل الاجتماعي		استخدام وسائل التواصل الاجتماعي عادة يومية بالنسبة لي.
		سوف ألقي نظرة على وسائل التواصل الاجتماعي قبل النوم، حتى لو كان الوقت متأخرًا
		غالبًا ما أستخدم وسائل التواصل الاجتماعي للراحة والتخفيف عن نفسي.
		تعليقات الآخرين ومتابعتهم على وسائل التواصل الاجتماعي تشعرني بالرضا.
		أشعر بالرضا عن العلاقة بيني وبين أصدقائي من خلال استخدام وسائل التواصل الاجتماعي.
		تجعلني وسائل التواصل الاجتماعي أشعر براحة أكبر مقارنةً بالعالم الحقيقي
		أشعر بالملل عندما لا أستطيع استخدام وسائل التواصل الاجتماعي.
		أنا أكثر سعادة عندما أكون اجتماعيًا على وسائل التواصل الاجتماعي مقارنةً مع العالم الحقيقي
		أشعر بالقلق عندما لا أستطيع استخدام وسائل التواصل الاجتماعي.
سلوك المستهلك عبر الإنترنت	الإدراك	لدي دراية بوجود التسوق عبر الإنترنت
		أعلم أنه يمكنني شراء ماركات عالمية من المنزل
		اعرف أنه يمكنني التسوق من أي مكان في العالم من المنزل
		أشعر أن معلوماتي الشخصية تظل سرية عند استعمالها في مواقع التسوق عبر الإنترنت.
		معلوماتي المالية آمنة ومحمية في مواقع التسوق عبر الإنترنت.
		لدي معرفة كافية بكيفية التسوق عبر الإنترنت.
	الوعي الاجتماعي	أشعر أن التسوق عبر الإنترنت ملائم أكثر لكل ظروف التسوق
		اتحفز للتسوق عبر الانترنت عندما يقوم زملائي بذلك
		اقتنع أكثر عندما يستخدم أصدقائي مواقع التسوق عبر الإنترنت
		أشعر بالتشجيع عندما يتسوق أفراد عائلتي من المواقع عبر الإنترنت.
		التسوق عبر الإنترنت يناسب مع عاداتي وتقاليدي
	تصور الأعمال التجارية عبر الانترنت	سهولة التنقل في مواقع الويب على الإنترنت تجعل التسوق أكثر سهولة
		الألوان الجذابة في تصميم مواقع التسوق عبر الانترنت تشعرني بالراحة.
		الفيديوهات والبطاقات التوضيحية المتحركة تشجعني اثناء التسوق عبر الإنترنت.
		يؤثر وضوح وصف المنتجات في مواقع التسوق عبر الانترنت على قراري بالشراء.
		سرعة موقع التسوق عبر الانترنت تساعد على تسهيل البحث بين منتجاته المتنوعة.
		يوفر التسوق عبر الإنترنت خيارات واسعة من المنتجات المناسبة.
		يحفزني توفر خدمة / دعم العملاء الجيد على التسوق عبر الإنترنت
		تجذبني أنظمة الدفع المالي المرنة للتسوق عبر الإنترنت.
		تحفزني المواقع التي تقدم نظام إعادة وارجاع للمنتجات على التسوق عبر الإنترنت.
تقبل استخدام التكنولوجيا	القيمة السعرية	منتجات التسوق عبر الإنترنت اسعارها معقوله.
		يعد التسوق عبر الإنترنت ذا قيمة مناسبة مقابل المال الذي يدفع له
		بالأسعار الحالية، يوفر التسوق عبر الإنترنت قيمة جيدة
	سهولة الاستخدام	يساعدني استخدام التسوق عبر الإنترنت في إنجاز الأشياء بسرعة أكبر
		استعمال مواقع التسوق عبر الإنترنت سهل بالنسبة لي
		التسوق عبر الانترنت واضح ومفهوم

	التسوق عبر الإنترنت سهل الاستخدام من السهل بالنسبة لي أن أصبح ماهرًا في استخدام التسوق عبر الإنترنت. من السهل الحصول على المعرفة اللازمة للتسوق عبر الإنترنت
الرغبة في الاستخدام	في المستقبل أنوي الاستمرار في استخدام التسوق عبر الإنترنت. سأحاول دائمًا استخدام التسوق عبر الإنترنت في حياتي اليومية. أخطط لمواصلة استخدام التسوق عبر الإنترنت بشكل متكرر.

Appendix 3: Ethic Approval Form

Evrak Tarih ve Sayısı: 09.09.2022-61323

T.C.
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