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How Consumers Accept Unmanned Smart Stores? – Introducing a Proposed Technology Acceptance Model

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Digitalization and technological innovation have revolutionized the retail sector. In recent years, a new trend has emerged in the form of unmanned stores, pioneered by Amazon Go. Unmanned solutions using artificial intelligence are beginning to enter the public consciousness and represent a new sustainability perspective (such as lowering paper waste, packaging or using sustainable construction materials) in trade. Although it is not yet widespread and is still a new solution for consumers, the global market dynamics suggest that it will expand in the future. Unmanned shops pose some challenges, but these can be effectively addressed by the appropriate introduction of new technology. To identify or filter out potential shortcomings of this technology on the consumer side, it is also necessary to examine the acceptance of this technology by customers. In this paper, the internationally accepted Extended Unified Theory of Acceptance and Use of Technology (UTAUT2) model was modified and used to examine how consumers accept this technology. For data analysis, Partial Least Squares-Structural Equation Modelling method was applied. In the proposed model six constructs were examined on how they influence the intention to use. In the performed query, Hungarian university students' behavioural intention is influenced by performance expectancy, effort expectancy, and hedonic motivation. However social influence, atmosphere, and price sensitivity have no significant influence on use intention.

1. Introduction

Due to rapid economic growth and urbanization, various problems appeared in the last decades in metropolitan areas (Ku et al., 2021). The emergence of the global pandemic has resulted in avoiding human contact of paramount importance to customers, so e-commerce and the number of consumers using online shopping considerably increased (Gazzola et al., 2022). Most countries are experiencing a transition to a "cashless" society (Maixé-Altés and Mourelle, 2023). Nowadays in a rapidly changing environment (Bartosova et al. 2021), organizations are rapidly changing their structures, systems, work processes and activities. This changing environment calls for managers to manage and respond to the changes in an appropriate manner (Yacob et al. 2018). The early adopters are the small and medium enterprises (SMEs) that see the present emerging economies and disruptive technology as an opportunity to increase their productivity and competitiveness (Kuok and Promentilla, 2021). One recent sustainable innovation is the cashierless concept, which is when a store is completely automated and human interaction is very limited (Schögel and Lienhard, 2020). The concept, which is a combination of artificial intelligence, computer vision, deep learning and edge computing, allows end users to enter the store and exit as quickly and with as little human contact as possible (Falcão et al. 2020). The shopping process is as follows: download an application; register, then, after the registration process, the consumer is free to simply buy products and exit the store without needing to "check out" in the traditional sense (Ponte and Bonazzi, 2021). Amazon, the world-famous online retailer founded by American Jeff Bezos, invented the concept to eliminate queuing in stores (Gross, 2019). On the 22nd of January 2018 after 5 y of development, Amazon opened the first self-service Amazon Go store with the so-called "Just Walk Out" technology (Türegün, 2019). Since then, several startups have developed similar technology, e.g., AIFI, Trigo, Bingobox, and Cloudpick (Szabó-Szentgróti et al., 2023). Although this technology has been available globally and sporadically

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for a few years, it is not yet widespread. It is important to examine how consumers react to such an innovative technology. The main purpose of this study is to analyse how university students accept this sustainable innovation concept of cashierless stores in Hungary. In this study, we use the terminology of cashierless store and unmanned store as synonyms. The rest of the paper is structured as follows: Section 2 – Methodology; Section 3 – Model assessment and hypothesis results; Section 4 – Conclusion and future works.

2. Methodology

2.1 Data collection and measures

The research is based on an online survey of 246 Hungarian university students. The questionnaire was designed to reveal the technology acceptance of unmanned stores using validated scales (Appendix A). Unified Theory of Acceptance and Use of Technology Model (UTAUT2) ensured the basis of our proposed model. The original UTAUT2 (Venkatesh et al., 2012) model had to be adapted to the objectives of this research. Concerning the model development Performance Expectancy, Effort Expectancy, Social Influence, Facilitating Conditions, Hedonic Motivation constructs were applied from Venkatesh et al. (2012). A new construct was created called Atmosphere, where the goal was to find out whether Behavioural Intention is influenced by the special indoor atmosphere of these shops. Technology penetration does not yet allow respondents to judge value for money, thus Price Value construct has been replaced by Price Sensitivity. Furthermore, Hungarian consumers are mostly price sensitive (Garai-Fodor et al., 2022) and these shops represent high price levels. Concerning Behavioural Intention construct statements, a few drafting corrections were needed to make them meaningful for the analysed technology. Use Behaviour variable was excluded from our model, because there is no everyday use for such shops in Hungary. For each of the 8 constructs, respondents rated 29 statements on a Likert scale of 1 to 7, where 1 was 'strongly disagree' and 7 was 'strongly agree'. Answers were collected to measure more expectations rather than experience-based opinions, due to the limited availability of these shops. The survey was conducted from February to May 2023 to collect as many answers as possible. In order to avoid misunderstanding, the questionnaire started with the definition of unmanned stores. Participants were informed about the anonymity and voluntarity of the survey, and they could stop giving answers without giving a reason. From 269 respondents 23 were excluded from the analysed database due to inconsistent answers, thus the final sample size was 246. Our respondents' ages ranged from 18 to 39 y including full-time and part-time university students. The sample's distribution between male and female respondents was 69.1 % and 30.9 %; 6.9 % live in the capital city, 43.1 % are residents of a county rank town while 22.8 % live in other towns, and 27.2 % live in villages. The results were analysed with SmartPLS version 4.0.9.3.

2.2 PLS-SEM

This study utilized the PLS-SEM (partial least squares-structural equation modeling) method, a widely used statistical tool by researchers in many scientific fields (Lowry and Gaskin, 2014). According to Hair et al. (2011) PLS-SEM consists of a measurement model and a structural model at the same time, where the measurement (outer) model describes the indirect relationships between the observed (indicator) and latent variables. The structural (inner) model shows the relationships (paths) between the latent constructs. PLS-SEM method can deal with both reflective and formative indicators simultaneously. Hypothesis formulation (Table 1 and Figure 1) was adapted to the structure of the model of how the examined latent variables influence Behavioural Intention.

Table 1: Model Hypothesises for cashierless intelligent stores

Hypothesises
H1: Performance Expectancy (PE) directly and positively influences Behavioural Intention (BI).
H2: Effort Expectancy (EE) directly and positively influences Behavioural Intention (BI).
H3: Social Influence (SI) directly and positively influences Behavioural Intention (BI).
H4: Facilitating Conditions (FC) directly and positively influences Behavioural Intention (BI).
H5: Hedonic Motivation (HM) directly and positively influences Behavioural Intention (BI).
H6: Atmosphere (AT) directly and positively influences Behavioural Intention (BI).
H7: Price Sensitivity (PS) directly and negatively influences Behavioural Intention (BI).

3. Results and discussion

3.1 Measurement model

Reflective measurement model was analysed in regard to its reliability using outer loading values, average variance extracted (AVE), Cronbach's alpha (α Value), and composite reliability (CR). Due to poor construct reliability, some statements and Facilitating Conditions (FC) were excluded from the final model (excluded variables see Appendix Table A1). It is shown in Table 2 that outer loadings are all greater than 0.7 and AVE values of the latent constructs are all above the limit value of 0.5 (Hair et al., 2010). Cronbach's alpha is another measure of internal consistency reliability with a threshold >0.7. Only Atmosphere has an α value of 0.610, but concerning the view of Boudreau et al. (2001), Cronbach's alpha is a less precise measure of reliability, and Griethuijsen et al. (2014) allows a 0.6 threshold value. As other measures are appropriate in the case of the Atmosphere latent variable, no exclusion was necessary. According to Hair et al. (2011), CR values of 0.60 to 0.70 in exploratory research and values from 0.70 to 0.90 in more advanced stages of research are considered to be satisfactory. All CR values in Table 2 are above that threshold. Variables that did not meet the thresholds were excluded (Appendix A) from the final model.

Table 2: Construct reliability, convergent validity and VIF values, own data generated by PLS-SEM analysis

Constructs	Items	Outer loadings	P values	AVE	α Value	CR	VIF
Performance Expectancy	PE2	0.877	0.000	0.739	0.824	0.895	2.024
	PE3	0.840	0.000				1.758
	PE4	0.862	0.000				1.848
Effort Expectancy	EE1	0.782	0.000	0.657	0.832	0.884	1.965
	EE2	0.855	0.000				1.957
	EE3	0.854	0.000				1.774
	EE4	0.746	0.000				1.857
Social Influence	SI1	0.872	0.000	0.784	0.862	0.916	2.013
	SI2	0.886	0.000				2.390
	SI3	0.898	0.000				2.302
Hedonic Motivation	HM1	0.911	0.000	0.840	0.905	0.940	2.987
	HM2	0.918	0.000				2.704
	HM3	0.920	0.000				3.120
Atmosphere	AT1	0.859	0.000	0.719	0.610	0.837	1.239
	AT3	0.837	0.000				1.239
Price Sensitivity	PS2	0.885	0.000	0.759	0.841	0.904	2.198
	PS3	0.894	0.000				2.516
	PS4	0.834	0.000				1.720
Behavioural Intention	BI1	0.891	0.000	0.770	0.851	0.909	2.285
	BI2	0.819	0.000				1.807
	BI3	0.921	0.000				2.784

Discriminant validity shows that constructs used in the model are distinct from one another (Hair et al., 2017) where Heterotrait-Monotrait Ratio (HTMT) and Fornell-Larker criteria are widely used in research to confirm that. Henseler et al. (2015) pointed out that Fornell-Larker criteria perform poorly and HTMT is recommended instead. In the present study, all HTMT values are below 0.9 (Table 3) confirming discriminant validity of our model.

Table 3: Discriminant Validity (HTMT criteria), own data generated by PLS-SEM analysis

	AT	BI	EE	HM	PE	PS	SI
AT							
BI	0.666						
EE	0.812	0.673					
HM	0.710	0.823	0.614				
PE	0.622	0.897	0.640	0.736			
PS	0.117	0.409	0.160	0.344	0.386		
SI	0.231	0.552	0.357	0.491	0.538	0.474	

A multicollinearity test was carried out before estimating the structural model, for which VIF (Variance Inflation Factor) values were tested. VIF values above 5.0 indicate multicollinearity, according to Hair et al. (2011); therefore, VIF values in Table 2 show no multicollinearity between latent constructs.

3.2 Structural model and hypothesis testing

The structural model assessment was performed by 5000 bootstrap calculations, during which the statistical significance of the path coefficient was carried out, allowing hypotheses to be tested. To examine model fitness Standardized Root Mean Square (SRMR) was used and must be less than 0.08 according to Henseler et al. (2016). This model shows an adequate level of model fitness with an SRMR value of 0.073, which indicates a good fit. The final proposed model is seen in Figure 1.

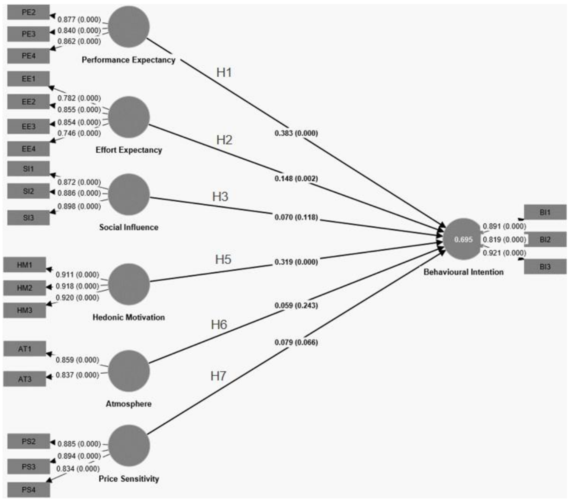

Figure 1: Proposed model of cashierless store technology acceptance. Source: own data generated by PLS-SEM analysis

R^2 was evaluated where the final model has 0.695 adjusted R^2 value, which suggests that a 69.5% variance in Behavioural Intention of cashierless stores can be explained by the analysed six latent variables. Accordingly, the structural model was considered to be moderate ($0.5 < r < 0.75$) (Hair et al., 2011) and 0.695 value means a sufficient explanatory power. Predictive relevance of the model was established by $Q^2_{predict}$ value of 0.683 that indicates good predictive accuracy. Relationships of the research model were analysed to test six hypothesises (due to poor construct reliability Facilitating Conditions [FC] was excluded [H4] from hypothesis testing). Results show in Table 4 that Performance Expectancy (ß=0.383, p=0.000), Effort Expectancy (ß=0.148, p=0.000) and Hedonic Motivation (ß=0.319, p=0.000) significantly influenced Behavioural Intention (BI), while Social Influence (ß=0.070, p=0.118), Atmosphere (ß=0.059, p=0.243) and Price Sensitivity (ß=0.079, p=0.066) have no significant effect on the BI variable.

Table 4: Bootstrap results and hypothesis results. Source: own data generated by PLS-SEM analysis

		Original sample	Sample mean	Standard deviation	T statistics	P values	Hypothesis validation
PE -> BI	(H1)	0.383	0.386	0.060	6.395	0.000*	supported
EE -> BI	(H2)	0.148	0.148	0.048	3.078	0.002*	supported
SI -> BI	(H3)	0.070	0.071	0.045	1.564	0.118	not supported
HM -> BI	(H5)	0.319	0.317	0.059	5.433	0.000*	supported
AT -> BI	(H6)	0.059	0.059	0.051	1.167	0.243	not supported
PS -> BI	(H7)	0.079	0.078	0.043	1.839	0.066	not supported

4. Conclusions

The purpose of this study was to assess which factors influence Behavioural Intention in the case of cashierless stores among Hungarian university students. Research in this area is still scarce in Hungary and there has been less research on it internationally, as well. The proposed model was based on the UTAUT2 method, combining validated scales that have been adapted to the research.

There are several conclusions that can be drawn from the result. Performance Expectancy significantly influences Behavioural Intention (H1), which means that according to the respondents shopping in cashierless stores it would help them to be more productive and finish shopping more quickly. As some technological skills and smartphone usage are required to shop at unmanned stores, H2 results show that respondents can easily cope with using this new technology. Social Influence has no significant effect on Behavioural Intention (H3), which indicates that respondents are not influenced by other people’s opinions to do their shopping in such stores. Unmanned stores provide a different shopping experience for consumers and our results show that respondents would find cashierless shopping fun, enjoyable and entertaining (H5). The Atmosphere variable was created to measure how current minimalist interior space of these shops influences Behavioural Intention (H6), but no significant effect was experienced, which means respondents would not require a minimalist interior. In the current phase of this technology, products have higher prices than in traditional brick-and-mortar shops. According to our results, Price Sensitivity has no significant effect on Behavioural Intention among Hungarian

university students (H7), which is a surprising result in that a significant proportion of Hungarian consumers are considered price sensitive (Garai-Fodor et al., 2022). In summary this paper investigated which factors affect the intention to use cashierless stores among Hungarian university students. Three factors were identified which determine Behavioural Intention. From a practical perspective, results support retailers in their market entry strategic decisions because university students could be an important target group of cashierless stores.
Limitations and future research possibilities should be outlined. Results show the current opinion of the respondents; moreover, as only one cashierless store is available in Hungary, results will probably vary, as this technology will spread. The results cannot be generalized to the whole population in Hungary; the results are valid only for Hungarian university respondents. Thus, in the future, a wider Hungarian sample needs to be analysed, which is already in progress. An international perspective is also planned to examine where more countries will be involved to ensure international comparisons.

Appendix A

Table A1: Research statements

Code	CONSTRUCTS AND STATEMENTS
PE1	I would find automated smart stores useful in my daily life (Venkatesh et al., 2012); deleted
PE2	Using automated smart stores would increase my flexibility daily (Kapser and Abdelrahman, 2020)
PE3	Using automated smart stores would help me accomplish things more quickly (Venkatesh et al., 2012)
PE4	Using automated smart stores would increase my productivity (Venkatesh et al., 2012)
EE1	Learning how to shop in automated smart stores would be easy for me (Venkatesh et al., 2012)
EE2	My interaction with automated smart stores would be clear and understandable (Venkatesh et al., 2012)
EE3	I would find automated smart stores easy to use (Venkatesh et al., 2012)
EE4	It would be easy for me to become skilful at shopping in automated smart stores. (Venkatesh et al., 2012)
SI1	People who are important to me expect me to shop at automated smart stores (Venkatesh et al., 2012)
SI2	People who influence my behaviour expect me to shop at automated smart stores (Venkatesh et al., 2012)
SI3	People whose opinions I value would prefer that I shop at automated smart stores (Venkatesh et al., 2012)
FC1	I have the resources necessary to shop at automated smart stores (Venkatesh et al., 2012); deleted
FC2	I have the knowledge necessary to shop at automated smart stores (Venkatesh et al., 2012); deleted
FC3	Automated smart stores are compatible with other technologies I use (Venkatesh et al., 2012); deleted
FC4	I can get help from others when shopping at automated smart stores (Venkatesh et al., 2012); deleted
HM1	Shopping at automated smart stores would be fun (Venkatesh et al., 2012)
HM2	Shopping at automated smart stores would be enjoyable (Venkatesh et al., 2012)
HM3	Shopping at automated smart stores would be very entertaining (Venkatesh et al., 2012)
AT1	I would prefer automated smart stores to be less crowded with customers (own statement)
AT2	I would prefer automated smart stores to have smaller selection of products (own statement; deleted)
AT3	I would prefer automated smart stores to have clean and simple interior (own statement)
AT4	I would find products easier in automated smart stores (own statement; deleted)
PS1	Automated smart stores would offer me better value for money (Indrawati and Putri, 2018); deleted
PS2	I would not mind paying more to try automated smart stores (Kapser and Abdelrahman, 2020)
PS3	I would not mind spending more to get my shopping done in automated smart stores. (Kapser and Abdelrahman, 2020)
PS4	If I knew that automated smart stores were likely to be more expensive than conventional shopping options that would not matter to me. (Kapser and Abdelrahman, 2020)
BI1	I intend to shop at automated smart stores in the future. (Venkatesh et al., 2012)
BI2	I would always try to shop at automated smart stores in my daily life. (Venkatesh et al., 2012)
BI3	I plan to shop at automated smart stores frequently when available in the future. (Kapser and Abdelrahman, 2020)

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