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Online food shopping under COVID-19 – a technology acceptance model to evaluate consumption motives and barriers

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ABSTRACT

Since the United Nations World Health Organization (WHO) declared the novel coronavirus disease-19 (COVID-19) a global pandemic, online food retailing has experienced tremendous growth. Initial forecasts expected global year-over-year growth rates of approximately 33% in 2020. The aim of this research is (1) to identify the relevant consumption motives and consumption barriers of Austrian online grocery trade using the technology acceptance model and (2) to evaluate the impact of the COVID-19 pandemic on the driving factors. The results of the empirical analysis showed that perceived usefulness has the greatest influence on acceptance behavior in online grocery retailing. Perceived ease of use of online stores also contributes to acceptance behavior. The higher the perceived shopping pleasure and visibility of grocery online retailers, the higher the perceived benefits and ease of use. Regarding barriers, the lack of possibility for consumers to sensory check the quality of food before purchase turned out to be a weak-significant barrier that reduces the perceived usefulness. In contrast to other studies, the time facets of delivery and ordering were significantly found to not be a barrier in this research. Since the COVID-19 pandemic, more people have been shown to purchase groceries online. Although a large portion of the sample believes that grocery shopping online is a way to reduce or protect against the risk of infection, neither health aspects nor the situational factor used significantly affect acceptance in this research. In contrast, aspects of COVID-19 have a moderating effect on the purchase intention and purchase behavior. People who perceive grocery online retailing as helpful in protecting themselves from COVID-19 infection perceive a significantly higher benefit and have an increased shopping pleasure than those people who perceive a low risk of contracting COVID-19 infection.

Keywords: grocery online retailing, consumer behavior, acceptance, technology acceptance model, food, e-commerce, COVID-19 pandemic.

1 Introduction

Since the COVID-19 pandemic, online sales are rising significantly. For instance, some experts expect growth rates in the UK of about 33 % (Mintel, 2020). Consequently, scientific research on online shopping investigated various aspects of consumer behavior that is triggered by the pandemic, e.g., motivational aspects (Koch et al., 2020). Online food sales rose accordingly, mainly due to consumers' threats of infections and recommendations of officials to avoid social contacts (Dannenberg et al., 2020; Debter, 2020). Early 2020, about 31 % of Italian and French consumers purchased their food mainly online. In comparison, in Austria (the research field of this study) the proportion of online consumers increased from 19 % before the pandemic to 28 % (Gittenberger and Teller, 2020) and reached a comparable European level. Motives and for online shopping of food are mainly time saving aspects, easiness of price comparisons, the comfort of online

shopping, the easy access to a huge range of products (Harris et al., 2017; Ramus and Nielsen, 2005). Conventional food shopping quite often is seen to be a necessary activity to fulfil basic needs (Roberts et al. 2003); research and reports from practitioners suggest that online food shopping is mainly considered to be a meaningful complement to conventional shopping in stores and not an better alternative in general (Hand et al., 2009).

However, there are also some important barriers for online food shopping, mainly connected to product quality aspects (for instance, it is not possible to inspect fresh food), delivery time restrictions, delivery charges, absence of sensory stimulation, etc. (Kühn et al., 2020). Table 1 lists a number of buying motives and barriers from literature.

Table 1. Buying motives and barriers for online food shopping confirming empirical research.

Buying motives	**Practical benefit**	**Empirical evidence**
Shopping comfort, avoidance of shopping stress	utilitarian	(Ganesh et al., 2010a; Harris et al., 2017; Ramus and Nielsen, 2005; Rohm and Swaminathan, 2004)
Time saving shopping		(Atkins et al., 2016; Chu et al., 2014; Dholakia and Zhao, 2010; Harris et al., 2017; Heitz, 2011; Picot-coupey, 2009)
Price comparison		(Atkins et al., 2016; Ganesh et al., 2010b; Ramus and Nielsen, 2005)
Convenient delivery of products to consumers' home		(Chu et al., 2014; Hübner et al., 2016; Van Droeggenbroeck and Van Hove, 2020)
Additional product diversity		(Atkins et al., 2016; Ramus and Nielsen, 2005; Rohm and Swaminathan, 2004)
Additional product information		(Dholakia and Zhao, 2010)
Shopping pleasure	hedonic	(Childers et al., 2001)
Buying barriers	**Practical benefit**	**Empirical evidence**
Insufficient delivery reliabity	utilitarian	(Brand et al., 2020; Hand et al., 2009; Nguyen et al., 2019)
No trust in product quality		(Harris et al., 2017; Poelman et al., 2020; Saphores and Xu, 2020)
Satisfaction with conventional shopping channels		(Pennerstorfer and Sinabell, 2016)
Delivery cost		(Arce-Urriza and Cebollada, 2013; Hübner et al., 2016)
No sensory quality control		(Chu et al., 2014; Kühn et al., 2020; Pechtl, 2003)
Insufficient delivery time		(Brand et al., 2020; Harris et al., 2017; Saphores and Xu, 2020)
Missing social interaction	hedonic	(Lewis et al., 2013; Mehta, 2014; Ramus and Nielsen, 2005; Rohm and Swaminathan, 2004)
Missing shopping experience		(Lewis et al., 2013; Mehta, 2014; Ramus and Nielsen, 2005; Rohm and Swaminathan, 2004)

Based on these theoretical findings, our study aims to investigate motives and barriers for online food shopping triggering consumers to (not) accept this shopping channel. In particular, we wanted to assess the influence of the COVID-19 pandemic on the acceptance of online food shopping as we saw that obviously more and more consumers have been using online trade channels to purchase food as well (and not only conventional non-food consumer goods). Therefore, the research questions of the study are twofold: (1) *Which motives and barriers are relevant for consumers when buying food online?* (2) *Is there an influence of the COVID-19 pandemic on the acceptance of online food shopping?* It can be easily understood that we focus on the acceptance of a specific technology (online shopping channels) that might be significantly influenced by particular circumstances (the COVID-19 pandemic). An appropriate theory to answer our research questions is the Technology Acceptance Model.

2 Technology Acceptance Model

The Technology Acceptance Model is based on the *Theory of reasoned action* (Ajzen and Fishbein, 1975). The model describes how a new technology is accepted by users (Jockisch, 2010). The acceptance can be explained and predicted by means of investigating the motivation of users which are influenced by specific characteristics of the analyzed technology. In particular, the model contains the variables "perceived usefulness" (PU) and "perceived ease of use" (PEOU) (Ajzen, 1991). These variables immediately influence the variable "attitudes" towards the technology which is an important predictor if the technology will be accepted or not. The acceptance variables are further influenced by external variables. As we can see from that, the original model by Ajzen and Fishbein (1975) intended to assess the acceptance of new computer systems in the working context. Since its introduction, the TAM proofed to be an adequate and valid model to analyze the consumer behavior, purchase intention, and actual acceptance for many other applications as well (Brand et al., 2020; King and He, 2006; Koufaris, 2002; Legris et al., 2003; Nguyen et al., 2019). It is an excellent model to predict real shopping behavior (Chayomchai, 2020; Driediger and Bhatiasevi, 2019). Accordingly, the TAM was adapted as various studies showed the attitudinal dimension was not a good predictor for the behavior of the users (Davis, 1989). The predictors influence the behavioral intention to use the technology and, finally, the variable "actual system use", the TAM was modified towards the TAM2 (Venkatesh and Davis, 2000). Other authors further modified and adapted the TAM considering variables from other theories, context relevant dimensions, more external factors, experiences, use of technology, etc. an (Marangunić and Granić, 2015). The TAM was also applied within the food sector to analyze the adoption of new technologies, in particular the acceptance of online food shopping (Childers et al., 2001; Driediger and Bhatiasevi, 2019; Ha and Stoel, 2009; Klopping, 2004; Pavlou, 2003). For this purpose, new variables were introduced into the TAM, such as time saving aspects, food security, or shopping convenience. For our purpose, we further modified the TAM to integrating the situational factor "affected by COVID-19" into the research model as we assume that the more consumers are personally affected by COVID-19, the more they should be willing to accept the technology "online food shopping". We considered important variables in view of online food shopping behavior (Chien and Kurnia, 2003).

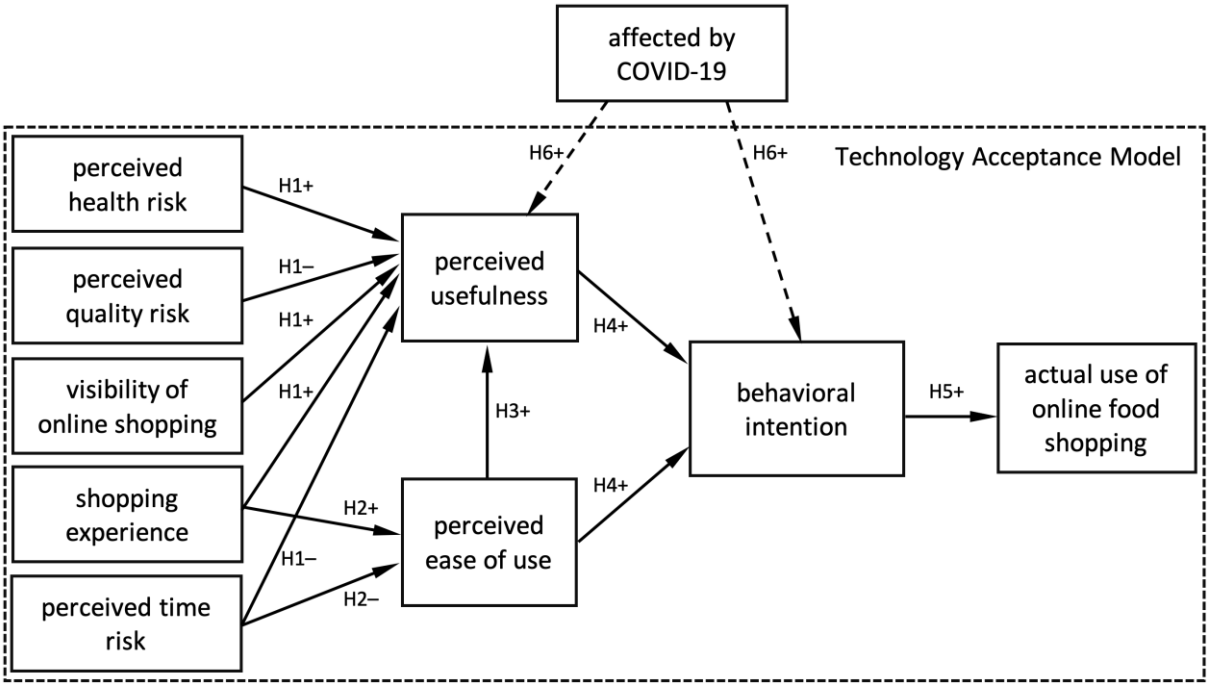

Figure 1. Research model for online food shopping under COVID-19

In the present research model, we included the following external variables in accordance with literature (Hand et al., 2009; Venkatesh and Davis, 2000): (1) Perceived health risk (risk to get infected during conventional shopping); (2) perceived quality risk (impossible to test the food products while shopping) (Grewal et al., 1984); (3) visibility of online shopping (Mortimer et al., 2016), (4) shopping experience (Childers et al., 2001; Venkatesh, 2000) (5) perceived time risk (mainly due to research on online platform, delivery time) (Featherman and Pavlou, 2003). In addition, a situational factor will be included: To what extent are consumers affected by the COVID-19 pandemic (Chayomchai, 2020; Meixner and Katt, 2020; Salem and Nor, 2020)? As a situational factor, we assume that this variable will influence the perceived usefulness of online food shopping and also the behavioral intention. Several studies have shown that the COVID-19 pandemic is influencing

consumer behavior significantly (Chayomchai, 2020; Salem and Nor, 2020). Insofar, the variable "affected by COVID-19" is a situational factor in our model. Altogether, the following hypotheses will be tested:

H1: *Perceived usefulness is positively influenced by the variables "perceived health risk", "visibility of online shopping", "shopping experience", and negatively influenced by the variables "perceived quality risk" and "perceived time risk".*

H2: *Perceived easiness of use is positively influenced by the variables "shopping experience", and negatively influenced by the variable "perceived time risk".*

H3: *Perceived easiness of use positively influences the variable "perceived usefulness".*

H4: *Perceived easiness of use and perceived usefulness positively influences the behavioral intention.*

H5: *Behavioral intention positively influences the actual use of online food shopping.*

H6: *Perceived usefulness and behavioral intention are positively influenced by the situational factor "affected by COVID-19".*

3 Materials and Methods

To test our research model and valuate the hypotheses we used an online survey (which is under the present pandemic circumstances the most appropriate way to conduct consumer surveys). However, the present sample is a convenience sample which limits the representativeness of the results. The model variables were operationalized by means of valid and tested scales from literature: perceived usefulness and behavioral intention are based on Davis (1989); behavioral intention, perceived quality risk, perceived time risk, and visibility of online shopping on Chien and Kurnia (2003); actual use of online food shopping on Moon and Kim (2001); perceived health risk on Hansen et al. (2018) and Salem and Nor (2020); shopping experience on Childers et al. (2001); and, the situational factor "affected by covid 19" on Meixner and Katt (2020). All scale items used a Likert scale from 1 (total agreement) to 7 (total disagreement). In total, 206 persons took part in the survey, most of them females (83 %), two thirds are between 26 and 50 years old, the same proportion of the sample is living in urban areas. Only very view participants were older than 65 years (3 %). Most of them are employees (64 %), 18 % are students. Altogether, the sample is too young, urban, educated to be compared to the Austrian average population.

The research model was tested by means of a structural equation modeling (SEM) approach using partial least squares (PLS) (software application SmartPLS 3.3.3). PLS-SEM are using non-parametric tests, normal distribution of variables is therefore not necessary (Awang et al., 2015). The application of PLS-SEM allows us to test full theories or concepts without requiring the data quality and sample sizes of covariance-based SEM approaches; PLS-SEM are rather confirmatory than explorative (Hair et al., 2011).

4 Results

At the beginning of the survey, the respondents were asked how often they used online food shopping before/after the COVID-19 pandemic. This delivers a very rough estimation of the general trend of online food shopping and the influence of the COVID-19 pandemic on that. We can clearly see that obviously most of the respondents increased the frequency of online food shopping (Table 2).

Table 2. Frequency of online food shopping before/after the COVID-19 pandemic

	response option	before	after	ratio	before	after	ratio
1	very often or exclusively	2.5 %	9.4 %	3,82			
2	often	3.9 %	9.9 %	2,51	9.9 %	29.7 %	3.01
3	rather often	3.4 %	10.4 %	3,01			
4	neither often, nor seldom	11.3 %	14.4 %	1,27	11.3 %	14.4 %	1.27
5	rather seldom	12.3 %	9.4 %	0,76			
6	seldom	25.6 %	15.8 %	0,62	78.8 %	55.9 %	0.71
7	very seldom or never	40.9 %	30.7 %	0,75			

The proportion of consumers doing online food shopping on a more or less regular basis tripled (from 10 % to 30 %); the proportion of consumers using this shopping channel (rather) seldom or never went down by about one third (from 79 % to 56 %). This result is not very surprising as, in the beginning, the pandemic led to significant restrictions when people were asked to stay at home as far as possible. Food shopping still was possible in Austria, but nevertheless, some people might have decided to stay at home to avoid social contacts. This result does not imply that the degree to which the consumers are affected by the pandemic immediately influences the change in the usage of online food shopping. We adapted a scale from literature to assess to what extent respondents are affected by the COVID-19 pandemic (Meixner and Katt, 2020) and integrated the scale items into our research model (Figure 1). The hypothetic construct "affected by COVID-19" is a situational factor complementing the TAM.

As we can see from Table 3, the results are more or less comparable (however, the original study refers to a time period early 2020 in the US; the present study refers to Austria mid 2021) despite the expectations for the future. As the present study was conducted in a much later stage of the pandemic, these differences are not really surprising. The results show that the consumers are highly affected by the pandemic, it is expected that it will change the society. But after all, respondents are rather optimistic. Consequently, the TAM of this study further investigates if the degree to which respondents agree to these statements has an influence on the willingness and valuation of online food shopping.

Table 3. Mean and standard deviation of COVID-19 items in comparison to Meixner and Katt (2020)

"affected by COVID-19" items	Mean	Std. Dev.	Meixner and Katt (2020) [a]
1 I feel the coronavirus pandemic has affected me personally.	2,79	1,62	1,97
2 I feel the coronavirus pandemic will change society.	2,24	1,24	1,51
3 COVID 19 influences my quality of life	2,48	1,50	[b]
4 I am optimistic regarding my financial situation.	2,47	1,25	2,04
5 I am worried about my financial future.	5,06	1,49	2,27

Scale meaning: 1 = "totally agree" to 7 = "totally disagree"; [a] transformed, as meaning of scale values 1 to 7 are reversed in Meixner and Katt (2020) with 7 = "totally agree" to 1 = "totally disagree"; [b] not in original scale of Meixner and Katt (2020)

First of all, the *reliability* of the model was tested. This proves the how reliable and stable the results are. Future measurements should deliver comparable results. As we used tested and well documented scales from literature, we expected that the reliability indicators delivered good results (Cronbach's alpha, composite reliability, factor loadings, and indicator reliability). Variables with factor loadings below 0.4 were excluded (Hair et al., 2011); Cronbach's alpha (0 to 1) should reach at least 0.7 to prove the internal consistency of scales (Tavakol and Dennick, 2011) – the same threshold should be reached with composite reliability (CR); however, if CR is too high (beyond 0.95), the relevant items might be considered to be identical and are therefore problematic as well (Sarstedt et al., 2020).

Concerning *validity* of our research model, we used as proposed the criterion discriminant validity (to analyze the relationship of latent variables). A usual indicator here is the heterotrait-monotrait ratio (HTMT) which delivers more reliable results compared to the traditionally used Fornell-Lacker criterion when PLS-SEM are applied (Modeling et al., 2015). HTMT should lie below the threshold of 0.85. Further indicators to assess the validity of the model are the convergence validity approximated via the average variance extracted (AVE) with a threshold of 0.5 or higher (Hair et al., 2011).

Table 4. Reliability and validity test of survey items (n = 206; approx. by Smart PLS)

	Number of survey items	Cronbach's alpha	CR	AVE
1 Perceived health risk (PHR)	2	,754	,754	,605
2 Perceived quality risk (PQR)	2	,913	,919	,851
3 Visibility of online shopping (VOS)	2	,704	,707	,547
4 Shopping experience (SE)	3	,884	,891	,733
5 Perceived time risk (PTR)	3	,723	,725	,473
6 Perceived usefulness (PU)	3	,897	,897	,686
7 Perceived easiness of use (PEU)	3	,708	,710	,450
8 Behavioral intention (BI)	4	,898	,897	,685

9 Actual use of online food shopping (AUOFS)	3	,942	,943	,892

For the research model of this study, the relevant indicators are satisfying for all hypothetical constructs besides the COVID-19 items where 4 out of 5 COVID-19 items had factor loadings below 0.4. The following analysis further showed that the variable "affected by COVID-19" had no significant effect on the perceived usefulness and behavioral intention (see below: effect size goes towards 0; R^2 would be lower if left in the model). Therefore, these variables were excluded from the model. The reliability and validity test of the remaining variables delivered good results. Cronbach's alpha, CR and AVE clearly fulfilled the above-mentioned conditions (Table 4). The threshold for HTMT of 0.85 was not exceeded, too (Table 5).

Table 5. Reliability test: HTMT (n = 206; approx. by Smart PLS)

HTMT	PHR	PQR	VOS	SE	PTR	PU	PEU	BI	AUOFS
PHR	-								
PQR	.131	-							
VOS	.346	.297	-						
SE	.413	.570	.396	-					
PTR	.145	.523	.089	.359	-				
PU	.454	.416	.621	.776	.393	-			
PEU	.273	.514	.419	.602	.573	.590	-		
BI	.377	.409	.404	.720	.491	.703	.674	-	
AUOFS	.291	.503	.448	.724	.253	.723	.605	.698	-

To test the *hypothetic relations and predictive power of the model variables* (after testing the predictor variables in view of multicollinearity via variance inflation factor VIF; should be below 10; this condition is fulfilled for all variables left in the model), several authors advise to use the coefficient of determination R^2 (0 to 1; thresholds of 0.66, 0.33, 0.19 for substantial, moderate, weak); cross validated redundancy Q^2 (0 to 1; Q^2 should be > 0; moderate if $Q^2 > 0.15$; high if $Q^2 > 0.35$); path coefficients (values from -1 to +1; below -0.2 and over +0.2 are considered to be meaningful) and their significance level (below 0.05; approximated by means of bootstrapping with at least 5,000 repetitions), and the effect size of the relations (f^2) (0 to 1; weak if $f^2 > 0.02$; moderate/high effect size if $f^2 > 0.15/0.35$) (Hair et al., 2011; Krafft et al., 2005). These tests also prove the validity of our hypotheses H1 to H6. As mentioned above, the situational factor "affected by COVID-19" should be deleted from the model, as R^2 is even higher without it. As we can see from Table 6, most of the hypothetic constructs can be explained at least moderately, in the case of PU even substantially.

Table 6. R^2 with and without situational factor „affected by COVID-19" for "perceived usefulness", "perceived easiness of use", "behavioral intention", "actual use of online food shopping" (n = 206; approx. by Smart PLS 3.0)

	with „affected by COVID-19"			*without „affected by COVID-19"*		
	R^2	adapted R^2	sig.	R^2	adapted R^2	sig.
PU	0.607	0.595	≤ 0.001	0.764	0.757	≤ 0.001
PEU	0.347	0.337	≤ 0.001	0.572	0.565	≤ 0.001
BI	0.498	0.494	≤ 0.001	0.623	0.619	≤ 0.001
AUOFS	0.418	0.415	≤ 0.001	0.492	0.490	≤ 0.001

To evaluate the overall *goodness of fit of our research model*, several further indicators are usually suggested by the SEM-literature which are, however, not one to one applicable for PLS-SEM, such as the normed fit index (NFI; calculates the Chi^2 value of the proposed model; lies between 0 and 1; NFI > 0.9 are good) or the standardized root mean square residual (SRMR; should be smaller than 0.1). These indicators are not fully understood for PLS-SEM, some authors even advise against using them (Hair et al., 2017). Considering these limitations, the interpretation of SRMR, NFI and the Chi^2 value of the model delivered the following results: SRMR is good and even better if we exclude the situational factor "affected by COVID-19"; NFI is at least in the latter model near the threshold of 0.9 (Table 7).

Altogether, the modified model where the COVID-19 items were deleted proves to be adequate to predict the actual use of online food shopping considering several external motives and barriers that could be relevant. For

this purpose, we formulated our hypotheses based on a broad literature review. In the final step of the analysis, we therefore test our hypotheses and approximate the path coefficients by means of PLS-SEM incl. bootstrapping with 5000 draws (as suggested by literature).

Table 7. Goodness of fit of the research model

	with „affected by COVID-19"		*without „affected by COVID-19"*	
	Saturated model	*Estimated model*	*Saturated model*	*Estimated model*
SRMR	.062	.079	.046	.072
Chi^2	916.076	1003.144	543.487	625.236
NFI	.778	.757	.851	.828

Table 8. Hypotheses test and path coefficients

Hypothesis	Path			Path coefficient		Hypotheses test
$H1_{PHR \rightarrow PU (+)}$	PHR	→	PU	0.072	n.s.	rejected
$H1_{PQR \rightarrow PU (–)}$	PQR	→	PU	-0.179	*	accepted
$H1_{VOS \rightarrow PU (+)}$	VOS	→	PU	0.404	***	accepted
$H1_{SE \rightarrow PU (+)}$	SE	→	PU	0.601	***	accepted
$H1_{PTR \rightarrow PU (–)}$	PTR	→	PU	-0.262	**	accepted
$H2_{SE \rightarrow PEU (+)}$	SE	→	PEU	0.334	***	accepted
$H2_{PTR \rightarrow PEU (–)}$	PTR	→	PEU	-0.449	***	accepted
$H3_{PEU \rightarrow PU (+)}$	PEU	→	PU	-0.021	n.s.	rejected
$H4_{PU \rightarrow BI (+)}$	PU	→	BI	0.509	***	accepted
$H4_{PEU \rightarrow BI (+)}$	PEU	→	BI	0.374	***	accepted
$H5_{BI \rightarrow AUOFS (+)}$	BI	→	AUOFS	0.702	***	accepted
$H6_{COVID\text{-}19 \rightarrow PU (+)}$	COVID-19	→	PU	0.026	n.s.	rejected
$H6_{COVID\text{-}19 \rightarrow BI (+)}$	COVID-19	→	BI	0.121	n.s.	rejected

Sig. * ≤ 0.05; ** ≤ 0.01; *** ≤ 0.001; bootstrapping: 5000 draws

Table 8 shows that most of our hypotheses could be accepted at a significance level below 0.001. The path coefficients partly reach high explanatory power; e.g., the path coefficient of AUOFS towards BI amounts to 0.702; the latter is significantly influenced by the perceived usefulness of online food shopping (0.509) and the perceived easiness of use (0.374).

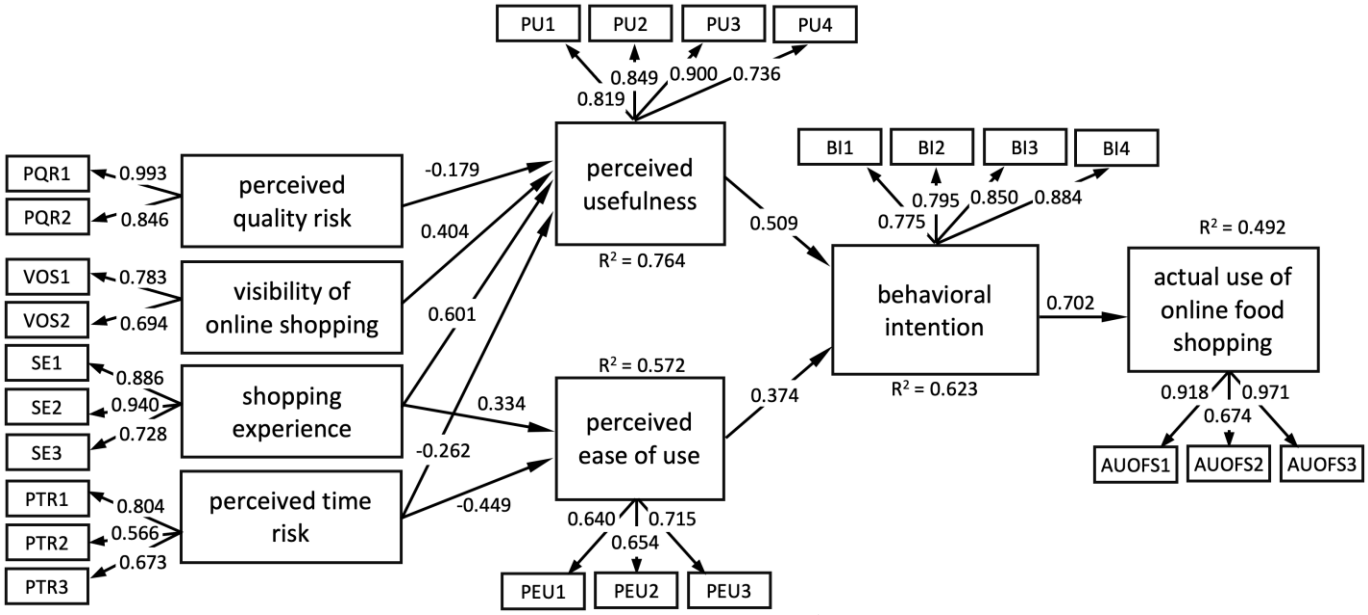

Figure 2. Evaluated TAM incl. factor loadings, R^2, and path coefficients (n = 206; approximated by Smart PLS 3.0, 5000 draws)

Figure 2 summarizes all valuated relations and contains the factor loadings of the individual items. This picture clearly shows that not all external or situational factors were relevant in our case (surprisingly, perceived health risk and the items related to "affected by COVID-19" had no significant path coefficients). One of the most important external factors seems to be shopping experience which significantly influences PU and PEU, as well. This means that the actual acceptance of online food shopping is highly influenced by past experiences of consumers. Another path, that should be mentioned concerns the visibility of online shopping: the more online shopping is integrated into the everyday life of people (which, in general, was massively boosted due to the COVID-19 pandemic), the more online food shopping is perceived to be useful.

5 Discussion, limitations and conclusions

This contribution has obviously some important limitations, many of them are connected to the sampling method (convenience sample) and small number of respondents. Future studies should definitely address these issues. Further, the operationalization of the situational factor of the TAM ("affected by COVID-19") should be assessed for future studies, as well. We only made slight changes in the original scale of Meixner and Katt (2020). Nevertheless, the measurement might not be optimal as it was developed in a very early stage of the pandemic. And meanwhile, other operationalizations are available, e.g., a scale measuring emotional responses to the COVID-19 pandemic (Grunert et al., 2022).

However, our findings also suggest a different interpretation which might be true as well: Obviously, the acceptance of the technology online food shopping has massively increased due to the COVID-19 pandemic. Even if the reactions of consumers might have been overestimated by the respondents of this study, the tendency is still the same if we compare it with findings in literature: e.g., a growth rate in the UK of about 33 % (Mintel, 2020); online food shopping-rates of about 31 % of Italian and French consumers; an increase of online food shopping in Austria from 19 % before the pandemic to 28 % (Gittenberger and Teller, 2020). However, this dramatic boost might obviously *not* be influenced by the individual estimate to what extent respondents were affected by the pandemic. This does not mean that the COVID-19 pandemic has no influence on the acceptance of online food shopping; it is just not a good predictor and not correlated with the TAM-variables. It is a general tendency, and therefore the predictor had to be eliminated from our TAM. Other motives or barriers are much more important to assess the acceptance of online food shopping. In particular, shopping experience and visibility of online food shopping seem to be highly adequate predictors here. One explicit barrier, the perceived time risk (e.g., late delivery), was considered in our model and has a considerable influence on the acceptance of online food shopping. Interestingly, the impossibility of proving the quality of the food products is much less important as the path coefficient is – although significant – quite low. Obviously, consumers (at least in our sample) more or less trust in the quality of foods also if they are delivered by online trade companies. This finding should be evaluated in future studies with bigger and representative samples, and also in other countries or cultures, as the assessment quality aspects might be significantly triggered by the provenience of the respondents.

The most important factor in our TAM for the actual use of online food sales seems to be perceived usefulness which is influenced mainly by the factor shopping experience. The importance of hedonic variables like this one are also confirmed in literature (Childers et al., 2001; Driediger and Bhatiasevi, 2019). The visibility of online shopping and the perceived time risk, that might be connected to online food shopping, are important predictors further explaining the perceived usefulness, too. Visibility can also be found in literature to be a significant predictor for the acceptance of online shopping (Chien and Kurnia, 2003). Insofar, our results are more or less in line with previous findings, even though we would have expected that the extent to what consumers are affected by COVID-19 would have moderated our TAM-variables.

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