Online shopping adoption during COVID-19 and social isolation: Extending the UTAUT model with herd behavior

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A B S T R A C T

The COVID-19 pandemic has created a new reality for consumers all around the globe. To cope, users of digital technologies have faced the necessity of adopting and using specific technologies practically overnight. They are doing this under the condition of social isolation, all while facing the fear of catching the disease. The purpose of the paper is to study the way unexpected circumstances cause disruptions in existing theoretical models and their implications for the post-COVID-19 era. Therefore, the paper examines the unified theory of acceptance and use of technology (UTAUT) model under the circumstances of the COVID-19 pandemic and social isolation, and it identifies herd behavior as a possible new mechanism affecting behavioral intention under these unique decision-making circumstances. Behavioral intention toward online shopping was analyzed using data from 420 individuals aged 60 and older who present an increasingly important potential market for electronic commerce and who are particularly affected by COVID-19. The main results show that performance expectancy still has the most important influence on behavioral intention, whereas the impact of social influence was not supported under these conditions. Rather, herd behavior was identified as particularly influential for behavioral intention. Based on the study results, the option to reconsider the social influence factor in the UTAUT model and its possible complementary mechanisms are discussed.

1. Introduction

Throughout history, disease outbreaks and pandemics have shaped politics, altered societies, affected personal relationships and changed world paradigms (Snowden, 2019). The coronavirus (COVID-19) pandemic has already heavily influenced the way we live. As governments try to minimize the spread of the pandemic, several lockdown restrictions have been imposed that directly affect the way people and businesses operate. The response to the pandemic has led to overnight changes to the daily lives of people and daily operations of businesses that would have otherwise occurred more slowly or not at all.

One of the sudden changes imposed by lockdowns is a higher use of various digital technologies such as internet-based services for communicating, interacting and working from home (De' et al., 2020). Consumers have been more inclined to change their preferences and behavioral patterns such as shifting to online shopping and alternative pickup and delivery options (Dey et al., 2020). The accelerated adoption of digital technologies has also spread among organizations, which have reported accelerated digitization of their customer and supply chain interactions by three to four years and of the share of digital or digitally enabled products in their portfolios by seven years (Laberge et al., 2020).

In many cases, users of digital technologies have faced the necessity of adopting and using a specific technology practically overnight to cope with the new reality. Technology adoption has already been an extensive research field based on several theoretical foundations, with the unified theory of acceptance and use of technology (UTAUT) being one of the most widely and commonly used theories in explaining the use and adoption of technologies by individuals in organizational and consumer settings (Dwivedi et al., 2019; Taherdoost, 2018), covering numerous technologies and contexts (Venkatesh et al., 2016) and being been successfully replicated numerous times (Venkatesh, 2021).

However, the emergence of special circumstances due to COVID-19 has created unique conditions where users do not have the time to go through the usual decision-making process of technology adoption, initial use and post-adoptive use phases as defined by Jasperson et al. (2005). Transitioning between various stages happens more rapidly and often under different levels of social isolation, where users do not have

the same access to information resources when making decisions (Raza et al., 2020). Therefore, a question arises about how and to what extent the effects of the existing UTAUT's (Venkatesh et al., 2003, 2012) direct determinants of user acceptance change under these decision-making circumstances. Moreover, it is important to examine whether these unique conditions also result in any new mechanisms affecting behavioral intention and the adoption of technology.

Social contacts between people have diminished during the COVID-19 pandemic either through lockdown restrictions or as a result of the fear of the virus (Korukcu et al., 2021; Soofi et al., 2020). Therefore, in the COVID-19 situation, the subjective norm of potential users of new technologies (Venkatesh et al., 2003) is affected by diminishing the element of social influence by not having the same amount of information available from their close social circles when deciding on whether to adopt a certain technology. On the other hand, sources such as social media and online news are more commonly used, thus making their users more prone to conform to a homogenous standard of behavior (Tankovska, 2021; Watson, 2021). When exposed to the latter, users might be more prone "to conform to a single, homogeneous standard of behavior which is like a type of social norm," an already existing concept (i.e., herd behavior; Bernheim, 1994). In regard to technology adoption, herd behavior is defined as a phenomenon wherein a person follows others when adopting a technology, with a specific focus on discounting one's own information and imitating others (Sun, 2013). The COVID-19 pandemic has impacted potential users' decision-making processes in such a way that they more often rely on information sources beyond their close social circles as well as how the information is obtained and the observations of other people's behavior, instead of depending on firsthand experience. This coincides with the way social influence and herd behavior are distinct from one another (Sun, 2013), and it provides an opportunity to study UTAUT in the context of herd behavior. Herd behavior as a phenomenon has already been suggested to be used in studies related to information management research (Popovič and Trkman, 2016) or as a further line of research in relation to UTAUT (Kim and Hall, 2020).

Even though UTAUT has been studied, applied and extended in various ways (Taherdoost, 2018; Venkatesh et al., 2016), only a few attempts have been made to study the influence of herd behavior on technology adoption (Handarkho and Harjoseputro, 2019; Y. Liu and Yang, 2018), while to our best knowledge no previous research has been conducted connecting UTAUT with herd behavior or has studied it in conditions of social isolation.

Therefore, the purpose of this paper is to examine the existing UTAUT model in the circumstances of the COVID-19 pandemic and to identify possible new mechanisms affecting behavioral intention under the decision-making circumstances caused by social isolation. This can be achieved because the COVID-19 pandemic has created unique conditions where researchers have the opportunity not just to address the peculiarities of technology adoption and use during the pandemic but also advance theories and practice of individuals' technology adoption and use beyond the pandemic (Dey et al., 2020). This study is also in line with previous research recommendations on integrating the baseline UTAUT model with other theories and identifying new context effects (Venkatesh et al., 2016). In addition, the study is in line with the call for future research to examine the way fear influences customer behavior in technology adoption (Naeem and Ozuem, 2021).

To answer the main research question, we analyzed the case of online shopping among individuals aged 60 and older (hereinafter older adults). The reason for choosing older adults is that they are becoming an increasingly important potential market for electronic commerce (Lian and Yen, 2014). They are the fastest growing consumer age group, have a rising share of income compared to other demographic groups, and are reaching retirement age in good health with many active years ahead of them (Baldwin, 2019; Credit Suisse, 2018; Vaughan, 2020). However, this group typically has more difficulties in learning to use and operate internet services, including online shopping, and are doing so at

lower rates than younger users are (Czaja et al., 2006). Furthermore, older adults are much less comfortable with online shopping than younger generations are, while also being more hesitant to use it (Jain and Kulhar, 2019). Online shopping among other age groups was already notably higher before the pandemic situation (Eurostat, 2020). Although the COVID-19 pandemic and several lockdowns with social isolation have influenced younger generations as well, a transition to online shopping did not present a major challenge or huge difference in behavior for them. Older adults thus present a unique opportunity to study the adoption under COVID-19 circumstances, since they are on the one hand reluctant to use online shopping, while on the other, they are often left with no choice other than to use it because of the COVID-19 situation and their higher vulnerability to the risk of severe illness (Hwang et al., 2020). In addition, the selected group is in line with one of the research propositions to examine the technology preferences for vulnerable customers (Dwivedi et al., 2020).

In the next section, we first present the theoretical background, followed by the hypotheses development and a theoretical model in the third section. In the fourth section, we present the methodology we used, followed by the results in the fifth section. In the discussion, we touch upon the contribution to theory, practical implications, limitations, and suggestions for further research.

2. Literature review and hypotheses development

2.1. Unified theory of acceptance and use of technology

UTAUT was initially designed to be applied to research primarily in organizational contexts to explain individuals' technology acceptance and use. UTAUT was developed as an answer to a plethora of various theoretical models on technology acceptance and use through the integration of eight previously established theoretical models that are used to study perception, acceptance, and willingness toward technology adoption (Venkatesh et al., 2003). It includes four core determinants of the intention to use and usage of technology in organizational settings: performance expectancy, effort expectancy, social influence, and facilitating conditions (Venkatesh et al., 2003). It was later expanded and modified (UTAUT2) for use in the consumer context by identifying three new constructs (hedonic motivation, price value, and habit), altering some of the previously established relationships, introducing new relationships, and adjusting the measuring instrument to consumer context use (Venkatesh et al., 2012). UTAUT and UTAUT2 have since been two of the most widely and commonly used technology acceptance and use models (Taherdoost, 2018), covering a wide array of applications, integrations, and extensions, including online shopping (Venkatesh et al., 2016), while also employing numerous other constructs (Dwivedi et al., 2019). Therefore, we consider it theoretically and practically useful as the basis for this research.

The time context dimension of UTAUT specifies three stages of technology acceptance and use: adoption, initial use and post-adoptive use (Jasperson et al., 2005). The decision for the transition between these three stages is based on information from training, trial usage and other secondhand resources (adoption), applying the technology to accomplish their work/life tasks (initial use) and engaging in feature-level use of the technology (post-adoptive use) (Venkatesh et al., 2016). The transition between the stages in normal circumstances takes a certain amount of time. In the COVID-19 situation, these transitions happen more rapidly (Laberge et al., 2020; UNCTAD, 2020) and thus affect the decision-making process of each individual user.

As previously mentioned, UTAUT was expanded with three additional constructs for use in a consumer context. However, because the additional constructs in UTAUT2 often yield inconsistent results, they are often omitted from the research models (Tamilmani et al., 2019). Additional arguments for their exclusion are that older adults find less enjoyment in online shopping (Lian and Yen, 2014), are less comfortable using online shopping (Jain and Kulhar, 2019), and use the internet less

for shopping than younger cohorts do (Czaja et al., 2006). Therefore, we decided to use only the original four constructs from UTAUT, adjusted for consumer context use.

Because COVID-19 has caused major changes and the majority of previous research has focused on the general population, while COVID-19 has affected older adults the most in some circumstances, we develop hypotheses relating to the effects of these four factors on behavioral intention in circumstances for this group that would not normally be exposed because the new normal after COVID-19 might not apply to them (Venkatesh, 2020).

The first core determinant of UTAUT applied to the consumer context is performance expectancy, defined as the degree to which an adopter benefits from using a technology (Venkatesh et al., 2012). Previous research has shown that older adults are more likely to use and accept online technologies if they perceive their usefulness and beneficial effects, such as with health services (Hoque and Sorwar, 2017) or online shopping (Lian and Yen, 2014). The latter effect has been proven to be particularly strong for older adults (Yan et al., 2020); however, the research was conducted in pre-pandemic times. In the pandemic times, this effect could be strengthened even more by the limited access to brick-and-mortar stores because of lockdowns, therefore older adults would benefit even more from the use of online shopping as compared to non-pandemic circumstances. Furthermore, technologies that help users perform quicker and more efficient online shopping experiences, such as remote mobile payments, have also been shown to be positively affected by their performance expectancy (Slade et al., 2015). As expected, the COVID-19 pandemic did not significantly affect this result, as recent research has shown that performance expectancy significantly influences user intention in using online technology under the COVID-19 lockdown conditions (Chayomchai et al., 2020). Since online shopping is one such technology, specifically addressing the nuances of limited access to brick-and-mortar stores, we assume the following hypothesis:

H1a. Performance expectancy will positively influence older adults' behavioral intention to adopt online shopping.

Effort expectancy is defined as the degree of ease associated with individuals' use of technology (Venkatesh et al., 2012). The use of online technologies can be challenging, particularly for older adults. As such, effort expectancy may be one of the key factors of the behavioral intention and use of these technologies. Additionally, the contemporary user interface design for online shopping is moving toward making the shopping experience as easy as possible for users so they are not irritated by it (Hasan, 2016). In some cases, such as health services (Hoque and Sorwar, 2017), effort expectancy has a positive impact on older adults' intention to use an online technology under non-pandemic conditions. However, this is not the case in other instances such as online shopping (Lian and Yen, 2014; Yan et al., 2020). Based on these findings, we hypothesize that effort expectancy has a positive impact in cases where a user's health is on the line, which also happens by visiting brick-and-mortar stores in pandemic times. Additionally, research during the COVID-19 pandemic has identified that effort expectancy is the core determinant significantly influencing users' intention to use online technologies under the COVID-19 lockdown conditions (Chayomchai et al., 2020). Therefore, this study postulates the following hypothesis:

H1b. Effort expectancy will positively influence older adults' behavioral intention to adopt online shopping.

In UTAUT, social influence is defined as the extent to which individuals perceive that people important to them believe they should use a technology (Venkatesh et al., 2012). Previous research on UTAUT has shown the effect of social influence on technology adoption differs significantly between the various sources of influence and the receivers of the influence (Eckhardt et al., 2009). This might be due to the fact that social influence, as defined in the UTAUT construct, combines normative and informative social influences into one component (Workman, 2014). It is therefore important to note that social influence in UTAUT

heavily relies on subjective norm (Venkatesh et al., 2012). It builds upon a notion that individuals are affected by a smaller group of close individuals that has not necessarily adopted the technology yet, even though it is opinionated about it, and can evaluate the potential adopter in relation to the adoption of the technology in question (Sun, 2013). Previous research has shown that social influence under pre-pandemic circumstances positively affects older adults' intention to shop online (Lian and Yen, 2014; Yan et al., 2020). Because social life will continue to be impacted even after the COVID-19 period, it is imperative that we understand these impacts and find ways to manage them effectively (Venkatesh, 2020). However, the specifics of social influence as defined in UTAUT led us to hypothesize that it might address the social effects too narrowly. We further elaborate on this in the next section, where we propose a way to extend UTAUT with herd behavior to address these issues. Therefore, this study proposes the following hypothesis:

H1c. Social influence will positively influence older adults' behavioral intention to adopt online shopping.

Venkatesh et al. (2012) defined facilitating conditions as consumers' perceptions of the resources and support available to perform a behavior. Several previous studies have claimed that facilitating conditions does not have a positive impact on older adults' intention to use online technologies (Chayomchai et al., 2020; Hoque and Sorwar, 2017; Lian and Yen, 2014). However, because digital literacy among older adults is increasing (Oh et al., 2021) with the increased availability of digital resources (Kuoppamäki et al., 2017), the positive effect of facilitating conditions might become prevalent in the future. Yan et al. (2020) already explored this in the non-pandemic context, and their research identified a positive relationship between facilitating conditions and older adults' perceptions, acceptance and willingness toward shopping online. Therefore, this study proposes the following hypothesis:

H1d. Facilitating conditions will positively influence older adults' behavioral intention to adopt online shopping.

2.2. Herd behavior and technology adoption

Herd behavior has been studied extensively in various economic fields such as finance, consumer behavior and organizational decision-making (Burke et al., 2010). It is defined as the rationale behind the decision-making process wherein decision makers use information about what everyone else is doing, even though their private information suggests doing something quite different (Banerjee, 1992). Therefore, herd behavior can be treated as a form of heuristics where individuals base their decisions on conforming to the majority of decision makers in their environment (Antony and Joseph, 2017) by choosing the same actions as the majority around them (Çelen and Kariv, 2004).

In the context of technology adoption, herd behavior describes individuals who follow others when adopting a technology, even when their private information suggests doing something else. This can happen because of two reasons: discounting own information (DOI) by disregarding personal information when making an adoption decision or by imitating others (IMI) by following previous adopters of a specific technology (Sun, 2013). Research has shown that IMI can have a positive effect on behavioral intention when adopting a new technology in the context of sharing-based applications and can even provide strong psychological cues when consumers are hesitant and their willingness to act is unclear (Y. Liu and Yang, 2018). Furthermore, perceived herd behavior has a direct effect on the behavioral intention to adopt a technology when individuals tend to follow the behavior of others' referrals (Handarkho and Harjoseputro, 2019). As one of the behavioral biases, herding bias has also been confirmed as a positive moderator between the behavioral intention of adopting and user behavior (Theerthaana and Manohar, 2021).

As the COVID-19 situation leads to social isolation (De Jong Gierveld et al., 2016), social influence as a subjective norm (i.e., a person's perception that most people who are important to him or her think he or she should or should not perform the behavior in question) will be diminished due to fewer social contacts, and other factors might become detrimental for behavioral intentions. Social influence as defined in UTAUT, draws mainly from social norm, and therefore relies heavily on gathering information from close circles of friends and family who may or may not have adopted the technology (Sun, 2013). It is also based on valuing others' opinions about the use and adoption and the ways others would think about use and adoption of a technology, therefore judging the user or adopter favorably or unfavorably (Sun, 2013). On the other hand, herd behavior uses a much wider array of information sources, depends more on the observations of other people, and follows those who have already adopted the technology (Sun, 2013). Older adults may have even more difficulties with trust and the usage of modern technological devices and services (Yan et al., 2020). Omitting beliefs that only conventional methods, resources and services are appropriate may be an important issue when considering new technology adoption. Therefore, herd behavior can be considered a potential factor influencing the behavioral intention of older adults to adopt a technology, and we propose the following hypotheses, following the two-factor herd model by Sun (2013):

H2. Herd factors on behavioral intention

H2a. Imitating others positively influences older adults' behavioral intention to adopt online shopping.

H2b. Discounting one's own information positively influences older adults' behavioral intention to adopt online shopping.

2.3. Fear of COVID-19

The COVID-19 pandemic has created an unprecedented contemporary situation, including lockdowns that have changed business and social norms in several countries. The fear of catching the disease (COVID-19 fear) has been fueled by health anxiety, the use of traditional and social media and risks for loved ones (Mertens et al., 2020). There is a higher likelihood of catching the disease indoors (Lewis, 2021), with grocery stores being a point of interest due to the relatively high chance of catching an infection (S. Chang et al., 2021). This has led shoppers to contemplate how frequently, if at all, they should go shopping (McKinsey and Company, 2020). However, it is important to note that with the grocery stores remaining open, potential shoppers still had the choice to shop in brick-and-mortar stores or online.

Traditionally, older adults tend to experience more barriers to online shopping adoption when compared to their younger counterparts (Lian and Yen, 2014). The escalation of the pandemic increased the lockdown, quarantine and isolation restrictions and caused individuals to worry and feel anxious about the virus, particularly in the case of older adults (Yıldırım and Güler, 2020). Limited research on COVID-19-related technology, such as contact tracing, has shown that COVID-19 fear has no effect on behavioral intention to use a technology (Walrave et al., 2020). However, this situation has been particularly influential for older adults, who were previously mobile, but voluntarily confined themselves due to the fear of catching COVID-19 (Cheung et al., 2020). Therefore, we hypothesize the following:

H3. COVID-19 fear on behavioral intention

H3a. COVID-19 fear will be positively associated with older adults' behavioral intention to adopt online shopping.

The dependency on information systems and technology has substantially increased during the COVID-19 period (Dey et al., 2020). Technology use is accelerating because it can provide social distance and higher safety (Clipper, 2020). During nonroutine events, as in the case of the pandemic, older adults quickly transition to broader information

worlds, such as broadcast media (Pang et al., 2020). Additionally, because face-to-face communication was abruptly suspended for older adults, they began to rely mostly on social media apps as the only source of information (Pan et al., 2020). Stronger messages in the media may induce more fear and therefore more compliance with the social-distancing and lockdown policies imposed (Mertens et al., 2020); therefore, COVID-19 fear has also been used as a moderating variable (Raza et al., 2020).

Furthermore, herding tends to occur when uncertainty increases (Bouri et al., 2019) or in situations in which there is already a great deal of uncertainty (Walden and Browne, 2009), which is also the case with the COVID-19 situation (Mertens et al., 2020). To reduce uncertainty, individuals make several judgments regarding their and others' behavior, and looking for proper information is claimed to be a primary communicative response to uncertainty (B. F. Liu et al., 2016). Uncertainty particularly increases for older adults, who may have limited access to information due to the fact that their ordinary sources of information (Nelson et al., 2016) are hindered because of the lockdowns. In addition, although older adults may have more difficulties trusting and using modern technological devices and services (Lian and Yen, 2014), they may discount their beliefs due to the danger of COVID-19. To summarize, in the COVID-19 pandemic situation, older adults are becoming more reliant on broader information sources that can induce more fear and uncertainty, which is a strong antecedent for herd behavior. Therefore, we hypothesize the following:

H4. COVID-19 fear on herd factors

H4a. COVID-19 fear will positively influence on imitating others when considering online shopping.

H4b. COVID-19 fear will positively influence users to discount their own information when considering online shopping.

2.4. Conceptual model

Fig. 1 shows the conceptual model of the role of UTAUT factors, herd behavior factors and COVID-19 fear on behavioral intention, as well as the proposed hypotheses.

3. Methodology

3.1. Research instrument

We prepared a paper questionnaire to test our research hypotheses. The questionnaire was composed of several items measuring various UTAUT factors, online shopping behavioral intention, herd behavior factors, COVID-19 fear and other items not relevant for this research.

We built the measurement items for the constructs in our hypothesized model based on existing studies. To maintain the validity of measures, we used measurement questions that were already validated in the literature; however, we adapted some measures to our research area, namely online shopping. All variables were measured with a 5-point Likert scale ranging from 1 (*strongly disagree*) to 5 (*strongly agree*). Table 1 presents all constructs together with measurement items, their descriptions and reference sources.

3.2. Data collection and analysis procedure

To address the research question, we analyzed a sample of older adult online shoppers, who are increasingly becoming an important potential market for electronic commerce (Lian and Yen, 2014). We outsourced the data collection to a specialized company in line with recommendations in Schoenherr et al. (2015). Data were collected through dissemination of the questionnaire by a specialized outsourcing company for data collection. We provided the outsourcing company with the complete questionnaire, which was then sent to the population
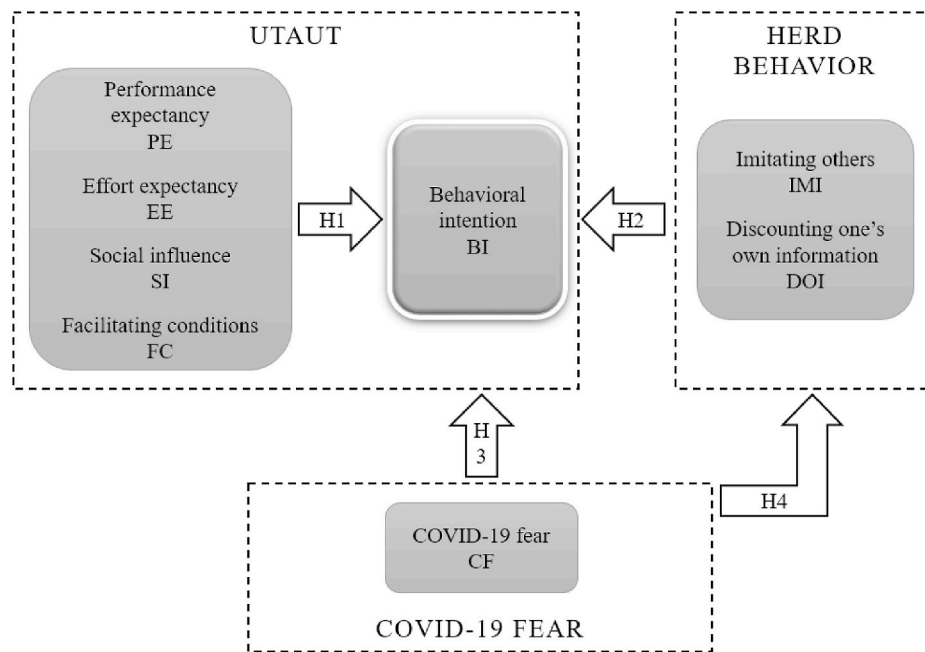
Fig. 1. Conceptual model of older adults' behavioral intention to adopt online shopping.

aged 60 and older.

Data were collected over the course of two weeks in November 2020. Altogether, 420 individuals completed the survey with the necessary data for the analysis. No data were missing in the completed surveys.

In the analysis, we used covariance-based structural equation modelling (SEM) with LISREL 8.80 to examine the hypothesized relationships between the constructs. First, we conducted confirmatory factor analysis (CFA) and evaluated the measurement model together with the convergent and discriminant validity, followed by assessing the structural part of the model and assessing the proposed hypotheses.

4. Results

4.1. Sample characteristics

The sample's demographic characteristics are similar to those of the population aged 60 and older (44.7% males and 55.3% females). Table 2 presents a profile of the respondents with some general demographic data.

4.2. Measurement model assessment

We first conducted a CFA for the model constructs. The model fit indices of measurement model, χ^2 (322) = 760.07, normed χ^2 = 2.36, RMSEA = 0.057, standardized RMR = 0.051, CFI = 0.98, GFI = 0.89, NFI = 0.97, NNFI = 0.98 and RFI = 0.96 are indicating a good fit. Additionally, we analyzed the measurement model by considering the reliability, convergent validity and discriminant validity. Cronbach's α determines the internal consistency reliability of the identified factors. In our model, all scales were internally consistent and reliable, with Cronbach's α values larger than 0.70 (P. Kline, 1999), except for the DOI latent variable, which had a value of 0.615. However, in exploratory studies, values above 0.50 are also considered acceptable (Hair et al., 1998). The values of composite reliability (CR) in our example exceed the suggested value 0.70 (Hair et al., 1998), except for the DOI latent variable. The latter was still greater than 0.6, which is also a proposed threshold value (Bagozzi and Yi, 1988). Average variance extracted (AVE) values ranged from 0.36 to 0.79 and were above the value of 0.50 (Hair et al., 1998), except for the FC and DOI latent variables.

As is evident from Table 3 and Table 4, all standardized loadings were significant at the 0.01 significance level. In addition, standardized loadings exceeded 0.7, except for two items measuring DOI latent variable and two items measuring FC latent variables. Because we used already validated measures, we did not exclude these items from the model. The results shown in Tables 3 and 4 thus indicate that the convergent validity of the measurement model is satisfactory.

We also used Harman's single-factor test to examine the common method bias. In our model, a single factor explained only 34.9% and not the majority of the variance, indicating no common method bias. Finally, we assessed the discriminant validity using the Fornell-Larcker criterion (Fornell and Larcker, 1981), in which the AVE values of the latent variables should be higher than the squared correlation between each pair of latent variables. The results are presented in Table 5.

Based on the presented results, we can confirm that the measurement model has satisfactory reliability, convergent validity and discriminant validity.

4.3. Structural model assessment

The structural model fit was examined using various model fit measures. Because there is no agreement on a single overall model fit index (Hayduk, 1996), Table 6 presents indices that are commonly used with the proposed reference values.

The majority of the presented fit indices imply a good overall model fit, except the *p* value for χ^2 statistics and the standardized root mean square residual (standardized RMR). However, in cases with sample sizes larger than 200, the χ^2 statistic is often significant, even though the model has a good fit (Hair et al., 1998). Thus, χ^2 statistics are used more often in comparison with degrees of freedom to test model fit (Diamantopoulos and Siguaw, 2000). In our model, the χ^2/df is 2.99, which is lower than the guideline of 3.0 (Gefen et al., 2000), but some less restrictive rules suggest the ratio should be lower than 5.00 (Wheaton et al., 1977). Likewise, GFI is also questionable in cases with larger samples (Sharma et al., 2005), and there is no consensus on GFI levels, although higher values are desirable and indicate a better fit (Hair et al., 1998). GFI in our model was 0.856, which is higher than the minimum threshold of 0.80 (Taylor and Todd, 1995); however, some more restrictive rules suggest a threshold of 0.90.

Table 1

Measurement items and their sources.

Construct		Corresponding item and its description	Items Sources
Performance expectancy (PE)	pe1	I find online shopping useful in my daily life.	Venkatesh et al. (2012)
	pe2	Using online shopping helps me buy things more quickly.	
	pe3	Online shopping allows me to buy things more efficiently.	
Effort expectancy (EE)	ee1	Learning how to shop online is easy for me.	
	ee2	When I interact with online shopping websites, they are always clear and easy to understand	
	ee3	I feel that online shopping is easy to use.	
	ee4	It is easy for me to become skillful at using online shopping.	
Social influence (SI)	si1	People who are important to me think that I should shop online.	
	si2	People who influence my behavior think that I should shop online.	
	si3	People whose opinions I value prefer that I shop online.	
Facilitating conditions (FC)	fc1	I have the necessary resources (computer, internet access …) for online shopping.	
	fc2	I have the skill and knowledge for online shopping.	
	fc3	The experience of using online shopping is similar to using other internet services.	
	fc4	When I have problems shopping online, someone can help me solve them.	
Behavioral intention (BI)	bi1	I intend to use online shopping in the future.	
	bi2	I will always try to use online shopping in my daily life.	
	bi3	I plan to continue to use online shopping frequently.	
Imitating others (IMI)	imi1	It seems that online shopping is the dominant type of shopping; therefore, I would like to use it as well.	Sun (2013)
	imi2	I follow others in accepting online shopping.	
	imi3	I would choose to accept online shopping because many other people are already using it.	
Discounting one's own information (DOI)	doi1	My acceptance of online shopping would not reflect my own preferences for shopping.	
	doi2	If I were to use online shopping, I would not be making the decision based on my own research and information.	
	doi3	If I did not know that a lot of people have already accepted online shopping, I might choose regular shopping instead.	
COVID-19 fear (CF)	cf1	My hands become clammy when I think about COVID-19.	Ahorsu et al. (2020)
	cf2	I am afraid of losing my life because of COVID-19.	
	cf3	When watching news and stories about COVID-19, I become nervous or anxious.	
	cf4	I cannot sleep because I'm worrying about getting COVID-19.	
	cf5	My heart races or palpitates when I think about getting COVID-19.	

Table 2

Profile of the respondents.

		Share (%)
Gender	Male	48.1
	Female	51.9
Education	Primary	2.6
	Secondary	56.7
	Undergraduate	30.0
	Graduate	10.7
Type of settlement	Urban settlement	46.4
	Suburban areas	17.4
	Small town or village	29.5
	Scattered houses	6.7
Distance to the nearest grocery store	Less than 300 m	35.5
	300–1 km	34.5
	1–5 km	24.0
	More than 5 km	6.0

Our model's standardized RMR index does not indicate a good model fit because values below 0.08 (Hu and Bentler, 1998) or, in some less restrictive rules, below 0.10 (T. J. B. Kline, 2005) present a good model fit. However, for standardized RMR, the optimal cut-off values vary considerably depending on sample size (Sivo et al., 2006). In contrast, the root mean square error of approximation (RMSEA), which is often considered one of the most popular (Kenny et al., 2015) and informative fit indices (McDonald and Ho, 2002), indicates a good model fit. Though the suggested values differ, values around 0.06 (Gefen et al., 2000; Hu and Bentler, 1999) or below 0.08 (Hair et al., 1998) present a good model fit. However, some more restrictive rules propose values below 0.05 as a good fit and values below 0.08 as a reasonable fit (Browne and Cudeck, 1992).

The issue of model parsimony was evaluated with a consistent Akaike information criterion (CAIC). There is no reference value for CAIC; however, the index value should be smaller compared to the value of the saturated and independence models (Diamantopoulos and Siguaw, 2000). In our hypothesized model, the CAIC value is lower than both. Moreover, the values of the comparative fit index (CFI), normed fit index (NFI), non-normed fit index (NNFI) and incremental fit index (IFI), which should exceed 0.9 (Hair et al., 1998), represent a good model fit in our hypothesized model. In contrast, acceptable values of parsimony goodness-of-fit (PGFI) may be much lower, and values above 0.50 indicate an acceptable fit (Mulaik et al., 1989). Similarly, relative fit index (RFI) is also above the threshold value for good model fit.

Finally, we examined the statistical significance of path coefficients, the size of the estimated parameters and the squared multiple correlation (R^2). In the proposed online shopping behavioral intention model as shown in Table 7 and Fig. 2, six path coefficients are statistically significant at the 0.05 significance level, whereas three are not. Moreover, the path directions are consistent with the hypothesized relationships between the constructs, except for the relationship between DOI and behavioral intention.

Regarding the relative impact of the estimated parameters, it is evident that performance expectancy has the largest impact on online shopping behavioral intention, but there are also important effects between COVID-19 fear, IMI and online shopping behavioral intention.

The squared multiple correlation (R^2) for online shopping behavioral intention is quite high at 0.69, indicating the independent latent variables (performance expectancy, effort expectancy, social influence, facilitating conditions, imitating others, discounting one's own information and COVID-19 fear) explain 69% of the variance in the online shopping behavioral intention latent variable. In contrast, the R^2 for the remaining two endogenous variables is quite low at 0.08 for IMI and 0.15 for DOI, indicating the COVID-19 fear latent variable explains only a small proportion of the variance in both herd behavior factors.

Table 3
Convergent validity results – Lambda-Y.

Concept	Latent variable	Item	*t* value	Standardized loadings	CR	AVE	Cronbach's α
Behavioral intention	BI	bi1	11.269	0.863	0.920	0.793	0.934
		bi2	24.358	0.884			
		bi3	26.237	0.924			
Herd behavior	IMI	imi1	12.282	0.706	0.849	0.654	0.845
		imi2	15.202	0.841			
		imi3	15.369	0.870			
	DOI	doi1	11.338	0.529	0.624	0.360	0.615
		doi2	6.801	0.704			
		doi3	6.815	0.551			

Table 4
Convergent validity results – Lambda-X.

	Latent variable	Item	*t* value	Standardized loadings	CR	AVE	Cronbach's α
UTAUT	PE	pe1	11.961	0.822	0.907	0.764	0.905
		pe2	22.489	0.900			
		pe3	22.461	0.899			
	EE	ee1	12.243	0.853	0.937	0.789	0.936
		ee2	25.875	0.915			
		ee3	24.861	0.896			
		ee4	24.481	0.888			
	SI	si1	10.942	0.870	0.927	0.810	0.925
		si2	27.918	0.955			
		si3	24.522	0.872			
	FC	fc1	13.858	0.502	0.767	0.475	0.736
		fc2	10.399	0.850			
		fc3	10.479	0.873			
		fc4	6.793	0.406			
COVID-19 fear	CF	cf3	14.650	0.726	0.903	0.653	0.900
		cf4	13.482	0.720			
		cf5	14.258	0.707			
		cf6	18.507	0.913			
		cf7	18.954	0.941			

Table 5
Discriminant validity test.

Latent variable	BI	IMI	DOI	PE	EE	SI	FC	CF
BI	**0.793**							
IMI	0.142	**0.654**						
DOI	0.001	0.012	**0.360**					
PE	0.510	0.001	0.002	**0.764**				
EE	0.403	0.000	0.000	0.551	**0.789**			
SI	0.110	0.004	0.008	0.149	0.087	**0.810**		
FC	0.360	0.000	0.000	0.403	0.626	0.092	**0.475**	
CF	0.017	0.081	0.151	0.015	0.000	0.055	0.003	**0.653**

Table 6
Fit indices of the online shopping intention model.

Fit index	Model value	Reference value	Hypothesized model fit
χ^2	990.30	Not applicable	
p value for χ^2	0.000	>0.05	no
χ^2/df	2.99	<5.00	yes
Standardized RMR	0.139	<0.10	no
RMSEA	0.0689	<0.08	yes
CAIC	1518.319	<CAIC saturated (2858.343)	yes
		<CAIC independence (21194.106)	
CFI	0.968	>0.90	yes
NFI	0.953	>0.90	yes
NNFI	0.963	>0.90	yes
IFI	0.968	>0.90	yes
GFI	0.856	>0.80 (0.90)	yes
PGFI	0.698	>0.50	yes
RFI	0.946	>0.90	yes

Table 7
Results of the structural model.

| Hypothesis	Relationship	Description	Path coefficient	t-Value	Result
H1a	PE → BI	UTAUT	0.49	7.87	**Supported**
H1b	EE → BI	UTAUT	0.11	1.41	*Not supported*
H1c	SI → BI	UTAUT	0.03	0.88	*Not supported*
H1d	FC → BI	UTAUT	0.20	2.88	**Supported**
H2a	IMI → BI	HERD → INTENTION	0.37	8.74	**Supported**
H2b	DOI → BI	HERD → INTENTION	−0.09	−2.11	**Supported**
H3a	CF → BI	COVID → INTENTION	0.01	0.14	*Not supported*
H4a	CF → IMI	COVID → HERD	0.28	5.10	**Supported**
H4b	CF → DOI	COVID → HERD	0.39	5.24	**Supported**
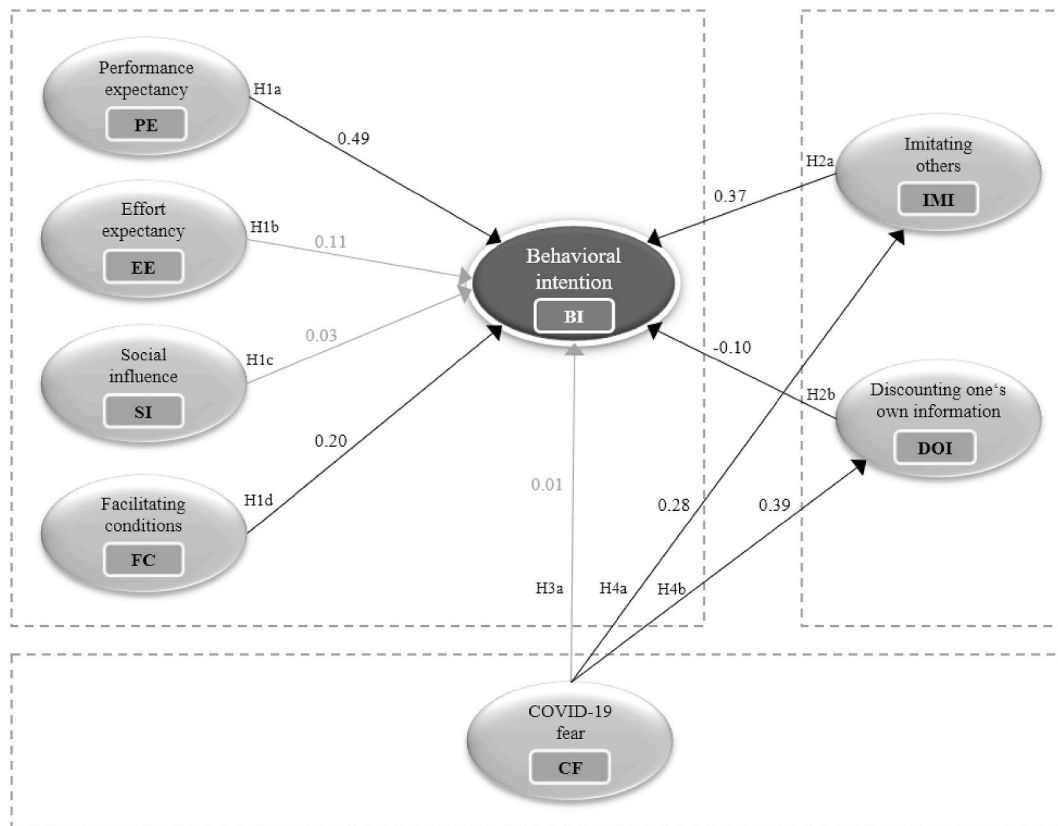
Fig. 2. Online shopping behavioral intention model.

5. Discussion

The COVID-19 pandemic had a significant impact on individuals and on society as a whole. Older adults constitute one particularly vulnerable group because COVID-19 presents a severe health risk for many of them. At the same time, they are still very actively involved in society. Therefore, we investigated the factors that led older adults to adopt online shopping behavior. The results indicate several interesting and important findings. Although we base the research on online shopping adoption amongst older adults during COVID-19 circumstances, we believe that the results are applicable to future situations because some older adults will always struggle with new technologies, while the tools to induce herd behavior will only be more widely spread.

In our study, we examined the interplay of three factors (i.e., UTAUT, COVID-19 fear and herd behavior) on older adults' behavioral intention to adopt online shopping. We found strong evidence that performance expectancy (H1a) presents the most influential factor for the analyzed participants. In addition, facilitating conditions (H1d) have an important impact when considering online shopping. However, effort expectancy (H1b) and social influence (H1c) do not have an impact on the behavioral intention, as neither effect is statistically significant. Furthermore, the impact of social influence on behavioral intention is close to zero. The impact of effort expectancy was also not supported in a recent study examining the intention to implement privacy protection (Bu et al., 2021). It has already been shown that effort expectancy has a stronger impact on shopping intention in cases when users have higher levels of technology readiness (Y.-W. Chang and Chen, 2021). Although some previous studies also reported indications that social influence is a less relevant factor in the UTAUT model (Chayomchai, 2020; Workman, 2014), this result is quite unexpected in light of the COVID-19 pandemic. The latter might have occurred because social isolation due to pandemic lockdowns led to fewer interactions with close social circles.

Similarly, COVID-19 fear, contrary to expectations, does not have a

direct influence (H3a) on online behavioral intention and it is thus not associated with older adults' behavioral intention to adopt online shopping. In addition, its impact is almost zero and statistically not significant. Although it was shown that consumer behavior during the COVID-19 pandemic depends on fear (Eger et al., 2021), we found no direct impact on online shopping adoption. However, COVID-19 fear is particularly influential on IMI (H4a) and DOI (H4b) when considering online shopping. These results indicate that COVID-19 fear significantly influences herd behavior. Individuals are prepared to imitate others and discount their own information due to the unknown circumstances and increased uncertainty.

Likewise, it seems that during the period of social isolation, herd behavior presents an important factor when considering technology adoption. Individuals in our sample were following others when considering online shopping because IMI (H2a) had an important (and one of the largest) influence on behavioral intention in our model. In contrast, when considering online shopping, DOI (H2b) had a negative but small effect. However, it is notably to add that the measures for the DOI construct were the least reliable in our model. However, we kept them in the model because they are strongly supported in the existing literature.

5.1. Theoretical contribution

Our research contributes to the theory in several ways. First, the research examined the UTAUT factors performance expectancy, effort expectancy, social influence and facilitating conditions (Venkatesh et al., 2003) under the condition of the COVID-19 pandemic. Because several lockdown restrictions are ongoing, individuals and organizations are exposed to unpredicted consequences. Moreover, the pandemic expedited several digital transformation initiatives (De' et al., 2020; Dey et al., 2020; Laberge et al., 2020), which also affected individuals and organizations because COVID-19 made digitalization almost a necessity

for all sectors (Nabity-Grover et al., 2020). In this unprecedented environment and pandemic situation, our research has shown that performance expectancy is the most influential factor when considering online shopping behavior. In addition, facilitating conditions have an important influence; however, effort expectancy and particularly social influence do not seem to be influential factors. Performance expectancy is often found as the most influential factor in UTAUT models and in non-COVID-19 pandemic research (Jadil et al., 2021), whereas social influence seems to have a smaller effect on behavioral intention (Patil et al., 2020) or merely an indirect effect (Shareef et al., 2017). Our research supports previous research on UTAUT that claims the effect of social influence on technology adoption differs significantly in various contexts (Eckhardt et al., 2009).

Second, the research confirmed the existence of other important factors that influence the intention to use online shopping among older adults. Due to reduced social contact between individuals during the COVID-19 pandemic resulting from lockdown restrictions or the fear of COVID-19 (Korukcu et al., 2021; Soofi et al., 2020), we examined the influence of herd behavior on the intention to use online shopping. Studies have examined the influence of herd behavior on technology adoption (Handarkho and Harjoseputro, 2019; Y. Liu and Yang, 2018; Shen et al., 2016), but none have coupled UTAUT with herd behavior or studied it under the conditions of social isolation. Therefore, we took advantage of the unique conditions caused by the COVID-19 pandemic to explore whether the effect of social influence as a subjective norm in technology acceptance models is diminished when the potential users face time pressure and social isolation.

We aimed to answer whether social influence still affects behavioral intention to adopt a technology and whether herd behavior has any significant influence. We found strong evidence for inclusion of herd behavior because IMI, as one herd behavior element (Sun, 2013), had the third largest impact on behavioral intention to use online shopping in our model. Its impact was larger than the impact of other UTAUT factors, except for performance expectancy. This lends strong support to the idea that for older adults, the COVID-19 pandemic has influenced their decision-making process such that they rely less on information sources within their close social network and instead observe other people's behavior.

In our research, we expanded the scope of the previous research claiming that IMI has a positive effect on behavioral intention when adopting a new technology, particularly when dealing with hesitant consumers (Y. Liu and Yang, 2018) to include the context of extending the UTAUT model with herd behavior as another endogenous mechanism. The latter is also aligned with the research recommendation to include new context effects in the UTAUT model (Venkatesh et al., 2016) and to examine the technology preferences for vulnerable customers (Dwivedi et al., 2020).

Moreover, we found that although COVID-19-related fear surprisingly has no direct influence on behavioral intention to use online shopping, it has an important effect on herd behavior. The effect of COVID-19 fear on herd behavior is the second (DOI) and the fourth (IMI) largest in our model of behavioral intention for online shopping. Our results are in line with previous research findings in which COVID-19-related stress had no direct influence on behavioral intention to use a contact-tracing application (Walrave et al., 2020). However, our research also supports studies claiming that under the conditions of increased ambiguity or concern, individuals may observe others' behavior and follow them (Walden and Browne, 2009). Individuals in these cases follow and imitate a particular group that they believe has better information and is thus more likely to make what they believe to be the best decision (Sun, 2013). The COVID-19 crisis caused additional uncertainty, which in our model resulted in the effect of COVID-19 fear on herd behavior.

Therefore, this research extends the UTAUT model with additional exogenous (COVID-19 fear) and endogenous (herd behavior) mechanisms, which is aligned with the research call recommendations to "combine/organize new context effects along the different dimensions of contextual factors less explored in previous research—i.e., environment factors, location factors, organization factors and events" (Venkatesh et al., 2016, p. 348).

It may be reasonable to reconsider the UTAUT model to complement or substitute social influence factors with herd behavior or other similar factors. The COVID-19 pandemic presented a unique situation for studying individuals' technology use during a period of increased uncertainty, but it also presents an opportunity to improve theories and practices beyond the pandemic's duration (Dey et al., 2020). Nevertheless, the use of sources such as social media platforms is becoming increasingly common. In addition, individuals are in touch with online and other media on a daily basis, with a high influence level of these media on each individual, so it may be reasonable to question whether this influence will overwhelm social influence in non-pandemic times as well. Considering that in many recent studies, social influence was not a particularly important factor, and considering the existence of ubiquitous media, we propose reconsidering the social influence factor in the UTAUT model and considering its possible complementary factors.

5.2. Practical implications

With the lockdowns, COVID-19 fear and other restrictions, the accessibility and attractiveness of shopping in physical stores have somewhat dwindled. In turn, online shopping has seen a substantial increase during COVID-19, with the food and beverages category having the most active users during the pandemic and facing an increased amount of spending per online purchase (UNCTAD, 2020). This has led various food companies to provide overnight technological solutions for the management of online orders and for alternative means of pickup and delivery, such as home delivery or in-store collection (Alaimo et al., 2020). Nevertheless, because of several challenges and issues caused by the COVID-19 pandemic, organizations need to prepare different plans for future strategic activities (Papadopoulos et al., 2020).

This research deals with the described unique situation related to COVID-19, regarding a specific technology and age group. However, the main research outcomes of this paper can still be applicable in practice beyond pandemic times, online shopping or older adults. Therefore, we present the implications related to older adults and online shopping, followed by implications of a more general nature for behavioral intentions to adopt and use a technology.

During the COVID-19 pandemic, retailers who failed to adapt quickly faced an existential crisis that they can overcome by getting to know their stakeholders better, including customers, as well as learning how they operate and how they interact and reassuring them that their needs will be met (Pantano et al., 2020). Although the COVID-19 pandemic has influenced all generations, a transition to online shopping did not present a major challenge or huge difference in behavior for younger generations because they were already shopping online. On the other hand, older adults are the fastest growing consumer age group, have a rising share of income compared to other demographic groups, and are reaching retirement age in good health with many active years ahead of them. Therefore, our research provides valuable insight into how and to what extent unpredictable situations such as the COVID-19 pandemic influence the behavior of this group, albeit indirectly through affecting herd behavior, when opting for online shopping. The latter may also explain unusual purchasing behavior during the COVID-19 pandemic (Laato et al., 2020) or panic buying (Islam et al., 2021; Prentice et al., 2020).

Our findings also show that older adults are largely influenced to adopt online shopping by seeing its direct benefits, whether they possess the necessary resources to perform it, and by following a wider crowd of previous adopters. Following these findings, retailers could focus more on creating an image that might persuade potential older adults to become online shoppers by seeing other people in their wider social circles doing so. The latter can occur when potential online shoppers

assume that their wider social circles are better informed than themselves (Mattke et al., 2020). Retailers could, analogous to, for example, running applications or similar, use applications to support the shopping experience of older adults and exploit social media activity-sharing capabilities to reach other potential online shoppers.

The adoption and use of new technologies in times of uncertainty and increasing social distancing is increasingly influenced by the information that individuals receive from the media, the Web and social networks, rather than the information that an individual receives from their immediate circle of family and friends. An increase in the number of people working from home (which is becoming a new reality because of COVID-19) will result in more social distancing and in turn might cause herd behavior to influence technology adoption more than social influence does. Therefore, companies need to consider that reaching out to people by exploiting the means of their wider social circles will play a major role in technology adoption in the future because herd behavior significantly influences behavioral intention in situations of uncertainty and exceeds the social influence of closer circles.

5.3. Limitations and future research

The presented research also has some limitations. First, we did not include potential demographic-moderating variables such as gender and income in our model. Even though the demographic data were collected, we chose not to include it in the model because previous research on the adoption of online shopping has shown that the behavior of online shoppers is similar regardless of socioeconomic characteristics (Hernandez et al., 2011). Second, the data were collected in November 2020, when stricter lockdown conditions were being imposed. However, grocery stores remained opened and, even though the accessibility and attractiveness of shopping in physical stores has decreased somewhat, potential shoppers still have a choice to visit brick and mortar stores or shop online. Finally, due to the prevalence and impact of COVID-19 on older adults, the research focuses primarily on them.

Future research could therefore focus on validating the conceptual model presented in this study on the general population as well. The presented research also addresses a potential gap in the basic UTAUT model, where the relevance of social influence might be diminishing in lieu of herd behavior. This could hold not just in the case of a pandemic situation, but also in other situations where sources of information more prone to herding, such as social media and news delivered online, take precedence over close social contacts. Nevertheless, individuals are in touch with social media and other media sources on a regular basis, and this influence may outweigh the social influence from close circles. Therefore, we propose the use of herd behavior as a complement to social influence in further technology adoption research where potential users are more inclined to use information sources that extend beyond their close social circles.

6. Conclusion

Due to several ongoing lockdown restrictions, increased uncertainty, and unpredicted consequences caused by the COVID-19 pandemic, consumers have had to change their behavior and their casual ways of living and working. The situation also influenced and expedited the usual decision-making process of technology adoption, which has been coupled in many cases with the unique circumstances of social isolation, resulting in a lack of access to information resources for the decision-making process. Therefore, in our study, we examined factors that influence behavioral intention to adopt online shopping among older adults in the context of the COVID-19 pandemic. The factors include the four core determinants of UTAUT, expanded to include COVID-19 fear and herd behavior, which we identify as a possible new mechanism influencing behavioral intention under these unique circumstances. Based on the findings, we proposed extending the UTAUT model by including herd behavior factors as complementary endogenous

mechanism to social influence in situations where potential users' information sources extend beyond their close social circles. This research shows that pandemics not only disrupt people's daily lives but also alter existing theoretical models.

Declaration of competing interest

None.

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References

Ahorsu, D.K., Lin, C.Y., Imani, V., Saffari, M., Griffiths, M.D., Pakpour, A.H., 2020. The fear of COVID-19 scale: development and initial validation. International Journal of Mental Health and Addiction. https://doi.org/10.1007/s11469-020-00270-8.

Alaimo, L.S., Fiore, M., Galati, A., 2020. How the COVID-19 pandemic is changing online food shopping human behaviour in Italy. Sustainability 12 (22), 1–18. https://doi.org/10.3390/su12229594.

Antony, A., Joseph, A.I., 2017. Influence of behavioural factors affecting investment decision—an AHP analysis. Metamorphosis: J. Manag. Res. 16 (2), 107–114. https://doi.org/10.1177/0972622517738833.

Bagozzi, R.P., Yi, Y., 1988. On the evaluation of structural equation models. J. Acad. Market. Sci. 16 (1), 74–94. https://doi.org/10.1007/BF02723327.

Baldwin, T., 2019. Silver Economy Spending Power Trends in Europe. World Data Lab. https://worlddata.io/blog/silver-economy-europe.

Banerjee, A.V., 1992. A simple model of herd behavior. Q. J. Econ. 107 (3), 797–817. https://doi.org/10.2307/2118364.

Bernheim, B.D., 1994. A theory of conformity. J. Polit. Econ. 102 (5), 841–877. https://doi.org/10.1086/261957.

Bouri, E., Gupta, R., Roubaud, D., 2019. Herding behaviour in cryptocurrencies. Finance Res. Lett. 29, 216–221. https://doi.org/10.1016/j.frl.2018.07.008. June 2018.

Browne, M.W., Cudeck, R., 1992. Alternative ways of assessing model fit. Socio. Methods Res. 21 (2), 136–162. https://doi.org/10.1177/0049124192021002005.

Bu, F., Wang, N., Jiang, B., Jiang, Q., 2021. International journal of information management motivating information system engineers ' acceptance of privacy by design in China : an extended UTAUT model. Int. J. Inf. Manag. 60 (April), 102358 https://doi.org/10.1016/j.ijinfomgt.2021.102358.

Burke, C.J., Tobler, P.N., Wolfram, S., Baddeley, M., 2010. Striatal BOLD response reflects the impact of herd information on financial decisions. Front. Hum. Neurosci. 4, 1–11. https://doi.org/10.3389/fnhum.2010.00048.

Çelen, B., Kariv, S., 2004. Distinguishing informational cascades from herd behavior in the laboratory. Am. Econ. Rev. 94 (3), 484–498. https://doi.org/10.1257/0002828041464461.

Chang, Y.-W., Chen, J., 2021. What motivates customers to shop in smart shops? The impacts of smart technology and technology readiness. J. Retailing Consum. Serv. 58, 102325 https://doi.org/10.1016/j.jretconser.2020.102325.

Chang, S., Pierson, E., Koh, P.W., Gerardin, J., Redbird, B., Grusky, D., Leskovec, J., 2021. Mobility network models of COVID-19 explain inequities and inform reopening. Nature 589 (7840), 82–87. https://doi.org/10.1038/s41586-020-2923-3.

Chayomchai, A., 2020. The online technology acceptance model of generation-Z people in Thailand during COVID-19 crisis. Manag. Market. 15 (s1), 496–512. https://doi.org/10.2478/mmcks-2020-0029.

Chayomchai, A., Phonsiri, W., Junjit, A., Boongapim, R., Suwannapusit, U., 2020. Factors affecting acceptance and use of online technology in Thai people during COVID-19 quarantine time. Management Sci. Lett 10 (13), 3009–3016. https://doi.org/10.5267/j.msl.2020.5.024.

Cheung, G., Rivera-Rodriguez, C., Martinez-Ruiz, A., Ma'u, E., Ryan, B., Burholt, V., Bissielo, A., Meehan, L., 2020. Impact of COVID-19 on the health and psychosocial status of vulnerable older adults: study protocol for an observational study. BMC Publ. Health 20 (1), 1–9. https://doi.org/10.1186/s12889-020-09900-1.

Clipper, B., 2020. The influence of the COVID-19 pandemic on technology: adoption in health care. Nurse Leader 18 (5), 500–503. https://doi.org/10.1016/j.mnl.2020.06.008.

Czaja, S.J., Charness, N., Fisk, A.D., Hertzog, C., Nair, S.N., Rogers, W.A., Sharit, J., 2006. Factors predicting the use of technology: findings from the center for research and education on aging and technology enhancement (CREATE). Psychol. Aging 21 (2), 333–352. https://doi.org/10.1037/0882-7974.21.2.333.

De Jong Gierveld, J., Van Tilburg, T., Dykstra, P., 2016. Loneliness and social isolation. In: Anita, V., Daniel, P. (Eds.), The Cambridge Handbook of Personal Relationship. Cambridge University Press, pp. 1–30.

Dey, B.L., Al-Karaghouli, W., Muhammad, S.S., 2020. Adoption, adaptation, use and impact of information systems during pandemic time and beyond: research and managerial implications. Inf. Syst. Manag. 37 (4), 298–302. https://doi.org/10.1080/10580530.2020.1820632.

De', R., Pandey, N., Pal, A., 2020. Impact of digital surge during Covid-19 pandemic: a viewpoint on research and practice. Int. J. Inf. Manag. 55 (June), 102171 https://doi.org/10.1016/j.ijinfomgt.2020.102171.

Diamantopoulos, A., Siguaw, J.A., 2000. Introducing LISREL. SAGE Publications.

Dwivedi, Y.K., Rana, N.P., Jeyaraj, A., Clement, M., Williams, M.D., 2019. Re-examining the unified theory of acceptance and use of technology (UTAUT): towards a revised theoretical model. Inf. Syst. Front 21 (3), 719–734. https://doi.org/10.1007/s10796-017-9774-y.

Dwivedi, Y.K., Ismagilova, E., Hughes, D.L., Carlson, J., Filieri, R., Jacobson, J., Jain, V., Karjaluoto, H., Kefi, H., Krishen, A.S., Kumar, V., Rahman, M.M., Raman, R., Rauschnabel, P.A., Rowley, J., Salo, J., Tran, G.A., Wang, Y., 2020. Setting the future of digital and social media marketing research: perspectives and research propositions. Int. J. Inf. Manag. https://doi.org/10.1016/j.ijinfomgt.2020.102168, 102168.

Eckhardt, A., Laumer, S., Weitzel, T., 2009. Who influences whom Analyzing workplace referents' social influence on IT adoption and non-adoption. J. Inf. Technol. 24 (1), 11–24. https://doi.org/10.1057/jit.2008.31.

Eger, L., Komárková, L., Egerová, D., Mičík, M., 2021. The effect of COVID-19 on consumer shopping behaviour: generational cohort perspective. J. Retailing Consum. Serv. 61, 102542 https://doi.org/10.1016/j.jretconser.2021.102542.

Eurostat, 2020. E-commerce Statistics for Individuals. https://ec.europa.eu/eurostat/statistics-explained/index.php?title=E-commerce_statistics_for_individuals.

Fornell, C., Larcker, D.F., 1981. Evaluating structural equation models with unobservable variables and measurement error. J. Market. Res. 18 (1), 39–50. https://doi.org/10.1177/002224378101800104.

Gefen, D., Straub, D., Boudreau, M.-C., 2000. Structural equation modeling and regression: guidelines for research practice. Commun. Assoc. Inf. Syst. 4 (1), 7. https://doi.org/10.17705/1CAIS.00407.

Hair, J.F., Anderson, R.E., Tatham, R.L., Black, W.C., 1998. Multivariate Data Analysis, fifth ed. Prentice-Hall.

Handarkho, Y.D., Harjoseputro, Y., 2019. Intention to adopt mobile payment in physical stores: individual switching behavior perspective based on Push–Pull–Mooring (PPM) theory. J. Enterprise Inf. Manag. 33 (2), 285–308. https://doi.org/10.1108/JEIM-06-2019-0179.

Hasan, B., 2016. Perceived irritation in online shopping: the impact of website design characteristics. Comput. Hum. Behav. 54, 224–230. https://doi.org/10.1016/j.chb.2015.07.056.

Hayduk, L.A., 1996. LISREL Issues, Debates, and Strategies. Johns Hopkins University Press.

Hernandez, B., Jimenez, J., Jose Martin, M., 2011. Age, gender and income: do they really moderate online shopping behaviour?, 35(1), 113–133. https://doi.org/10.1108/14684521111113614.

Hoque, R., Sorwar, G., 2017. Understanding factors influencing the adoption of mHealth by the elderly: an extension of the UTAUT model. Int. J. Med. Inf. 101 (September 2015), 75–84. https://doi.org/10.1016/j.ijmedinf.2017.02.002.

Hu, L., Bentler, P.M., 1998. Fit indices in covariance structure modeling: sensitivity to underparameterized model misspecification. Psychol. Methods 3 (4), 424–453. https://doi.org/10.1037/1082-989X.3.4.424.

Hu, L., Bentler, P.M., 1999. Cutoff criteria for fit indexes in covariance structure analysis: conventional criteria versus new alternatives. Struct. Equ. Model.: A Multidisciplinary Journal 6 (1), 1–55. https://doi.org/10.1080/10705519909540118.

Hwang, T.-J., Rabheru, K., Peisah, C., Reichman, W., Ikeda, M., 2020. Loneliness and social isolation during the COVID-19 pandemic. Inter. Psychogeriatrics 32 (10), 1217–1220. https://doi.org/10.1017/S1041610220000988.

Islam, T., Pitafi, A.H., Arya, V., Wang, Y., Akhtar, N., Mubarik, S., Xiaobei, L., 2021. Panic buying in the COVID-19 pandemic: a multi-country examination. J. Retailing Consum. Serv. 59, 102357 https://doi.org/10.1016/j.jretconser.2020.102357.

Jadil, Y., Rana, N.P., Dwivedi, Y.K., 2021. A meta-analysis of the UTAUT model in the mobile banking literature: the moderating role of sample size and culture. J. Bus. Res. 132, 354–372. https://doi.org/10.1016/j.jbusres.2021.04.052.

Jain, R., Kulhar, M., 2019. Barriers to online shopping. Int. J. Bus. Inf. Syst. 30 (1), 31. https://doi.org/10.1504/IJBIS.2019.097043.

Jasperson, S., Carter, P.E., Zmud, R.W., 2005. A comprehensive conceptualization of post-adoptive behaviors associated with information technology enabled work systems. MIS Q. 29 (3), 525–557.

Kenny, D.A., Kaniskan, B., McCoach, D.B., 2015. The performance of RMSEA in models with small degrees of freedom. Socio. Methods Res. 44 (3), 486–507. https://doi.org/10.1177/0049124114543236.

Kim, M.J., Hall, C.M., 2020. What drives visitor economy crowdfunding? The effect of digital storytelling on unified theory of acceptance and use of technology. Tourism Manag. Perspect. 34, 100638 https://doi.org/10.1016/j.tmp.2020.100638.

Kline, P., 1999. The Handbook of Psychological Testing, second ed. Routledge.

Kline, T.J.B., 2005. Psychological Testing: A Practical Approach to Design and Evaluation. Sage Publications.

Korukcu, O., Ozkaya, M., Faruk Boran, O., Boran, M., 2021. The effect of the COVID-19 pandemic on community mental health: a psychometric and prevalence study in Turkey. Health & Social Care in the Community. https://doi.org/10.1111/hsc.13270. *July*, 1–10.

Kuoppamäki, S.M., Taipale, S., Wilska, T.A., 2017. The use of mobile technology for online shopping and entertainment among older adults in Finland. Telematics Inf. 34 (4), 110–117. https://doi.org/10.1016/j.tele.2017.01.005.

Laato, S., Islam, A.K.M.N., Farooq, A., Dhir, A., 2020. Unusual purchasing behavior during the early stages of the COVID-19 pandemic: the stimulus-organism-response approach. J. Retailing Consum. Serv. 57, 102224 https://doi.org/10.1016/j.jretconser.2020.102224.

Laberge, L., O'toole, C., Schneider, J., Smaje, K., 2020. How COVID-19 Has Pushed Companies over the Technology Tipping Point—And Transformed Business Forever. McKinsey & Company, October.

Lewis, D., 2021. Why indoor spaces are still prime COVID hotspots. Nature 592 (7852), 22–25. https://doi.org/10.1038/d41586-021-00810-9.

Lian, J.W., Yen, D.C., 2014. Online shopping drivers and barriers for older adults: age and gender differences. Comput. Hum. Behav. 37, 133–143. https://doi.org/10.1016/j.chb.2014.04.028.

Liu, Y., Yang, Y., 2018. Empirical examination of users' adoption of the sharing economy in China using an expanded technology acceptance model. Sustainability 10 (4). https://doi.org/10.3390/su10041262.

Liu, B.F., Bartz, L., Duke, N., 2016. Communicating crisis uncertainty: a review of the knowledge gaps. Publ. Relat. Rev. 42 (3), 479–487. https://doi.org/10.1016/j.pubrev.2016.03.003.

Mattke, J., Maier, C., Reis, L., Weitzel, T., 2020. Herd behavior in social media: the role of Facebook likes, strength of ties, and expertise. Inf. Manag. 57 (8), 103370 https://doi.org/10.1016/j.im.2020.103370.

McDonald, R.P., Ho, M.-H.R., 2002. Principles and practice in reporting structural equation analyses. Psychol. Methods 7 (1), 64. https://doi.org/10.1037/1082-989X.7.1.64.

McKinsey, Company, 2020. COVID-19 US Consumer Pulse Survey. https://www.mckinsey.com/featured-insights/coronavirus-leading-through-the-crisis/charting-the-path-to-the-next-normal/some-changes-to-grocery-shopping-habits-likely-to-stick-after-the-crisis.

Mertens, G., Gerritsen, L., Duijndam, S., Salemink, E., Engelhard, I.M., 2020. Fear of the coronavirus (COVID-19): predictors in an online study conducted in March 2020. J. Anxiety Disord. 74 (June), 102258 https://doi.org/10.1016/j.janxdis.2020.102258.

Mulaik, S.A., James, L.R., Van Alstine, J., Bennett, N., Lind, S., Stilwell, C.D., 1989. Evaluation of goodness-of-fit indices for structural equation models. Psychol. Bull. 105 (3), 430–445. https://doi.org/10.1037/0033-2909.105.3.430.

Nabity-Grover, T., Cheung, C.M.K., Thatcher, J.B., 2020. Inside out and outside in: how the COVID-19 pandemic affects self-disclosure on social media. Int. J. Inf. Manag. 55, 102188 https://doi.org/10.1016/j.ijinfomgt.2020.102188.

Naeem, M., Ozuem, W., 2021. The role of social media in internet banking transition during COVID-19 pandemic: using multiple methods and sources in qualitative research. J. Retailing Consum. Serv. 60, 102483 https://doi.org/10.1016/j.jretconser.2021.102483.

Nelson, E., Ijiekhuamhen, O.P., Emeka-ukwu, U., 2016. Elderly people and their information needs. Libr. Philos. Pract. 1332, 1–16.

Oh, S.S., Kim, K.A., Kim, M., Oh, J., Chu, S.H., Choi, J.Y., 2021. Measurement of digital literacy among older adults: systematic review. J. Med. Internet Res. 23 (2) https://doi.org/10.2196/26145.

Pan, S.L., Cui, M., Qian, J., 2020. Information resource orchestration during the COVID-19 pandemic: a study of community lockdowns in China. Int. J. Inf. Manag. 54 (May), 102143 https://doi.org/10.1016/j.ijinfomgt.2020.102143.

Pang, N., Karanasios, S., Anwar, M., 2020. Exploring the information worlds of older persons during disasters. J. Assoc. Inform. Sci. Technol. 71 (6), 619–631. https://doi.org/10.1002/asi.24294.

Pantano, E., Pizzi, G., Scarpi, D., Dennis, C., 2020. Competing during a pandemic? Retailers' ups and downs during the COVID-19 outbreak. J. Bus. Res. 116 (May), 209–213. https://doi.org/10.1016/j.jbusres.2020.05.036.

Papadopoulos, T., Baltas, K.N., Balta, M.E., 2020. The use of digital technologies by small and medium enterprises during COVID-19: implications for theory and practice. Int. J. Inf. Manag. 55, 102192 https://doi.org/10.1016/j.ijinfomgt.2020.102192.

Patil, P., Tamilmani, K., Rana, N.P., Raghavan, V., 2020. Understanding consumer adoption of mobile payment in India: extending Meta-UTAUT model with personal innovativeness, anxiety, trust, and grievance redressal. Int. J. Inf. Manag. 54, 102144 https://doi.org/10.1016/j.ijinfomgt.2020.102144.

Popovič, A., & Trkman, P. (2016). The Role of Herd Behavior in Implementing Planned Organizational Changes. AMCIS 2016 Proceedings. Technology Research, Education, and Opinion (TREO) Talk Sessions. 22nd Americas Conference on Information Systems (AMCIS).

Prentice, C., Chen, J., Stantic, B., 2020. Timed intervention in COVID-19 and panic buying. J. Retailing Consum. Serv. 57, 102203 https://doi.org/10.1016/j.jretconser.2020.102203.

Raza, S.A., Qazi, W., Khan, K.A., Salam, J., 2020. Social isolation and acceptance of the learning management system (LMS) in the time of COVID-19 pandemic: an expansion of the UTAUT model. J. Educ. Comput. Res. https://doi.org/10.1177/0735633120960421.

Schoenherr, T., Ellram, L.M., Tate, W.L., 2015. A note on the use of survey research firms to enable empirical data collection. J. Bus. Logist. 36 (3), 288–300. https://doi.org/10.1111/jbl.12092.

Shareef, M.A., Dwivedi, Y.K., Kumar, V., Kumar, U., 2017. Content design of advertisement for consumer exposure: mobile marketing through short messaging service. Int. J. Inf. Manag. 37 (4), 257–268. https://doi.org/10.1016/j.ijinfomgt.2017.02.003.

Sharma, S., Mukherjee, S., Kumar, A., Dillon, W.R., 2005. A simulation study to investigate the use of cutoff values for assessing model fit in covariance structure models. J. Bus. Res. 58 (7), 935–943. https://doi.org/10.1016/j.jbusres.2003.10.007.

Shen, X., Zhang, K.Z., Zhao, S.J., 2016. Herd behavior in consumers' adoption of online reviews. J. Assoc. Inform. Sci. Technol. 67 (11), 2754–2765. https://doi.org/10.1002/asi.23602.

Sivo, S.A., Fan, X., Witta, E.L., Willse, J.T., 2006. The search for "optimal" cutoff properties: fit index criteria in structural equation modeling. J. Exp. Educ. 74 (3), 267–288. https://doi.org/10.3200/JEXE.74.3.267-288.

Slade, E.L., Dwivedi, Y.K., Piercy, N.C., Williams, M.D., 2015. Modeling consumers' adoption intentions of remote mobile payments in the United Kingdom: extending UTAUT with innovativeness, risk, and trust. Psychol. Market. 32 (8), 860–873. https://doi.org/10.1002/mar.20823.

Snowden, F.M., 2019. Epidemics and Society: from the Black Death to the Present. Yale University Press.

Soofi, M., Najafi, F., Karami, B., 2020. Using insights from behavioral economics to mitigate the spread of COVID - 19. Appl. Health Econ. Health Pol. 18 (3), 345–350. https://doi.org/10.1007/s40258-020-00595-4.

Suisse, Credit, 2018. Supertrend Silver Economy: Investing in the Spending Power of Seniors. https://www.credit-suisse.com/about-us-news/en/articles/news-and-expertise/supertrend-silver-economy-investing-in-the-spending-power-of-seniors-201808.html.

Sun, H., 2013. A longitudinal study of herd behavior in the adoption and continued use of technology. MIS Q. 37 (4), 1013–1041. https://doi.org/10.25300/MISQ/2013/37.4.02.

Taherdoost, H., 2018. A review of technology acceptance and adoption models and theories. Procedia Manufac. 22, 960–967. https://doi.org/10.1016/j.promfg.2018.03.137.

Tamilmani, K., Rana, N.P., Prakasam, N., Dwivedi, Y.K., 2019. The battle of Brain vs. Heart: a literature review and meta-analysis of "hedonic motivation" use in UTAUT2. Int. J. Inf. Manag. 46, 222–235. https://doi.org/10.1016/j.ijinfomgt.2019.01.008.

Tankovska, H., 2021. Number of Social Network Users Worldwide from 2017 to 2025. Statista. https://www.statista.com/statistics/278414/number-of-worldwide-social-network-users/.

Taylor, S., Todd, P.A., 1995. Understanding information technology usage: a test of competing models. Inf. Syst. Res. 6 (2), 144–176. https://doi.org/10.1287/isre.6.2.144.

Theerthaana, P., Manohar, H.L., 2021. How a doer persuade a donor ? Investigating the moderating eﬀects of behavioral biases in donor acceptance of donation crowdfunding. J. Res. Indian Med. https://doi.org/10.1108/JRIM-06-2019-0097.

UNCTAD, 2020. COVID-19 and E-Commerce: Findings from a Survey of Online Consumers in 9 Countries, p. 52.

Vaughan, E., 2020. Don't underestimate the market power of the 50+ crowd. Harvard Business Review. https://hbr.org/2020/01/dont-underestimate-the-market-power-of-the-50-crowd.

Venkatesh, V., 2020. Impacts of COVID-19: a research agenda to support people in their fight. Int. J. Inf. Manag. 55, 102197 https://doi.org/10.1016/j.ijinfomgt.2020.102197.

Venkatesh, V., 2021. Adoption and use of AI tools: a research agenda grounded in UTAUT. Ann. Oper. Res. https://doi.org/10.1007/s10479-020-03918-9, 0123456789.

Venkatesh, Morris, Davis, Davis, 2003. User acceptance of information technology: toward a unified view. MIS Q. 27 (3), 425. https://doi.org/10.2307/30036540.

Venkatesh, V., Thong, J.Y.L., Xu, X., 2012. Consumer acceptance and use of information technology: extending the unified theory of acceptance and use of technology. MIS Q.: Manag. Inf. Syst. 36 (1), 157–178. https://doi.org/10.2307/41410412.

Venkatesh, V., Thong, J.Y.L., Xu, X., 2016. Unified theory of acceptance and use of technology: a synthesis and the road ahead. J. Assoc. Inf. Syst. Online 17 (5), 328–376. https://doi.org/10.17705/1jais.00428.

Walden, E.A., Browne, G.J., 2009. Sequential adoption theory: a theory for understanding herding behavior in early adoption of novel technologies. J. Assoc. Inf. Syst. Online 10 (1), 31–62. https://doi.org/10.17705/1jais.00181.

Walrave, M., Waeterloos, C., Ponnet, K., 2020. Ready or not for contact tracing? Investigating the adoption intention of COVID-19 contact-tracing technology using an extended unified theory of acceptance and use of technology model. Cyberpsychol., Behav. Soc. Netw. 1–7. https://doi.org/10.1089/cyber.2020.0483, 00(00).

Watson, A., 2021. *Digital News Purchases Worldwide 2020*. Statista. https://www.statista.com/statistics/262348/digital-news-purchases-purchases-worldwide/.

Wheaton, B., Muthen, B., Alwin, D.F., Summers, G.F., 1977. Assessing reliability and stability in panel models. Socio. Methodol. 8 (1), 84. https://doi.org/10.2307/270754.

Workman, M., 2014. New media and the changing face of information technology use: the importance of task pursuit, social influence, and experience. Comput. Hum. Behav. 31 (1), 111–117. https://doi.org/10.1016/j.chb.2013.10.008.

Yan, P., Hui, S., Heng, B., Selvachandran, G., Quynh, L., Hoang, A., Minh, T., 2020. Perception, acceptance and willingness of older adults in Malaysia towards online shopping: a study using the UTAUT and IRT models. J. Ambient Intellige. Humanized Comput. https://doi.org/10.1007/s12652-020-01718-4, 0123456789.

Yıldırım, M., Güler, A., 2020. Factor analysis of the COVID-19 perceived risk scale: a preliminary study. Death Stud. 1–8. https://doi.org/10.1080/07481187.2020.1784311, 0(0).