

## Article

# Assessing the Effects of the COVID-19 Pandemic on M-Commerce Adoption: An Adapted UTAUT2 Approach

Simona Vinerean <sup>1,\*</sup>, Camelia Budac <sup>1</sup>, Lia Alexandra Baltador <sup>1</sup> and Dan-Cristian Dabija <sup>2</sup>

<sup>1</sup> Department of Management, Marketing and Business Administration, Lucian Blaga University of Sibiu, 550024 Sibiu, Romania; camelia.budac@ulbsibiu.ro (C.B.); lia.baltador@ulbsibiu.ro (L.A.B.)

<sup>2</sup> Department of Marketing, Babeş-Bolyai University Cluj-Napoca, 400591 Cluj-Napoca, Romania; dan.dabija@ubbcluj.ro

\* Correspondence: simona.vinerean@ulbsibiu.ro

**Abstract:** The COVID-19 pandemic has impacted consumers' lives and their shopping patterns, leading them towards mobile commerce. To address current shopping circumstances, an adapted UTAUT2 model aims to integrate trust and perceptions of the effects of the COVID-19 pandemic on consumers' behavioral intention to rely on m-commerce during this period. The study proposes a research model which is investigated with the help of structural equation modelling in AMOS. Using the framework of a cross-sectional study, data were collected from an emerging market in Romania, where internet speed ranks 4th worldwide and where the yearly increase in internet and social media users is approximately 10%. By using confirmatory factor analysis and structural equation modelling, the research validates the applicability of UTAUT2 in examining consumers' behavioral intent of using m-commerce during a pandemic. Hedonic motivation is the strongest predictor of consumers' behavioral intentions to continue using m-commerce. The findings contribute to understandings of consumers' behavior with m-commerce in an emerging market, extending knowledge based on the adapted UTAUT2 model and allowing for comprehension of the key role of trust and social influences in affecting consumers' perceptions of the COVID-19 outbreak in relation to shopping patterns.

**Keywords:** m-commerce; behavioral intention; trust; digital marketing strategy; Unified Theory of Acceptance and Use of Technology (UTAUT2); COVID-19 pandemic



check for updates

**Citation:** Vinerean, S.; Budac, C.; Baltador, L.A.; Dabija, D.-C.

Assessing the Effects of the COVID-19 Pandemic on M-Commerce Adoption: An Adapted UTAUT2 Approach.

*Electronics* **2022**, *11*, 1269. <https://doi.org/10.3390/electronics11081269>

Academic Editors: Shu-Nung Yao and Chun-Hsiang (Michael) Chuang

Received: 21 March 2022

Accepted: 14 April 2022

Published: 17 April 2022

**Publisher's Note:** MDPI stays neutral with regard to jurisdictional claims in published maps and institutional affiliations.



**Copyright:** © 2022 by the authors. Licensee MDPI, Basel, Switzerland. This article is an open access article distributed under the terms and conditions of the Creative Commons Attribution (CC BY) license (<https://creativecommons.org/licenses/by/4.0/>).

## 1. Introduction

COVID-19 is widely regarded as one of the most pressing crises in the world, with global economic and social consequences. Since COVID-19 is easily transmitted by respiratory droplets or physical contact [1–3], countries were put in lockdown, with multiple restrictions for businesses and citizens. “The enforcement of social distancing, lockdowns, and other measures in response to the COVID-19 pandemic have led consumers to ramp up online shopping, social media use, internet telephony and teleconferencing, and streaming of videos and films” [4]. Thus, the pandemic has led to multiple changes in consumer behavior due to widespread lockdowns, social distancing, limited shopping possibilities, and other precautions meant to minimize the spread of the virus.

As a result of severe containment efforts to prevent the spread of the pandemic, consumers had to adapt to new shopping behaviors [5], by resorting to online acquisitions, home deliveries, and/or contactless payments. These changes have led to the emergence of different forms of remote shopping [6], with e-retailing increasing in importance. Therefore, examining the premises of m-commerce is of utmost importance due to its multimedia extension and opportunities for businesses to provide qualitative customer experiences.

Multiple industry reports anticipate perpetual changes in consumers' behavior due to the pandemic in terms of their shopping reasons, habits, living situations, and work prospects [7–9]. Academic research is also focusing on studying the consequences of online

consumer switching behavior induced by the pandemic and the restrictions that have impacted consumers' lives [6,10–12].

With significant effects of the COVID-19 pandemic on consumers' purchasing behaviors [5,6], consumers tend to rely more frequently on mobile apps for their multimedia characteristics, and they tend to engage more in online purchases to protect themselves from contacting the virus. Although the impact of COVID-19-induced online shopping behavior through m-commerce apps has been examined in the last two years [11–14], there is a limited set of studies showcasing emerging contexts, such as in Romania, where Internet speed ranks 4th worldwide [15], thus enabling consumers to focus more on m-commerce and online shopping. Furthermore, this paper seeks to show the repercussions of the pandemic on Romanian consumers' perceptions regarding their shopping behavior during the COVID-19 pandemic. Therefore, the aim of this paper is to investigate consumers' behavioral intentions to buy products via m-commerce apps during the COVID-19 pandemic, as induced/determined by consumers' hedonic motivations, social influence, performance expectancy, and trust.

This paper extends knowledge on the use of the Unified Theory of Acceptance and Use of Technology (UTAUT) in its adapted form as UTAUT2, which examines "performance expectancy, effort expectancy, social influence, facilitating conditions, hedonic motivation, habit, and price value" [16]. As various authors have encouraged research that explores diverse samples of respondents from multiple countries to examine key UTAUT2 relationships in depth [17], the present paper conceptualizes and aims to validate an adapted model of UTAUT2 in the Romanian context. Besides addressing consumers' acceptance and use of m-commerce [18,19], this paper adds significantly to the existing research on the UTAUT2 framework by incorporating consumers' trust in using m-commerce apps. Compared to previous studies that have only highlighted the pandemic context [6,10,11], this paper offers original contributions by examining the impact of the COVID-19 outbreak on mobile shoppers and their purchasing patterns in a UTAUT2 theoretical setting.

This paper is structured as follows: Section 2 provides an in-depth explanation of the UTAUT2 approach, along with a systematic literature review of the main theoretical constructs (m-commerce, use of mobile apps, consumer-related perceptions, and their impact on behavioral intentions towards using m-commerce apps), thus also developing research hypotheses and highlighting the proposed conceptual model. Section 3 contains research methodology, research design, sampling, and a presentation of the analysis procedures. Section 4 includes interpretations of the results, and Section 5 continues with a discussion of the findings compared to previous research. Finally, Section 6 highlights the conclusions, encompassing theoretical contributions and managerial implications for m-commerce apps, as well as study limitations, thus providing future research perspectives.

## 2. Theoretical Framework: Hypothesis and Conceptual Model Development

### 2.1. Unified Theory of Acceptance and Use of Technology (UTAUT2)

Various theories have been proposed to understand consumers' behavior of accepting and using m-commerce apps, such as the Expectancy Confirmation Model (ECM); Task-Technology Fit; the Technology Acceptance Model (TAM, [20]); the Theory of Reasoned Action (TRA); and the Unified Theory of Acceptance and Use of Technology (UTAUT). In academic research, UTAUT has become a popular theory for anticipating consumers' behavioral intention to use new technologies [21–23]. In its extended version, UTAUT2 is relevant for examining multiple drivers that impact consumers' experiences and acceptance of m-commerce by using mobile shopping apps. As the literature shows in various research contexts [24–26], there is a need to further analyze and understand the use of m-commerce acceptance in different settings [17].

Numerous theories have proven useful in understanding technology uptake by final consumers, such as the "Technology Acceptance Model (TAM)", which aids in the comprehension of consumer attitudes toward using and accepting technologies [27], or the Innovation Diffusion Theory (IDT), which investigates technology acceptance at an

individual level [28]. In fact, the Unified Theory of Acceptance and Use of Technology (UTAUT2) constitutes a theoretical expansion and progression of previous approaches, namely: the Theory of Reasoned Action (TRA); TAM; the Motivational Model (MM); the Theory of Planned Behavior (TPB); Combined TAM and TPB (C-TAM-TPB); the Model of PC Utilization (MPCU); IDT; and Social Cognitive Theory (SCT) [16,22].

The initial proposal of UTAUT involved four main components: “performance expectancy, social influence, effort expectancy, and facilitating conditions” [22], which aimed at explaining how the intention to use a certain technology may determine consumers’ behavior [29]. Scholars criticized this approach, as it overlooked consumers’ voluntary and intentional use of different technologies [25]. Consequently, in 2012, Venkatesh et al. [16] extended the UTAUT model by incorporating the impacts of seven constructs (i.e., performance expectancy, effort expectancy, social influence, facilitating conditions, hedonic motivation, habit, and price value) on behavioral intention [16]. Fishbein and Ajzen [30] define behavioral intention as “the strength of one’s intention to perform a specific behavior”. Thus, behavioral intention represents a measure of a consumer’s power of desire or willingness to try to exert effort while performing a particular behavior [27], but it also reflects an individual’s strength to perform a certain behavior [30,31]. Compared to previous theoretical frameworks, UTAUT2 allows improved predictive ability for moderators [16,31].

UTAUT2 reflects a thorough theoretical framework that has been applied in various settings, thus proving its applicability and adaptability in various contexts that address consumers’ adoption and use of technologies [32]. For instance, such research was examined in the context of NFC mobile payments in hotels [33], mobile banking [17,34,35], mobile tourism shopping frameworks [36], tourists’ intention to use travel apps [37], gaming [38], or the impact on consumers’ intents to use mobile payments [39]. As a conceptual framework, UTAUT2 was also explored in relation to consumers’ predisposition to use health apps or telemedicine [40–42], travel and tourism apps [43,44], electric car-sharing services [45], and acceptance of artificial intelligence [46]. Thus, these many different research settings highlight the vast applicability of UTAUT2.

Regarding m-commerce research, various authors have contributed to the expansion of UTAUT2. For instance, certain authors considered additional dimensions (such as trust and perceived security) in examining low-income consumers’ intentions to embrace m-commerce in Ecuador in an expanded UTAUT2 framework [24]. Other authors have linked UTAUT2 m-commerce adoption research to satisfaction [47], perceived risk and shopping app usage [48], retail app usage [13,14,49], adopting food delivery apps [50,51], or mobile payment app usage [52–54]. Thus, UTAUT2 research is often used to assess factors impacting consumers’ continued intent to rely on m-commerce apps.

## 2.2. M-Commerce and the Use of Mobile Apps

Mobile devices have become essential in consumers’ daily lives. Worldwide, there were 4.66 billion active internet users in January 2021, comprising 59.5% of the global population [55]. Moreover, 4.32 billion people (or 92.6%) are considered active mobile internet users [55]. Worldwide smartphone subscriptions have exceeded six billion and are expected to increase rapidly in future years [56]. As consumers spend more time secluded during the COVID-19 pandemic, they tend to use their mobile devices even more often [57]. On mobile devices, content is predominantly accessed via apps (up to 96% in some countries), with 88% of consumers using apps that provide key services (financial services and shopping) [57]. Given the widespread appeal of mobile devices and constant development of wireless networks, m-commerce is rapidly growing in popularity [31,58,59].

M-commerce is considered the possible “extension of e-commerce where business activities are performed in a wireless environment using mobile devices” [60]. M-commerce apps include various features, from seamless shopping experiences to mobile payments, thus contributing to the incontestable rise in popularity of m-commerce. In 2017, global m-commerce sales accounted for 1.36 billion USD, whereas in 2021, m-commerce generated

worldwide 3.56 billion USD in revenue [61]. By 2024, Europe and North America are projected to be the most prosperous regions for m-commerce use [62,63].

As an expansion of e-commerce, m-commerce is based on its additional capabilities that are “enabled through the use of a mobile platform and a wireless network” [25]. In fact, mobile technologies may have triggered a paradigm shift in consumers’ decision-making process [56]. Mobile apps have the potential to “foster engagement by providing a richer, and deeper shopping experience than traditional e-stores” [64]. M-commerce apps also include certain key advantages [64], such as (1) instantaneous “one-click” access to organizations; (2) the use of push notifications which generate sales and improve customer retention; and (3) the tailoring ability of apps in determining consumer preferences towards brands, products, etc.

Leveraging user-friendly multimedia functionalities and omnichannel integration, m-commerce apps have enabled businesses to create tailored shopping experiences [65–69]. Customers seem to prefer m-commerce compared to e-commerce due to its increased convenience and flexibility, unique offers, immediacy, and speedier qualitative shopping experiences [58]. When shopping, consumers may use their mobile devices to engage in retail time with friends, retailers, and other shoppers [70]. Therefore, the apps constitute proper tools that can be used for engaging customers and stimulating their purchasing behavior [64,70,71]. M-commerce retailers guide customers to use their apps by offering incentives and stimulating app downloading for further purchases through attractive prices, vouchers, etc. Amid the COVID-19 pandemic, retailers must focus on comprehending the reasons that encourage consumers to continue using m-commerce apps [72,73].

### 2.3. Antecedents of Behavioral Intention in M-Commerce

The main goal of retailers is to influence consumers’ behavioral intention of using m-commerce. Intentions are there “to capture the motivational factors that influence” customer behavior, being proper indicators for an individual’s willingness to perform certain behaviors [74]. In fact, an “individual’s tendency to perform some behavior” is the main aspect of the ‘Theory of Reasoned Action’ (TRA) [30]. Thus, intentions represent an indicator of consumers’ “perceived likelihood of using a particular innovation” [20,25], such as m-commerce. Behavioral intentions [25,36] or continuance intention [29,39,75] have been considered several times in relation to examining m-commerce and the UTAUT2 approach. In m-commerce settings, when consumers anticipate more benefits and entertainment value from using such apps, they are more inclined to further rely on them [13,14,48,49]. UTAUT2 prerequisites, such as social influence, hedonic motivation, and performance expectancy, may present significant determinants of customers’ intention to continue using mobile shopping applications [25,26,48].

**Social Influence** reflects the extent to which an “individual perceives that important other believe he or she should use a new system” [16]. As a standalone concept, social influence is grounded on (a) subjective norms, (b) social factors, and (c) image. Customers are more inclined to revert to their “social system” [26] to learn more and broaden their understanding on the use of new technology, or to receive social acceptance for their decision to utilize a new system [32]. Extending this idea to m-commerce, consumers who rely on shopping apps tend to seek “approval from friends, family, colleagues and others while engaging with them” [48]. Users may assimilate ideas from their peers as they interact and have physical and social media exchanges, which may further influence their decision to adopt shopping apps. Although m-commerce use and/or shopping is usually conducted privately, consumers may be tempted to rely on these apps, as their relatives and friends are pursuing similar avenues [25]. Existing studies that examine the impact of social influence on consumers’ intent to continue to use m-commerce in their daily lives have shown certain discrepancies in reported results; social influence often constitutes a key element in triggering consumers’ intention towards m-commerce use [16,21,33,39,48,75–77], although this relation is very much context-related and does not always exert a significant influence [17,24–26,29]. Based on these arguments, we infer that:

**Hypothesis (H<sub>1</sub>):** *Social influence has a positive impact on consumers' intentions to use m-commerce.*

**Performance Expectancy (PE)** represents “the degree to which consumers will consider getting some benefits while using a technology” [16]. Performance expectancy is based on several concepts, namely: perceived usefulness, extrinsic motivation, job-fit, relative advantage, and outcome expectations [16,22]. This concept has been theorized by its characteristics focused on usefulness, efficiency, and time saving opportunities for consumers [16,22]. These features provide m-commerce apps an important competitive advantage [33]. M-commerce is beneficial in terms of time efficiency, personalization, and flexibility [78]. Performance expectancy acts as an influencing factor of consumers' behavioral intention to use m-commerce apps, which stands in line with the UTAUT2 approach. When consumers anticipate more benefits from using m-commerce apps (such as shopping or food delivery apps), they tend to reuse them more often [26,48].

Performance expectancy also constitutes one of the most important factors in forecasting whether technology will be adopted by individuals [75]. The relevance of a positive connection between performance expectancy and consumers' behavioral intention to use m-commerce has been intensively researched based on food delivery apps [16,21], shopping apps [36,48,75,79], or NFC mobile payments [33,38,76]. In some cases, the relationship between performance expectancy and m-commerce proved to have an insignificant impact [24,39]. Therefore, we consider that:

**Hypothesis (H<sub>2</sub>):** *Performance expectancy has a positive impact on consumers' intentions to use m-commerce.*

**Hedonic Motivation** is described as “the fun or pleasure derived from using a certain technology”, such as m-commerce, due to its essential impact on accepting it [16]. This enjoyment gained from using the considered technology impacts consumers' intention to adopt and rely on it in the future [80]. “Hedonic motives tend to be prominent determinants in a consumer's likelihood to adopt self-service technologies” [34]. Customers are more willing to adopt m-commerce if it provides additional entertainment and/or possesses increased multimedia value [17,25,48].

Various app features are beneficial to customers, such as browsing, content and social sharing, collecting incentives/rewards in a multimedia environment, etc. These features aid in increasing the m-commerce app's entertainment value, which may further assist in generating customer engagement and maintaining consumer interest in m-commerce apps. When consumers have positive experiences with m-commerce apps, while considering them entertaining and enjoyable, they are more likely to reuse them in the future [34,48]. Hedonic motivation constitutes a key driver of consumers' behavioral intention to continue to use m-commerce apps [16,17,24,25,48]. Therefore, we put forth the following hypothesis:

**Hypothesis (H<sub>3</sub>):** *Hedonic motivation has a positive impact on consumers' intentions to use m-commerce.*

**Trust** represents a widely used marketing concept of major prominence for m-commerce due to the increased risk perceived by customers when engaging with such technology [13,78]. As a result of consumers' susceptibility of mobile apps' security and the impression of distrust towards mobile vendors, m-commerce carries a higher degree of uncertainty and risk [6,21]. Trust is also considered an all-encompassing construct; consumers who tend to trust brands, products, or companies are more vulnerable to the actions of their trusted counterpart [78,81–84]. Transposed to m-commerce platforms, consumers show an increased willingness, receptiveness, and openness to engage with the platform in which they have placed their trust.

When customers trust m-commerce apps, they tend to spend less time looking for reassuring information, thus requiring less cognitive efforts to make a purchasing decision. Trusting customers are more inclined to continue to use m-commerce, as “they believe

that the service provider would not exhibit any opportunistic behavior" [78]. Thus, in m-commerce settings, trust has been established as an important and reliable indicator of consumers' intention to continue using mobile technology [6,85–87]. Trust can be examined from three perspectives [86]: "ability, integrity, and benevolence". Ability denotes that m-commerce providers possess the knowledge and skills required to properly implement their strategies. Integrity refers to m-commerce platforms' ability to maintain their promises and avoid misleading customers. Benevolence indicates that m-commerce apps and suppliers prioritize the interests of their customers. As a "complex and multidimensional concept" [88], trust shows "undeniable importance for both transacting parties due to increased uncertainty in an online environment" [76].

Trustworthiness may considerably shape users' mental expectations to think that m-commerce can deliver dependable service. Thus, if users accumulate a higher level of trust from mobile shopping apps, they tend to display a higher willingness to continue to use these apps [21]. In other words, experienced users' intention to continue using m-shopping is impacted by trust. Trust is established because of an app's performance and extended development of app-related operations [19]. Positive and significant relationships between m-shoppers' trust and their intention to continue using m-commerce platforms have been intensively researched [21,76,85,86]; therefore, we infer that:

**Hypothesis (H<sub>4</sub>):** *Trust exerts a positive impact on consumers' intentions to use m-commerce.*

**Impact of COVID-19 on Customers.** In multimedia retail settings, there are many opportunities for addressing the impact of COVID-19 on consumer behavior [67,69,89,90]. The recent pandemic has been intensively studied as scholars aim to showcase the repercussions and effects of this outbreak on consumers' purchasing patterns, shopping motives, attitudes, perceptions, preferences, etc. [10,77,91]. Throughout the COVID-19 pandemic, research has focused on the impact of social relationships on an individual's perceptions of this new epidemic context [12]. Thus, social influence affects an individual's predisposition in believing certain ideas and driving certain behaviors [76].

With social distancing measures in place, people have gravitated towards other types of communication technologies to connect with friends, family, and/or coworkers. People have been using social media for "social support and information seeking" during the pandemic [92]. Social influence is predicted to exert an impact on how people perceive the pandemic in relation to their shopping behavior. A similar study discovered that "consumers tend to imitate the actions of others amid a pandemic" [10]. While exploring COVID-19 phobia and news exposure, smartphone addiction, and consumer pessimism in relation to mobile shopping, 'social influence' has been found to be a strong predictive moderator [12]. As this study aims to expand previous COVID-19-related knowledge on the adverse impacts of the pandemic as well as the negative effects of subjective norms in assessing the COVID-19 threat while shopping, we posit that:

**Hypothesis (H<sub>5</sub>):** *Social influence has a negative effect on consumers' perceptions of COVID-19 in relation to their shopping behavior.*

As they have been confronted with lockdowns and restrictions [89], consumers have focused and relied more on online shopping [4], with m-commerce playing an increased role in their daily lives. During the last two years, the COVID-19 pandemic may have expedited the adoption of m-commerce platforms [77]. Various reports predict a permanent change in consumer behavior after the pandemic [7,8] with the anticipation that individuals may exhibit more conscious shopping behavior by focusing on "buying local [products] and embracing m-commerce" [7]. Due to strong and intensive disturbances during their normal living experiences, consumers have been increasingly hesitant about traditional purchasing from brick-and-mortar stores during the COVID-19 pandemic. To protect themselves against the deadly virus, consumers increasingly resorted to click-and-order shopping [10], but also to mobile apps to acquire food, brands, and other products [90].

As a result of today’s extensive internet connectivity [15] and increased use of technology, consumers’ preferences for mobile purchasing are further changing [91], exhibiting new shopping habits [5]. Consumers are more likely to engage more frequently in m-shopping as a type of retail therapy to cope with the continuing COVID-19 crisis [12]. To reflect novel insights on how COVID-19 impacts consumer behavior in the context of m-commerce, we propose the following hypothesis:

**Hypothesis (H<sub>6</sub>):** *Consumers’ perceptions of COVID-19 in relation to their shopping behavior have a negative effect on their behavioral intention to continue relying on m-commerce.*

2.4. Moderation of Gender and Consumer Generations

Previous UTAUT2 research [16,25,31] has also considered examining moderation effects for interactions between trust for mobile shopping apps and an individual’s behavioral intentions to rely on m-shopping. Depending on their birth years, consumers tend to have common traits and experiences based on social, cultural, and economic contexts. As such, consumers can be classified into different generational cohorts or generations [5,58,93–95]. Generations consist of “groups of individuals born during the same period of time who share similar values, attitudes, beliefs and expectations which are constant throughout the generation’s lifetime”, leading to the formation of a ‘generational identity’ [5]. Such generational cohorts have the potential to greatly alter consumer buying patterns and shopping behaviors [58]. Opposite to older generations, which are represented by Baby Boomers (born after the second World War until 1964) and Generation X (born usually between 1965 and 1979), Millennials/Generation Y (born between 1980 and 1994) and Generation Z (born between 1995 and 2010) exhibit stronger online addiction, social media exposure, and social media usage [5,58,93–95]. For instance, Gen Z relies more on mobile purchases than older cohorts [9]. Thus, we infer that:

**Hypothesis (H<sub>7</sub>):** *Trust perceptions of Generation Z members exert stronger positive effects on their behavioral intention to continue to rely on m-shopping than those of Millennials.*

As m-commerce users are predominantly young people [5,58,94], the present research considers the moderation effect of gender and generational cohorts between trust and m-commerce behavioral intentions (see Figure 1). Gender variations were found to influence decision making and information processing [36]. As men and women make decisions in different manners, especially when shopping, such decisions may also extend to m-commerce acquisitions [36,96]. Therefore, we assume that:

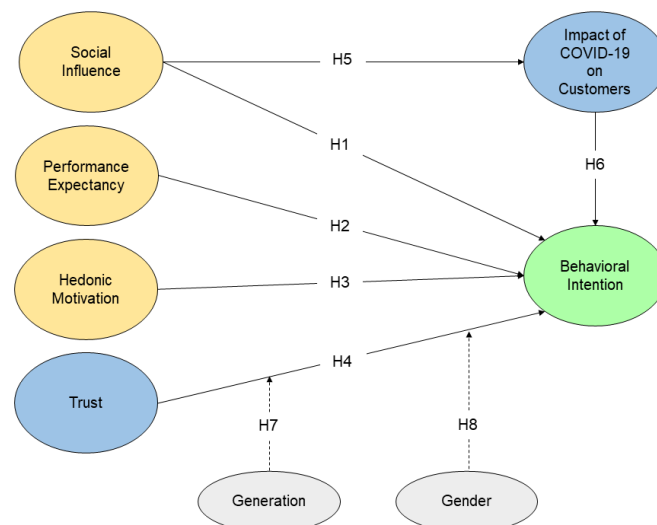


Figure 1. Proposed conceptual model.

**Hypothesis (H<sub>8</sub>):** *Female respondents' perceptions of trust exert stronger positive effects on their behavioral intention to continue to rely on m-shopping than those of males.*

Figure 1 highlights the proposed hypotheses of this model.

### 3. Research Methodology

#### 3.1. Research Scope and Context

The scope of this paper was to explore consumers' behavioral intentions to buy products via m-commerce apps during the COVID-19 pandemic, as induced and determined by consumers' hedonic motivations, social influence, performance expectancy, and online trust. To implement this research question, a conceptual model (Figure 1) was proposed as a basis for investigation. The investigated concepts (social influence, performance expectancy, hedonic motivations, trust, behavioral intention, and impact of COVID-19 on customers) were operationalized based on scales adapted from the existing literature that were considered for the current research context.

Research was based on an empirical questionnaire-based investigation among Romanian consumers. The survey was implemented in 2021 during the 3rd and 4th wave of the COVID-19 pandemic in Romania, which had a tremendous effect on the population and the sanitary system as the number of daily new infections peaked at over 18,000 cases [97].

The authors chose to conduct their investigation in this emerging market, as Romania ranked 4th place worldwide for internet speed (in 2021) and registered an increase of 1.3 million people (+10.8%) in the number of internet and social media users in 2021 [15]. Moreover, the number of mobile connections equaled 143.7% of the total registered Romanian population in January 2022 [15]. Although the official population in Romania is approximately 19 million inhabitants, in December 2021 there were 27.41 million mobile cellular connections [15]. Thus, the access of Romanians to m-commerce apps is very high. The market situation introduces new marketing opportunities for companies relying on m-commerce apps [29]. To a certain extent, the rapid rise of the mobile market may also be related to the pandemic situation, as Romanians had to rapidly change their previous shopping behavior (mainly focused on brick-and-mortar stores) and to adapt to the new click-and-order environment [90,98,99].

For this research, respondents consisted of Romanian m-commerce customers who had experience with mobile commerce apps. According to national statistics, m-commerce apps were among the most utilized ones in 2021, followed by mobile banking and gaming apps [98]. In Romania, the average order value using m-commerce was approximately 43.5 EUR in 2020 [99], thus leaving great opportunity for future developments, as the average order value at the global level was around 73 EUR/mobile order [100].

#### 3.2. Questionnaire Design and Measures

To examine the research scope, the considered constructs (see Figure 1) were developed based on the existing literature. The items of all constructs are measured on five-point Likert scales, with values ranging from 1 ('Strongly disagree') to 5 ('Strongly agree') and adapted to the present research context (presented in Table 1). The six reflective latent constructs are: hedonic motivation, social influence, performance expectancy, and behavioral intention extracted from the Venkatesh et al. [16], as well as trust encompassed from Zhao and Bacao's study [21] and perceptions of COVID-19 in relation to shopping patterns adapted from Zenker et al. [101]. The questionnaire is divided into several sections to help with the completion of the survey and to minimize the impact of biases. Additionally, we provided respondents the opportunity to select their preferred mobile commerce apps to avoid the issue of common method bias.



**Table 1.** Constructs and Measures, Confirmatory Factor Analysis, and Convergent Validity.

Construct/Item	Measures	St. Est.	$\alpha$	AVE	CR
Hedonic Motivation (HM) adapted from Venkatesh et al. [16]			0.738	0.559	0.788
HM1	Using m-commerce is fun	0.639			
HM2	Using m-commerce is enjoyable	0.900			
HM3	Using m-commerce is very entertaining	0.678			
Social Influence (SI) adapted from Venkatesh et al. [16]			0.791	0.590	0.808
SI1	People who are important to me support me to use m-commerce	0.591			
SI2	People who are important to me think m-commerce apps are beneficial	0.826			
SI3	People who are important to me think it is a good idea to use m-commerce	0.859			
Performance Expectancy (PE) adapted from Venkatesh et al. [16]			0.789	0.558	0.791
PE1	I find m-commerce useful in my daily life	0.730			
PE2	Using m-commerce increases my productivity	0.742			
PE3	Using m-commerce helps me accomplish things more quickly	0.768			
Behavioral Intention (BINT) adapted from Venkatesh et al. [16]			0.841	0.627	0.834
BINT1	I intend to continue using m-commerce in the future	0.728			
BINT2	I will always try to use m-commerce in my daily life	0.853			
BINT3	I plan to continue to use m-commerce frequently	0.790			
Trust (TR) adapted from Zhao and Bacao [21]			0.803	0.728	0.889
TR1	"I believe m-commerce apps are trustworthy	0.879			
TR2	I believe m-commerce apps keep customers' interests in mind	0.782			
TR3	I feel secure with ordering and receiving my orders through m-commerce	0.901			
Impact of COVID-19 on customers (COV) adapted from Zenker et al. [101]			0.912	0.776	0.912
COV1 *	COVID-19 makes me worry a lot about my normal ways of shopping	0.888			
COV2 *	When watching news about COVID-19, I become nervous or anxious in regard to traditional shopping	0.889			
COV3 *	I do not feel safe to shop in stores due to COVID-19	0.867			

Note: St. Est.: Standardized Estimates;  $\alpha$ : Cronbach Alpha > 0.7; AVE: Average Variance Extracted > 0.5; CR: Composite reliability > 0.7; \* item presents reverse coding.

### 3.3. Data Collection and Sampling

To acquire data for testing the proposed research hypotheses, we conducted a survey of Romanian mobile buyers. The data collection process began by assessing the necessary sample size before administering the survey. The sample size for this study was estimated using Cochran's [102] formula:  $N = \frac{Z^2[P(1-P)]}{E^2}$ , where  $Z$  represents the "level of confidence expressed in standard errors" [103],  $E$  reflects the "acceptable amount of sampling error", and  $P$  stands for "the proportion in population that may exhibit a certain behavior" [103]. For this formula, a 95 percent confidence level was considered, along with a precision of  $\pm 6\%$ , and a 50 percent expected variability. Based on these considerations, the sample size was computed to be 267 respondents. To aid in the feasibility of replicating an SEM model in similar contexts, Hair et al. [104] suggested utilizing a sample size consisting of 200 up to 400 participants. To establish a correct sample size for model analysis, Nunnally and Bernstein [105] proposed the "rule of ten", meaning that for each construct/indicator of a model, ten observations should be considered [106]. These recommendations were considered in establishing the final dataset.

The data collection process implied gathering responses based on convenience sampling and snowball sampling [107]. First, participants were invited to partake in the study using convenience sampling among acquaintances. Second, participants were encouraged to share the online survey with other users of m-commerce apps. These practices are widely used in m-commerce research [24,29,77]. Data were collected using a self-administered questionnaire completed on a voluntary and anonymous basis. A total of 449 responses were gathered. Based on respondents' answers to a screening question and other data

inspection techniques [106], the final valid data set included 351 respondents who engage in m-commerce. The respondents' profiles are presented in Table 2.

**Table 2.** Socio-demographic characteristics of the Respondents ( $n = 351$ ).

Variable		Frequency	Percent
Preferred m-commerce apps	Food and delivery apps	79	22.5%
	Clothing, shoes, and apparel apps	160	45.6%
	Grocery items apps	18	5.1%
	Cosmetics, fragrances, and beauty products apps	55	15.7%
	Other types of apps	39	11.1%
Experience with m-commerce	Less than 1 year	19	5.4%
	1–3 years	180	51.3%
	3–6 years	104	29.6%
	More than 6 years	48	13.7%
Gender	Female	255	72.6%
	Male	96	27.4%
Generational cohort	Generation Z	242	68.9%
	Millennials/Generation Y	75	21.4%
	Generation X	34	9.7%
Employment status	Student	184	52.4%
	Employed	155	44.2%
	Searching for a job	11	3.1%
	Retired	1	0.3%
Education level (last level of obtained diploma)	High school diploma	215	61.3%
	Bachelor studies	103	29.3%
	Master studies	30	8.5%
	PhD studies	3	0.9%
Personal monthly income	Less than 500 EUR/month	178	50.7%
	501–1000 EUR/month	109	31.1%
	1001–1500 EUR/month	41	11.7%
	More than 1501 EUR/month	23	6.6%

Respondents were requested to provide their birth year. Considering their birth year, we were able to establish the generation cohort of each respondent and their age. Consequently, we discovered that the respondents' average age was 26.10 years old (standard deviation of 8.31). To classify respondents based on their associated generational cohort, we used the widely accepted classification proposed by established studies [5,58,96–99]. We obtained a sample consisting of 68.9% Zers, 21.4% Millennials, and 9.7% Xers. Females comprised most of the participants (72.6%). From the sample, 90.6% obtained their high school and bachelor studies diplomas, and most of the respondents classified themselves as students (52.4%). Additionally, 81.8% of this study's participants reported a personal monthly income lower than 1000 EUR/month.

Regarding mobile shopping, the 351 respondents expressed their preference for different types of apps: 45.6% of participants mentioned they use clothing, shoes, and apparel apps; 22.5% use food and delivery apps; 15.7% use apps that sell cosmetics, fragrances, and beauty products; 5.1% chose the category of apps that allows them to purchase grocery items (beverages, cereals, snacks); and 11.1% use other types of apps. Most respondents (94.6%) have used m-commerce apps for at least one year. The survey also included a ratio scale regarding the frequency of engaging in mobile shopping. As a result, the respondents mentioned an average of 4.03 mobile app purchases per month.

### 3.4. Evaluation of the Measurement Models

To uncover any breaches of the normality condition, data screening was performed prior to the use of more extensive statistical procedures. Skewness and Kurtosis were

computed to evaluate the distribution of data. Based on the literature's recommendations [106,108], skewness values had to fall in the range of  $\pm 2$ , and kurtosis values had to be classified in the range of  $\pm 6$  [106]. Both requirements were fulfilled. Following the first inspection of the dataset, IBM SPSS and AMOS were used to compute structural equation modeling (henceforth SEM). The main data analysis procedures comprised of confirmatory factor analysis (henceforth CFA) and multi-group for moderation analysis. CFA helps to identify how well measurement items reflect the main components explored in an empirical study [104]. Upon evaluation of the CFA, the proposed model's hypotheses are investigated in the frame of reference of a structural equation model. SEM represents "a statistical method that examines the relationships among numerous variables in a simultaneous way" [106]. Most notably, SEM is used to examine the "significance and the strength of relationships" within a proposed model [109]. To improve the understanding of the findings, data analysis extends through the application of a moderation analysis, considering the previously recommended hypotheses ( $H_7$  and  $H_8$ ). These analyses and their respective results are detailed in their subsequent sections.

#### 4. Results

Anderson and Gerbing [110] proposed a two-step strategy to data analysis: first, verify the measurement model's reliability and validity; and second, assess the research hypotheses and structural model framework. This approach was previously developed by various authors in explaining the UTAUT2 model in m-commerce settings [17,21,24,29].

##### 4.1. Confirmatory Factor Analysis

As a data analysis technique that allows researchers to test (affirming or dismissing) a measurement model, CFA is described by Collier [106] as a "statistical technique that analyzes how well indicators measure unobserved constructs." To examine the accuracy of the CFA, various authors propose examining goodness-of-fit indicators, convergent validity, and discriminant validity [104,106]. As recommended by Hu and Bentler [111], the first step of CFA implies the evaluation of goodness-of-fit indicators, such as: Chi-square ( $X^2$ ) ratio degrees of freedom (df) ( $X^2/df$ )  $< 5.0$ , the comparative fit index (CFI)  $\geq 0.9$ , the goodness-of-fit index (GFI)  $\geq 0.9$ , the normed-fit index (NFI)  $\geq 0.9$ , the Tucker-Lewis coefficient (TLI)  $\geq 0.9$ , and the root mean square error of approximation (RMSEA)  $< 0.08$ . An initial development of CFA with a total of 20 scale items, associated with the constructs of the model, presented certain issues. More specifically, two scale items (SI4 and TRS4) had to be removed from CFA due to low factor loadings. After their removal, CFA was reapplied. The new CFA showed congruence with the cut-off values of model relevancy, according to Hu and Bentler [111]:  $X^2(115)$ : 265.206 ( $p < 0.001$ ), ( $X^2/df$ ): 2.306, CFI: 0.958, GFI: 0.924, NFI: 0.929, TLI: 0.944, and RMSEA: 0.061. Considering these results, we can assert that CFA meets the goodness-of-fit requirements (see Table 1).

The second phase in CFA is to establish convergent validity using the following evaluation criteria: Cronbach's alpha  $> 0.7$ , standardized loading estimates, composite reliability (CR)  $> 0.7$ , and average variance extracted (AVE)  $> 0.5$ . Table 1 presents the results of these evaluation criteria. Firstly, the values for Cronbach's alpha met the 0.7 threshold [111,112], as the lowest value of 0.738 was recorded for 'Hedonic motivation'. Secondly, regarding the standardized loading estimates, Hair et al. [104] proposed a minimum level of 0.5, and this criterion was met based on the values recorded in Table 1. Thirdly, CFA requires the evaluation of composite reliability (CR) based on values higher than 0.7 [113,114]. Lastly, in relation to convergent validity, various authors [104,114] recommended reviewing the calculated values of average variance extracted (AVE). The generally accepted threshold for AVE is 0.5, and this criterion was met, as the lowest AVE value was recorded for performance expectancy (0.558), and the highest value was registered for the variable examining the impact of COVID-19 on customers' perceptions (0.776). As a general assessment, all the requirements for convergent validity were fulfilled [104,112–114]. Table 1 also includes descriptive data for the scale items used in this empirical investigation.

The last step in examining the relevancy of confirmatory factor analysis is the inspection of discriminant validity. A widely applied method for asserting this criterion was proposed by Bagozzi and Yi [113], and it implies the evaluation of pairwise correlations between factors without surpassing the 0.85 level. Thus, considering the results showcased in Table 3, this condition was fulfilled. Hair et al. [104] as well as Fornell and Larcker [114] established a more rigorous method for discriminant validity, namely that the square root of AVE for any latent construct should be higher than any of the other pairwise correlations calculated in CFA. The computed results reflect that CFA aligns both requirements for discriminant validity (Table 3).

**Table 3.** Results of discriminant validity of CFA (Fornell–Larcker Criterion).

	BINT	HM	SI	PE	TR	6. COV
BINT	<b>0.853</b>					
HM	0.709	<b>0.748</b>				
SI	0.674	0.560	<b>0.768</b>			
PE	0.740	0.652	0.678	<b>0.747</b>		
TR	0.692	0.613	0.614	0.735	<b>0.792</b>	
COV	−0.238	−0.204	−0.317	−0.212	−0.171	<b>0.881</b>

Note: The bolded values displayed on the diagonal reflect the square root of AVE. Off-diagonal values reflect the pairwise correlations between the constructs. BINT: Behavioral Intention; HM: Hedonic Motivation; SI: Social Influence; PE: Performance Expectancy; TR: Trust; COV: Impact of COVID-19 on customers.

To offer an accurate examination of the proposed model, we used the framework provided by Podsakoff et al. [115] and by MacKenzie and Podsakoff [116] to address the issue of common method bias. To limit the influence of biases on the reliability of the results, a priori procedures were developed. To avoid potential biases, the research scope was general and allowed respondents to choose their preferred m-commerce apps. After the data collection process was complete, we used two tests to assess the probability of common method bias [115,116]. First, we proceeded to evaluate common method bias in SPSS using Harman’s one-factor test and exploratory factor analysis [115]. Based on the results, one factor accounts for only 40.6% of the variance, which is considerably lower than the recommended threshold of 50%. Second, we also inspected the common method bias in CFA [80]. The new model displayed a poor fit, considering the previously applied CFA, more specifically: ( $\chi^2/\text{df}$ ): 10.935 (>3), CFI: 0.625 (<0.9), NFI: 0.604 (<0.9), TLI: 0.575 (<0.9), and RMSEA: 0.168 (>0.08). Thus, the model that included a common latent factor reflected inadequacy. Overall, we can state that common method bias is not an issue in this set of observations.

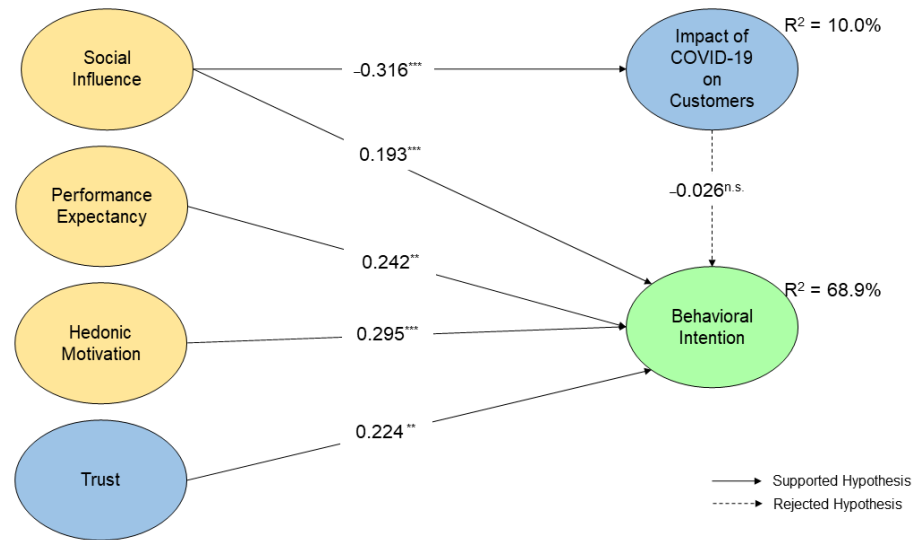
#### 4.2. Hypotheses Testing with SEM

Following the validation of CFA, we proceeded to examine the model’s hypotheses using SEM. Similar to the steps required to validate CFA, the first phase for the assessment of SEM is to evaluate its accuracy, considering the premises established by Hu and Bentler [111]. Computation of SEM yielded the following results:  $\chi^2(119)$ : 279.009 ( $p < 0.001$ ), ( $\chi^2/\text{df}$ ): 2.345 (<5), CFI: 0.955 (>0.9), GFI: 0.920 (>0.9), NFI: 0.925 (>0.9), TLI: 0.942 (>0.9), and RMSEA: 0.062 (<0.08). All the indicators reflect the requirements established by Hu and Bentler [111]. Thus, the data fit the proposed model’s hypotheses. Table 4 and Figure 2 present the findings associated with testing the hypotheses of the proposed model.

**Table 4.** Results of hypothesis evaluation in SEM.

Effects	Path Coefficients ( $\beta$ )	t-Value	Sig.	Effects
SI→BINT	0.193	3.227	0.000 ***	H <sub>1</sub> —Supported
PE→BINT	0.242	2.931	0.003 **	H <sub>2</sub> —Supported
HM→BINT	0.295	4.932	0.000 ***	H <sub>3</sub> —Supported
TRS→BINT	0.224	2.835	0.005 **	H <sub>4</sub> —Supported
SI→COV	−0.316	−5.286	0.000 ***	H <sub>5</sub> —Supported
COV→BINT	−0.026	−0.724	0.469 n.s.	H <sub>6</sub> —Not Supported

Note: \*\*\* Significant at  $p \leq 0.001$  (two-tailed), \*\* Significant at  $p < 0.010$  (two-tailed), n.s. Not significant.



**Figure 2.** Hypothesis testing of the proposed conceptual model. Note: \*\*\* Significant at  $p \leq 0.001$  (two-tailed), \*\* Significant at  $p < 0.010$  (two-tailed), n.s. Not significant.

The results of the structural model (Table 4) reveal that social influence has a positive, direct, and considerable impact on consumers’ behavioral intention ( $\beta$ : 0.193,  $p < 0.001$ ). Thus, H<sub>1</sub> is accepted in the context of the proposed model. The findings demonstrate that consumers’ behavioral intention to use m-commerce is impacted by performance expectancy ( $\beta$ : 0.242,  $p$ : 0.003, confirming H<sub>2</sub>). There is also a significant and positive connection established between hedonic motivation and customers’ behavioral intentions ( $\beta$ : 0.295,  $p < 0.001$ ), supporting H<sub>3</sub>. Thus, out of the hypotheses associated with UTAUT2, hedonic motivation is established as the strongest predictor of consumers’ behavioral intention to continue using m-commerce. This model proposes the inclusion of trust as a latent variable meant to expand UTAUT2. The results highlight a direct and significant relationship between consumers’ trust for m-commerce apps and their intention to use this shopping outlet in the future. Therefore, H<sub>4</sub> can also be validated ( $\beta$ : 0.224,  $p$ : 0.005).

Another original contribution of the proposed model is reflected in the inclusion of consumers’ perceived impact of COVID-19 on their shopping behavior. This latent variable was examined in connection to two hypotheses. H<sub>5</sub> is confirmed by the negative and significant result computed for the connection between consumers’ social influence of using m-commerce and the impact of COVID-19 on their perceptions ( $\beta$ : −0.316,  $p < 0.001$ , confirming H<sub>5</sub>). However, the results identify an insignificant estimate for the connection between ‘Impact of COVID-19 on customers’ and ‘Behavioral Intention’ ( $\beta$ : −0.026,  $p$ : 0.469, confirming H<sub>5</sub>). Thus, H<sub>6</sub> is rejected. In its current form, the current model accounts for 68.9% of the variance in consumers’ behavioral intention and 10.0% of the variance in consumers’ perceived impact of COVID-19 on their shopping behavior.

### 4.3. Moderation Testing

Moderation enables the testing of the idea that “direct influence of an independent variable on a dependent variable is altered or changed because of a third variable” [106]. For moderation testing, we used the premises established by Collier [106] regarding the application of a two-group analysis. Upon the development of a two-group analysis in AMOS, we aimed to examine the interaction of two moderators (gender and generational cohort) on the relationship between trust and behavioral intention of consumers to continue using m-commerce. Initially, we proposed the examination of two generational cohorts (Y/Millennials and Z), anticipating a higher response rate in these two groups of respondents.

The results of the moderation analysis indicate a significant difference between the groups associated with the two generational cohorts. More specifically, we observed a chi-square test difference of 5.164 (1 df) and a  $p$ -value of 0.023 ( $<0.05$ ). According to the results in Table 5, there is a significant and positive influence of trust on consumers’ behavioral intention for Generation Z ( $\beta$ : 0.261,  $p$ : 0.010) respondents. However, the analysis presents an inconsequential outcome for Millennial respondents. Thus, respondents classified as Generation Z have no issues with trusting m-commerce apps, and this trust tends to be related to a clear intent to continue using this form of shopping.  $H_7$  is partially accepted from the perspective of Millennials.

**Table 5.** Difference Test for Hypothesis  $H_7$ .

Effects	Path Coefficients ( $\beta$ )	t-Value	Sig.
TRS → BINT (for Zers)	0.261	2.577	**
TRS → BINT (for Millennials)	−0.291	−1.030	0.303

Note: \*\* Significant at  $p < 0.010$  (two-tailed).

$H_8$  is based on another moderation analysis that focuses on the same relationship but explores this connection from the perspective of male and female respondents. However, upon conducting the analysis, we noticed that the chi-difference test shows no difference at the model level, both for the overall model ( $X^2$ : 17.951 at a  $p$ -value of 0.459) and for the constrained relationship between trust and behavioral intention ( $X^2$ : 1.117 at a  $p$ -value of 0.290). Therefore,  $H_8$  is rejected.

## 5. Discussions

Based on the premises of UTAUT2 with additional original contributions, this study was undertaken to discover which factors influence customers’ adoption of m-commerce in Romania, during the COVID-19 pandemic. These data analysis procedures applied in this study are consistent with previous developments in the relevant literature that also employed SEM to investigate different conceptual frameworks of UTAUT2 [24,29,76]. Our findings show that UTAUT2 constitutes a robust paradigm that may considerably increase knowledge of a key digital marketing phenomenon, such as m-commerce adoption. Furthermore, we address the ramifications of these relationships and hypotheses for a comprehensive conceptual framework.

To a large extent, social influences have an impact on customers’ inclinations and intentions to use m-commerce. Customers are more inclined to accept and use new technologies (such as m-commerce) in their lives if m-shopping is suggested and approved by key figures. As part of a community, consumers’ intent toward m-shopping acceptance and usage is strongly determined by the standards and beliefs of their peers. Thus, this study validates a fundamental component associated with UTAUT2 [16] and stands in line with previous empirical investigations [21,22,31,33,38,48,75–77].

Moreover, according to UTAUT2’s hypotheses, our study’s findings demonstrate a positive relationship between performance expectancy and consumers’ behavioral intentions to use m-commerce. Theoretical frameworks assess consumers’ performance

expectancy based on attributes such as “usefulness, efficiency, and time savings” [16,22,23]. When a customer perceives mobile shopping as easy-to-use and timesaving, that customer tends to exhibit a higher likelihood of embracing this type of commerce. Additionally, when compared to traditional shopping, the omnipresent dimension of m-commerce apps provides consumers with supplementary benefits, such as rapid access to a wide range of market offerings and the ability to be more productive in shopping activities (saving favorite products or monitoring products in wish-lists). Thus, this paper highlights performance expectancy as a strong predictor of consumers’ intent towards using m-shopping. This status of a strong predictor is congruent with our initial expectation of the proposed hypothesis [21,26,29,34,48,75,79].

Similarly, considering another UTAUT2 construct, the results suggest that hedonic motivation represents a significant and valuable driver of consumers’ behavioral intention. Customers appreciate multimedia experiences available on their mobile devices. From a multimedia perspective, consumers associate their m-shopping experiences with fun, escapism, enjoyment, playfulness, and a general sense of pleasure. As shown in this study, hedonic motivation reflects a relevant element for consumers who engage in m-shopping. Thus, this research has enhanced previous studies in this area, complementing previous findings [16,17,22,25,26,34,38,48]. Thus, the main insight is that consumers are more inclined to use an interactive, multimedia, fun, and well-developed app for their m-commerce needs, over a variety of applications that accomplish similar activities.

The previous literature has found that consumers’ intents to engage in future purchases are facilitated by trust in the supplier, especially within the setting of m-commerce. Sarkar et al. [78] define m-commerce as “a new technological interface that improves transactions and helps in building long term relationships with customers”. Thus, the authors posit trust as a key factor in enhancing the relationship between m-commerce vendors and targeted customers. Consumers’ abilities and impressions of reliability are often used to describe trust [18,19,112]. As such, this study proposes trust as an additional construct that can extend and improve UTAUT2. The impact of trust on consumers’ behavioral intention is confirmed, showcasing results that support previous studies [21,77,85–87,117,118]. In other words, customers who have developed a favorable and trustworthy connection with m-commerce vendors are more inclined to further rely on the same shopping apps for other transactions. Strong and long-term connections are based on trust between companies and consumers [119]. To this effect, trust represents an essential success element for any online company that operates e-commerce, m-commerce, or s-commerce [118,119]. Therefore, one can state that customers’ intents to use m-commerce are influenced by their trust perception, which either restricts or supports acceptance and use of m-shopping [78,117].

In addition, an innovative component of this model involves the examination of customers’ perceptions of the COVID-19 pandemic. To assess this research objective, H<sub>5</sub> highlights a negative interaction between social influences and consumers’ perceptions of COVID-19 regarding their shopping behavior. This relationship is supported, and this outcome leads to the conclusion that friends and family members can impact consumers’ perceptions of COVID-19 regarding their shopping behavior. When individuals find themselves in uncertain and potentially harmful health conditions, they rely on family and friends to process certain information and to evaluate existing circumstances, such as engaging in traditional shopping compared to new modes of purchasing products and/or brands. This is one of the first investigations aiming at exploring how COVID-19 influences consumer behavior in terms of operationalized and implemented scale items [101], thus also highlighting the novelty of the research as compared to prior studies that focus only on adjusting their measurement items to reflect the pandemic [91]. As COVID-19 technology-based shopping is still developing, additional studies may bring more insight on the prerequisites that lead to consumers’ behavioral intention to rely on m-commerce apps.

Furthermore, this study aimed to explore a negative interaction between customers’ perceptions of COVID-19 and their intention to rely on m-shopping. However, the findings reveal an insignificant impact of this relationship. One plausible explanation for this

inconsequential result can be attributed to the level of experience these respondents have with m-commerce. Most respondents (94.6%) have a vast experience with m-shopping, and the pandemic does not generate a high level of adjustment, in their case. Due to the novelty of this proposed hypothesis, supplementary investigations are required to provide a more thorough understanding of this relationship.

In discussing the results of structural equation modeling, it is important to highlight the level of explained variance in the main dependent variable. According to the findings, the expanded UTAUT2 model explains that 68.9% of consumers expressed behavioral intent of using m-shopping. Thus, this integrative version of the model demonstrates the model's predictive power. However, social influences have determined a small proportion of variation in consumers' perceptions of the COVID-19 pandemic (10%).

Finally, to expand the comprehension of the proposed model, this research aims to understand contrasts of trust perceptions between Millennials and Zers regarding mobile shopping intent [93]. As previously stated, buying decisions are influenced by generational patterns. This study adds to the knowledge of generational cohorts in this context and expands the understanding of UTAUT2, as previously recommended [16]. The findings are consistent with those of Lissitsa and Kol [58], who use a generational approach to examine purchase intention for m-commerce. Additionally, different generational perspectives are found in the study developed by Eger et al. [5], examining modifications in consumer behavior during the COVID-19 pandemic.

Considering  $H_8$ , our model finds no differences between female and male respondents in relation to their perceptions of trust impacting their behavioral intent of using m-commerce apps. This result contradicts a previous discovery by Marinkoviæ et al. [109] in their application of an invariance test on gender as a moderator in their UTAUT2 model. Moreover, in the initial UTAUT2 model proposal, Venkatesh et al. [16] finds that respondents' gender is a valuable moderator. Thus, our inconsistent result should be examined in additional studies. In a recent study related to the pandemic, Sheth [120] asks the following question: "Will the consumers permanently change their consumption habits due to lockdown and social distancing or will they go back to their old habits once the global crisis is over?". Additionally, a BCG report [121] states that, during the pandemic, consumers' spending patterns change as consumers tend to renounce expensive products due to uncertainty, and they lean more towards using local products. In future studies, these aspects should guide additional efforts that examine modifications at a consumer behavioral level [66–69,122–126] in different countries.

## 6. Conclusions

### 6.1. Theoretical Contributions

This study examines consumers' intention to use m-commerce during the difficult circumstances generated by the worldwide COVID-19 pandemic. The scope of this research is to ascertain consumers' behavioral intentions to use m-commerce based on a model that includes five main determinants (hedonic motivation; social influence; performance expectancy; trust; impact of COVID-19 on customers). The current study adds to the body of knowledge in several ways.

This research acknowledges and responds to calls for studying UTAUT and UTAUT2 in various settings. The research model for m-commerce examines eight hypotheses based on the UTAUT2 theoretical framework. Thus, one of the most notable conceptual contributions is that it expands prior UTAUT2 m-commerce research. UTAUT2 components have been shown to be accurate predictors of m-commerce buying intentions during the COVID-19 pandemic. Derived from this empirical analysis, we can state that performance expectancy, hedonic motivation, and social influences constitute important drivers of consumers' behavioral intention. Results also show consistency and convergence with these three hypotheses associated with UTAUT2. Assessing the extent to which social influences impact customer intentions, the results reinforce and contribute to a clearer comprehension of this connection within a model focused on m-commerce. Moreover,



results reconfirm performance expectancy as an antecedent of consumers' intent towards m-shopping. Consumers who engage in m-commerce focus on the usefulness of these apps, their provided opportunity to increase their productivity in shopping experiences, and timely achieving their purchasing goals. Furthermore, m-commerce apps provide consumers with fun, enjoyable, and entertaining shopping experiences.

This research further adds to the existing literature of understanding trust in the context of m-commerce. Mobile devices serve as a platform for consumers to conduct different commercial or financial operations in m-commerce. Therefore, the first touchpoint between consumers and companies operating in m-settings is based on establishing consumers' trust. M-commerce business organizations must minimize customers' concern and confusion about the security and threats of m-commerce. This study is valuable in its assessment of the COVID-19 pandemic, reflecting a new theoretical contribution. The worldwide repercussions of the COVID-19 outbreak, as well as its consequences on consumer behavior, are unparalleled in recent history. As an important contribution, this is among the first studies to examine how COVID-19 affects consumers' behavior by using established scale items. During this pandemic, our study highlights the need to examine the effect of social relationships on people's perceptions and behaviors. As presented by the results, social influences effectively impact consumers' perceptions of COVID-19 as they relate to shopping. Moreover, initially, consumers' views of COVID-19 were proposed to establish a negative influence on their intent of using m-commerce. However, this hypothesis is rejected in the context of this model, due to an inconsistent result. Nonetheless, more studies are required to further explain this potential relationship.

### *6.2. Managerial Implications*

Due to technological advancements, widespread usage of mobile communication devices, and changes in customer behavior, m-commerce has gained prominence in recent years, especially compared to online sales and/or e-commerce. During the COVID-19 lockdowns and restrictions characterized by confinement and insecurities of health risks, consumers have largely adopted and relied on online orders directly from e-shops or through m-commerce apps. This change in customer behavioral patterns has led marketers to advance their marketing strategies in m-commerce settings, thus modernizing and adapting offers to the new social context. Enhancing customers' experiences on mobile apps is more important now than ever before.

Companies can focus on providing a seamless customer experience, improving customer trust and satisfaction, and generating relevant customer analytics as key strategies to address in the new m-commerce landscape. Most importantly, m-commerce apps provide a basis for improving customer engagement, increasing sales, allowing higher customer response rates, and generating higher levels of customer loyalty. In m-commerce, retailers can engage consumers through apps by push notifications, which often enable a fast response. In congruence with current findings, vendors should focus on developing engaging and entertaining app content, supplemented by push notifications. To boost m-shopping customer engagement, content personalization may represent a proper objective for any vendor. Even before the COVID-19 pandemic, personalization started to surge in digital marketing practices. From an elementary marketing perspective, organizations should rely on push notifications in the form of m-coupons to intensify customers' enjoyment level through app use (hedonic motivation), thus increasing their performance expectancy while using the app.

From a more complex marketing perspective, retailers and online vendors should focus on gathering consumer data and using new customer datapoints in developing and implementing targeted and comprehensive digital marketing strategies. Digital marketing enables a seamless customer experience. Thus, data gathered from m-commerce can be primarily used to enhance modern customer targeting strategies. Furthermore, such data can be examined and utilized in segmenting customers and designing specific services and marketing communication campaigns.

### 6.3. Limitations and Future Research Perspectives

A theoretical limitation of this paper regards the constructs included in the model, which are based on UTAUT2. The proposed model can be extended with additional constructs, for instance, with customer satisfaction and/or loyalty towards m-commerce apps, but also with mobile advertising alert content, which may increase consumers' behavioral intention to use m-commerce. Additionally, as this research offers broad viewpoints on m-commerce apps from multiple product categories, future research can focus on distinct product categories, m-commerce apps, or specific mobile vendors. Moreover, this cross-sectional study reflects a limited dataset gathered from Romanian m-shoppers. Thus, future research is needed to confirm these concepts in various research contexts and circumstances. Lastly, as a result of this study reflecting a cross-sectional design, it cannot detect changes in time of the examined constructs. To this effect, longitudinal research may aid the understanding of changing behavior towards m-commerce, from the perspective of m-shoppers' panels.

As technology continues to progress at a frenetic pace, future studies can also address new advances in artificial intelligence or augmented reality (AR), as well as product recommendations' impacts on adopting m-commerce. In digital commerce settings, AR can bridge the gap between the intangibility of mobile apps and developing a realistic product/brand experience. Thus, there is an increasing requirement to comprehend the impact of AR on consumers' experience in m-commerce. In m-commerce, product recommendations can be enhanced by generating higher levels of engagement from m-shoppers. Future studies can also expand on comparing m-shoppers' behaviors on different emerging versus developed countries, as well as their switching behavior towards relying on m-commerce apps before and during the COVID-19 pandemic and/or during and after the COVID-19 pandemic. The pandemic has dramatically changed traditional shopping behavior, and thus, m-commerce relevance is likely to expand.

**Author Contributions:** Conceptualization, S.V., C.B. and L.A.B.; methodology, S.V.; validation, S.V.; formal analysis, S.V.; investigation, S.V., C.B., and L.A.B.; data curation, S.V.; writing—original draft preparation, S.V., C.B. and L.A.B.; writing—review and editing, S.V., C.B., L.A.B. and D.-C.D.; visualization, S.V. and D.-C.D.; supervision, L.A.B. and D.-C.D.; funding acquisition, D.-C.D. All authors have read and agreed to the published version of the manuscript.

**Acknowledgments:** This work was supported by a grant of the Romanian Ministry of Education and Research, CNCS - UEFISCDI, project number PN-III-P1-1.1-TE-2019-1356, within PNCDI III.

**Conflicts of Interest:** The authors declare no conflict of interest.

## References

1. WHO. Coronavirus Disease (COVID-19) Dashboard. Available online: <https://covid19.who.int/> (accessed on 27 October 2021).
2. WHO. Coronavirus Disease (COVID-19) Advice for the Public. Available online: <https://www.who.int/emergencies/diseases/novel-coronavirus-2019/advice-for-public>. (accessed on 27 October 2021).
3. Ahmed, I.; Ahmad, M.; Jeon, G. Social distance monitoring framework using deep learning architecture to control infection transmission of COVID-19 pandemic. *Sustain. Cities Soc.* **2021**, *69*, 102777. [[CrossRef](#)] [[PubMed](#)]
4. World Trade Organization (WTO). *E-Commerce, Trade and the COVID-19 Pandemic*; World Trade Organization: Geneva, Switzerland, 2020; Volume 5. [[CrossRef](#)]
5. Eger, L.; Komarkova, L.; Egerova, D.; Micik, M. The effect of COVID-19 on consumer shopping behaviour: Generational cohort perspective. *J. Retail. Consum. Serv.* **2021**, *61*, 102542. [[CrossRef](#)]
6. Gao, X.; Shi, X.; Guo, H.; Liu, Y. To buy or not buy food online: The impact of the COVID-19 epidemic on the adoption of e-commerce in China. *PLoS ONE* **2020**, *15*, e0237900. [[CrossRef](#)] [[PubMed](#)]
7. Accenture. How will COVID-19 change the Consumer? Available online: <https://www.accenture.com/za-en/insights/retail/how-will-covid-19-change-consumer> (accessed on 11 December 2021).
8. McKinsey & Company. How COVID-19 is Changing Consumer Behavior—Now and Forever? Available online: <https://www.mckinsey.com/~{} /media/mckinsey/industries/retail/our%20insights/how%20covid%2019%20is%20changing%20consumer%20behavior%20now%20and%20forever/how-covid-19-is-changing-consumer-behaviornow-and-forever.pdf> (accessed on 11 December 2021).

9. GlobalWebIndex. Commerce Flagship Report 2020. Available online: <https://www.gwi.com/reports/commerce-2020> (accessed on 1 November 2021).
10. Gu, S.; Slusarczyk, B.; Hajizada, S.; Kovalyova, I.; Sakhbieva, A. Impact of the COVID-19 Pandemic on Online Consumer Purchasing Behavior. *J. Theor. Appl. Electron. Commer. Res.* **2021**, *16*, 2263–2281. [[CrossRef](#)]
11. Laato, S.; Islam, A.K.M.N.; Farooq, A.; Dhir, A. Unusual purchasing behavior during the early stages of the COVID-19 pandemic: The stimulus-organism-response approach. *J. Retail. Cons. Serv.* **2020**, *57*, 102224. [[CrossRef](#)]
12. Chopdar, P.K.; Paul, J.; Prodanova, J. Mobile shoppers' response to Covid-19 phobia, pessimism and smartphone addiction: Does social influence matter? *Technol. Forecast. Soc. Change* **2022**, *174*, 121249. [[CrossRef](#)]
13. Hanif, M.S.; Wang, M.; Mumtaz, M.U.; Ahmed, Z.; Zaki, W. What attracts me or prevents me from mobile shopping? An adapted UTAUT2 model empirical research on behavioral intentions of aspirant young consumers in Pakistan. *Asia Pac. J. Mark. Logist.* **2022**, *34*, 1031–1059. [[CrossRef](#)]
14. Chimborazo-Azogue, L.-E.; Frassetto, M.; Molla-Descals, A.; Miquel-Romero, M.-J. Understanding Mobile Showrooming Based on a Technology Acceptance and Use Model. *Sustainability* **2021**, *13*, 7288. [[CrossRef](#)]
15. Datareportal. Digital 2021: Romania. Available online: <https://datareportal.com/reports/digital-2021-romania> (accessed on 20 March 2022).
16. Venkatesh, V.; Thong, J.Y.L.; Xu, X. Consumer acceptance and use of information technology: Extending the unified theory of acceptance and use of technology. *MIS Q.* **2012**, *36*, 157–178. [[CrossRef](#)]
17. Baptista, G.; Oliveira, T. Understanding mobile banking: The unified theory of acceptance and use of technology combined with cultural moderators. *Comput. Hum. Behav.* **2015**, *50*, 418–430. [[CrossRef](#)]
18. Liébana-Cabanillas, F.; Singh, N.; Kalinic, Z.; Carvajal-Trujillo, E. Examining the determinants of continuance intention to use and the moderating effect of the gender and age of users of NFC mobile payments: A multi-analytical approach. *Inf. Technol. Manag.* **2021**, *22*, 133–161. [[CrossRef](#)]
19. Liébana-Cabanillas, F.; Japutra, A.; Molinillo, S.; Singh, N.; Sinha, N. Assessment of mobile technology use in the emerging market: Analyzing intention to use m-payment services in India. *Telecom. Policy.* **2020**, *44*, 102009. [[CrossRef](#)]
20. Vărzaru, A.A.; Bocean, C.G.; Rotea, C.C.; Budică-Iacob, A.-F. Assessing Antecedents of Behavioral Intention to Use Mobile Technologies in E-Commerce. *Electronics* **2021**, *10*, 2231. [[CrossRef](#)]
21. Zhao, Y.; Bacao, F. What factors determining customer continuingly using food delivery apps during 2019 novel coronavirus pandemic period. *Int. J. Hospit. Manag.* **2020**, *91*, 102683. [[CrossRef](#)]
22. Venkatesh, V.; Morris, M.G.; Davis, G.B.; Davis, F.D. User acceptance of information technology: Toward a unified view. *MIS Q.* **2003**, *27*, 425–478. [[CrossRef](#)]
23. Alyoussef, I.Y. Factors Influencing Students' Acceptance of M-Learning in Higher Education: An Application and Extension of the UTAUT Model. *Electronics* **2021**, *10*, 3171. [[CrossRef](#)]
24. Dakduk, S.; Santalla-Banderali, Z.; Siqueira, J.R. Acceptance of mobile commerce in low-income consumers: Evidence from an emerging economy. *Heliyon* **2020**, *6*, e05451. [[CrossRef](#)]
25. Shaw, N.; Sergueeva, K. The non-monetary benefits of mobile commerce: Extending UTAUT2 with perceived value. *Internat. J. Info. Manag.* **2019**, *45*, 44–55. [[CrossRef](#)]
26. Alalwan, A.A. Mobile food ordering apps: An empirical study of the factors affecting customer e-satisfaction and continued intention to reuse. *Int. J. Commun. Inf. Technol.* **2020**, *50*, 28–44. [[CrossRef](#)]
27. Davis, F.D. Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS Q.* **1989**, *13*, 319–340. [[CrossRef](#)]
28. Moore, G.C.; Benbasat, I. Development of an instrument to measure the perceptions of adopting an information technological innovation. *Inf. Syst. Res.* **1991**, *2*, 192–222. [[CrossRef](#)]
29. Tam, C.; Santos, D.; Oliveira, T. Exploring the influential factors of continuance intention to use mobile apps: Extending the expectation confirmation model. *Inf. Syst. Front.* **2020**, *22*, 243–257. [[CrossRef](#)]
30. Fishbein, M.; Ajzen, I. *Belief, Attitude, Intention, and Behavior: An Introduction to Theory and Research*; Addison-Wesley: Boston, MA, USA, 1975.
31. Dwivedi, Y.K.; Rana, N.P.; Jeyaraj, A.; Clement, M.; Williams, M.D. Re-examining the unified theory of acceptance and use of technology (UTAUT): Towards a revised theoretical model. *Inf. Syst. Front.* **2019**, *21*, 719–734. [[CrossRef](#)]
32. Sułkowski, Ł.; Aczorowska-Spychalska, D. Determinants of the adoption of AI wearables—Practical implications for marketing. *Hum. Technol.* **2021**, *17*, 294–320. [[CrossRef](#)]
33. Moroşan, C.; DeFranco, A. It's about time: Revisiting UTAUT2 to examine consumers' intentions to use NFC mobile payments in hotels. *Int. J. Hospit. Manag.* **2016**, *53*, 17–29. [[CrossRef](#)]
34. Farah, M.F.; Hasni, M.J.S.; Abbas, A.K. Mobile-banking adoption: Empirical evidence from the banking sector in Pakistan. *Int. J. Bank Mark.* **2018**, *36*, 1386–1413. [[CrossRef](#)]
35. Jung, J.H.; Kwon, E.; Kim, D.H. Mobile payment service usage: U.S. consumers' motivations and intentions. *Comput. Hum. Behav. Rep.* **2020**, *1*, 100008. [[CrossRef](#)]
36. Tan, G.W.-H.; Ooi, K.-B. Gender and age: Do they really moderate mobile tourism shopping behavior? *Telemat. Inform.* **2018**, *35*, 1617–1642. [[CrossRef](#)]

37. Gupta, A.; Dogra, N.; George, B. What determines tourist adoption of smartphone apps? An analysis based on the UTAUT-2 framework. *J. Hosp. Tour. Technol.* **2018**, *9*, 50–64. [[CrossRef](#)]
38. Wang, X.; Goh, D.H.L.; Lim, E.P. Understanding Continuance Intention toward Crowdsourcing Games: A Longitudinal Investigation. *Int. J. Hum. Comp. Interact.* **2020**, *36*, 1168–1177. [[CrossRef](#)]
39. Khalilzadeh, J.; Ozturk, A.B.; Bilgihan, A. Security-related factors in extended UTAUT model for NFC based mobile payment in the restaurant industry. *Comput. Hum. Behav.* **2017**, *70*, 460–474. [[CrossRef](#)]
40. Schmitz, A.; Díaz-Martín, A.M.; Guillén, M.J.Y. Modifying UTAUT2 for a cross-country comparison of telemedicine adoption. *Comput. Hum. Behav.* **2022**, 107183. [[CrossRef](#)] [[PubMed](#)]
41. Wu, P.; Zhang, R.; Zhu, X.; Liu, M. Factors Influencing Continued Usage Behavior on Mobile Health Applications. *Healthcare* **2022**, *10*, 208. [[CrossRef](#)] [[PubMed](#)]
42. Damberg, S. Predicting future use intention of fitness apps among fitness app users in the United Kingdom: The role of health consciousness. *Int. J. Sports Mark. Spons.* **2022**, *23*, 369–384. [[CrossRef](#)]
43. Medeiros, M.; Ozturk, A.; Hancer, M.; Weinland, J.; Okumus, B. Understanding travel tracking mobile application usage: An integration of self determination theory and UTAUT2. *Tour. Manag. Perspect.* **2022**, *42*, 100949. [[CrossRef](#)]
44. Rauscher, M.; Humpe, A. Traveling the Past: Raising Awareness of Cultural Heritage through Virtual Reality. *J. Promot. Manag.* **2022**, *28*, 128–143. [[CrossRef](#)]
45. Curtale, R.; Liao, F.; Waerden, P.V.D. User acceptance of electric car-sharing services: The case of the Netherlands. *Transp. Res. A Policy Pract.* **2021**, *149*, 266–282. [[CrossRef](#)]
46. Gansser, O.A.; Reich, C.S. A new acceptance model for artificial intelligence with extensions to UTAUT2: An empirical study in three segments of application. *Technol. Soc.* **2021**, *65*, 101535. [[CrossRef](#)]
47. Min, Q.; Ji, S.; Qu, G. Mobile commerce user acceptance study in China: A revised UTAUT model. *Tsinghua Sci. Technol.* **2008**, *13*, 257–264. [[CrossRef](#)]
48. Chopdar, P.K.; Sivakumar, V.J. Understanding continuance usage of mobile shopping applications in India: The role of espoused cultural values and perceived risk. *Behav. Inf. Technol.* **2018**, *38*, 42–64. [[CrossRef](#)]
49. García-Milon, A.; Olarte-Pascual, C.; Juaneda-Ayensa, E. Assessing the moderating effect of COVID-19 on intention to use smartphones on the tourist shopping journey. *Tour. Manag.* **2021**, *87*, 104361. [[CrossRef](#)]
50. Zanetta, L.D.A.; Hakim, M.P.; Gastaldi, G.B.; Seabra, L.M.A.J.; Rolim, P.M.; Nascimento, L.G.P.; Medeiros, C.O.; Cunha, D.T.D. The use of food delivery apps during the COVID-19 pandemic in Brazil: The role of solidarity, perceived risk, and regional aspects. *Food Res. Int.* **2021**, *149*, 110671. [[CrossRef](#)] [[PubMed](#)]
51. Chotigo, J.; Kadono, Y. Comparative Analysis of Key Factors Encouraging Food Delivery App Adoption Before and During the COVID-19 Pandemic in Thailand. *Sustainability* **2021**, *13*, 4088. [[CrossRef](#)]
52. Ly, H.T.N.; Khuong, N.V.; Son, T.H. Determinants Affect Mobile Wallet Continuous Usage in Covid 19 Pandemic: Evidence From Vietnam. *Cogent Bus. Manag.* **2022**, *9*, 2041792. [[CrossRef](#)]
53. Bailey, A.A.; Bonifield, C.M.; Arias, A.; Villegas, J. Mobile payment adoption in Latin America. *J. Serv. Mark.* **2022**. ahead-of-print. [[CrossRef](#)]
54. Chen, C.C.B.; Chen, H.; Wang, Y.C. Cash, credit card, or mobile? Examining customer payment preferences at chain restaurants in Taiwan. *J. Foodserv. Bus. Res.* **2022**, *25*, 148–167. [[CrossRef](#)]
55. Statista. Global Digital Population as of January 2021. Available online: <https://www.statista.com/statistics/617136/digital-population-worldwide/> (accessed on 1 March 2022).
56. Statista. Number of Smartphone Users from 2016 to 2021. Available online: <https://www.statista.com/statistics/330695/number-of-smartphone-users-worldwide/> (accessed on 1 March 2022).
57. Comscore. Global State of Mobile. Available online: <https://www.comscore.com/Insights/Presentations-and-Whitepapers/2020/Global-State-of-Mobile> (accessed on 20 March 2022).
58. Lissitsa, S.; Kol, O. Four generational cohorts and hedonic m-shopping: Association between personality traits and purchase intention. *Electron. Commer. Res.* **2019**, *21*, 545–570. [[CrossRef](#)]
59. Dabija, D.C.; Lung, L. Millennials versus Gen Z: Online shopping behaviour in an emerging market. In *Applied Ethics for Entrepreneurial Success: Recommendations for the Developing World, Proceedings of the 2018 Griffiths School of Management Annual Conference on Business, Entrepreneurship and Ethics (GMSAC), Oradea, Romania, 20 September 2019*; Văduva, S.A., Fotea, I.S., Văduva, L.P., Wilt, R., Eds.; Springer International: Cham, Switzerland, 2019; pp. 1–18.
60. Zhang, L.; Zhu, J.; Liu, Q. A meta-analysis of mobile commerce adoption and the moderating effect of culture. *Comput. Hum. Behav.* **2012**, *28*, 1902–1911. [[CrossRef](#)]
61. Statista. Global Mobile Retail Commerce Revenue 2016–2021. Available online: <https://www.statista.com/statistics/806323/mobile-retail-commerce-revenue-worldwide/> (accessed on 1 March 2022).
62. Statista. Mobile Retail Commerce Sales as Percentage of Retail E-Commerce Sales Worldwide from 2016 to 2021. Available online: <https://www.statista.com/statistics/806336/mobile-retail-commerce-share-worldwide/> (accessed on 1 March 2022).
63. AppInventiv. Future of Mobile Commerce: Stats & Trends to Know in 2021–2025. Available online: <https://appinventiv.com/blog/mobile-commerce-trends-infographics/> (accessed on 1 March 2022).
64. Heerde, H.J.V.; Dinner, I.M.; Neslin, S.C. Engaging the unengaged customer: The value of a retailer mobile app. *Int. J. Res. Mark.* **2019**, *36*, 420–438. [[CrossRef](#)]

65. Popa, I.D.; Dabija, D.C.; Grant, D. Exploring Omnichannel Retailing Differences and Preferences among Consumer Generations. In *Applied Ethics for Entrepreneurial Success: Recommendations for the Developing World, Proceedings of the 2018 Griffiths School of Management Annual Conference on Business, Entrepreneurship and Ethics (GMSAC)*; Oradea, Romania, 20 September 2019; Văduva, S.A., Fotea, I.S., Văduva, L.P., Wilt, R., Eds.; Springer International: Cham, Switzerland, 2019; pp. 129–146. [\[CrossRef\]](#)
66. Andronie, M.; Lăzăroiu, G.; Ștefănescu, R.; Ionescu, L.; Cocoșatu, M. Neuromanagement decision-making and cognitive algorithmic processes in the technological adoption of mobile commerce apps. *Oecon. Copern.* **2021**, *12*, 863–888. [\[CrossRef\]](#)
67. Kliestik, T.; Zvarikova, K.; Lăzăroiu, G. Data-driven machine learning and neural network algorithms in the retailing environment: Consumer engagement, experience, and purchase behaviors. *Econ. Manag. Financ. Mark.* **2022**, *17*, 57–69. [\[CrossRef\]](#)
68. Hopkins, E. Machine learning tools, algorithms, and techniques in retail business operations: Consumer perceptions, expectations, and habits. *J. Self Gov. Manag. Econ.* **2022**, *10*, 43–55. [\[CrossRef\]](#)
69. Nica, E.; Sabie, O.-M.; Mascu, S.; Lutan (Petre), A.G. Artificial intelligence decision-making in shopping patterns: Consumer values, cognition, and attitudes. *Econ. Manag. Financ. Mark.* **2022**, *17*, 31–43. [\[CrossRef\]](#)
70. Liu, H.; Lobschat, L.; Verhoef, P.C.; Zhao, H. App adoption: The effect on purchasing of customers who have used a mobile website previously. *J. Interact. Mark.* **2019**, *47*, 16–23. [\[CrossRef\]](#)
71. Grewal, D.; Bart, Y.; Spann, M.; Zubcsek, P.P. Mobile advertising: A framework and research agenda. *J. Interact. Mark.* **2016**, *34*, 3–14. [\[CrossRef\]](#)
72. Muangmee, C.; Kot, S.; Meekawekunchorn, N.; Kassakorn, N.; Khalid, B. Factors Determining the Behavioral Intention of Using Food Delivery Apps during COVID-19 Pandemics. *J. Theor. Appl. Electron. Commer. Res.* **2021**, *16*, 1297–1310. [\[CrossRef\]](#)
73. Elvandari, C.D.R.; Sukartiko, A.C.; Nugrahini, A.D. Identification of technical requirement for improving quality of local online food delivery service in Yogyakarta. *J. Ind. Inf. Technol. Agric.* **2017**, *1*, 1–7. [\[CrossRef\]](#)
74. Ajzen, I. The theory of planned behavior. *Organ. Behav. Hum. Decis. Process* **1991**, *50*, 179–211. [\[CrossRef\]](#)
75. Lu, J.; Yu, C.; Liu, C.; Wei, J. Comparison of mobile shopping continuance intention between China and USA from an espoused cultural perspective. *Comput. Hum. Behav.* **2017**, *75*, 130–146. [\[CrossRef\]](#)
76. Sim, J.J.; Loh, S.H.; Wong, K.L.; Choong, C.K. Do We Need Trust Transfer Mechanisms? An M-Commerce Adoption Perspective. *J. Theor. Appl. Electron. Commer. Res.* **2021**, *16*, 2241–2262. [\[CrossRef\]](#)
77. Xie, J.; Ye, L.; Huang, W.; Ye, M. Understanding FinTech Platform Adoption: Impacts of Perceived Value and Perceived Risk. *J. Theor. Appl. Electron. Commer. Res.* **2021**, *16*, 1893–1911. [\[CrossRef\]](#)
78. Sarkar, S.; Chauhan, S.; Khare, A. A meta-analysis of antecedents and consequences of trust in mobile commerce. *Int. J. Inf. Manag.* **2020**, *50*, 286–301. [\[CrossRef\]](#)
79. Tak, P.; Panwar, S. Using UTAUT 2 model to predict mobile app based shopping: Evidences from India. *J. Ind. Bus. Res.* **2017**, *9*, 248–264. [\[CrossRef\]](#)
80. Brown, S.A.; Venkatesh, V. A Model of Adoption of Technology in the Household: A Baseline Model Test and Extension Incorporating Household Life Cycle. *MIS Q* **2005**, *29*, 399–426. [\[CrossRef\]](#)
81. Pavlou, P.A. Consumer acceptance of electronic commerce: Integrating trust and risk with the technology acceptance model. *Int. J. Electron. Commer.* **2014**, *7*, 101–134. [\[CrossRef\]](#)
82. Sirdeshmukh, D.; Singh, J.; Sabol, B. Consumer trust, value, and loyalty in relational exchange. *J. Mark.* **2002**, *66*, 15–37. [\[CrossRef\]](#)
83. Morgan, R.M.; Hunt, S.D. The commitment-trust theory of relationship marketing. *J. Mark.* **1994**, *58*, 20–38. [\[CrossRef\]](#)
84. McKnight, D.H.; Choudhury, V.; Kacmar, C. Developing and validating trust measures for e-commerce: An integrative typology. *Inf. Syst. Res.* **2002**, *13*, 334–359. [\[CrossRef\]](#)
85. Hung, M.C.; Yang, S.T.; Hsieh, T.C. An examination of the determinants of mobile shopping continuance. *Int. J. Electron. Bus. Manag.* **2012**, *10*, 29–37.
86. Zhou, T. An empirical examination of continuance intention of mobile payment services. *Decis. Support Syst.* **2013**, *54*, 1085–1091. [\[CrossRef\]](#)
87. Gao, L.; Waechter, K.A.; Bai, X. Understanding consumers' continuance intention towards mobile purchase: A theoretical framework and empirical study—A case of China. *Comput. Hum. Behav.* **2015**, *53*, 249–262. [\[CrossRef\]](#)
88. Pop, R.-A.; Săplăcan, Z.; Dabija, D.-C.; Alt, M.-A. The impact of social media influencers on travel decisions: The role of trust in consumer decision journey. *Curr. Issues Tour.* **2022**, *25*, 823–843. [\[CrossRef\]](#)
89. Vătămănescu, E.M.; Dabija, D.C.; Gazzola, P.; Cegarra-Navarro, J.G.; Buzzi, T. Before and after the outbreak of COVID-19: Linking fashion companies' corporate social responsibility approach to consumers' demand for sustainable products. *J. Clean. Prod.* **2021**, *321*, 128945. [\[CrossRef\]](#)
90. Pop, R.A.; Dabija, D.C.; Pelau, C. Dinu, V. Usage Intentions, Attitudes, and Behaviours towards Energy-Efficient Applications during the COVID-19 Pandemic. *J. Bus. Econ. Manag.* **2022**. (forthcoming).
91. Al-Hattami, H.M. Determinants of intention to continue usage of online shopping under a pandemic: COVID-19. *Cogent Bus. Manag.* **2021**, *8*, 1936368. [\[CrossRef\]](#)
92. Drouin, M.; McDaniel, B.T.; Pater, J.; Toscos, T. How parents and their children used social media and technology at the beginning of the COVID-19 pandemic and associations with anxiety. *Cyberpsychol. Behav. Soc. Netw.* **2020**, *23*, 727–736. [\[CrossRef\]](#)
93. Dabija, D.-C.; Bejan, B.M.; Tipi, N. Generation X versus Millennials communication behaviour on social media when purchasing food versus tourist services. *E M Ekon. A Manag.* **2018**, *21*, 191–205. [\[CrossRef\]](#)

94. Meghisan-Toma, G.-M.; Puiu, S.; Florea, N.M.; Meghisan, F.; Doran, D. Generation Z' Young Adults and M-Commerce Use in Romania. *J. Theor. Appl. Electron. Commer. Res.* **2021**, *16*, 1458–1471. [CrossRef]
95. Dabija, D.C.; Băbuț, R. Enhancing Apparel Store Patronage through Retailers' Attributes and Sustainability. A Generational Approach. *Sustainability* **2019**, *11*, 4532. [CrossRef]
96. Hew, J.J.; Badaruddin, M.N.B.A.; Moorthy, M.K. Crafting a smartphone repurchase decision making process: Do brand attachment and gender matter? *Telemat. Inform.* **2017**, *34*, 34–56. [CrossRef]
97. Datelazi. Daily Statistics on COVID-19 Evolution in Romania. Available online: <https://datelazi.ro/> (accessed on 20 March 2022).
98. Statista. Most Popular Mobile Applications Accessed in Romania in 2021, by type. Available online: <https://www.statista.com/statistics/1272847/romania-most-popular-mobile-apps-by-type/> (accessed on 20 March 2022).
99. GPEC. Raport GPeC E-Commerce România 2020: Cumpărături online de 5,6 miliarde de euro, în creștere cu 30% față de 2019. Available online: <https://www.gpec.ro/blog/raport-gpec-e-commerce-romania-2020-cumparaturi-online-de-56-miliarde-de-euro-in-crestere-cu-30-fata-de-2019> (accessed on 1 March 2022).
100. Statista. Average Value of Global Online Shopping Orders as of 3rd Quarter 2020, by Device. Available online: <https://www.statista.com/statistics/239247/global-online-shopping-order-values-by-device/> (accessed on 20 March 2022).
101. Zenker, S.; Braun, E.; Gyimothy, S. Too Afraid to Travel? Development of a Pandemic (COVID-19) Anxiety Travel Scale (PATS). *Tour. Manag.* **2021**, *84*, 104286. [CrossRef]
102. Cochran, W.G. *Sampling Techniques*, 3rd ed.; Wiley: New York, NY, USA, 1977.
103. Burns, A.C.; Veeck, A. *Marketing Research*, 9th ed.; Pearson Education: New York, NY, USA, 2020.
104. Hair, J.F.; Black, W.C.; Babin, B.J.; Anderson, R.E.; Tatham, R.L. *Multivariate Data Analysis*, 7th ed.; Prentice Hall: Upper Saddle River, NJ, USA, 2010.
105. Nunnally, J.C.; Bernstein, I.H. *Psychometric Theory*, 3rd ed.; McGraw-Hill: New York, NY, USA, 1994.
106. Collier, J.E. *Applied Structural Equation Modeling Using AMOS*; Routledge: London, UK, 2020.
107. Malhotra, N. *Marketing Research: An Applied Orientation*, 7th ed.; Pearson Education: Harlow, UK, 2020.
108. Kline, R.B. *Principles and Practice of Structural Equation Modeling*, 4th ed.; Guilford Press: New York, NY, USA, 2015.
109. Marinkoviã, V.; Đorđeviã, A.; Kaliniã, Z. The moderating effects of gender on customer satisfaction and continuance intention in mobile commerce: A UTAUT-based perspective. *Technol. Anal. Strateg. Manag.* **2019**, *32*, 306–318. [CrossRef]
110. Anderson, J.C.; Gerbing, D.W. Structural equation modeling in practice: A review and recommended two-step approach. *Psychol. Bull.* **1988**, *103*, 411–423. [CrossRef]
111. Hu, L.; Bentler, P.M. Cutoff criteria for fit indexes in covariance structure analysis: Conventional criteria versus new alternatives. *Struct. Equ. Modeling* **1999**, *6*, 1–55. [CrossRef]
112. Cronbach, L.J. *Essentials of Psychological Testing*; Harper and Row: New York, NY, USA, 1970.
113. Bagozzi, R.P.; Yi, Y. On the evaluation of structural equation models. *J. Acad. Mark. Sci.* **1988**, *16*, 74–94. [CrossRef]
114. Fornell, C.; Larcker, D.F. Evaluating Structural Equation Models with Unobservable Variables and Measurement Error. *J. Mark. Res.* **1981**, *18*, 39–50. [CrossRef]
115. Podsakoff, P.M.; MacKenzie, S.B.; Lee, J.Y.; Podsakoff, N.P. Common method biases in behavioral research: A critical review of the literature and recommended remedies. *J. Appl. Psychol.* **2003**, *88*, 879–903. [CrossRef]
116. MacKenzie, S.B.; Podsakoff, P.M. Common Method Bias in Marketing: Causes, Mechanisms, and Procedural Remedies. *J. Retail.* **2012**, *88*, 542–555. [CrossRef]
117. Gull, H.; Saeed, S.; Iqbal, S.Z.; Bamarouf, Y.A.; Alqahtani, M.A.; Alabbad, D.A.; Saqib, M.; Qahtani, S.H.A.; Alamer, A. An empirical study of mobile commerce and customers security perception in Saudi Arabia. *Electronics* **2022**, *11*, 293. [CrossRef]
118. Meilatinova, N. Social commerce: Factors affecting customer repurchase and word-of-mouth intentions. *Int. J. Inf. Manag.* **2021**, *57*, 102300. [CrossRef]
119. Bozic, B. Consumer trust repair: A critical literature review. *Eur. Manag. J.* **2017**, *35*, 538–547. [CrossRef]
120. Sheth, J. Impact of Covid-19 on consumer behavior: Will the old habits return or die? *J. Bus. Res.* **2020**, *117*, 280–283. [CrossRef] [PubMed]
121. Rogers, K.; Pérez-Moiño, J.; Leon, H.; Poncela, A. The Fast Track to Digital Marketing Maturity—A BCG Report. Available online: <https://www.bcg.com/en-hu/publications/2021/the-fast-track-to-digital-marketing-maturity> (accessed on 1 March 2022).
122. Kliestik, T.; Kovalova, E.; Lăzăroiu, G. Cognitive decision-making algorithms in data-driven retail intelligence: Consumer sentiments, choices, and shopping behaviors. *J. Self-Gov. Manag. Econ.* **2022**, *10*, 30–42. [CrossRef]
123. Vinerean, S.; Opreana, A. Measuring Customer Engagement in Social Media Marketing: A Higher-Order Model. *J. Theor. Appl. Electron. Commer. Res.* **2021**, *16*, 16070145. [CrossRef]
124. Jurek, P.; Olech, M.; Brycz, H. Perceived technostress while learning a new mobile technology: Do individual differences and the way technology is presented matter? *Hum. Technol.* **2021**, *17*, 197–212. [CrossRef]
125. Puiu, S.; Demyen, S.; Tănase, A.-C.; Vărzaru, A.A.; Bocean, C.G. Assessing the Adoption of Mobile Technology for Commerce by Generation Z. *Electronics* **2022**, *11*, 866. [CrossRef]
126. McLean, G.; Wilson, A. Shopping in the digital world: Examining customer engagement through augmented reality mobile applications. *Comput. Hum. Behav.* **2019**, *101*, 210–224. [CrossRef]