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Intention to use scan&go system by Czech customers – Applying diffusion of innovations and a UTAUT 2 model

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Abstract

This article presents the most significant factors influencing the adoption of scan&go UTAUT 2 (Unified Theory for Acceptance and Use of Technology) model application. The study offers possible approaches to appropriately working with individual factors using a newly presented research connection between UTAUT 2 and diffusion of innovation. The research is based on analyzing data from a questionnaire survey conducted among 420 Czech consumers. Respondents were first divided into categories according to their approach to innovation based on the diffusion of innovations theory. Although scan&go systems are already widespread in the Czech Republic, only about 56% of addressed customers have included them in their shopping habits. Among non-users, the main causes of their current behavior were identified and their future decision-making was also examined. The UTAUT 2 model was subsequently applied to verify the main drivers of behavior among active users. Thus, a total of 235 responses were utilized to validate the model (using PLS-SEM via SmartPLS 4). Of the essential constructs defined in UTAUT 2, performance expectancy, hedonic motivation and habit on behavioral intention indicated the most significant decision-making influence. The user's behavior is mainly explained by the factors of behavioral intention and habit. The established routines thereby show the most powerful effect when it comes to the adoption of scan&go systems among young people. The assignment of managers trying to attract consumers to adopt similar technological innovations or to motivate non-users is, therefore, to focus on user habits with an emphasis on the involvement of entertaining elements (hedonic motivation) and promotion of benefits arising from the use (performance expectancy).

Keywords: *scan&go; retail business; self-service technologies; UTAUT 2; diffusion of innovations theory*

JEL Classification*: L81, O31*

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1 INTRODUCTION

The field of retail, like other areas of business activity, is sharply affected and influenced by the rapid development of technology. In 2023, retail was formed by the following main directions (Kohan, 2022):

- Retail media networks (sharing of advertising spaces between retailers and sellers),
- Social media sentiment monitoring (collection and analysis of information about how people talk about a given retailer on social networks and how they perceive specific brands),
- Hybrid shopping and seamless shopper journey (providing an ideal shopping experience for all distribution channels and their combinations: online, in stores, on mobile devices or social media),

- Store design shifts and mixed-use spaces (adaptation of new stores to current requirements to achieve an optimal shopping experience),
- Consumerism curtailment (consumers will think more about recycling, further use of already purchased products and extending the product's life cycle).

The outline expands on predictions from previous years, where the authors also drew attention to the ever-growing e-commerce and re-e-commerce area (Rick, 2022), the increasing importance of sales via social media and omnichannel shopping ('the future is phygital' = physical + digital) (Kim et al., 2022). Furthermore, they consider supply change challenges such as speeding up delivery times and optimizing supplier-customer relationships (Souiden et al., 2019), investing in digitization and automation (Huskova & Dyntar, 2022), and reaching out to new workforces to supplement the ranks of employees (Inman & Nikolova, 2017).

The increasingly widespread use of scan&go technology can also be included in the latter direction. It is responding to the pressure to introduce technological innovations into the static and old-fashioned supermarket environment, which has mostly remained unchanged in the last hundred years since the first store in the United States opened (Stanton, 2018). Scan&go technology, already widely used in supermarkets, allows customers to load their purchases directly into the prepared scanners without transferring the goods at the checkout.

It works as such. The customer places their loyalty card against the reader device that is located on the scanner wall. Therefore, it is absolutely necessary to be enrolled in the loyalty program of the selected store. Afterwards, the customer takes the scanner when the card is applied, which lights up. In many stores, a mobile phone with the store's mobile application installed can be used instead of a scanner. The system behaves similarly in the following steps. During shopping, the customer points the scanner at the product barcode from about 15 cm and presses the button. For fruits, vegetables, meat products and delicacies, the label is scanned after weighing. A code is available on the shelf next to the product price for pastries. The current price of the entire purchase can be seen and checked on the display. Customers can delete individual items at any time with the minus button. Payment will then take place at self-service cash registers designed for scan&go purchases. To complete the purchase, the customer scans a unique barcode and places the scanner in the holder. Then all customers have to do is reload the card and pay. Even during the first purchase, there may be a random check of the purchase by the attendant. One control worker can thus handle and monitor several self-service cash registers. Customers positively evaluate the current overview of expenses and products, the possibility of internal navigation, time saving and assess this experience as fun (Lawo et al., 2021).

By its nature, it belongs to the so-called smart retail technologies (SRT) or self-service technologies (SST), which improve the retail system and include effective management of customer contact points (Fazal-e-Hasan et al., 2021). SRT can enhance the customer experience and increase the performance of the retail unit (Roy et al., 2017). As one of the cornerstones of retail technology, automation aims to streamline retail store processes. In 2023, the global retail automation market reached USD 13.5 billion (Sabanoglu, 2022). According to Next Move Strategy Consulting estimates, the market is expected to grow to USD 33 billion by 2030 (Sabanoglu, 2022). Self-service technologies allow users in retail stores to achieve desired services without the physical presence of staff. They allow clients to save time, avoid unwanted interaction with staff and record purchases made. Moreover, the COVID-19 pandemic has brought about significant challenges for retailers, emphasizing the urgency for the implementation of smart retailing strategies and tactics to mitigate the negative impact on the retail industry (Kotb, 2020).

This article defines the key drivers of scan&go implementation in Czech retail stores. The research study applies a unified theory for acceptance and use of technology, second version (UTAUT 2) and diffusion of innovations. Czechs are generally known for their positive acceptance of technological innovations (Castellani et al., 2022; Statista, 2022). Therefore, the given article offers a relevant overview of the researched topic. A similar form of recording and paying for purchases is already offered to Czech customers by several significant players: Kaufland (No. 2 on the Czech retail market in terms of turnover), Albert (No. 3), Tesco (No. 5) and Globus (No. 9).

In order to fulfil the objectives of this paper, its structure is as follows. After the short introduction comes a brief literature review concentrating on the introduction of the used methods: the development of UTAUT (2) theory and basic principles of diffusion of innovations. This part is finished by a proposed research model. Within methodology, the third section presents specifics of the conducted survey. The results of the data analysis are summarised in the next section. A short conclusion with limitations and plans for future research are provided at the end.

2 THEORETICAL BACKGROUND

The conducted research builds on the principles of Rogers' diffusion of innovation and UTAUT 2. Both of these theories are briefly introduced in the theoretical review. At the end of the chapter, a researched structural model based on the principles of UTAUT 2 is presented and briefly described.

2.1 Diffusion of innovations theory

The theory of diffusion of innovations (DOI, IDT), developed by E. M. Rogers in 1962, originated in communication research to explain how an idea or product gains traction over time and spreads through a particular population or social group. The end result of this diffusion is the adoption of a new idea, behavior, product or technology into an established system. Adoption means that one does something differently than before. The key to adoption is that the person must perceive the idea, behavior or product as new or innovative. This makes diffusion possible (Rogers, 1962).

Rogers' theory relies on four main diffusion dimensions determining the success of a new technology: perception of innovation characteristics, communication channels, timing of acceptance, and social system (Franceschinis et al., 2017).

The essence of each dimension in Rogers' theory is defined by specific factors. Those in the first dimension describe the basic characteristics of the innovation (Franceschinis et al., 2017). Complexity can be defined as the degree to which an innovation is perceived as difficult to use or (un)understandable (Shah Alam et al., 2007), compatibility as the degree to which an innovation is perceived as consistent with existing practices and habits (Vijayasarathy, 2002), trialability as the degree to which we can experiment with an innovation before applying it (Moore & Benbasat, 1991), and relative advantage as the degree to which an innovation is perceived as better than current practice (Bjørnstad, 2012).

The second dimension of diffusion concerns communication channels and is less structured. Rogers sees communication as a process in which participants create and share information with each other to achieve mutual understanding (Rogers, 2010).

The third dimension, the relative timing of adoption, is determined by each individual's degree of innovativeness. Rogers classified members of a social system as follows: innovators, early adopters, early majority, late majority and laggards (Franceschinis et al., 2017). Their distribution in the group is presented in Figure 1. The red curve shows the share of the innovation on the market. The blue curve shows the ranking and market share of individual categories of innovators.

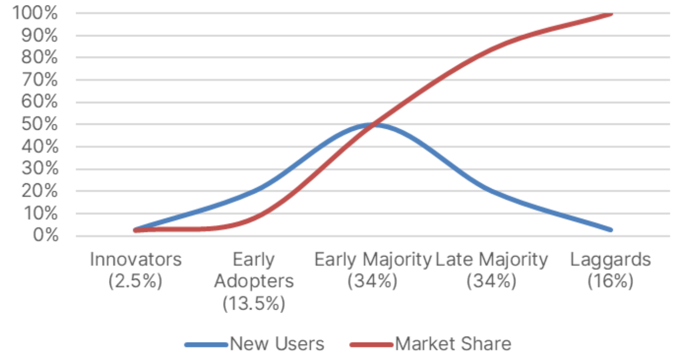

Figure 1: Diffusion of innovation theory. Source: own processing according to Rogers, 1962

The first individuals to adopt a new innovation were identified by Rogers as innovators (2.5%). These individuals are willing to take a risk that is closely related to their often young age. They are characterized by financial literacy and a higher social class that likes to follow scientific news. Innovators are also expected to have a high level of interaction with other innovators. Thanks to their risk appetite, they are not afraid to embrace innovations that may ultimately fail (Rogers, 2010).

First adopters (13.5%), as the second fastest category of adopters of a product, service or technology, show the highest degree of opinion leadership. Again, mostly younger adopters from a higher social class belong here. However, their decision-making about technology adoption is of a more discrete nature. They also carefully consider the adoption of the chosen technology. After its adoption, however, they are an important communication channel towards other groups of adopters (Rogers, 2010).

The early majority (34%) have a significantly longer period of adoption. The variance of time to acceptance is also typically greater than that of innovators and early adopters. They usually make their adoption decision after contacting the first adopters. Thus, they can be assigned a similar social status, but without the position of opinion leader. They therefore make decisions more slowly and over a longer time horizon (Rogers, 2010).

Although more than half of society has already adopted the innovation, individuals from the late majority (34%) are still skeptical about adoption. These are often individuals with a below-average social status and low financial literacy. These adopters are mainly in contact with the early majority and do not have a good opinion of innovators (Rogers, 2010).

Laggards (16%) are the last to innovate. These individuals are usually characterized by risk aversion and react negatively to changes. These are mostly older individuals who like to follow tradition. They are often only in contact with the immediate family, have a rather low social status and are not personalities determining the current of opinion (Rogers, 2010).

The diffusion of a new product or service usually takes place in a social environment, which is often referred to as a social system and represents the fourth dimension of Rogers' theory. Sometimes in the context of consumer behavior, the term market segment and target market may be used instead of social system. It is an arrangement of interconnected units characterized by common critical thinking to achieve a goal (Sahin, 2006). The spread of product innovation is significantly influenced by the social structure of the social framework. The nature of the social framework is shown to influence people's innovativeness, which is a primary prerequisite for introducing innovation (Mannan & Haleem, 2017).

2.2 UTAUT (2)

The unified theory of acceptance and use of technology (UTAUT) was proposed as a combination of eight earlier theories dealing with acceptance and motivation to adopt technology to create a unified theory (Venkatesh et al., 2003). This theory has been commented on, improved upon, and modified over time. The original version identified four main areas of influence on technology adoption: performance expectancy, effort expectancy, social influence and facilitating conditions (Venkatesh et al., 2003).

All the factors and relationships defined in the original UTAUT model from 2003 are represented by the dashed box in Figure 2. However, after almost ten years, the theory was extended to study the adoption and use of technology in a consumer context. Considering the limitations of the first version of the UTAUT model, new aspects were integrated into the model: consumer impact, automation and monetary costs (Venkatesh et al., 2012).

The model newly included hedonic motivation, price value and habit. Furthermore, the authors also hypothesized that individual age, gender and experience differences moderate the effects of selected factors on behavioral intention and technology use (Venkatesh et al., 2012).

The complete diagram of UTAUT 2 with markings of the original version of UTAUT is shown in Figure 2.

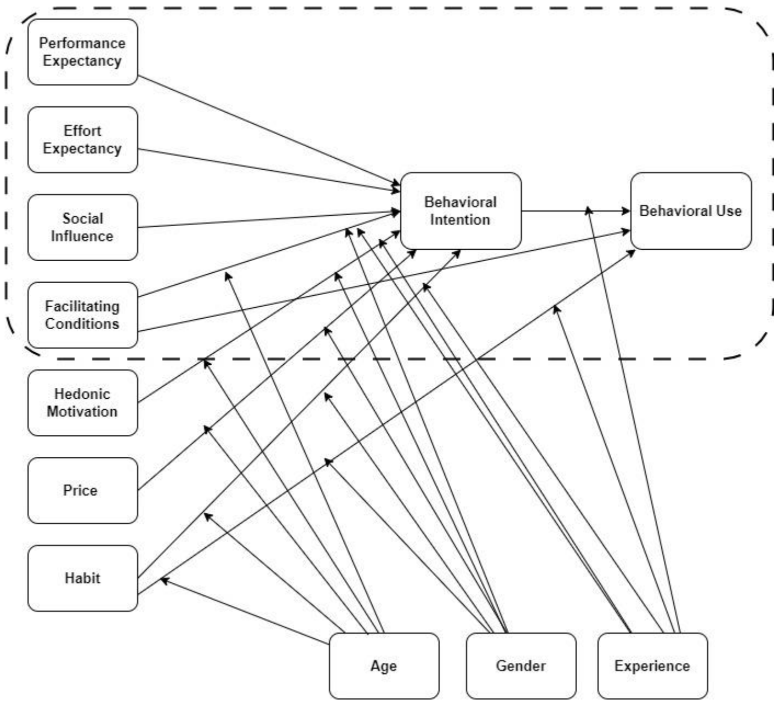

Figure 1: UTAUT and UTAUT 2. Source: Own processing according to Venkatesh et al. (2003, 2012)

Considering the consumer context of the research topic, this study is based on UTAUT 2. Furthermore, the meaning and basic application of individual constructs are presented. Relevant tested hypotheses are also added.

Performance expectancy expresses the extent to which an individual assumes that using a system or technological innovation will help them perform better. In other words, expected performance characterizes the degree to which potential users believe their performance will improve if they adopt the system or innovation (Alblooshi & Abdul Hamid, 2022).

H1: Performance expectancy (PE) positively influences the intention to use (BI) scan&go.

Venkatesh et al. (2003) viewed effort expectancy as the simplicity/complexity associated with IS (information system) use. It, therefore, expresses the degree of expectation that using an innovation or system will not be associated with physical or mental effort. The principle of effort expectancy consists of (favorable) relationships between the effort expended, the performance achieved during this effort and the rewards obtained for this effort (Ghalandari, 2012).

H2: Effort expectancy (EE) positively influences the intention to use scan&go.

Social influence can be characterized as the degree to which an individual perceives that essential persons expect them to use the new system. Positive environmental encouragement increases individuals' interest in using a new system or adopting an innovation (Venkatesh et al., 2003b). The social influence factor expresses expectations when one or more people in the environment approve of a particular behavior and motivate the given individual to follow them (Rakhmawati et al., 2020).

H3: Social influence (SI) positively influences the intention to use scan&go.

Facilitating conditions refer to the degree to which individuals believe the management and technical infrastructure exists and is available to support the introduced system or innovation. Therefore, facilitating conditions are closely related to the support provided and the availability of resources necessary for the use of technology (Ambarwati et al., 2020). Lack of assistance, insufficient timely support, incomplete information and limited resources can prevent individuals from adopting new technologies (Kamaghe et al., 2020). Providing facilitating conditions significantly influences behavioral intentions and user behavior (Venkatesh et al., 2012).

H4: Facilitating conditions (FC) positively influence the intention to use scan&go.

H7: FC positively influence behavioral use (BU) of scan&go.

Researchers have defined hedonic motivation as the perceived pleasure of using technology, pointing to its influence on positive acceptance (Thong et al., 2006). Willingness to accept a new system or innovation increases with previous positive experiences with similar technology. In general, individuals are more likely to initiate behavior that leads to pleasure and rewards or guarantees the avoidance of punishment (Kaczmarek, 2017).

H5: Hedonic motivation (HM) positively influences the intention to use scan&go.

After an extended period, when the continuous use of technology becomes a fixed part of working time, the habit factor starts to work. Environmental stimuli can activate learned sequences, which can be repeated without conscious intention (Bandyopadhyay & Fraccastoro, 2007). Learning automatisms and routines reflecting prior experience predict behavioral intention and technology use decisions (Venkatesh et al., 2012).

H6: Habit (HB) positively influences the intention to use scan&go.

H8: HB positively influences BU of scan&go.

In the consumer environment, the use of a product is influenced by the factor of price value, which indicates the product's perceived value at a given price (Ul-Ain et al., 2015). This factor is often overlooked in organizations and businesses (including retail) because systems or innovations are provided free of charge according to job classification and responsibility. For this reason, the price value factor is likewise not included in the conducted study. Scan&go is provided free of charge.

Behavioral intention is guided by the sum of the determining motivational factors that influence the given behavior. It is assumed that the stronger the behavioral intention, the more likely the contemplated behavior will occur. Simply put, it is the level of motivation to perform a specific action (Fishman et al., 2020).

H9: BI positively influences BU of scan&go.

Behavioral use can be measured and based on the frequency of using a particular technology or system. According to the principles of the first version of the UTAUT theory, an individual's behavior is directly influenced by the intentions of use and the level of facilitating conditions (Venkatesh et al., 2003).

Each construct was composed of a different number of items. Six latent variables and two dependent variables were included in the model, as seen in Figure 3. A part of a questionnaire survey devoted to the PLS-SEM analysis was based on original statements defined in UTAUT 2 (Venkatesh et al., 2012). In accordance with the specific characteristics of the tested model, the definitive number and statements were only partly revised: performance expectancy (composed of 3 items in a questionnaire survey), effort expectancy (4), social influence (3), facilitating conditions (4), habit (2), hedonic motivation (2), behavioral intention (3).

The research model is presented in Figure 3.

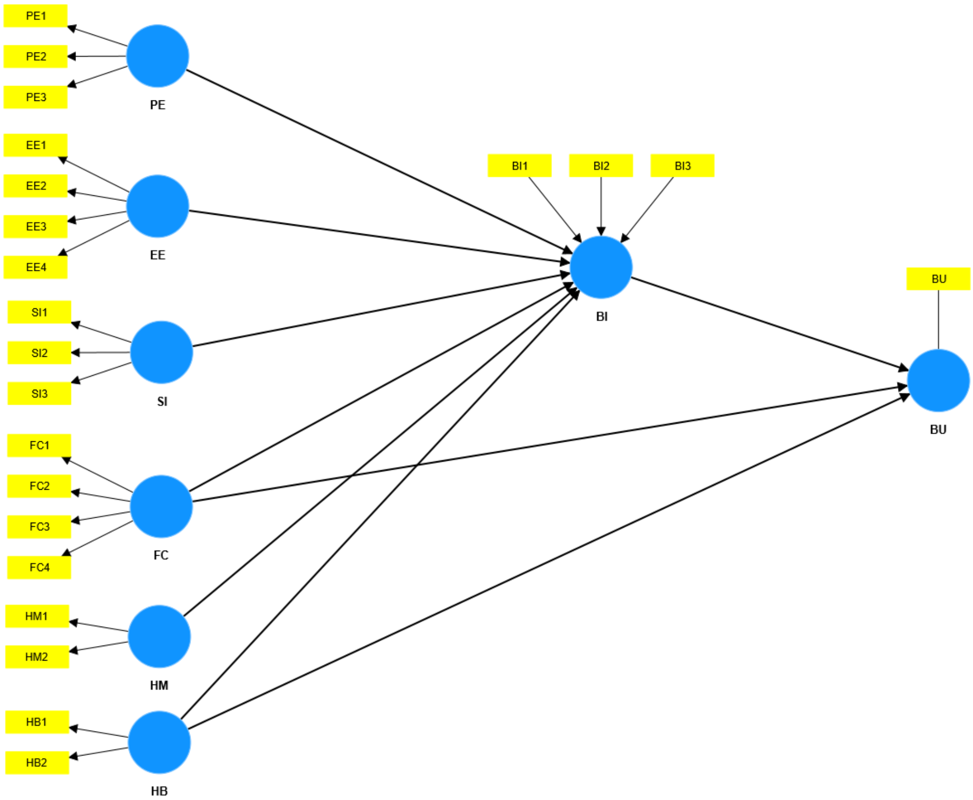

Figure 3: Researched model. Source: Own processing via SmartPLS 4

3 METHODOLOGY

This article is built on a quantitative questionnaire survey conducted among Czech consumers in April 2023. A total of 420 respondents participated, and 235 responses (active or experienced users of scan&go) were included in the data analysis using UTAUT 2. The remaining respondents were classified together with active users according to the diffusion of innovation theory. The classification was based on the analysis of questions following the reasons for the previous non-adoption of scan&go and the respondents' future behavior tendencies. Subsequent verification of the structural model using UTAUT 2 represents the main drivers influencing active user behavior. The PLS-SEM method, via SmartPLS 4, was used to verify a structural model. The methodological procedure was implemented in several steps, the sequence is described in following text.

STEP 1: Compilation of the questionnaire survey based on a literature review

The UTAUT 2 model was chosen as a result of the literature search to find the critical success factors for the adoption of scan&go. This theory also includes factors typical of the consumer environment, so it fits well into the researched topic. It is also widely used, so there are plenty of ways to compare results. The questionnaire was therefore compiled according to the recommendations from the original version of UTAUT 2 (Venkatesh et al., 2012). Individual statements were only partially modified according to the specifics of scan&go adoption. For a comprehensive overview of the consumer behavior of all respondents (users and non-users), a classification according to the principles of Rogers' diffusion of innovations was also applied. This theory offers a wide application in the adoption of a product, service or innovation and appropriately complements the research on consumer behavior in the adoption of scan&go.

STEP 2: Questionnaire distribution – securing a representative sample according to age structure

The survey among Czech consumers was conducted in April 2023. Four hundred and twenty respondents participated in the survey and expressed their current preferences for using scanning devices in Czech supermarkets in the questionnaire. The data was collected using the CAWI method (the questionnaire was available online), and the representativeness of the sample structure was determined according to a robust consumer survey conducted in 2015 (POPAI, 2015). The age of the respondents was chosen as a critical attribute, as it is significantly reflected in the classification of users into individual groups according to diffusion of innovations. Table 1 summarizes the achieved frequencies in individual age categories in the original representative research (2015) with the own conducted research (2023).

Table 1: Age Structure Comparison. Source: Own processing.

Age Group	POPAI (2015) 3 255 respondents	Own research (2023) 420 respondents
up to 18	0 %	1 %
18 to 34 years old	32 %	40 %
35 to 54 years old	39 %	44 %
55 years and older	29 %	15 %

Due to the generally lower willingness of older individuals to participate in similar surveys, it was not possible to obtain a sufficient number of respondents in the 55 and over category. However, the behavior of the respondents within the individual clusters defined by diffusion of innovations corresponded to the fundamental assumptions. After evaluation the sample was as such found to be sufficient.

For the verification of the model according to UTAUT 2, all criteria were met, and the sample was even sufficient according to the ‘10-times rule’. This means that the optimal sample size should be ten times the number of internal or external links to the latent variables. Some scholars draw attention to the drawbacks of applying this rule. As examples, they cite the inability to take effect size, reliability or the number of indicators into account (Belle, 2011; Goodhue et al., 2012). Peng and Lai (2012) therefore only recommend using this computation if several conditions are met: primarily significant strength of effects and high reliability of measured items.

This regulation is widely used in UTAUT verification (Naranjo-Zolotov et al., 2018; Seethamraju et al., 2018; Senyo & Osabutey, 2020). The authors pay attention to the need to reflect on the weaknesses of the selected rule. However, the general difficulty of obtaining a relevant number of responses in such surveys, the application of the rule serves very well for determining the minimum sample. The structural model examined in this study contains nine bonds, and 112 answers were obtained. It meets the principle mentioned above with a sufficient margin.

STEP 3: Clustering respondents according to diffusion of innovations

At the beginning of the survey, all respondents filled in their primary demographic data such as sex, age and highest education. In order to obtain a basic overview of shopping habits, another question monitored the frequency of supermarket purchases. Based on the attained information, specific categories were defined with an emphasis on the behavior of scan&go non-users. Potential adopters further stated their reasons for not using scan&go and their possible future behavior. The expressed opinions were used for their subsequent classification into groups and according to diffusion of innovations. As part of the discussion, possible approaches to influencing their future decision-making about admission are presented.

STEP 4: Application of PLS-SEM

The opening part of the survey was concluded with a statement referring to experience with scan&go (I have used scan&go (or a similar tool) at least once, or I know how to use it.). If the respondents answered YES, they were redirected to the next part of the questionnaire based on the UTAUT theory. If they answered NO, the reasons for their behavior and possibilities to influence their future decision-making were followed.

In part, based on UTAUT, respondents answered 22 statements. A Likert scale was used to assess agreement. Marking the maximum seven stars means absolute agreement, and marking one star means absolute disagreement. A total of 235 respondents clicked through to this part of the questionnaire. The responses of users familiar with scan&go served as the basis for the final evaluation using the PLS-SEM method through SmartPLS 4.

In recent years, PLS-SEM has gained popularity due to its ability to estimate relationships in complex models with many variables and structural paths. A normal distribution is not a prerequisite for the input data so it can be classified as a non-parametric statistical method. Emphasis is placed on the predictive approach that is so valued among managers. The effort is to provide causal explanations for the researched phenomena (Hair et al., 2018).

Verification of the model, defined factors and relationships was implemented using bootstrapping. This non-parametric method tests the statistical significance of various PLS-SEM results, such as path coefficients, Cronbach’s alpha, HTMT (discriminant validity value) and R^2 values (Sarstedt et al., 2020). In bootstrapping, subsamples are created by randomly drawing observations from the original data set. In this way, many simulated selections (so-called bootstrap selections) are created. This process is repeated until a large number of random subsamples are generated, typically about 10,000. Based on these selections and the estimates of the parameter of interest in each, robust estimates of standard errors and confidence intervals can be obtained (Becker et al., 2022).

Parameter estimates (e.g., extrinsic weights, extrinsic loadings, and path coefficients) obtained from subsamples derive 95% confidence intervals for significance testing (e.g., original PLS-SEM results are significant when outside the confidence interval). In addition, bootstrapping also evaluates the standard errors of the estimate, which allows the calculation of test t-values to assess the significance of each estimate (Becker et al., 2022).

The evaluation must be carried out with due regard to internal consistency, convergent and discriminant validity. Composite reliability (CR) and Cronbach's α are used to evaluate internal consistency reliability. It is recommended that the composite reliability and Cronbach's values are greater than 0.7 (Hair et al., 2016). Convergent validity shall be supported if all standard loadings for each standardized item are higher than 0.70 and the average variance extracted (AVE) values obtained from every construct exceed 0.5 (Fornell & Larcker, 1981).

STEP 5: Discussion of results and presentation of recommendations for managers

The attained results are discussed at the end of the study. Recommendations on how to transfer theoretical outputs to the managerial level are also presented. In the final part, the limits of the research are given and possible directions for further research are outlined.

4 RESULTS

In the next part, summarizing the achieved outputs, the results of the classification of all consumers according to their attitude towards innovations are first presented. The responses of active or experienced users were also used to verify the success factors of scan&go adoption using UTAUT 2.

4.1 Diffusion of innovations

Table 2 summarizes the key characteristics of respondents.

Table 2: Demographics. Source: Own processing.

	Active users (out of 235)	Non-users (out of 185)	Total sample (out of 420)
Gender	**Frequency**	**Frequency**	**Frequency**
Male	95	77	172
Female	140	108	248
Age	**Frequency**	**Frequency**	**Frequency**
Under 18	2	2	4
18-34	125	44	169
35-54	82	101	183
55 and older	26	38	64
Highest level of education	**Frequency**	**Frequency**	**Frequency**
Grammar school	6	8	14
High school with an apprenticeship	8	22	30
High school with A-Levels	126	102	228

University degree	95	53	148

Shopping frequency	Frequency	Frequency	Frequency
Daily	21	20	41
2-3x per week	116	65	181
1x per week	70	56	126
1x per two weeks	18	26	44
1x per month	9	12	21
I prefer online shopping	0	2	2
I do not shop	1	4	5

Regarding the elementary classification of respondents into scan&go users and non-users, 56% (235 out of 420) of consumers are already familiar with the researched technology. From the point of view of Rogers' theory of innovation, it has already gained the attention of innovators, first adopters and the early majority (a total of 50%), and individuals from the late majority are also partially adopting scan&go. Consumers with a high school diploma (54%) and university education (40%) predominate among users, which corresponds to the assumptions defined for individuals with a positive attitude to innovation. The influence of age on the adoption of the innovation was also confirmed. More than half (125 out of 235) of experienced consumers fall into the 18 to 34 age category. While non-users most often, 55% (101 out of 185), fell into the category of 35 to 54 years. Scan&go users also shop more frequently (most often 2-3 times per week), which may reflect a greater willingness to try newly introduced technologies to save time and get an immediate overview of purchases made.

Respondents who have not yet adopted scan&go technologies were further interviewed in the questionnaire about the reasons for their current consumption behavior and about a possible change in future decision-making. Tables 3 and 4 present the results of follow-up research. Opinions are related both to individual age categories and to education. Respondents could check any number of reasons and directions for future behavior. In both cases, it was also possible to fill in the 'other' field.

Table 3: Reasons of non-users for their behavior. Source: Own processing.

Reasons for non-adoption	***System complexity***	***I'm afraid of purchase control***	***I do not want to join a loyalty programme***	***I do not know Scan&Go***	***I do not have confidence in Scan&Go***
Grammar school	0	1	2	3	0
High school with an apprenticeship	1	0	3	12	2
High school with A-Levels	19	8	23	42	10
University degree	5	1	18	15	3
Age					
Under 18	0	0	1	1	0
18-34	6	0	15	15	2
35-54	14	7	24	47	13

55 and older	5	3	6	9	0
Total	**25**	**10**	**46**	**72**	**15**

From the analysis of the main causes of the behavior of non-users thus far, it follows that almost 17% (72 out of 420) of respondents do not know this system at all. This fact almost exactly replicates the 16% threshold that Rogers set for latecomers. Ignorance of this technology can primarily be observed among older research participants and those with secondary education. Among other factors influencing the approach to scan&go adoption, we can select the obligation to register in the loyalty programme of selected supermarkets. This reason prevailed among university-educated respondents, who are apparently more aware of the potential misuse of stored data.

Table 4: Future behavior – possible customer tendencies. Source: Own processing.

Future behaviour	***I will never try***	***I might give it a try if someone explains it to me***	***I might try when I sign up for the loyalty programme***	***I am going to try it next time I shop***
Grammar school	1	3	3	0
High school with an apprenticeship	3	10	6	1
High school with A-Levels	20	42	29	1
University degree	10	18	13	0
Age				
Under 18	0	1	1	0
18-34	10	17	12	1
35-54	21	44	34	1
55 and older	3	11	4	0
Total	**34**	**73**	**51**	**2**

And what direction can the future behavior of non-users take? More than 68% (126 out of 185) of them admit the possibility of trying scan&go in the future. Most often, their behavior would be positively influenced by the assistance of a more experienced consumer (73 out of 185). A total of 51 respondents are also considering enrolling in a loyalty program, which they have not yet done. It can therefore be stated that these roughly two-thirds of scan&go users who are not yet familiar with it are willing to adopt these systems. About 30% of the total number of respondents would be new users. The potential therefore reaches up to 86% (56% of current users and 30% respondents are considering use). Figure 4 summarizes the outputs achieved using the diffusion of innovation principles.

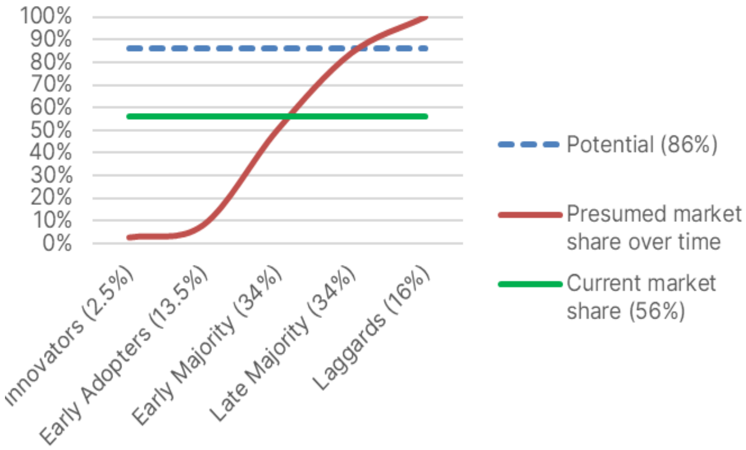

Figure 4: Diffusion of scan&go. Source: Own processing.

The red S-shaped curve shows the presumed cumulative market share over time as the scan&go is adopted by different segments of the population. The green horizontal line indicates the current utilization of scan&go. The dashed blue line indicates the potential maximum market share. The graph shows that scan&go has currently penetrated up to the late majority phase, achieving a 56% market share. There is still potential for further growth, with the maximum potential market share estimated at 86%. By addressing the specific concerns and preferences of the late majority, retailers can effectively encourage customers to adopt scan&go, thereby increasing market penetration and moving closer to the potential market share of 86%. They can provide targeted support, highlight not only cost benefits, offer discount and promotions or ensure the scan&go system is user-friendly and intuitive (Inman & Nikolova, 2017; Lawo et al., 2021).

4.2 Structural model

The structural model could be assessed because the design measures were found to be reliable and valid (see Appendix A). The path coefficients, the significance of them and their relevance shall be examined. Figure 5 demonstrates the R2 and path coefficient values.

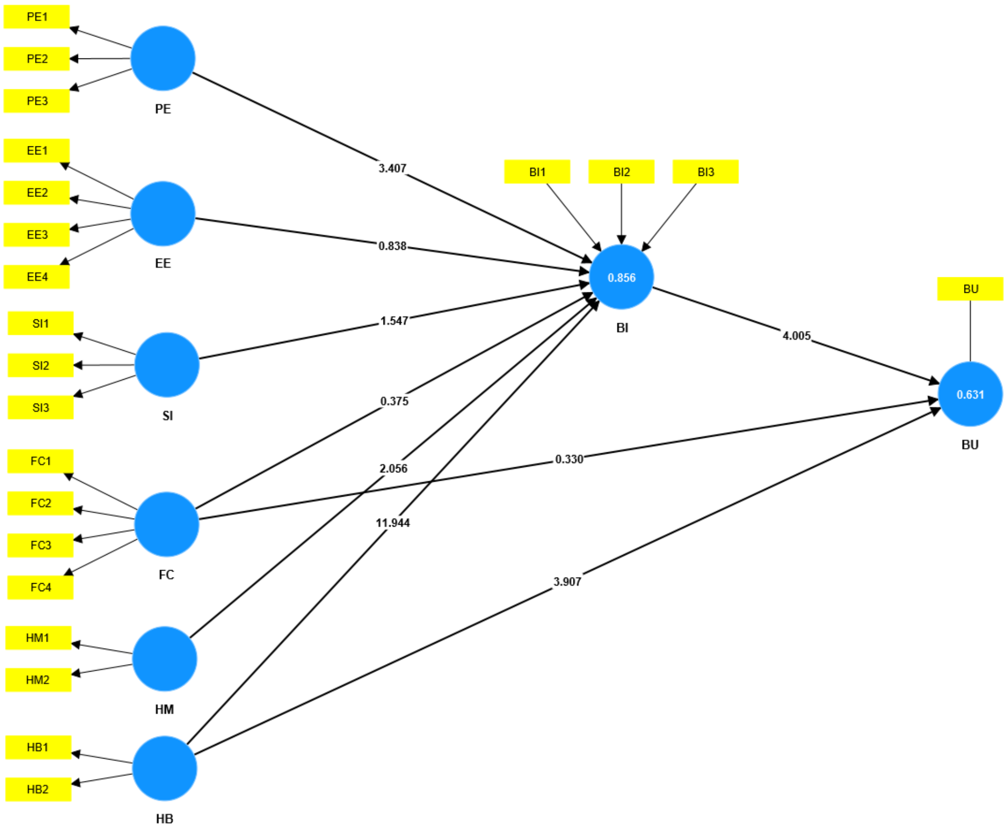

Figure 5: Assessed structural model. Source: Own processing.

The variance in behavioral intentions was explained by an 85.6% influence of the performance expectancy, hedonic motivation and habit, as seen in Figure 5. The variance in the use of scan&go was approximately 63.1%, explained by behavioral intention and habit. R-squared value explaining behavioral use falls into the category $0.5 < R2 < 0.7$, and these values are generally considered a moderate effect size. However, R-squared value explaining behavioral intention reaches 85.6%, and the effect of both variables can be marked as significant or high. Latent variables can generally be explained by the model, as it holds sufficient explanatory power (Henseler et al., 2009).

Table 5 summarizes t-statistic and p-values (significance level) for all the hypothesized relationships. Performance expectancy ($\beta = 0.182$, T-Statistics = 3.407, $p < 0.05$), hedonic motivation ($\beta = 0.107$, T-statistics = 2.056, $p < 0.05$) and habit ($\beta = 0.636$, T-statistics = 11.944, $p < 0.05$) positively influenced behavioral intention. H1, H5 and H6 were thereby supported.

However, effort expectancy ($\beta = 0.039$, T-statistics = 0.838, $p > 0.05$), social influence (β = 0.056, T-statistics = 1.547, $p > 0.05$) and facilitating conditions ($\beta = 0.015$, T-statistics = 0.375, $p > 0.05$) had no effect on behavioral intention. H2, H3 and H4 were thereby not supported. Furthermore, habit ($\beta = 0.420$, T-statistics = 3.907, $p < 0.05$) and behavioral intention ($\beta = 0.384$, T-statistics = 4.005, $p < 0.05$) positively influenced behavioral use of scan&go. Thus, H8 and H9 were supported. Only facilitating conditions ($\beta = 0.024$, T-statistics = 0.330, $p > 0.05$) had no effect on behavioral use of scan&go. Thus, H7 was not supported.

Table 5: Hypothesis testing. Source: Own processing.

Hypothesis	T-Stat.	β values	P-Value	Hypothesis
H1: PE positively influences BI to use Scan&Go.	3.407	0.182	0.001**	Supported
H2: EE positively influences BI to use Scan&Go.	0.838	0.039	0.402	Rejected
H3: SI positively influences BI to use Scan&Go.	1.547	0.056	0.122	Rejected
H4: FC positively influence BI to use Scan&Go.	0.375	0.015	0.708	Rejected
H5: HM positively influences BI to use Scan&Go.	2.056	0.107	0.040*	Supported
H6: HB positively influences BI to use Scan&Go.	11.944	0.636	0.000***	Supported
H7: FC positively influence BU of Scan&Go.	0.330	0.024	0.741	Rejected
H8: HB positively influences BU of Scan&Go.	3.907	0.420	0.000***	Supported
H9: BI positively influences BU of Scan&Go.	4.005	0.384	0.000***	Supported

5 DISCUSSION

In this study, a combination of two methods dedicated to adopting technological innovations (diffusion of innovations and UTAUT 2) was newly used in the retail sector. Previous studies investigated only factors influencing consumer behavior but not practical methods to influence future decision-making.

In the first part of the research, respondents were divided according to Rogers' diffusion of innovations. Different approaches to accepting new products or services were also evident in the examined sample. The adoption of scan&go in Czech supermarkets has already completed the first phase, when individuals with the most positive attitude to innovation adopted this technology. The early majority has already joined these innovators. In the examined sample, 56% of respondents already know scan&go. Managers therefore have to address individuals whose behavior can be classified as late majority and laggards. The follow-up study applying UTAUT 2, following the initial classification, had the goal of revealing factors influencing user behavior and behavioral intention across Czech consumers.

The explanatory power, especially when explaining the intention of the behavior, reached a high value. Performance expectancy, hedonic motivation and habit thereby explain 85.6% of the total variance. According to the determined values, habit is the most crucial driver of behavioral intention. The main task of managers, if they want to motivate customers to use such systems, is to find ways to break existing habits in usually routine activities. The results show that combining a change in shopping habits with a focus on expected performance (and achieving it) and hedonic motivation is best.

Wang et al. (2017) recommend gradually introducing fundamental changes to develop new habits, and it is essential to reach user satisfaction and awaken self-efficacy (Wang et al., 2017). Another way to support the adoption of self-service technologies is to divide customers into four categories according to their approach and payment habits: traditional users of classic cash registers, customers using self-service systems, situational users and drifting users. Based on this segmentation, a campaign promoting the newly introduced system can be targeted (Rinta-Kahila & Penttinen, 2021). This classification can thus suitably supplement the initial classification according to the general approach to innovation.

Already from the initial division of the obtained sample (only 235 respondents familiar with scan&go out of 420), it follows that almost half (44%) of customers still need to become familiar with the systems of self-scanning and paying for purchases. Thus, the respondents in the examined sample probably follow long-lasting shopping habits. These findings support the theory of personalizing incentives and helping customers to motivate them to try these technologies and build trust over time (Sharma et al., 2021). If organizations are to succeed in disrupting established habits, the technology must meet performance expectations. This finding aligns with other studies (Blut et al., 2022; Lin, 2022; Venkatesh et al., 2016). Performance expectancy may be supported by reward of cash or a bonus. This positive motivation was confirmed as a one of the efficient strategies to promote the use of mobile payment among young adults in Taiwan (Wei et al., 2021).

Scan&go adoption will also proceed better with the inclusion of hedonic motivation, i.e., users must enjoy themselves by applying technological innovation. Any kind of innovation is closely related to the awakening of the hedonic motivation of individuals by presenting the application itself as entertainment or enjoyment derived from technological progress (not only) in retail (Brown & Venkatesh, 2005).

The non-supported impact of the basic constructs of effort expectancy and facilitating conditions on behavioral intention may be related to the above-mentioned positive attitude of Czechs towards technological innovations. The possible difficulty and complexity that may appear during the first attempts to try a new technology will not deter Czech users from further use. According to data provided by Jörg Bauer, the CEO of Kaufland (the second largest retailer in the Czech Republic), almost 55% of daily turnover already passes through self-service devices (15% in 2021). Globus, the first to implement this system in the Czech Republic, is already over 60% of sales (in 2019, only 23%) (Adamcová, 2019; Vacovský, 2021).

The narrowly non-supported hypothesis H3 already reflects the exclusion of social influence from the testing in recent studies (Adapa et al., 2020; Blut et al., 2022; Sharma et al., 2021). The attitude towards using self-service or scanning devices in retail seems to be primarily driven by personal settings and experiences, regardless of the close surroundings. In the specific case of adopting technology in retail, it is possible to look for connections in the general habits associated with shopping. A large part of everyday shopping is done by individuals alone, so behavior is not determined by other people. It is only sometimes the case that having a shopping companion will lead to higher value and enjoyment of shopping (Borges et al., 2010).

In order to optimally influence the approach of individuals, the segmentation of the customer portfolio can therefore be considered again. A fundamental classification, which should help managers specify the requirements of individual groups, classifies customers into three groups: solitary shoppers, those who shop with friends, and those who shop with family. Two of the three categories involve group shopping; therefore, even though this hypothesis was not supported in this study, the influence of the social environment must be considered (Merrilees & Miller, 2019). On the contrary, it was shown that almost two-fifths of scan&go non-users (73 out of 185) would welcome additional explanations from another person. For the initiation phase of the adoption process, the involvement of other, already experienced, people is therefore crucial, especially for the late majority.

Regarding the explanation of the user behavior itself, 63.5% of the total variance can be explained by habit and behavioral intention variables. Once more, the initial hypothesis investigating the influence of facilitating conditions on the final decision to use scan&go was not confirmed, the reasons for which were already described in the last part of the discussion. The evident influence of user habits on their decision-making underlines the importance of including this factor across studies and research fields (Kašparová, 2022; Martinez & McAndrews, 2022; Nair et al., 2022; Wang et al., 2017).

6 CONCLUSION

The presented research focused on factors influencing the intention and behavior of customers when using scan&go technology in Czech stores. The article presents the results of a questionnaire survey conducted in April 2023 in the Czech Republic. In the first phase, all 420 respondents were classified according to their approach to innovation. This analysis was carried out on the diffusion of innovations basis. The main reasons for the thus far non-adoption of the researched technology and the intentions of the future behavior of non-users were also identified.

The data obtained from active users was processed using SmartPLS 4 based on the principles of the UTAUT 2 theory. The outputs indicate that when adopting new technologies, managers of retail companies should focus on the gradual disruption of existing habits, preferably emphasizing the new fun elements of the implemented innovations. The benefits of the (expected) performance that the given technology meets should also be highlighted. Specifically, with the scan&go system, customers could be interested in saving time, the possibility of continuous control of spent funds, easy payment and automatic registration of purchase receipts.

Like other studies, this one has its limitations. The research was only conducted in the Czech Republic. Moreover, the results achieved can thereby only be applied to a selected group of users. Czechs are considered supporters of technological innovation; therefore, they can serve as a suitable model for data collection in similar research. The theoretical basis was only built on UTAUT 2, and it would be possible to expand the examined constructs. Most scholars propose an extension of the investigated constructs based on the complexity of the technology environment. However, the increasing difficulty of collecting similar data, even on the basis of the results obtained from this study (non-supporting almost half of constructs), should rather lead to the specification and narrowing of the monitored factors. In such a case, when the questionnaire survey is too long, the reader's attention can wane, and the data loses its relatability.

Furthermore, in future research, the UTAUT 2 model could be verified by testing a different type of innovation. Similar studies would make it possible to compare the achieved results with another research on the same basis. With a more extensive database it would additionally be possible to appropriately define and supplement the current constructs specifically for young users. The goal of this direction should be to simplify the entire model so that it cannot only be used on a theoretical level, but also in practice. Further research should therefore be based on the identified outputs; the latest literary review focused on the selection/addition of suitable constructs and the presentation of practical recommendations applicable at all managerial levels.

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APPENDIX A: EVALUATION OF THE MEASUREMENT MODEL

Table I and Table II show an assessment of the construct's reliability and validity. The above criteria are met by all measured values; therefore, their convergent validity can be regarded as good for all constructs.

Table I: Internal consistency reliability. Source: Own processing.

Construct	Cronbach's alpha	Composite reliability
Performance expectancy	0.881	0.883
Effort expectancy	0.952	0.954
Social influence	0.916	0.918
Facilitating conditions	0.803	0.804
Hedonic motivation	0.915	0.942
Habit	0.935	0.935
Behavioural intention	0.945	0.947

Table II: Convergent validity. Source: Own processing.

Construct	Average variance extracted (AVE)	Outer loadings
Performance expectancy	0.808	
PE1		0.870
PE2		0.923
PE3		0.903
Effort expectancy	0.873	

EE1		0.912
EE2		0.952
EE3		0.917
EE4		0.957
Social influence	0.856	
SI1		0.943
SI2		0.930
SI3		0.901
Facilitating conditions	0.630	
FC1		0.794
FC2		0.803
FC3		0.832
FC4		0.742
Hedonic motivation	0.921	
HM1		0.951
HM2		0.968
Habit	0.939	
HB1		0.968
HB2		0.970
Behavioural intention	0.902	
BI1		0.944
BI2		0.931
BI3		0.973

If the square root of each construction AVE exceeds the squared correlation of any other construction, the discriminant validity shall be achieved (Hair et al., 2016). The square root of the AVE (ranging from 0.793 to 1), as shown in Table III (diagonal values) for each of the constructs, was also higher than its highest correlation with any other construct. The discriminant validity of those scales has therefore been validated in this model.

Table III: Discriminant validity – square root of AVE (in bold) and inter-construct correlations. Source: Own processing.

Construct	BI	BU	EE	FC	HB	HM	PE	SI
Behavioural intention	**0.950**							
Behavioural use	0.770	**1.000**						
Effort expectancy	0.588	0.490	**0.935**					
Facilitating conditions	0.467	0.385	0.673	**0.793**				
Habit	0.897	0.775	0.523	0.437	**0.969**			
Hedonic motivation	0.747	0.555	0.562	0.478	0.708	**0.959**		
Performance expectancy	0.771	0.578	0.681	0.433	0.700	0.705	**0.899**	
Social influence	0.613	0.489	0.272	0.218	0.604	0.541	0.541	**0.925**

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